Development of a Context-aware Telemedicine Framework and it's use in Promoting Safe Aging in Place through Wearable and Smart Home Technology

Development of a Context-aware Telemedicine Framework and it's use in Promoting Safe Aging in Place through Wearable and Smart Home Technology

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Michael Zon, B. Sc

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AUTHOR: Michael Zon, B.Sc; University of Guelph

SUPERVISOR: Qiyin Fang, Ph.D.

Lay Abstract

With the advance of low cost IoT technology and embedded sensors, telemedical systems have become more common within medical research. Thanks to various vendors with automated processes for creating printed circuit boards, computationally powerful microcontrollers can easily be integrated with sensors that measure physiological parameters to build telemedical monitoring systems. Although many remote monitoring systems have been created, very few have made their way into patient's lives despite the increasing need to pre-emptively detect mobility decline and disease in older adults to reduce strain on healthcare systems. One major limitation with these medical systems is their lack of understanding regarding users' context which ultimately limits their decision making capabilities. For instance, a remote system may detect a heart rate of 160 BPM, however, without the context surrounding whether the user is active at that time or immobile it is impractical to determine whether this is a benign or dangerous situation. The aim of this research was to develop a framework for telemedical systems that integrates context to build remote monitoring systems which can better understand physiological data and make informed decisions to pre-emptively detect conditions/diseases. A systematic review was conducted to identify which contexts are most prevalent in context-aware medical systems, and what the various categories of context-aware medical applications are. The important contexts discovered were then used to build a framework for context-aware medical systems that converts sensor data into contexts/situations in order to run clinical tests and quantify the likelihood a patient has a given condition, disease or adverse event. Lastly, the framework was used to develop a smart home system with a context-aware emergency alert application and then piloted in older adults' homes.

Abstract

The present work focused on building a framework for context-aware telemedical systems which can leverage physiological data from sensors within its context to quantify the likelihood of medical events, conditions, and diseases for users. A context-aware smart home system was built for both validating the framework and demonstrating how it could be used to build medical applications. A systematic review was conducted in order to identify which contexts are most prevalent in context-aware medical systems and what the various categories of context-aware medical applications were. A total of 23 articles passed all screening levels and underwent data extraction. The most common contexts used were the user location (8/23 studies), demographic info (5/23 studies), movement status/activity level (6/23 studies), time of day (5/23 studies), phone usage patterns (5/23 studies), lab/vitals (7/23 studies), and patient history data (8/23 studies). The important contexts discovered used to build a framework for context-aware medical systems that converts sensor data into contexts/situations in order to run clinical tests and quantify the likelihood a patient has a given condition, disease or adverse event. Context probabilities, clinical test/situation results, and post-test probabilities for Parkinson's and falling within 12 months were compared between experiments where healthy users emulated mobility impaired and unimpaired adults who had a positive or negative outcome for common clinical tests. The post-test probabilities determined by the system for falling within 12 months or having Parkinson's were statistically significantly ($p < 0.05$) higher in the mobility impaired group relative to the unimpaired group, thus validating the theory's utility in autonomously establishing contexts and using them to conduct tests. This framework was then used to develop a smart home system with a context-aware emergency alert application that could utilize mobility and heart rate data within its context to determine if physiological data was (or was not) indicative of an emergency. The context-unaware alarm triggered an emergency when the user's heart rate was elevated during exercise, whereas the context-aware alarm was not triggered as it was able to recognize the active context for the user. The context-unaware alarm also triggered while the user emulated sleeping, whereas the context-aware alarm was not triggered since it could recognize the time of day was within normal sleeping hours. Lastly, the system was piloted in older adults' homes and it was demonstrated that select contexts such as immobility time, the time users started or ended their day, and whether users were moving between rooms could be determined autonomously using the framework.

Acknowledgements

I would like to thank my supervisor Dr. Qiyin Fang for his guidance throughout my PhD, which was pivotal to learning how to develop novel/practical research questions and to properly validate hypotheses stemming from these questions. Additionally, I would like to thank Dr. Deen for his guidance in characterizing the sensors/systems developed through my PhD both through committee meetings and his work/reviews within the smart home field. Dr. Francombe's feedback throughout the committee meetings was also invaluable for developing the emergency system and understanding the practical applications and possible drawbacks around integrating these systems in current healthcare systems. Lastly, I would like to thank Dr. Hayward for his insights throughout the committee meetings and feedback during my comprehensive exam, which was invaluable for understanding the grant application process and how to form and request funding to test research questions.

Having had the privilege to study under both the Biomedical Engineering department and Michael DeGroote School of Medicine, I would like to thank both these faculties for their support over the last 5 years. My medical student supervisor, Dr. Margetts, and MD/PhD program director, Dr. Van Lieshout, were also great sources of support throughout both degrees who I would like to thank for their guidance. I would also like to thank the Natural Sciences and Engineering Research Council of Canada for funding my research throughout my doctoral studies.

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List of Abbreviations

ADC	Analog to Digital Converter
ADL	Activities of Daily Living
AI	Artificial Intelligence
ALS	Amyotrophic Lateral Sclerosis
BLE	Bluetooth Low Energy
BP	Blood Pressure
BPM	Beats Per Minute
CKD	Chronic Kidney Disease
DLI	Drug Lab Interactions
EMR	Electronic Medical Records
FOG	Freezing of Gait
FP	False Positive
FN	False Negative
FSR	Force Sensitive Resistor
HCP	Healthcare Provider
HR	Heart Rate
IADL	Instrumental Activities of Daily Living
ICU	Intensive Care Unit
IPS	Indoor Positioning System
IQR	Interquartile Range
IST	Inappropriate Sinus Tachycardia
IoT	Internet of Things
LR	Likelihood Ratio
LR+	Positive Likelihood Ratio
LR-	Negative Likelihood Ratio
MIRA	McMaster Institute of Research in Aging

Declaration of Academic Achievement

First Author

Gendoo, D. M., **Zon, M (co-first author)**., Sandhu, V., Manem, V. S., Ratanasirigulchai, N., Chen, G. M., ... & Haibe-Kains, B. (2019). MetaGxData: Clinically Annotated Breast, Ovarian and Pancreatic Cancer Datasets and their Use in Generating a Multi-Cancer Gene Signature. *Scientific Reports*, 9(1), 8770.

Zon, M., Ganesh, G., & Fang, Q. (2022). Context Aware Medical Systems within Healthcare Environments: A systematic scoping review to identify subdomains and significant medical contexts. Submitted to *IEEE Journal of Biomedical and Health Informatics*.

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.

Zon, M., Ganesh, G., & Fang, Q. (2022). Autonomous Context Detection for Safe Aging in Place using Fuzzy Probability and Context-Aware Smart Home Technology. Manuscript in preparation for submission.

Co-Author

Bednar, E. D., **Zon, M.,** & Abu-Hilal, M. (2022). Morbidity and Mortality of Melanoma on the Trunk and Extremities Treated With Mohs Surgery Versus Wide Excision: A Systematic Review. *Dermatologic Surgery*, *48*(1), 1-6.

Paul, M., Saibil, S., Lien, S., Han, S. J., Sayad, A., Mulder, D., Garcia-Batres, C., Elford, A., Israni-Winger, K., Robert-Tissot, C., **Zon, M**., ... & Ohashi, P. (2019). IL-6 induces an IL-22+ CD8+ T cell subset with potent anti-tumor function. *Cancer immunology research*, In Press.

Zhao, K., **Zon, M**., Fang, Q., & Santaguida, P. (2021). Smart homes to aid in the early diagnosis of mobility decline: A scoping review. Submitted to *IEEE Sensors*

Software Packages & Protocols

Zon M, Sandhu V, Haibe-Kains B (2019). MetaGxPancreas: Transcriptomic Pancreatic Cancer Datasets. R package version 1.6.0.

Zon M, Gendoo DM, Haibe-Kains B (2018). MetaGxBreast: Transcriptomic Breast Cancer Datasets. R package version 1.6.0.

Zon M, Gendoo DM, Haibe-Kains B (2018). MetaGxOvarian: Transcriptomic Ovarian Cancer Datasets. R package version 1.6.0

Zhao, K., **Zon, M**., Fang, Q., & Santaguida, P. (2020). *Smart homes to aid in the early diagnosis of mobility decline: A scoping review*. Retrieved from osf.io/qsnd3

Project Contributions

For the review paper presented in **Chapter 2** I developed a search strategy, wrote the reviews protocol, searched eight databases for relevant papers, screened the 1300+ resulting abstracts, extracted data from the relevant papers, and wrote the manuscript. I then used the data to investigate/report common algorithms used for context detection and developed subdomains for context-aware medical applications based on the results. Guha Ganesh served as a second screener for the study and Dr. Fang supervised the study.

The smart-home system developed in **Chapter 3** was initially developed by the author using Raspberry Pi devices. The smartwatch prototype that broadcasted the user's location to the beacons was developed by the author along with the Flutter mobile application that received the accelerometer data. Guha Ganesh replaced the Raspberry Pi beacons with ESP32's and wrote software to broadcast the sensor and BLE data to the central Raspberry Pi. The fuzzy probability theory for context determination, method to leverage multiple sensors to increase the certainty of contexts, and spatio-temporal context networks used to model situations/clinical tests was developed by the author. Additionally, the derivation to adjust the prognostic value of clinical tests given probabilistic uncertainty in the contexts comprising the test was done by the author. Dr. Fang reviewed the theory and manuscript, supervised the study, and identified context-awareness sensing as pivotal to useful medical systems

The real-time emergency system presented in **Chapter 4** using the context-aware smart home hardware/software was developed by the author. I built smartwatch software that uploaded mobility/heart-rate data to the cloud which was subsequently downloaded and processed by server-side code I developed to check if emergency conditions were triggered. I also built a desktop application that could be used by healthcare providers to set emergency alarm conditions and view data collected by the system in real-time. The updated context-aware medical framework that categorizes physiological data according to the context was theorized by the author. Dr. Qiyin Fang supervised the study, helped devise the context-aware versus no context experiments, and reviewed the manuscript.

Chapter 5 contains my final contribution to the context-aware smart home project. I completed a research ethics board (REB) application to get permission to send our system to older adults across Hamilton. I then built/shipped multiple systems, recruited participants, devised a remote calibration system in light of the no contact requirements during COVID19, and wrote R code to synchronize the smart-watch and ESP32 beacon data. Subsequently, I identified key contexts we could obtain from the data, wrote analysis code to identify the accuracy that we could find these contexts in the study data, and prepared a manuscript describing the results. Guha Ganesh helped build multiple systems and Cody Cooper helped develop the smartwatch code that was sent to participants. The pilot study was devised by Dr. Fang, and Dr. Fang supervised the research resulting from the study's data.

Chapter 1

Introduction

Modern improvements in healthcare have led to increased life expectancy in many countries, causing an increased older adult demographic over the past few decades. A consequence of this has been financial strain on many healthcare systems due to problems that primarily affect older adults. For instance, falls cause over 85% of seniors' injury related hospitalizations in Canada and 2 billion a year in direct healthcare costs[1]. Additionally, these falls are the cause of 95% of all hip fractures, of which the 12 month morbidity rate in those with a hip fracture is 21%[2]. Many of these older adults are placed in retirement homes after a fall/fracture, which also reduces their overall quality of life relative to being able to live independently at home. One primary issue is the reactive nature of current healthcare systems, which deal with the problem once it occurs as opposed to pre-emptively detecting individuals at high risk for falling or other aging related diseases (e.g Parkinsons, Alzheimer's, etc)[3]. A need exists for regular assessments of older adults to intervene in advance of these issues and promote safe aging in place. However, it is well understood that it is not practical to have healthcare providers regularly assess every older adult to look for high risk individuals. Thus, regular assessments of older adults must be conducted in an automated, remote, and cost-effective manner using telemedical systems in order to promote safe aging in place. Indeed, many groups have begun to work towards building these remote monitoring systems for gait assessment using infrared sensors[4], cameras[5], and other devices[6] to improve quality of life in society's older demographic.

1.1 Motivation

The goal of the present work was to develop a framework for telemedical systems that promotes safe aging in place. We hoped to create a system for automating clinical tests so that information relevant to specific diseases or dangerous events, like falling, could be obtained regularly to pre-emptively detect these issues, intervene early, and thus prolong safe aging within one's primary residence. We chose to develop a smart home system to implement the developed framework given that an older adult's primary residence is their most frequented location, and thus the place that measurements can be taken most often.

Given that mobility decline is seen in many diseases, and can be treated as a more general indicator of a person's current health if they are not (known to be) suffering from a chronic illness,[7] [8] we chose to link our smart home system to a smartwatch that could collect step count data through its inertial measurement unit. Mobility decline can also be used as a metric for fall risk or disease progression in the case of various chronic diseases such as Parkinson's, Alzheimer's, and Amyotrophic Lateral Sclerosis (ALS)[9]–[13]. Thus, by focusing on capturing mobility levels the system could have the potential to monitor disease progression in some cases, or can at least be reasonably tested to be useful for tracking the progression of diseases in the future. Activities of daily living (ADLs) have similar prognostic relevance for pre-emptive detection of falls as many people reduce their ADLs, or take longer to complete them, as their gait declines[14]. Thus, the smart home system was prepared to capture mobility information through an indoor positioning system so we could better understand users ADLs.

Physiological data, such as heart rate, blood pressure, respiratory rate, etcetera, are relevant for determining whether a patient's overall health is within a safe range and avoiding the exacerbation of acute problems. However, it became apparent that without the context surrounding physiological data (and other sensor data), it would be impractical to make correct medical decisions with a smart home system. For instance, if the system returns a heart rate of 160, how does one know if this is sinus tachycardia due to

exercise, or a dangerous arrhythmia outside of the person's normal range? Context-awareness sensing, which is the notion of using context within medical systems[15], was identified as a pivotal requirement for the system as it provides a solution for this by categorizing the heart rate based on the activity. As an example, if the person's heart rate is 160 while their activity levels are higher than usual, and their GPS says they are at the gym, then one may classify this as benign based on the activity and location context. By contrast, if the person is not moving in their bedroom in the middle of the night the context suggests the same heart rate (160) is much more likely to be a dangerous event. Contextual conditions must also be met for many clinical tests, such as the requirement that a patient must be sitting with back support and their legs uncrossed during a blood pressure measurement[16]. Given the importance of context for understanding medical data, the system was adapted to become context-aware and a generalized approach to determining contexts and using them to conduct clinical tests was developed.

Although context became one of our requirements, most groups seemed to collect it through ground truth labeling of recorded contexts and then use this data to build machine learning (ML) models[17]–[19]. However, it became apparent that clinicians were both hesitant to base their decisions on results from ML[20] models and that labeling data each time a new context is desired would not be a practical long term solution[21]. Thus, we sought to create a method to autonomously determine contexts through sensor data so systems could be installed in older adults' homes and used to detect useful contexts immediately instead of requiring months of training data collection. Additionally, the approach developed was designed to be deterministic, instead of stochastic like many ML models, so that the relationship between the data and patient outcomes would be clear to healthcare providers and more likely to be adopted. We realized that many clinical tests could be broken into simple, high certainty contexts, and that the known relationship between these tests and diseases through likelihood ratios could be used to avoid complicated models and assign a probability to a user that they have a condition.

In addition to developing a framework for quantifying users likelihood of adverse outcomes for safe aging in place applications, we wanted to demonstrate how context-aware systems could be used to build intelligent context-aware applications. Thus, a context-aware emergency system was developed in order to demonstrate how context can be used to rule out false positives, such as an elevated heart rate that is appropriate for the users activity level. We felt it was important to formalize this notion of assessing physiological data in its context to better define the structure of context-aware medical systems. Thus, prior context-aware frameworks were adapted to develop a context-aware medical framework. Lastly, the goal of the work was to build a context-aware smart home system that could promote safe aging in place. Thus, we wanted to pilot the system and framework in older adults to demonstrate its viability. To this end, a small pilot study was conducted with research ethics board approval to demonstrate the system and framework could autonomously detect some medically relevant contexts.

1.2 Research Roadmap

A roadmap was developed to direct research towards the development of telemedical systems for safe aging in place through pre-emptive detection of adverse medical events. The complete system comprises 6 primary chronologically ordered modules.

Module 1 entails the development of a low cost and scalable system to enable data acquisition. In this work, simple plug and play devices were developed so any older adult could implement the system in their primary residence. The system relies on low cost and low power IoT sensors with a scalable software architecture that allows for easy integration of new devices through the ESP_NOW protocol[22]. As shown in the broader roadmap, older adults' electronic medical records should eventually be linked to their remote

health monitoring systems so sensor data which is relevant for disease management can be relayed to healthcare providers when necessary (e.g blood pressure data in hypertension monitoring).

Module 2 is the processing of the collected data and its use in determining contexts. First the data is preprocessed, which may include time synchronization between the various sensor modules, interpolation in the presence of missing data, or applying filters to smooth noisy sensor data. Next, the sensor data is analyzed to create new parameters. An example of this would be using known algorithms to obtain step counts from accelerometer data[23]-[24]. Lastly, a context determination step is needed to translate the data into useful contexts (which may be user activities) such as sitting, walking, eating, etcetera.

Once the data has been processed to obtain contextual data, module 3 is used to understand the user's situation, defined through aggregates of contexts,[25] and apply clinical tests that can be modeled through situations in order to understand/update a user's probability for a given disease or outcome. The framework provides the slow gait speed test as an example, where the smart home system detects a 0.5 m/s gait speed which leads to a 2.0 times increased likelihood of falling over 12 months[26]. In the present work, tests for fall risk and Parkinson's are emulated as a starting point to demonstrate the framework.

Module 4 focuses on using the situations/test results to determine the likelihood an older adult has a disease or event based on the known relationships between the tests and disease/event. Baseline pre-test probabilities are assigned to users based on epidemiological data (e.g 33% chance to fall in 12 months if over 65), and likelihood ratios relating the known test results impact on a disease's odds are used to generate post-test probabilities [26]. For instance, in figure 1.1 module 4b John Smith is positive for the slow gait, support to rise, and taking more then 3 medications tests. Multiplying the individual likelihood ratios on to his pre-test odds of 0.5 leads to a post-test probability of 85% for falling. Additionally, module 4a shows how learning algorithms can be used to identify new tests based on the relationship between multiple older adults that have a disease/event (outcome) and the measured contexts (inputs/predictors). The likelihood ratios resulting from these new clinical tests can then be applied to further determine the post-test probabilities older adults have a given condition for pre-emptively detecting the issue [27].

Module 5 of the research roadmap focuses on utilizing the post-test probabilities that define an older adult's likelihood for a given outcome. The post-test probability of the disease or event is used to trigger diagnosis/detection based on known clinical criteria or thresholds provided by healthcare providers. For instance, the system may diagnose Stage 1 Hypertension on its own if systolic blood pressure is constantly over 140 mmHg [28], or a physician may decide to implement a fall intervention program for any older adult with a chance of falling greater than 80% in the next 12 months.

Lastly, module 6 applies the interventions by changing medical applications within or outside of the smart home based on the findings. This makes the system truly context-aware according to the modern definition, which requires changes to the application based on context [15]. For instance, an external mobile app may request that the patient check their blood pressure regularly to ensure it is under 140/90 mmHg given the new information about their hypertensive state. Alternatively, the smart home may start prompting the older adult to take their blood pressure pills regularly through a smart-pillbox [29]-[30].

This generalized research roadmap for telemedical systems starts from sensor data and quantitatively assigns probabilities to diseases/events by autonomously determining contexts to conduct known clinical tests and avoid cumbersome training data labeling. Thus, it satisfies the goal of providing a practical approach to pre-emptive detection of medical issues for promoting safe aging in place.

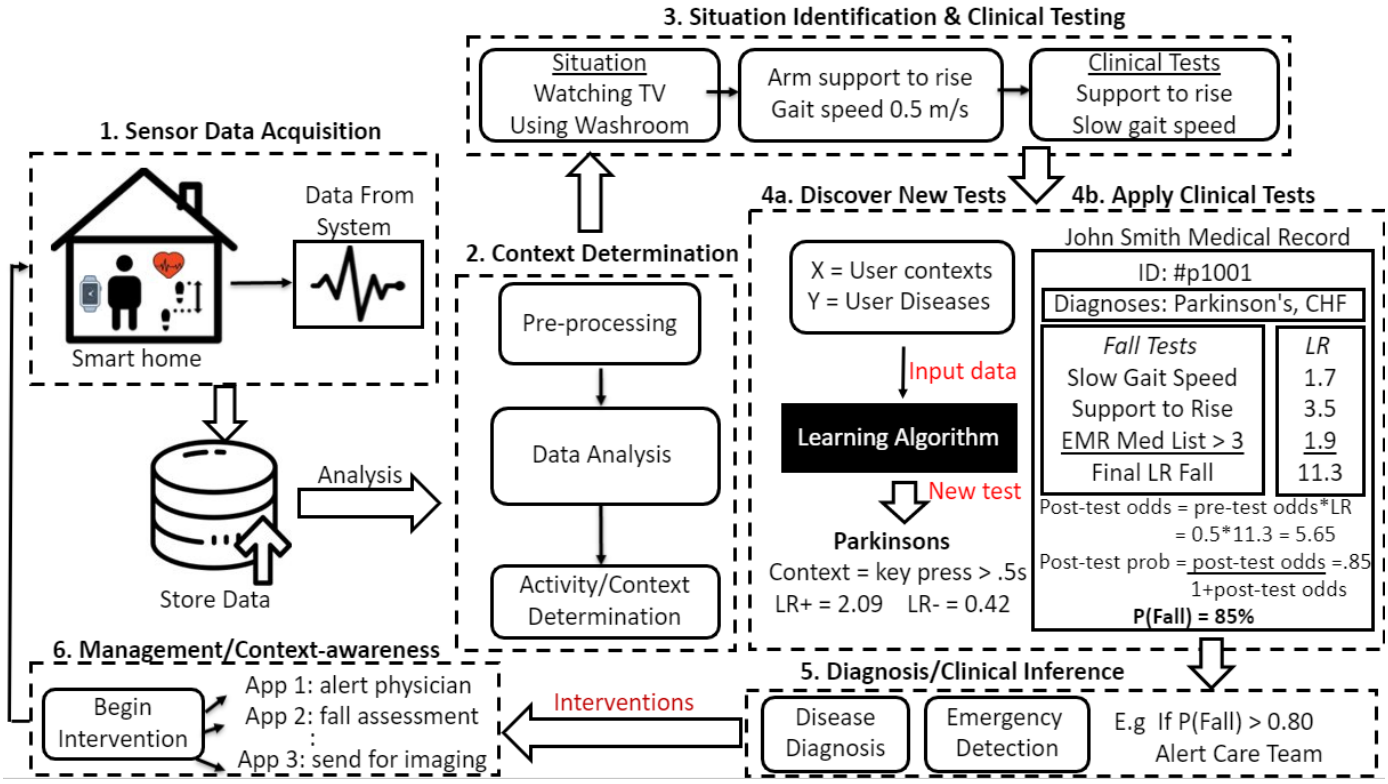

Figure 1.1 Proposed research roadmap for context-aware telemedical systems for safe aging in place through pre-emptive detection of adverse medical events

1.3 Thesis Overview

The goal of the present work was to develop a telemedical system and framework that could be used to pre-emptively detect medical problems and advance the research roadmap for promoting safe aging in place. The implementation of a context-aware smart home system was identified as an effective way to conduct regular assessments on older adults to track longitudinal changes in their health and eventually intervene when trends deviated from normal. Thus, a context-aware smart-home system was developed to meet the goal of pre-emptively detecting medical problems to promote safe-aging in place. In the first chapter of this thesis, a systematic scoping review of past context-aware medical systems is conducted in order to determine what contexts our system should prioritize prior to being built. Following this, a system is built that prioritizes these contexts (namely location, mobility level, and time of day) and an algorithm is developed to determine user contexts and quantify the probability that a medical problem exists. Next, chapter 4 presents an application of this system/algorithm for detecting emergencies to show the frameworks viability. Lastly, the system was sent to multiple older adults as part of a pilot study to demonstrate its viability in a clinically relevant setting using data from actual participants. Through completing this work, four milestones and contributions were accomplished towards completing the context-aware telemedical research roadmap for safe aging in place outlined in figure 1.1.

In milestone 1, a systematic scoping review (paper I) was conducted to determine what the most significant medical contexts being leveraged across systems are, and what the most common context detection algorithms were in systems being used in clinical settings. This was done to ensure the system developed in the present work collected the most clinically relevant contexts, and to understand what algorithmic options existed for determining contexts via the system. Subdomains of context–aware medical applications were also created based on the findings to partially validate the domains that were

hypothesized for ambient intelligent systems [31] and to create specific domains for context-aware systems based on the current research climate.

Next, many of the general modules in the research roadmap were completed in the process of using the most relevant contexts identified in the review to develop the health smart home system for safe-aging in place used in the remaining work (paper II). First, hardware and software pertaining to a plug and play context-aware smart home system was developed (Sensor Data Acquisition module of the roadmap). Following this, the Context Determination Module was completed through the development of a context determination algorithm that leveraged Zadeh's fuzzy probability[32] to determine high certainty contexts autonomously without ground truth data. The algorithm was then extended to situation detection by representing situations as spatiotemporal context networks in order to model medical emergencies, adverse events, and common clinical tests as situations consisting of contexts that are measured by the system. Clinical tests were modeled as situations so they could be conducted on users by the system and then used to determine their probability of having an adverse medical event or disease. The system and algorithm were then used to emulate fall risk and Parkinson's tests to demonstrate the systems usefulness in pre-emptively detecting medical problems (Situation Identification & Clinical Testing module). In order to convert the test results into an actual probability of users having a medical problem, the test results likelihood ratios were applied to the baseline odds of the user having the condition/disease and then these new odds were converted to probabilities (Apply Clinical Tests module) [27].

After the framework and technology was built, it was applied in an emergency detection setting to demonstrate the need for context in emergency detection and to show the systems use in the Diagnosis/Clinical Inference and Management/Context-Awareness module (paper III). Software was developed which allows healthcare providers to determine under what mobility, location, time of day, and heart rate contexts an emergency alarm should be triggered. The system's software was extended to allow it to read these settings in real-time. It was also extended to transmit the data to a server where it could be analyzed in real-time to determine if the emergency conditions were met, thus showing its viability for emergency detection (Diagnosis and Clinical Inference module). Both the desktop software controlled by the healthcare provider and smartwatch worn by the user were updated based on the emergency alert in order to provide an example of the system adapting to contexts and thus being used in a context-aware application (Clinical Management/Context-Awareness module).

Finally (paper IV), after building the hardware/software, developing the framework, and using the framework to build a context-aware application the system was sent to multiple older adults in Hamilton in order to obtain data from real users, test whether it could easily be used by older adults, and to demonstrate that contexts can be determined autonomously in older adults' homes via the system. This pilot study aimed to reinforce what was demonstrated in the prior work, but to do so with data collected in a clinically relevant setting as a first step towards using the system in older adults' homes for pre-emptive detection of medical events/conditions.

1.4 Thesis Organization

The first chapter of the present work represents an introduction to the problem, the motivations for conducting the research, and a roadmap of what is required to build the telemedical system for safe aging in place. It also discusses how the work presented in this thesis fits into the roadmap.

Chapter 2 presents a review of context-aware medical systems that have been used by patients and healthcare professionals. Subdomains of context-aware medical applications are developed based on the classes of applications that resulted from the search strategy. The most common contexts used in these systems are identified along with trends in the algorithms used for context determination. Location and

time of day were identified as pivotal contexts to be prioritized in the remaining work and no common context determination algorithm was found, leading to the need to develop a custom solution in chapter 3.

Chapter 3 focuses on building the algorithms and technology that support the context-aware telemedical framework for pre-emptive detection of diseases/adverse events. The system is built to prioritize obtaining the most important contexts that were identified in chapter 2. A portable plug and play smart home system consisting of an indoor positioning system and smartwatch is built, and the fuzzy probability theory used to establish contexts without ground truth data is described. Situations and clinical tests are described as spatiotemporal context networks and a derivation which adjusts the prognostic value of clinical tests as a function of the probability that the system conducted the test is shown. The algorithms and smart home system are then used to demonstrate how the system can quantify the likelihood of Parkinson's and falls in older adults and identify high risk individuals in general.

Chapter 4 applies the framework to build a context-aware application, namely an context-aware emergency system, and demonstrates the limitations of emergency systems that lack context. Context-aware alarms are compared to those that lack context to demonstrate that context can be used to rule out false positives in different circumstances. Additionally, a framework for classifying physiological data within the context it was measured in is developed.

Chapter 5 describes a pilot study where the system was sent to older adults throughout Hamilton for testing in a clinically relevant setting. High certainty contexts (e.g sleeping once a day) are used to establish the systems accuracy in determining contexts autonomously to demonstrate the framework's ability to detect contexts in a non–simulated environment.

Chapter 6 concludes the thesis, providing a summary of the main findings of the chapters along with a brief discussion. Additionally, future work is discussed in the context of the research roadmap. Areas of the roadmap that were not covered in the present work but are needed to build an optimal context-aware telemedical system for safe aging in place, are emphasized.

The **Appendix** of the thesis contains 3 works relevant to chapters 2-5. The first appendix heading, titled Compact Bluetooth Low Energy based Indoor Positioning System for Smart Home's, contains a more detailed characterization of the hardware, software, and indoor positioning system accuracy of the smart-home system used in the present work. The section titled, Scoping Review Protocol, contains details about the search strategy and study inclusion/exclusion criteria used to conduct the scoping review presented in chapter 2. Lastly, the section titled REB protocol describes the protocol and inclusion/exclusion criteria used for recruiting participants for the pilot study, whose results are described in chapter 5.

1.5 Contributions

The present work sought to further develop telemedical systems for safe aging in place applications. Theory and findings pertaining to this field were summarized into 4 manuscripts which were written by the author and reviewed by Dr. Qiyin Fang.

The review paper presented in **Chapter 2** comprised a systematic scoping review of current context-aware medical systems being used by healthcare providers or their patients. I developed a search strategy, wrote the reviews protocol, searched eight databases for relevant papers, screened the 1300+ resulting abstracts and extracted data from the relevant papers. I then used the data to investigate common algorithms used for context detection and developed subdomains for context-aware medical applications based on the results. Guha Ganesh served as a second screener for the study. Dr. Fang supervised the study and reviewed the paper. The significant contribution of the review was the identification of the most widely

used medical contexts, the discovery that no common context determination algorithm is being used across systems, and the creation of the subdomains of context-aware medical systems.

The system and theory developed in **Chapter 3** was initially developed by the author using Raspberry Pi devices. Sensors were connected to the Raspberry Pi and software was written that uploaded the data to the cloud and stored it on the device. The smartwatch prototype that broadcasted the user's location to the beacons was developed by the author along with the Flutter mobile application that received the accelerometer data. Guha Ganesh replaced the Raspberry Pi beacons with ESP32's and wrote software to broadcast the sensor and BLE data to the central Raspberry Pi. The fuzzy probability theory for context determination, method to leverage multiple sensors to increase the certainty of contexts, and spatio-temporal context networks used to model situations/clinical tests was developed by the author. Additionally, the derivation to adjust the prognostic value of clinical tests given probabilistic uncertainty in the contexts comprising the test was done by the author. Dr. Fang reviewed the theory and manuscript, supervised the study, and identified context-awareness sensing as pivotal to useful medical systems. The significant contributions of this work include the development of a non machine learning (ML) based method of autonomously establishing contexts without ground truth data (roadmap module 2), a standardized way of obtaining contexts/clinical tests from sensor data (roadmap module 3), the derivation for adjusting the prognostic value of clinical tests from telemedical systems, and a framework to quantify the likelihood an older adult has a disease or is susceptible to an adverse event (roadmap module 4).

Once the system and theory were developed I was inspired to demonstrate via **Chapter 4** that there is a need for context in medical systems, and that these systems must categorize physiological data according to the context it is measured in. The smartwatch prototype was replaced with an Android smartwatch with custom software developed by the author and Cody Cooper. Server-side code and a desktop application were developed by the author that allowed healthcare providers to set the location and mobility/heart rate conditions under which an emergency would be triggered (roadmap module 5 & 6 demonstration). Dr. Qiyin Fang supervised the study, helped devise the context versus no context experiments, and reviewed the manuscript. The significant contribution of this work was the demonstration that context is needed to differentiate whether the same physiological data is from a benign or dangerous event and that this is needed to rule out false positives in emergency alert systems. An additional contribution was the update to Musumba and Nyongesa context-awareness framework[33], which summarized Bardram and Hansen's work[34], that classifies physiological data according to its context to reduce false positives.

Chapter 5 contains the final contribution of this work, where data was collected from older adults through a pilot study. A research ethics board (REB) application was completed by the author in order to obtain permission to pilot the system in 30 older adults. Guha Ganesh and the author built multiple systems and sent them to older adults. The author devised and wrote software for remotely calibrating and controlling the system through cloud scripts in light of the no contact requirements during COVID19. Additionally, the author developed preprocessing and analysis software to apply the theory from Chapter 3 to the study data in order to obtain contexts throughout the pilot study. The pilot study was devised by Dr. Fang, and Dr. Fang supervised the research resulting from the study's data. The significant contributions of the work were the demonstration that contexts could be established autonomously in a clinically relevant setting (older adults' primary residence) using the theory described in chapter 3 of this thesis.

References

[1] Public Health Agency of Canada, "Seniors' Falls in Canada - Infographic," Jan. 15, 2015. https://www.canada.ca/en/public-health/services/health-promotion/aging-seniors/publications/publications-general-public/seniors-falls-canada-second-report/seniors-falls-canada-infographic.html (accessed May 06, 2022).

[2] S. Schnell, S. M. Friedman, D. A. Mendelson, K. W. Bingham, and S. L. Kates, "The 1-year mortality of patients treated in a hip fracture program for elders," *Geriatr. Orthop. Surg. Rehabil.*, vol. 1, no. 1, pp. 6–14, Sep. 2010.

[3] E. D. Blair, B. R. Clarke, and T. O'Neill, "Sustaining development of stratified medicines in the UK healthcare system: a commentary," *Per. Med.*, vol. 8, no. 5, pp. 517–521, Sep. 2011.

[4] J. Kaye *et al.*, "One walk a year to 1000 within a year: continuous in-home unobtrusive gait assessment of older adults," *Gait Posture*, vol. 35, no. 2, pp. 197–202, Feb. 2012.

[5] F. Wang, E. Stone, M. Skubic, J. M. Keller, C. Abbott, and M. Rantz, "Toward a passive low-cost in-home gait assessment system for older adults," *IEEE J Biomed Health Inform*, vol. 17, no. 2, pp. 346–355, Mar. 2013.

[6] F. Wang, M. Skubic, M. Rantz, and P. E. Cuddihy, "Quantitative gait measurement with pulse-Doppler radar for passive in-home gait assessment," *IEEE Trans. Biomed. Eng.*, vol. 61, no. 9, pp. 2434–2443, Sep. 2014.

[7] M. Rantakokko, M. Mänty, and T. Rantanen, "Mobility decline in old age," *Exerc. Sport Sci. Rev.*, vol. 41, no. 1, pp. 19–25, Jan. 2013.

[8] T. M. Manini, "Mobility decline in old age: a time to intervene," *Exerc. Sport Sci. Rev.*, vol. 41, no. 1, p. 2, Jan. 2013.

[9] B. Yoon *et al.*, "Balance and Mobility Performance Along the Alzheimer's Disease Spectrum," *J. Alzheimers. Dis.*, vol. 73, no. 2, pp. 633–644, 2020.

[10] N. M. F. Sousa and R. C. Macedo, "Relationship between cognitive performance and mobility in patients with Parkinson's disease: A cross-sectional study," *Dement Neuropsychol*, vol. 13, no. 4, pp. 403–409, Oct. 2019.

[11] O. Hardiman, L. H. van den Berg, and M. C. Kiernan, "Clinical diagnosis and management of amyotrophic lateral sclerosis," *Nat. Rev. Neurol.*, vol. 7, no. 11, pp. 639–649, Oct. 2011.

[12] M. Thibaud *et al.*, "Impact of physical activity and sedentary behaviour on fall risks in older people: a systematic review and meta-analysis of observational studies," *Eur. Rev. Aging Phys. Act.*, vol. 9, no. 1, pp. 5–15, Jun. 2011.

[13] G. Rao *et al.*, "Does this patient have Parkinson disease?," *JAMA*, vol. 289, no. 3, pp. 347–353, Jan. 2003.

[14] T. Yokoya, S. Demura, and S. Sato, “Relationships between physical activity, ADL capability and fall risk in community-dwelling Japanese elderly population,” *Environ. Health Prev. Med.*, vol. 12, no. 1, pp. 25–32, Jan. 2007.

[15] G. D. Abowd, A. K. Dey, P. J. Brown, N. Davies, M. Smith, and P. Steggles, “Towards a Better Understanding of Context and Context-Awareness,” in *Handheld and Ubiquitous Computing*, 1999, pp. 304–307.

[16] E. O’Brien *et al.*, “Practice guidelines of the European Society of Hypertension for clinic, ambulatory and self blood pressure measurement,” *J. Hypertens.*, vol. 23, no. 4, pp. 697–701, Apr. 2005.

[17] T. L. M. van Kasteren, G. Englebienne, and B. J. A. Kröse, “Activity recognition using semi-Markov models on real world smart home datasets,” *J. Ambient Intell. Smart Environ.*, vol. 2, no. 3, pp. 311–325, 2010.

[18] S. Azzi, A. Bouzouane, S. Giroux, C. Dallaire, and B. Bouchard, “Human activity recognition in big data smart home context,” in *2014 IEEE International Conference on Big Data (Big Data)*, Oct. 2014, pp. 1–8.

[19] V. Bianchi, M. Bassoli, G. Lombardo, P. Fornacciari, M. Mordonini, and I. De Munari, “IoT Wearable Sensor and Deep Learning: An Integrated Approach for Personalized Human Activity Recognition in a Smart Home Environment,” *IEEE Internet of Things Journal*, vol. 6, no. 5, pp. 8553–8562, Oct. 2019.

[20] S. Oh, J. H. Kim, S.-W. Choi, H. J. Lee, J. Hong, and S. H. Kwon, “Physician Confidence in Artificial Intelligence: An Online Mobile Survey,” *J. Med. Internet Res.*, vol. 21, no. 3, p. e12422, Mar. 2019.

[21] S. Ramasamy Ramamurthy and N. Roy, “Recent trends in machine learning for human activity recognition—A survey,” *WIREs Data Mining and Knowledge Discovery*, vol. 8, no. 4, p. e1254, Jul. 2018.

[22] R. Pasic, I. Kuzmanov, and K. Atanasovski, “ESP-NOW communication protocol with ESP32,” *Journal of Universal Excellence*, vol. 6, no. 1, pp. 53–60, Feb. 2021.

[23] Y.-K. Kim, S.-M. Kim, H.-S. Lho, and W.-D. Cho, “Real-Time Step Count Detection Algorithm Using a Tri-Axial Accelerometer,” *Journal of Internet Computing and Services*, vol. 12, no. 3, pp. 17–26, 2011.

[24] M. B. Rhudy and J. M. Mahoney, “A comprehensive comparison of simple step counting techniques using wrist- and ankle-mounted accelerometer and gyroscope signals,” *J. Med. Eng. Technol.*, vol. 42, no. 3, pp. 236–243, Apr. 2018.

[25] J. Ye, S. Dobson, and S. McKeever, “Situation identification techniques in pervasive computing: A review,” *Pervasive Mob. Comput.*, vol. 8, no. 1, pp. 36–66, Feb. 2012.

[26] D. A. Ganz, Y. Bao, P. G. Shekelle, and L. Z. Rubenstein, “Will my patient fall?,” *JAMA*, vol. 297, no. 1, pp. 77–86, Jan. 2007.

[27] A. K. Akobeng, “Understanding diagnostic tests 2: likelihood ratios, pre- and post-test probabilities and their use in clinical practice,” *Acta Paediatr.*, vol. 96, no. 4, pp. 487–491, Apr. 2007.

[28] A. V. Chobanian, G. L. Bakris, and H. R. Black, "The seventh report of the Joint National Committee on prevention, detection, evaluation, and treatment of high blood pressure. The JNC 7 report," *ACC Current Journal Review*, vol. 12, no. 4. pp. 31–32, 2003. doi: 10.1016/s1062-1458(03)00270-8.

[29] H.-K. Wu *et al.*, "A smart pill box with remind and consumption confirmation functions," in *2015 IEEE 4th Global Conference on Consumer Electronics (GCCE)*, Oct. 2015, pp. 658–659.

[30] P. K. N. J. Najeeb, A. Rimna, K. P. Safa, M. Silvana, and T. K. Adarsh, "Pill Care-The Smart Pill Box with Remind, Authenticate and Confirmation Function," *2018 International Conference on Emerging Trends and Innovations In Engineering And Technological Research (ICETIETR)*. 2018. doi: 10.1109/icetietr.2018.8529030.

[31] G. Acampora, D. J. Cook, P. Rashidi, and A. V. Vasilakos, "A Survey on Ambient Intelligence in Healthcare," *Proceedings of the IEEE*, vol. 101, no. 12. pp. 2470–2494, 2013. doi: 10.1109/jproc.2013.2262913.

[32] L. A. Zadeh, "Probability measures of Fuzzy events," *J. Math. Anal. Appl.*, vol. 23, no. 2, pp. 421–427, Aug. 1968.

[33] G. W. Musumba and H. O. Nyongesa, "Context awareness in mobile computing: A review," *International Journal of Machine Learning and Applications*, vol. 2, no. 1, p. 5, May 2013.

[34] J. E. Bardram and T. R. Hansen, "Context-Based Workplace Awareness," *Comput. Support. Coop. Work*, vol. 19, no. 2, pp. 105–138, Apr. 2010.

Introduction to Chapter 2

After identifying the goal of developing a context-aware telemedical system for safe aging in place, and understanding the importance of context within medical applications, we sought to understand how to best use context in medical applications. To gain this understanding, a systematic scoping review was conducted and summarized into a manuscript (Paper I in this chapter) to identify current context-aware systems being used by healthcare providers/patients and the specific contexts used in these systems. This was deemed to be pertinent prior to building the hardware and software of our context-aware smart home system in order to be sure the hardware/software built allowed us to capture key contexts that were being used in context-aware medical applications. A secondary objective was to determine if currently used context-aware systems relied on similar algorithms for detecting contexts. Thus, we also extracted the context determination algorithm used in each paper. Interestingly, these papers did not use a consistent algorithm for determining contexts. Additionally, there were a few key contexts such as time of day, mobility level, and location which were found to be prevalent in many of the studies/systems. As a result, the system built in chapter 3 was intentionally setup to allow for us to detect these key contexts. Lastly, a third objective of the review was to determine what subdomains of context-aware medical applications exist so we could better define the context-aware medical landscape. Surprisingly, only 23 articles were identified which contain systems that are being used in practice, which shows that the application of context-awareness to medicine is still quite recent.

My contribution to the paper presented in this chapter was creating the study protocol and search strategy, searching the databases, screening the papers, extracting data from the final articles, and writing the manuscript. Guha Ganesh served as the second screener for validation purposes and helped with the manuscript formatting. Dr. Qiyin Fang supervised the study, edited the manuscript, acted as corresponding author, and handled the submission process. The significance of the present review is in identifying context-awareness applications being used in clinical settings, determining the most common medical contexts used in these settings, and creating subdomains for context-aware medical applications.

Chapter 2

Context-Aware Medical Systems within Healthcare Environments: A Systematic Scoping Review to Identify Subdomains and Significant Medical Contexts

Michael Zon[1,2,*], Guha Ganesh[1], and Qiyin Fang[1,3]
[1]McMaster University, School of Biomedical Engineering, Hamilton, ON
[2]Michael G. DeGroote School of Medicine, Hamilton, ON,
[3]McMaster University, Department of Engineering Physics, Hamilton, ON,
***Corresponding author (qiyin.fang@mcmaster.ca)**

Contents of Review Paper

Abstract of Review Paper

Objective: Context-awareness is an emerging field in pervasive computing with applications that have started to emerge in medical systems. The present work seeks to determine which contexts are important for medical applications and what various domains of context-aware applications exist in healthcare. *Methods:* A systematic scoping review of context-aware medical systems currently being used in healthcare settings was conducted. A search strategy was designed and applied to 8 databases, articles were then filtered based on their abstract, and then relevant articles had a screening questionnaire applied to their full texts prior to data extractions. Applications were grouped into context-aware healthcare application domains based on past reviews and the results of the screening. *Results:* A total of 23 articles passed all screening levels and underwent data extraction. The most common contexts used were user location (8/23 studies), demographic info (5/23 studies), movement status/activity level (6/23 studies), time of day (5/23 studies), phone usage patterns (5/23 studies), lab/vitals (7/23 studies), and patient history data (8/23 studies). *Conclusions:* The present work demonstrates that context-aware healthcare applications are still in their infancy but have started to reach healthcare providers and patients. *Significance:* The present work has illuminated many of the early successful context-aware healthcare applications. Additionally, the pivotal contexts leveraged by these systems have been discovered allowing future systems to focus on prioritizing the integration of these key contexts.

2.1 INTRODUCTION

Context-aware computing is the notion of using situational and environmental information about users, places and objects to adapt a computer application to fit a user's needs [1]. Debate surrounding the precise definition of context-awareness dates back to the term's first use by Schilit and Theimer in 1994 [2]. However, the definitions of context and context-awareness that are widely accepted by researchers in the domain of computer science were formulated by Abowd and Dey 5 years later [1]. Regarding context, Abowd and Dey define it as,

"*any information that can be used to characterise the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves [1].*"

With respect to understanding context, Abowd and Mynatt identified the 5 W's, namely: Who, What, Where, When, and Why, as the minimum information necessary to determine context[3]. Following the successful definition of context, the application of contexts to computing systems was defined by Dey, who said,

"*A system is context-aware if it uses context to provide relevant information and/or services to the user, where relevance depends on the user's task*[1]*."*

Within a medical setting, a telemedical system is context-aware so long as it uses context to change its behaviour in a useful manner. This notion is pivotal in many remote monitoring medical applications as medical data can often not be differentiated between being benign and dangerous without context. For instance, a heart rate of 160 could either be caused by sinus tachycardia as a user's context is exercising or a dangerous arrhythmia given the user's context is that they are in bed sleeping. Advanced telemedical systems will need to be developed that not only monitor users' medical data, but can also interpret it in a meaningful way. This requirement has led medical researchers to explore how common frameworks within the domain of pervasive computing, specifically context-aware computing, can be utilized by telemedical systems to determine user context from sensor data to make decisions within medical systems.

Despite the increased use of context identification techniques in medical systems to build more advanced applications, a review on context-aware applications in healthcare conducted by Bricon-Souf and Newman in 2007 found that current systems are vastly lab prototypes[4]. Thus, as of 2007 the actual application of context-aware systems in patient populations was minimal[4]. The other limited number of reviews on context-awareness in healthcare also primarily report on prototypes, such as the review by Quinde et al. on methods in asthma management[5] and Tobon et al. on context-awareness in wireless body area networks.[5], [6]. A recent systematic review by Gubert et al. was useful for identifying the major challenges in the field of context-aware healthcare[7]. However, because the objective of the review was not to report on the current state of context-aware applications in the medical field, systems that are currently being used by patients/healthcare providers were not identified. Additionally, it is unclear what contexts are important for medical context-aware systems and what the different domains of applications are.

The objective of this scoping review is to determine what field-tested context-aware medical systems exist and to use these to understand the most common contexts needed in medical systems, as well as what the different categories of context-aware healthcare applications are. We have systematically reviewed the literature and screened for papers which use context-aware systems in conjunction with healthcare providers, or in patients, to provide an overview of the progress made in integrating context into healthcare applications since the review by Bricon-Souf and Newman [4].

2.2 METHODS

2.2.1 Objectives

The objective of this scoping review is to determine what medical context-aware systems are currently being used by healthcare providers and patients. As this goal is focused on broadly identifying what exists within the literature at present, the review question lends itself well to a scoping review. Additionally, the present work aims to identify which contexts are being used by these systems and to find themes/categories for the context-aware applications that are identified throughout the review. An adapted Population, Intervention, Comparison, and Outcomes (PICO) framework for the research question is provided in the protocol attached to the appendix of this thesis.

2.2.2 Design

Reporting followed established guidelines, and standard scoping review methodology has been used.[8], [9] A protocol for this scoping review is attached to the article's supplementary materials.

2.2.3 Study Eligibility

Studies that had context-aware technology used by either patients or healthcare providers were included in this review. After level 1 screening of abstracts, a level 2 screening questionnaire was used to rule out studies that included prototypes, which were not used by patients or healthcare providers outside of a lab setting. Additionally, the questionnaire was used to exclude systems which did not utilize contextual information to change the end application, and thus were not truly context-aware. For instance, Wagner's initial study on a context-aware blood pressure measurement system was excluded as it did not utilize contexts collected such as whether the user had their legs resting for 5 minutes or was not talking[10]. However, the follow up study using this system was included since the application changed based on these contexts by telling users not to change their stance or activity (e.g., no talking) based on the collected contexts.[11]. Peer reviewed journal articles were included and grey literature (conference proceedings or abstracts) and articles not in English were not included in this review.

2.2.4 Search Design

The following online reference databases were searched: Wiley, ACM, EBSCO, IEEE Xplore, Pubmed, ScienceDirect, and SpringerLink. For SpringerLink, an option was not provided to filter for words within the abstract, so a customized filter program was developed in R. It executed the search strategy on the results from the search that was conducted by their system for the keywords present in the full text. These steps reduced the initial articles count from 1,369 to 111.

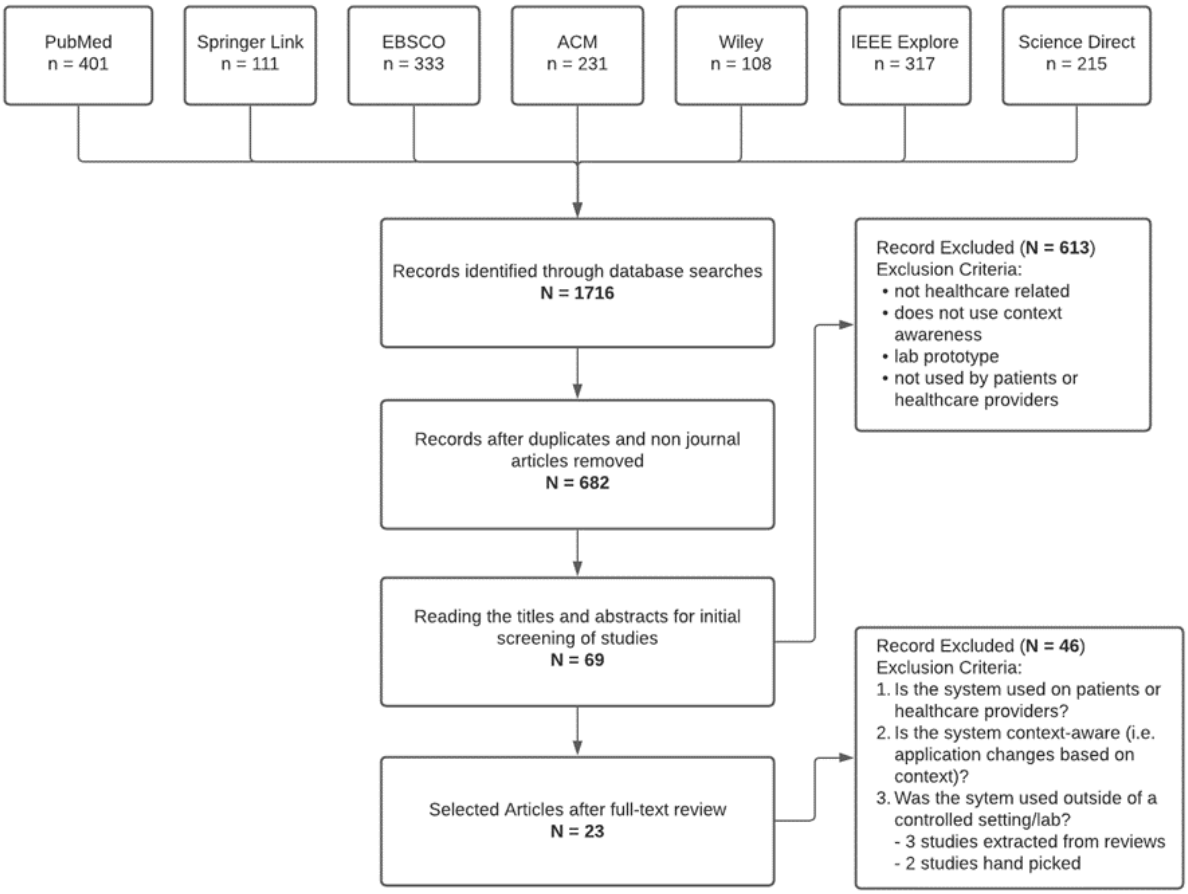

Figure 2.1 PRISMA Diagram of Selection Process

2.2.5 Screening and Extraction Methods

Title and abstract were independently screened using Rayyan by two reviewers and all conflicts were resolved prior to level 2 screening. Articles that passed the initial screening were then included if 3 questions were answered with YES by each reviewer. Question 1 asked whether the system was used by patients or healthcare providers. Question 2 asked whether the system was context-aware by changing its application based on context data and question 3 asked if the system was used outside of a controlled setting (e.g., non-simulated activities outside of a research lab). For studies that passed all three screening questions, standardized spreadsheets (Microsoft Excel) were used to extract general study characteristics, TIDieR checklist items, contexts used within each study, and some general info regarding the technology such as the types of sensors used.

TABLE 2.1
Study Characteristics and Context Selection/Use

Article	Year	General Description	Sample Size	Mean Age	Test Length	Measured Signal	Assessment Method	Contexts Used	Context-Awareness (How did the app Change)
Patient Satisfaction in a Context-Aware Hospital Guidance System[12]	2012	7.1-inch Galaxy Tablet with the hospital guidance system app[12]	13	44	Hospital visit	Patients' location within the hospital	Patient satisfaction survey	Patient location within hospital, appointments and procedures patient needs to complete	The application changed based on both the patients specific next task in the hospital. Additional, guidance changed based on their current location
A Hospital Bed Allocation Hybrid Model Based on Situation Awareness[13]	2018	Web app for hospital bed allocation [13]	50	N/A	5 days	Rate of successful placement	Verify whether bed selected was correct	Room type based on patients' health plan, physician specialty, sex, type of treatment, risk (e.g infectious), degree of dependency, age, time of hospitalization	Bed displayed to bed manager varied based on patient specific context
A situation-aware system for the detection of motion disorders of patients with autism spectrum disorders[14]	2014	Wristwatch with accelerometer worn by patients [[14]	5	N/A	N/A	Detection of movement disorders	Compared with ground truth	Hand gesture type, time of day, gesture duration	The clinical reports varied based on contexts such as the duration of each gesture, time of day of the gesture, and type of movement disorder
A ubiquitous asthma monitoring framework based on ambient air pollutants and individuals' contexts[15]	2019	Smartphone with a context-aware asthma management app[15]	3	36.33 (32F, 35M, 42M)	N/A	Predicted peak expiratory flow (PEF)	Compared predicted PEF to actual PEF from device that patients used	environment/pollutant variables, user location, user age-gender-height	App warns patients of potential asthma attacks though predicted PEF which changed based on various contexts (e.g., environment/pollutant variables, user location, user age-gender-height and PEF)
A Visual Context-Awareness-Based Sleeping-Respiration Measurement System[16]	2010	Near-infrared camera which monitored users as they sleep to determine respiratory rate[16]	18	N/A	N/A	Respiratory rate	Compared RR results to those of the CO2SMO PLUS respiratory monitoring machine	Body motion of user	The system determining respiratory rate changes its action based on the body motion context (proceeds to RR calculation if still)
A wearable system to assist walking of Parkinson s disease patients.[17]	2010	Accelerometers used to detect freezing of gait (FOG) context in Parkinson's in real time[17]	10	66.4	237 FOG events	freezing of gait	Physiotherapists observed video to determine FOG events and detection by system was compared to ground truth	Gait state (i.e moving vs frozen)	Auditory stimuli delivered if FOG context detected
CARE: Context awareness for elderly care[18]	2020	Android mobile app that shows activities of older adults determined by sensors in retirement home[18]	15 patients, 17 nurses	N/A	2 months	long term trends in resident activity level, time in bed, proximity to nurses, proximity to other residents	Questionnaire was used to determine if nurses found the application useful	user location, nurse location, time in bed, level of activity	different data displayed to nurses through android app depending on user contexts (e.g. how often resident is near nurses or other residents, their level of activity, etc.)
Connected Elbow Exoskeleton System for Rehabilitation Training Based on Virtual Reality and Context-Aware[19]	2020	VR based physiotherapy application paired with elbow exoskeleton device[19]	5	N/A	1 month	performance of patient over time in VR rehab exercise where patient moves ring along cable, but the ring should not touch the cable	position, angle, and time deviation during the exercise relative to a perfect performance (e.g., wire kept in center of ring for position performance)	Performance on exercise	Patients' performance on current exercise is used to inform how difficult the app makes the next exercise
Effects of context-aware patient guidance on blood pressure self measurement adherence levels[11]	2019	smart chair and tablet paired to a blood pressure (BP) monitor to ensure proper contexts for BP measurement [11]	100	29.9	One time	Adherence to the requirements for proper blood pressure measurements when recommended by the system versus not recommended	percent adherence to the different requirements	user rest time, legs crossed, back-supported, ambient noise/talking, participant compliance	App recommended rest time and not talking if motion/talking contexts were detected. Other contexts not recommended
Evaluation of an optimized context-aware clinical decision support system for drug-drug interaction screening[20]	2021	Drug-Drug Interaction Intervention Application in Hospitals[20]	2630 alarms	N/A	8 months	Drug drug interactions and acceptance rate of alerts	Tracked number of alerts that results in a change to a prescription	Patients current medications, age, sex, last potassium levels, and renal function	Application utilized patient specific data to determine if it flags the current prescription as dangerous
Harnessing Context Sensing to Develop a Mobile Intervention for Depression[21]	2011	mobile application to improve and predict Major Depressive Order[21]	8	37.4	8 weeks	Mood, location, activity, who the users were with or near	Compared predictions to those entered manually by participants	Location, time of day, who users are with, conversing or not, mood, contexts from phone apps such as recent calls, active applications	Moods predicted and thus tracked/displayed to users changed based on machine learning models that predicted mood from context data derived from phone sensors
Integrating Personalized Health Information from MedlinePlus in a Patient Portal[22]	2014	Patient portal in hospital that provides medical info specific to patient's context[22]	80,000	N/A	1 year	use of the lab test info buttons and MedlinePlus explanatory information buttons	Number of clicks and percent of sessions the buttons were used in	Patients' lab test results and condition/disease	The information offered to patients through the patient portal varied based on what disease they had, or lab tests they received

Article	Year	General Description	Sample Size	Mean Age	Test Length	Measured Signal	Assessment Method	Contexts Used	Context-Awareness (How did the app Change)
MHS: A Multimedia System for Improving Medication Adherence in Elderly Care[23]	2011	Pill station equipped with webcam that registers new medications and devices that prompt user to take meds[23]	5	over 60	3 weeks	Adherence to taking medication	Unclear how ground truth medication taking is established, but likely assumed they take the medication when a pill box is opened	Users' current activities such as watching tv, talking on phone, eating, sitting, moving. Exact list of used contexts not clear	The application prompts users to take medication based on their current contexts. I.e., if pill is required with a meal, then they are prompted based on the eating context
A Study of Medication-Taking and Unobtrusive, Intelligent Reminding[24]	2009	Medication reminders auditory/visual cues at user's location in their home[24]	10	82.7	10.7 weeks	Adherence rate for taking medication	pill recorded as taken when the smart pill box container is opened	Location in home, when they are leaving home, phone call in progress, in bed, using laptop, preferred time for medication	Audio and visual prompts around the home were triggered based on contexts such as the user's location, if they are not on the phone, the normal time they take the pill, if they have not taken the pill, if they are about to leave home
Mobile Sensing and Support for People With Depression: A Pilot Trial in the Wild[25]	2016	Mobile app for depression intervention and depression scores[25]	126	20-57	Over 9 months	PHQ-9 depression score	Compared PHQ-9 scores obtained from patients through questionnaire over time	time of day, location, smartphone usage, activity level, walking time, time at home, geographic movement, number of unique Wi-Fi fingerprints, number of calls, calendar events	Interventions recommended varied based on user's context (e.g., low activity level, walk recommended) and users' feedback on interventions
Online updating of context-aware landmark detectors for prostate localization in daily treatment CT images[26]	2015	Prior treatment images used to improve landmark detection and prostate segmentation[26]	24	N/A	Length of treatment	Accuracy in segmenting prostate volume for algorithm relative to segmentation by physicians	Dice ratio and average surface distance	patients' inter-landmark distance, intra-landmark distance, and prostate segmentation from their prior images	The algorithm that identified landmarks and performs prostate segmentation varied based on the patient's prior treatment images and any adjustments from the physicians on the landmark/segmentation
Pilot evaluation of an optimized context-specific drug–drug interaction alerting system: A controlled pre-post study[27]	2015	E4 wristband determine users' availability for memory training [27]	1116	N/A	14 months	acceptance rate of alerts when new system that included context data was implemented	Tracked number of alerts that results in a change to a prescription	Patients current medications, age, sex, last potassium levels, and renal function	Application utilized patient specific data to determine if it flags the current prescription as dangerous
Prompto: Investigating Receptivity to Prompts Based on Cognitive Load from Memory Training Conversational Agent[28]	2020	Rule based software application to prevent dangerous prescriptions[28]	7	67.4	1 week	responses to prompts and appropriateness of prompt timing according to user feedback	percent of prompts that were accepted for memory training to commence	cognitive load of user determined through heart rate variability and electrodermal activity	Application prompted users for memory training when cognitive load measured by E4 wristband was low
Translation of evidence into kidney transplant clinical practice: managing drug-lab interactions by a context-aware clinical decision support system[29]	2020	Smartphone application that prompts CKD patients to take BP measurements and symptoms[29]	100	47.44	N/A	clinician satisfaction with the system	The "Questionnaire for user interface satisfaction"	renal function via creatine clearance, lean body weight, pregnancy status	The system generated drug lab interaction alerts based on the patient's specific lab values (creatine clearance), lean body mass, and pregnancy status
Integrating a Smartphone–Based Self–Management System into Usual Care of Advanced CKD[30]	2016	Mobile app focused on predicting stability of bipolar disorder patients[30]	47	59.4	6 months	user satisfaction with app, change in blood pressure, change in CKD relevant lab values	exit interviews to assess satisfaction, BP measured by hoe monitoring device and results compared between baseline and end of study	Patients' adherence to BP measurements, their symptoms, and their medications	Frequency of messaging patient for BP changes based on their compliance, alerts sent to healthcare providers if symptoms warrant it, and medication discrepancies checked by system throughout
Automatic detection of social rhythms in bipolar disorder[31]	2016	social and activity contexts inferred from smartphone sensor data are used to predict social rhythm metrics[31]	7	4 users 25-34, 3 were 34-64	4 weeks	Social rhythm metric	compared SRM from models to that determined by manual inputs from patient	phone usage patterns, location, distance traveled, number of conversations per day, duration of conversations, time speaking to others, speaking rate, speech pitch, time active vs sedentary, SMS/call activity	inferred behavioral rhythmicity and SRM changes based on contexts measured
Alarm Fatigue vs User Expectations Regarding Context-Aware Alarm Handling in Hospital Environments Using CallMeSmart[32]	2017	handheld communication system considers healthcare providers current context/activity to understand whether to page the user [32]	N/A	N/A	2014-2017	Satisfaction of healthcare workers with new system relative to old system	Interviews with users	users calendar events (e.g no call while in patient consult), location (e.g operating room)	messages are relayed to healthcare workers based on urgency and their current availability as determined by their context (e.g., unavailable during patient consult)
MultiSense—Context-Aware Nonverbal Behavior Analysis Framework: A Psychological Distress Use Case[33]	2017	topic of the discussion and what a normal, positive, or negative response looks like is used as context to determine distress levels[33]	100	N/A	One interview session	distress levels of person being interviewed	Root mean square error in systems predicted distress levels relative to ground truth levels	users eye contact, smile level, and other behaviour indicators along with what the users affect should be based on the topic of conversation (e.g smile while describing a trauma atypical)	applications use patients' non-verbal behavioral contexts to predict their distress levels and generate a patient specific report

TABLE 2.2
Application Categories and their Contexts

Application Category	Description	Subcategories	Reference Number	Contexts Found	Important Contexts	Technology Descriptions
Smart Inpatient and Outpatient Software and Medical Devices	Software systems to improve communication between healthcare staff and patients within the hospital	A) Hospital/ Inpatient systems B) Outpatient systems	A)[12],[13],[20], [22],[27],[29] ,[32] B)[18],[11]	healthcare provider location*, Patient location*, appointment time*, procedure type*, age*, sex*, physician specialty, medication list, lab test results, renal function/*, weight, user taking or not*, activity level, time in bed*	location, calendar, medical history, medication list, demographic info,	Software applications using expert systems or machine learning and known contexts to make decisions. Smart equipment using context to improve medical devices
Smart Diagnostic and Disease Management Systems	Diagnose patients' using algorithms and identify ideal treatment plans	A) Diagnostic systems B) Disease management	A) [14] B)[15],[17],[21], [26],[31]	Movement type/status*, time of day*, age*, sex*, height, medical history, location*, who user is with*, phone use*, conversing or not*, medical images, disease specific contexts (e.g., pollutant levels asthma)	Lab results, medical history, demographic data, time of day	Wearable sensors, machine learning, and user input used to make diagnoses and manage disease
Continuous Health Monitoring	Wearable and ambient sensors for continuous healthcare monitoring	A) Longitudinal physiological data monitoring, C) emergency detection	A)[16] B)	Motion of user's body	location, time of day, vitals, medical history, lab results,	wearable sensors/medical devices to understand patients' health and contexts like past medical history used to determine what physiologically normal is
Assisted Living	Developing smart environments to assist patients in their daily living activities	A) Disease tracking B) Physical Support C) Social Support	A) [23], [24],[30] B) C)	User current activity (e.g., eating, tv), location*, conversing or not*. time in bed*, medication list*, symptoms, adherence to taking measurements (BP)	IADLs, location, time of day, symptoms, medication list,	Mobile, web app and IoT devices used around the house to understand daily activities to help user perform tasks (e.g taking medication) and manage disease
Therapy and Rehabilitation	Providing psychological based therapy to improve or heal a disorder	A) Smart rehabilitation B) Psychology based therapy	A) [19], [33] B) [28]	current performance in rehab task, cognitive load	body position, mood,	Wearable devices or software used to guide therapy or provide outputs that can be used in therapy
Persuasive and Emotional Well Being	Systems aimed at improving physical and mental well-being	A) Emotional analysis/state systems	A) B)[25]	Location, time of day, who users are with (alone, friends, family), conversing or not, mood, contexts from phone apps such as recent calls, active applications	mood, activities, user specific goals	Mobile and web app software leverages smartphone sensors and IoT devices to understand the users state and lead them to better lifestyle choices

* context found in more than 1 study

2.4 RESULTS

2.4.1 Study Selection

A total of 1,716 records underwent title and abstract review, which led to 69 papers reviewed at the full text level. After full text review 23 papers passed the 3 level 2 screening questions and were thus eligible. The PRISMA flow diagram illustrating this can be seen in figure 2.1. The study characteristics, contexts used, and how the systems were context-aware can be seen in table 2.1. The studies were categorized into domains based on both a review by Acampora et al. and new domains that have been created based on the results from screening[34]. The categories, their descriptions, and which papers fell into each category can be seen in Table 2.2. In total, 9/23 studies were in the Smart Inpatient/Outpatient Software and Medical Device category, 1/23 in Continuous Health Monitoring, 3/23 were in Assisted Living, 3/23 were in Therapy and Rehabilitation, 6/23 were in Smart Diagnostic and Disease Management Systems, and 1/23 were in Persuasive and Emotional Well Being.

2.4.2 Study Characteristics

Twelve studies conducted small field tests involving less than 25 patients, eight studies tested their systems in 25-150 patients, and 3 studies conducted large scale trials by running the system in either the entire hospital or in more than 1000 patients (table 2.1). Twelve studies implemented the context-aware solution for over 1 month and the remaining 11 studies either implemented the technology during a single patient visit or in a timeframe that was less than 1 month. No pre-existing condition or target population/disease was the sole focus of more than two of the studies.

2.4.3 Technology and Contexts

Most studies relied on either a mobile phone or tablet (9/23), smartwatches (2/23), or integrating a software application into a hospital's current system (5/23). The remaining studies used other technology (e.g virtual reality headset) or relied on other ambient sensors such as thermal cameras, infrared motion sensors, wearable accelerometers, etcetera. The most common contexts used were the user location (8/23 studies), demographic info (5/23 studies), movement status/activity level (6/23 studies), time of day (5/23 studies), phone usage patterns (5/23 studies), lab/vitals (7/23 studies), and patient history data (8/23 studies). Patient history was defined according to the way it is collected in practice (i.e medical, surgical, medications, allergies, family, social). The majority of the studies which used patient history relied on their medication history (6 of 8). Other contexts were more specific to the context-aware system of interest.

2.5 DISCUSSION

The present work sought to determine the current state of context-aware systems in healthcare relative to Bricon-Souf and Newman's review in 2007, where it was determined that the majority of systems were still lab prototypes[4]. It appears that in the decade following this review, various research teams have managed to develop functional context-aware systems which have been tested in healthcare environments through their use by patients or healthcare providers. Most of these applications are still in their early stages having been used in less than 150 people in a brief field test. The notable exceptions are the system implemented by Borbolla et al., where half of the patients in the hospital were able to view information explaining medical tests/disease specific to their current context, and the drug-drug interaction system built by Cornu et al. that was tested in a 721 bed hospital.[22], [27] We have used the results of the search in conjunction with the ambient intelligent medical application categories proposed by Acampora et

al. to develop the 6 domains for context-aware healthcare systems shown in table 2.1[34]. Although Acampora et al.'s categories were formed for ambient intelligent systems, context-awareness is a pivotal requirement of ambient intelligent systems[34]. Thus, there is much overlap between these systems and their application categories. Evidently, the Smart Inpatient/Outpatient Software and Medical Device category, which uses context-aware systems within hospitals and clinics to improve patient care, has had the most success in reaching healthcare providers and patients (9/23 studies). The second most prominent category in terms of the number of applications being used by patients/healthcare providers is the smart diagnostic and disease management systems (6/23). Following this category are assisted living applications (3/23) and therapy and rehabilitation applications (2/23). We choose to create sub domains when appropriate, such as further dividing smart diagnostic and disease management systems into diagnostic systems and disease management systems. However, in the future if major differences in required contexts are discovered it may be more logical to divide many of these subcategories into their own domains.

2.5.1 Smart Inpatient/Outpatient Software and Medical Device

The Smart Inpatient/Outpatient Software and Medical Device class of context-aware applications aim to improve the quality of life (work efficiency, measurement accuracy, etc) of hospital stakeholders. These stakeholders can be the patients, doctors, nurses, staff, or anyone else working at the hospital. Many of these applications solely rely on software to help these stakeholders, however, some interesting applications have emerged that use smart-equipment to provide medical information on patients to healthcare providers or to simplify procedures performed by providers by integrating context.

Smart hospital applications of context-aware systems are likely the earliest use cases of context-awareness in medicine and seem to be the most prevalent source of context-aware applications to date. The earliest context-aware application identified in this review, dating back to 2011, is a navigation system created by Kim et al., that was used to direct patients within a hospital. In this study, each patient was given a tablet with an app which showed them how to navigate to their final destination, what to do at that location, and communicated with the hospital's information system to know when they completed a task and should be directed to their next required task[12]. Regarding smart-equipment, one field tested application developed by Lindahl et al., involves a context-aware smart-chair equipped with a blood pressure (BP) cuff/monitor to facilitate BP measurements of pregnant women at their 12 month ultrasound appointment. The purpose of the system is to diagnose hypertensive disease and preeclampsia[11]. The primary contexts used by the system were the users position/state during the BP measurement, including whether their legs were uncrossed, back was against the chair, and whether they were resting or talking. An interesting result shown in the study was that when resting and not talking were enforced by the system and legs/back position were not enforced, the compliance for the enforced activities was more than 20% higher than the not enforced activities. This shows how a context-aware system can improve medical measurements by providing users with feedback on what is needed for the system to obtain proper medical measurements. Researchers are also working towards integrating context into operating rooms as shown by the system by Franke et al[35]. This system was not field tested and thus was not included in our final studies list. Instead, the system was tested on 24 recordings of real surgical operations and showed how the current context of the surgery (e.g., next step in procedure) can be used to predict what the surgeon would like to occur next and adapt the equipment settings and hospital software accordingly. Some examples include automatically determining the billing code based on the procedure, changing the lighting of the endoscope based on the current image, automatically switching to navigation displays whenever the pointer is being used, and reducing the force of the surgical equipment near sensitive structures [35].

One final emerging area of applications in smart-hospitals is those that analyze a patient's specific context through their electronic medical records to detect possible errors. One application of this that has

been field tested is looking at patients' lab values and drug prescriptions to decide whether the drug dosage is incorrect or the drug itself should not have been prescribed given the patient's current kidney and liver function. Niazhani et al. used clinical guidelines regarding drugs prescribed by nephrologists at a kidney transplant clinic to determine the proper dosages and prescribing rules given a patient's specific context, such as their kidney function, liver function, pregnancy status and other demographic data. Their system was then field tested in 100 patients and used these rules to alert physicians when problematic drug lab interactions (DLI) exist, of which 260 DLI's were found [29]. The largest field tested study identified was a similar system tested in a 721 bed hospital over 14 months developed by Cornu et al. that used contexts such as patients' current medications, age, sex, last potassium levels, and renal function to develop clinical decision rules that warn physicians about dangerous drug-drug interactions [27]. Similar systems are being worked on for general drug monitoring in the elderly, illustrating that this context-aware healthcare domain is a highly active research area [36].

2.5.2 Assisted Living

Assisted living applications of context-aware systems primarily focus on supporting patients and the elderly during their daily activities to facilitate independent living within their primary residencies and an improved quality of life. For instance, an application which may be highly beneficial in those living with cognitive impairments due to neurological diseases (e.g., dementia) are context-aware medication reminder systems. These systems, which could be used to remind patients of activities other than taking their medications, attempt to understand a user's current context to optimize the chance they will see a reminder and act on it. An excellent study that was field tested in 10 users over 28 weeks by Hayes et al. demonstrated the efficacy of this approach by comparing the results when users underwent 10 weeks without prompts, 10 weeks with prompts, and 10 weeks with context-aware prompts [24]. The context-aware prompts used motion sensors to detect where a user was in their home and then sent a visual/audio prompt to a beacon in that room, as well as a message to their smartwatch, when the user should take their meds. However, if they were in bed (bed sensor) or on the phone, already took the med from the pill box, or not at home (contact sensor) the prompts were not sent. Additionally, prompts were only sent within 90 minutes of when they should have taken the meds. The context-based prompting resulted in significantly better adherence (92.3%) as compared to time-based (73.5%) or no prompting (68.1%) conditions ($p < 0.0002$, $\chi 2 = 17.0$) [24]. Another class of assisted living applications would be those that focus on managing patients' pre-existing diseases. The best field tested example of a system which focuses on this is the smartphone based self-management system developed by Ong et al. for chronic kidney disease (CKD) [30]. In this system patients were given a smartphone with an application that was linked to their BP recording device. They were asked to answer questions about symptoms and medication changes regularly, and this info was shared with the care team to facilitate continuous monitoring. If dangerous medication changes existed, or symptoms worsened significantly and warranted intervention according to clinical guideline-based rules, then the care team received an urgent update. Feedback on BP control was provided to patients through the application and the application would make recommendations depending on the patient's context/circumstances. For instance, if the patient had elevated potassium levels dietary modifications would be recommended [30]. The final results of the study were quite compelling as the mean systolic and diastolic blood pressure of the 47 patients decreased by 3.4 mmHg and 2.2 mmHg, respectively.

2.5.3 Smart Diagnostic and Disease Systems

Smart diagnostic systems focus on determining a patient's condition/disease in the absence of physicians and context-aware disease management systems help patients manage user' conditions according to the contexts surrounding their current disease state. This includes applications based on sensor

systems that aim to help reduce symptoms and issues present in patient's living with chronic diseases. A good example from Yin et al.'s review of context-aware systems for chronic disease patients is the wearable system developed by Bachlin et al. to assist those with Parkinson's in walking [17], [37]. Given that evidence suggests rhythmic auditory stimulation can help Parkinson's patients move when they are stuck due to Freezing of gait, Bachlin et al. developed a system that detects freezing of gait in real-time so they can then provide audio cueing to assist patients. In this case the context is the patient's gait status according to the accelerometer data from the patient's knee and ankle. Although the system was not proven to improve FOG in their small test of 10 PD patients, the physiotherapists did believe the system was helpful [17].

Coronata et al.'s work is an example of a system that is used for diagnostic purposes, although not to diagnose a disease, but instead to detect motion disorders for those with autism spectrum disorder [14]. Motion disorders were detected by training an artificial neural network on accelerometer data and using contexts such as time of day and duration of the gestures. The system was used on 5 patients within a hospital and the online classifier achieved an accuracy of 92%, showing that there is promise for the approach [14]. Another application of context-awareness in disease management is the system by Dai et al. where they improve prostate segmentation during image guided radiation therapy by using patient-specific contexts obtained from their prior images. The system was tested on 24 patients and they found that using prior personalized image data led to improved prostate segmentation accuracy, as defined by the dice ratio and average surface distance [26]. As disease management is quite specific to the condition of interest, and often the patient's ability to follow complex guidelines, context-aware disease management systems have the potential to improve patient health by helping them complete necessary daily tasks required to manage their disease. Furthermore, it may reduce emergencies like asthma exacerbations, as systems like Kaffash-Charandabi et al.'s use environmental contexts to predict possible hazardous conditions for patients to guide them to avoid scenarios that can lead to the emergency room (asthma exacerbation in this case) [15].

2.5.4 Therapy and Rehabilitation

The therapy and rehabilitation category of context-aware healthcare systems focuses on systems that provide psychological based therapy for mental illnesses or physical rehabilitation to people with conditions that may benefit from physiotherapy. One interesting therapy related system developed by Stratou et al. was field tested in 100 patients and demonstrated promising results for determining the state of patients during psychological interviews [33]. Their camera based system investigated the users eye contact, smile level, and other behavioural indicators to determine their distress levels. An example of the context used by the system would be what the users affect should be based on the topic of conversation. For instance, if asked to describe a recent positive event in their life and then a negative event, the system would expect a smile during the first story and a less positive facial expression during the second story. The results were promising as the team was able to show that the models which considered context variables had a much better correlation with post-traumatic stress disorder and depression scores in 100 patients taken from the general and US veteran population [33].

The present work only identified one rehabilitation related context-aware system that was field tested in patients and utilized context. In this application which was tested in users with epicondylitis, the difficulty of arm exercises which utilize the VR systems controller, and the chosen activity itself, were recommended based on the users current progress. Users were instructed to do 20 of exercises with their arm, 10 of which were conducted with a virtual weight and 10 with the user holding a real weight while using the VR app. Although clinical benefits were not assessed, it was demonstrated that the time taken to complete tasks and the amount of deviation from the optimal trajectory decreased as users went from their first session to their last. Integrating user specific performance/context into rehabilitation applications will

likely be an important development in personalizing programs for patients to improve their mobility, especially when physiotherapists are not present to correct imperfections in the patient's form during the exercise [19].

2.5.5 Continuous Heath Monitoring and Persuasive and Emotional well being

We defined continuous health monitoring as systems that constantly track physiological data of patients (e.g., vitals, blood glucose, etc.). Additionally, we removed activity monitoring from this category relative to Acampora et al., given that most behavioural monitoring applications usually monitor behaviour to use it to build applications in the other categories such as assisting older adults in their home (assisted living)[23], [24], [30], delivering psychological based therapies (therapy and rehabilitation)[28], providing emotional support (emotional well-being)[25], etc. Our screening captured minimal continuous health and activity monitoring applications that are presently being used by patients and healthcare providers. In reality, there are likely many emergency and fall detection systems that use basic contexts like immobility, fall sounds, and rapid altitude or acceleration changes to detect falls or emergencies [38]-[39]. However, these systems do not focus on, and thus do not mention, context-awareness. Thus, by design they were not captured by our search criteria since the present work focuses on systems intentionally integrating context-awareness. One interesting application was captured that uses a non-contact method to determine respiratory rates of people as they sleep. Near infrared cameras assessed the users body context, and if it was below a threshold representing a still user the system would focus on the users subtle remaining motion (e.g., chest during breathing) to determine their respiratory rate. Results were promising as the correlation with another commercially available system (CO2SMO PLUS) was 0.9 [16].

Limited studies were found for the persuasive and emotional wellbeing based context-aware systems that were currently being used by patients or healthcare providers. This too is likely due to a lack of emphasis on understanding context-awareness techniques in healthcare applications that focus on persuading people to make better physical (e.g diet) and mental health (e.g meditation apps) choices. We have defined a primary difference between persuasive and emotional wellbeing applications versus therapy applications (different subdomain) to relate to how the former is readily available to the public and does not only focus on improving the mental health of those with known psychiatric related issues. Wahle et al. developed a mobile app that allowed any individual to download and use it. The app recommends personalized interventions to help reduce depression levels. Contexts such as the user's calendar events, walking time, time at home, and number of calls were used to predict their depression levels. Results were promising as a significant reduction in PHQ-9 depression scores from the initial questionnaire were found for those with a clinically relevant baseline, and they were able to predict scores above a threshold better than a random binary classifier [25].

2.5.6 Important Contexts and Technology within the Domains

As each of the 6 categories of context-aware healthcare systems aims to solve a different medical challenge, the contexts and technology utilized within each category seem to differ (table 2.1). However, there seem to be a few pivotal contexts that are present across domains that most context-aware medical systems leverage. User location, time of day, and whether the user is in an active or resting state appear to be important in many applications. This is an intuitive result as the user's location and time of day often dictate what the application should do. For instance, a nurse may not be sent a low priority pager request in the operating room if the time of day aligns with an operations time or a patient consult [32]. Additionally, many applications rely on user activity levels to understand whether notifying them to do something is likely to be accepted or not [24], [28]. These 3 contexts likely hold significance in any context-aware application involving people. Regarding health-related contexts that seem to span multiple health

categories, a user's past medical history (e.g., medications, illnesses, past surgeries), demographics (age, sex, weight) and lab values seem to be prevalent across categories. Regarding contexts within each subdomain, for smart diagnostic and disease management systems the important contexts aside from past medical history seem to be unique to the disease of interest, such as pollutant levels in Kaffash-Charandabi et al.'s asthma application and the movement types in Coronata et al.'s motion disorder detection system [14], [15]. For assisted living applications the user's current activity in conjunction with location and time of day information seems to be a key context to understanding whether it is a good time to interact with them (e.g que to take medicine). Disease specific contexts are also used to understand what the application must do (e.g que BP measurements) and when to intervene (e.g BP over 140 regularly). Too few therapy and rehabilitation applications were found to confidently comment on the important contexts. However, the user's current performance during exercises and whether the user has a low cognitive load at that time, and is thus available for therapy related interventions, seem to be promising domain specific contexts. Too few continuous health monitoring, and persuasive/emotional well-being applications were found to confidently comment on the domain specific contexts as well. However, continuous health monitoring will presumably leverage contexts extrapolated from vitals/physiological parameters (e.g tachycardia) and persuasive/emotional well-being will likely rely on contexts that help understand the users' activities and availability for prompting to engage in applications that push towards better lifestyle choices.

On top of contexts varying between categories, the technology implemented also varied with some categories relying on software versus hardware. For instance, the smart inpatient/outpatient application mostly relied on software to improve workflow efficiency in current clinical settings. Smart devices in this case mostly relay data to servers to better understand patient measurements, although the potential for hardware to help ensure proper measurement conditions has been shown [11]. The smart diagnostic systems will likely rely upon wearable sensors whereas disease management systems may leverage software more to understand how a user is managing their disease based on their symptoms and self-reported measurements. We have defined continuous health monitoring applications to be those that constantly obtain medical data and ensure it is within normal bounds, so these will presumably rely on wearable sensors and software applications that que users and HCPs if anomalies are detected. Assisted living applications seem to rely on Internet of Things (IoT) devices and smart phone sensors to understand a user's context and determine when to que them to do things like take their meds or to complete something else that is required to manage their disease (e.g., BP measurement high blood pressure). Rehabilitation applications will likely rely upon wearable sensors paired with software to encourage and guide a user through exercises, whereas therapy related applications will likely rely more on software to guide and encourage users through evidence-based treatments. Lastly, we predict that persuasive/emotional well-being applications will mostly leverage smartphone or smartwatch sensors and software to encourage people to make good decisions when they seem to be under low cognitive load, and thus available for prompting.

2.6 LIMITATIONS

Looking at the date of the applications found in this review, it appears that all applications found to be in use within patient populations or used by healthcare providers have been published after Bricon-Souf and Newman's review of context-aware healthcare systems in 2007 [4]. Thus, whereas the field of context-aware medical systems was mostly in its concept phase until 2007, it appears that we are now in the infancy of its development phase. Most of the current applications focus on smart hospitals, assisted living, and helping users manage their medications/diseases. Minimal continuous health monitoring and persuasive/emotional well-being applications were found in this review, which likely partially reflects the lack of current applications emphasis on context-awareness rather than the actual state of context-aware systems in this application class. After assessing each paper for its context determination method it became

apparent that the majority of context-aware systems currently used by healthcare providers do not have a general method of quantitatively determining the likelihood of each context. Some papers relied on machine learning methods[19], [26]. However, manually labelling of training data for generating models that predict context may not be practical at scale or extrapolate well to users of different demographics in new settings.

2.7 CONCLUSION

Although context-aware applications are still in their infancy, systems have finally begun to reach healthcare providers and patients. Contexts such as user location, time of day, patient demographic data, and medical history have been pivotal to the success of these early applications. Additionally, different applications have different context requirements. The present work set out to leverage the information in these early applications to better understand the contexts needed to build different healthcare applications. Hopefully with this better understanding of the key contexts used within various subdomains of context-aware healthcare systems researchers can leverage these findings to ensure their systems contain contexts that have been useful in the early applications identified in the present work.

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Author Contributions

MZ created the protocol, screened the studies, extracted the data, and wrote the paper. GG screened the studies and helped organize the results. QF supervised the study and planned/wrote the paper.

References

[1] G. D. Abowd, A. K. Dey, P. J. Brown, N. Davies, M. Smith, and P. Steggles, “Towards a Better Understanding of Context and Context-Awareness,” in *Handheld and Ubiquitous Computing*, 1999, pp. 304–307.

[2] B. N. Schilit and M. M. Theimer, “Disseminating active map information to mobile hosts,” *IEEE Netw.*, vol. 8, no. 5, pp. 22–32, Sep. 1994.

[3] G. D. Abowd and E. D. Mynatt, “Charting past, present, and future research in ubiquitous computing,” *ACM Trans. Comput.-Hum. Interact.*, vol. 7, no. 1, pp. 29–58, Mar. 2000.

[4] N. Bricon-Souf and C. R. Newman, “Context awareness in health care: A review,” *International Journal of Medical Informatics*, vol. 76, no. 1. pp. 2–12, 2007. doi: 10.1016/j.ijmedinf.2006.01.003.

[5] M. Quinde, N. Khan, J. C. Augusto, A. van Wyk, and J. Stewart, "Context-aware solutions for asthma condition management: a survey," *Universal Access in the Information Society*, vol. 19, no. 3. pp. 571–593, 2020. doi: 10.1007/s10209-018-0641-5.

[6] D. P. Tobon, T. H. Falk, and M. Maier, "Context awareness in WBANs: a survey on medical and non-medical applications," *IEEE Wireless Communications*, vol. 20, no. 4. pp. 30–37, 2013. doi: 10.1109/mwc.2013.6590048.

[7] L. C. Gubert, C. A. da Costa, and R. da Rosa Righi, "Context awareness in healthcare: a systematic literature review," *Universal Access in the Information Society*, pp. 1–15, 2020.

[8] A. C. Tricco *et al.*, "PRISMA extension for Scoping Reviews (PRISMA-ScR): Checklist and explanation," *Ann. Intern. Med.*, vol. 169, no. 7, pp. 467–473, Oct. 2018.

[9] M. D. J. Peters, C. Godfrey, P. McInerney, Z. Munn, A. C. Tricco, and H. Khalil, "Chapter 11: scoping reviews (2020 version)," *JBI manual for evidence synthesis, JBI*, vol. 2020, 2020.

[10] S. Wagner, N. H. Buus, B. Jespersen, P. Ahrendt, O. W. Bertelsen, and T. S. Toftegaard, "Measurement adherence in the blood pressure self-measurement room," *Telemed. J. E. Health.*, vol. 19, no. 11, pp. 826–833, Nov. 2013.

[11] C. Lindahl, S. Wagner, N. Uldbjerg, J. M. Schlütter, O. Bertelsen, and P. Sandager, "Effects of context-aware patient guidance on blood pressure self-measurement adherence levels," *Health Informatics J.*, vol. 25, no. 2, pp. 417–428, Jun. 2019.

[12] E. Kim, S. Yoo, H. Hee, H. Park, G. Kim, and S. Ha, "Patient satisfaction in a context-aware hospital guidance system," *Stud. Health Technol. Inform.*, vol. 180, pp. 1177–1179, 2012.

[13] M. da S. Grübler, C. A. da Costa, R. da R. Righi, S. J. Rigo, and L. D. Chiwiacowsky, "A Hospital Bed Allocation Hybrid Model Based on Situation Awareness," *Comput. Inform. Nurs.*, vol. 36, no. 5, p. 249, May 2018.

[14] A. Coronato, G. De Pietro, and G. Paragliola, "A situation-aware system for the detection of motion disorders of patients with Autism Spectrum Disorders," *Expert Syst. Appl.*, vol. 41, no. 17, pp. 7868–7877, Dec. 2014.

[15] N. Kaffash-Charandabi, A. A. Alesheikh, and M. Sharif, "A ubiquitous asthma monitoring framework based on ambient air pollutants and individuals' contexts," *Environ. Sci. Pollut. Res. Int.*, vol. 26, no. 8, pp. 7525–7539, Mar. 2019.

[16] Y.-M. Kuo, J.-S. Lee, and P.-C. J. Chung, "A visual context-awareness-based sleeping-respiration measurement system," *IEEE Trans. Inf. Technol. Biomed.*, vol. 14, no. 2, pp. 255–265, Mar. 2010.

[17] M. Bächlin, M. Plotnik, D. Roggen, N. Giladi, J. M. Hausdorff, and G. Tröster, "A wearable system to assist walking of Parkinson s disease patients," *Methods Inf. Med.*, vol. 49, no. 1, pp. 88–95, 2010.

[18] S. Klakegg *et al.*, "CARE: Context-awareness for elderly care," *Health Technol.* , vol. 11, no. 1, pp. 211–226, Jan. 2021.

[19] D. H. de la Iglesia, A. S. Mendes, G. V. González, D. M. Jiménez-Bravo, and J. F. de Paz Santana, "Connected Elbow Exoskeleton System for Rehabilitation Training Based on Virtual Reality and Context-Aware," *Sensors* , vol. 20, no. 3, Feb. 2020, doi: 10.3390/s20030858.

[20] K. M. Muylle, K. Gentens, A. G. Dupont, and P. Cornu, "Evaluation of an optimized context-aware clinical decision support system for drug-drug interaction screening," *Int. J. Med. Inform.*, vol. 148, p. 104393, Apr. 2021.

[21] M. N. Burns *et al.*, "Harnessing context sensing to develop a mobile intervention for depression," *J. Med. Internet Res.*, vol. 13, no. 3, p. e55, Aug. 2011.

[22] D. Borbolla *et al.*, "Integrating personalized health information from MedlinePlus in a patient portal," *Stud. Health Technol. Inform.*, vol. 205, pp. 348–352, 2014.

[23] L. Tang, X. Zhou, Z. Yu, Y. Liang, D. Zhang, and H. Ni, "MHS: A Multimedia System for Improving Medication Adherence in Elderly Care," *IEEE Syst. J.*, vol. 5, no. 4, pp. 506–517, Dec. 2011.

[24] T. L. Hayes *et al.*, "A study of medication-taking and unobtrusive, intelligent reminding," *Telemed. J. E. Health.*, vol. 15, no. 8, pp. 770–776, Oct. 2009.

[25] F. Wahle, T. Kowatsch, E. Fleisch, M. Rufer, and S. Weidt, "Mobile Sensing and Support for People With Depression: A Pilot Trial in the Wild," *JMIR Mhealth Uhealth*, vol. 4, no. 3, p. e111, Sep. 2016.

[26] X. Dai, Y. Gao, and D. Shen, "Online updating of context-aware landmark detectors for prostate localization in daily treatment CT images," *Med. Phys.*, vol. 42, no. 5, pp. 2594–2606, May 2015.

[27] P. Cornu, S. Steurbaut, K. Gentens, R. Van de Velde, and A. G. Dupont, "Pilot evaluation of an optimized context-specific drug–drug interaction alerting system: A controlled pre-post study," *International Journal of Medical Informatics*, vol. 84, no. 9. pp. 617–629, 2015. doi: 10.1016/j.ijmedinf.2015.05.005.

[28] S. W. T. Chan, S. Sapkota, R. Mathews, H. Zhang, and S. Nanayakkara, "Prompto: Investigating Receptivity to Prompts Based on Cognitive Load from Memory Training Conversational Agent," *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, vol. 4, no. 4, pp. 1–23, Dec. 2020.

[29] Z. Niazkhani *et al.*, "Translation of evidence into kidney transplant clinical practice: managing drug-lab interactions by a context-aware clinical decision support system," *BMC Med. Inform. Decis. Mak.*, vol. 20, no. 1, p. 196, Aug. 2020.

[30] S. W. Ong *et al.*, "Integrating a Smartphone–Based Self–Management System into Usual Care of Advanced CKD," *Clin. J. Am. Soc. Nephrol.*, vol. 11, no. 6, pp. 1054–1062, Jun. 2016.

[31] S. Abdullah, M. Matthews, E. Frank, G. Doherty, G. Gay, and T. Choudhury, "Automatic detection of social rhythms in bipolar disorder," *J. Am. Med. Inform. Assoc.*, vol. 23, no. 3, pp. 538–543, May 2016.

[32] T. Solvoll, H. Arntsen, and G. Hartvigsen, "Alarm Fatigue vs User Expectations Regarding Context-Aware Alarm Handling in Hospital Environments Using CallMeSmart," *Stud. Health Technol. Inform.*, vol. 241, pp. 159–164, 2017.

[33] G. Stratou and L. Morency, "MultiSense—Context-Aware Nonverbal Behavior Analysis Framework: A Psychological Distress Use Case," *IEEE Transactions on Affective Computing*, vol. 8, no. 2, pp. 190–203, Apr. 2017.

[34] G. Acampora, D. J. Cook, P. Rashidi, and A. V. Vasilakos, "A Survey on Ambient Intelligence in Healthcare," *Proceedings of the IEEE*, vol. 101, no. 12. pp. 2470–2494, 2013. doi: 10.1109/jproc.2013.2262913.

[35] S. Franke, M. Rockstroh, M. Hofer, and T. Neumuth, "The intelligent OR: design and validation of a context-aware surgical working environment," *Int. J. Comput. Assist. Radiol. Surg.*, vol. 13, no. 8, pp. 1301–1308, Aug. 2018.

[36] F. Lagrange, J. Lagrange, C. Bennaga, F. Taloub, M. Keddi, and B. Dumoulin, "A context-aware decision-support system in clinical pharmacy: Drug monitoring in the elderly," *Le Pharmacien Hospitalier et Clinicien*, vol. 52, no. 1, pp. 100–110, Mar. 2017.

[37] K. Yin *et al.*, "Context-Aware Systems for Chronic Disease Patients: Scoping Review," *J. Med. Internet Res.*, vol. 21, no. 6, p. e10896, Jun. 2019.

[38] F. Wu, H. Zhao, Y. Zhao, and H. Zhong, "Development of a wearable-sensor-based fall detection system," *Int. J. Telemed. Appl.*, vol. 2015, p. 576364, Feb. 2015.

[39] S. Abbate, M. Avvenuti, F. Bonatesta, G. Cola, P. Corsini, and A. Vecchio, "A smartphone-based fall detection system," *Pervasive Mob. Comput.*, vol. 8, no. 6, pp. 883–899, Dec. 2012.

Introduction to Chapter 3

Through the scoping review in chapter 2, it became apparent that time of day, location, mobility level, past medical history, and a few other contexts were pivotal for context-aware medical systems given their prevalence in systems that are currently being used in healthcare settings. Thus, the hardware and software developed and described in chapter 3 focuses on building a context-aware smart home system that can use many of these key contexts. Additionally, through the review it became apparent that no general algorithm was used by the systems for calculating the probabilities that different contexts occurred. As a result, a larger focus of chapter 3 is developing a generalized method for determining the probability of different contexts.

In addition to creating/describing the system and a context determination algorithm, this chapter also focuses on building a generalized approach to quantifying the probability an older adult has a given condition or will succumb to an adverse medical event (e.g fall). This is necessary for the overarching goal of promoting safe aging in place through pre-emptive detection, as there must be a method to quantify the level of risk of each individual so that the context-aware medical smart home system can calculate individuals risks over time. By doing so, the system can either intervene when individuals are above some risk threshold or when their risk is increasing too rapidly.

In terms of quantifying an individual's risk, the standard approach used in many medical fields is to conduct clinical tests for conditions with known likelihood ratios that increase the odds of users having a given condition or disease, and use these test results to quantify users disease probabilities. Thus, this approach is adopted in the following chapter and clinical tests are modeled as networks of contexts so they can be conducted on users to demonstrate the framework can move from sensor data acquisition to quantification of diseases or adverse outcomes. More specifically, in chapter 3 a demonstration of running clinical tests with the system for falling in 12 months and having Parkinson's is conducted to show the system can differentiate those at high risk and low risk. However, one significant difference between the system completing the tests versus a healthcare provider is that the system does not always have 100% certainty that the contexts/conditions comprising the tests have occurred, unlike a human observer. Thus, a method is established in chapter 3 that reduced the prognostic value of clinical tests as a function of the level of uncertainty in the contexts/conditions.

My contribution to the paper presented in this chapter was building the smart home system, smart-watch, and mobile application, designing the study, writing the manuscript, and developing the context algorithms/framework. Guha Ganesh helped develop the smart home beacons by changing the hardware from Raspberry Pi's to lower cost ESP32s. Dr. Qiyin Fang supervised the study, edited the manuscript, acted as corresponding author, and handled the submission process. The significance of the present work is in connecting raw sensor data to clinically validated tests through automatically established contexts and providing a framework for context-aware telemedical systems to aid in diagnosis by determining the probability that users have a condition/disease.

Chapter 3

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

Michael Zon[1,2,*], Guha Ganesh[1], and Qiyin Fang[1,3]

[1]McMaster University, School of Biomedical Engineering, Hamilton, ON
[2]Michael G. DeGroote School of Medicine, Hamilton, ON,
[3]McMaster University, Department of Engineering Physics, Hamilton, ON,
*Corresponding author (zonm@mcmaster.ca)

Contents of Paper I

Abstract

Telemedical technologies for remote monitoring of patients has become an active area of research, especially for smart-home and aging-in-place applications. There is a critical need to establish contexts autonomously (without manually labeling data), and use them to aid in pre-emptive detection of conditions/disease to promote aging-in-place. In this work, we designed and developed a general framework that connects sensor data to the probability of specific contexts. Using these autonomously established contexts, clinical tests were defined as situations through temporal context networks that identify the order in which events must occur for a user to have a positive or negative test result. An indoor positioning system, a smartwatch, and a smart-chair were used to test the framework using sensor data obtained from users emulating mobility of older adults. Two fall risk clinical tests and one Parkinson's test were modeled via context networks and the LR results from the experiments were used to determine the post-test probability of falling or having Parkinson's. The post-test probabilities determined by the system for falling or having Parkinson's were statistically significantly ($p < 0.05$) higher in the mobility-impaired group relative to the unimpaired group. The framework represents an important step in connecting raw sensor data to clinically validated tests through automatically established contexts (determined without training data), calculating the impact of context uncertainty on the prognostic value of these tests, and allowing context-aware telemedical systems to aid in diagnosis by determining the probability that users have a condition/disease.

3.1 INTRODUCTION

Context-aware computing is the notion of using situational and environmental information about users, places and objects to determine a user's context and adapt a computer application to fit their needs[1]. For medical computing applications, clinically relevant context is pivotal for defining intervention thresholds and clinical tests. For instance, inappropriate sinus tachycardia (IST), a known risk factor for all-cause coronary and cardiovascular mortality in middle-aged men and women, requires heart rates over 100 beats per minute (BPM) to be measured while a person is in a resting context[2]. Thus, a

telemedical system must be able to identify the resting context, or periods where users are not very active, in order to properly conduct this clinical test. Traditionally, once a set of clinical tests for a given condition have been performed they are used to quantify the probability a person has a condition or disease. Common medical examples of this include Well's Criteria for pulmonary embolism [3] or deep vein thrombosis [4], qSOFA score for sepsis [5], and the HEART score for major cardiac events [6]. These medical tools often determine the probability a user has a disease or event by first assigning them pre-test odds based on how likely the outcome is for that demographic from prior studies. Next, these baseline odds are multiplied by likelihood ratios (LRs) which represent the increased chance of the disease given a positive or negative outcome for each clinical test, as determined from clinical studies mapping the tests to the disease [7]. For a single clinical test, the effect is as follows

$$\text{post-test odds} = \text{pre-test odds} \cdot LR_{test} \qquad \text{Equation 3.1}$$

$$\text{post-test probability} = \frac{\text{post-test odds}}{1+\text{ post-test odds}} \qquad \text{Equation 3.2}$$

where post-test probability is a simple conversion of the person's odds for the disease to a probability for the disease, and LR_{test} is the likelihood ratio (LR) of that test for the disease of interest. If the test result is positive then the positive LR (LR+) is applied which increases the odds (LR+ > 1), if it is negative then the odds are reduced via the negative (LR-) LR (LR- <1). As mentioned in Haider et al's survey of health monitoring systems, context is pivotal to building useful health monitoring systems, but integration of context is still an open challenge given most systems do not reach a high level of context-awareness [8]. This is in part because many clinical tests have specific context requirements (e.g user at rest in IST). Furthermore, past works have not looked at how context identification techniques can be used to conduct context-dependent clinical tests so telemedical smart-home frameworks can use standard tools (i.e Eq 1 and 2) that physicians utilize to aid in diagnosis [9]–[11]. Despite there being standardized methods to determine the probability a person has a given disease in medicine, to the best of our knowledge, a framework defining how context-aware telemedical systems can use these tools to quantify a person's disease probability has not been developed to date. The development of this framework, and a context determination method that can support it, is the primary goal of the present work.

In order to use these standard medical tools to quantify disease probabilities, clinical tests must be conducted by telemedical systems. Given the dependency of these tests on contexts, mapping each test to a set of context conditions is necessary to ensure the system fulfills the requirements of each test. Two primary methodologies have emerged to allow pervasive computing systems to measure context, namely specification and learning-based approaches [12]. Learning-based approaches, such as neural networks, support vector machines, and random forests, focus on using statistical methods to determine when contexts occur by learning the relationships between sensor data and manually labelled data describing the true context during various sensor readings. These techniques are commonly used in smart-home systems to determine activities of daily living, with the end goal being to pre-emptively detect functional decline to permit safe aging in place [13]–[15]. Although highly accurate, learning based approaches suffer from the need to manually label data to predict contexts and being difficult to explain to clinical decision makers and patients [16]-[18]. This lack of transparency in how these methods diagnose is likely why ML algorithms are not used by healthcare providers when making diagnoses, despite the vast number of studies focused on using ML for disease diagnosis [19]-[21].

Specification-based context determination approaches focus on utilizing expert knowledge in order to infer simple situations from sensor data [12]. Additionally, it is common in these methods to create rules which define how contexts form situations, as in Lakehal et al's work [22]. A simple example would be conducting a test for supine tachycardia to assess the odds of hypovolemia due to blood loss using a

commercial smartwatch [23]. Based on standard clinical practice, a clinician may request that the heart rate assessment take place while the patient is supine and at rest. Thus, one may define the resting state as no motion from a wrist-worn accelerometer while in bed and then set a threshold of 100 BPM for tachycardia only when pressure sensors under the patient's bed detect their head is near the headboard (supine). A result of over 100 BPM increases a patients' post-test odds of having greater than 630 milliliters of blood loss by 3 folds. Unlike with learning based approaches, upon testing positive a healthcare provider can easily explain why they are calling a patient in for further assessment [23]. Specification-based approaches are powerful when important clinical information can be derived from simple sensor data as in the aforementioned example. Although specification-based approaches, such as spatiotemporal logic and logic programming, are effective for defining rules/relationships, current specification-based approaches do not provide contexts probabilities [24]-[25]. This is problematic given that contexts based on sensor data often cannot be known for certain, and clinical tests/situations based on less certain contexts must have a lower LR than the same test conducted using higher certainty contexts. As a result, a new fuzzy probability-based specification approach to context-determination is developed in the present work in order to take advantage of the rule-based methods of specification techniques while still obtaining probabilities for each contexts likelihood as in learning based approaches.

The present work aims to provide a telemedical smart-home framework for translating sensor data to the probability that a patient may have a given condition/disease via standard clinical tools/tests and automatically generated contexts. To validate the approach, experiments/clinical tests that relate to established medical outcomes through LRs are modeled as networks of contexts. The framework is then applied through a case study where the post-test probabilities for falling within 1 year and having Parkinson's are determined from data collected by a context-aware telemedical smart-home system we built. The primary novelties/contributions of the present work are as follows,

1. The application of fuzzy probability to quantify the probability that a context has occurred.
2. The development of spatiotemporal context networks which use fuzzy probability to model clinical tests
3. A generalized framework for quantifying the probability users have conditions/diseases using context-aware telemedical systems
4. A method to adjust LRs of known clinical tests in light of probabilistic uncertainty in the test conditions, thus allowing known clinical tests to be used by telemedical systems.

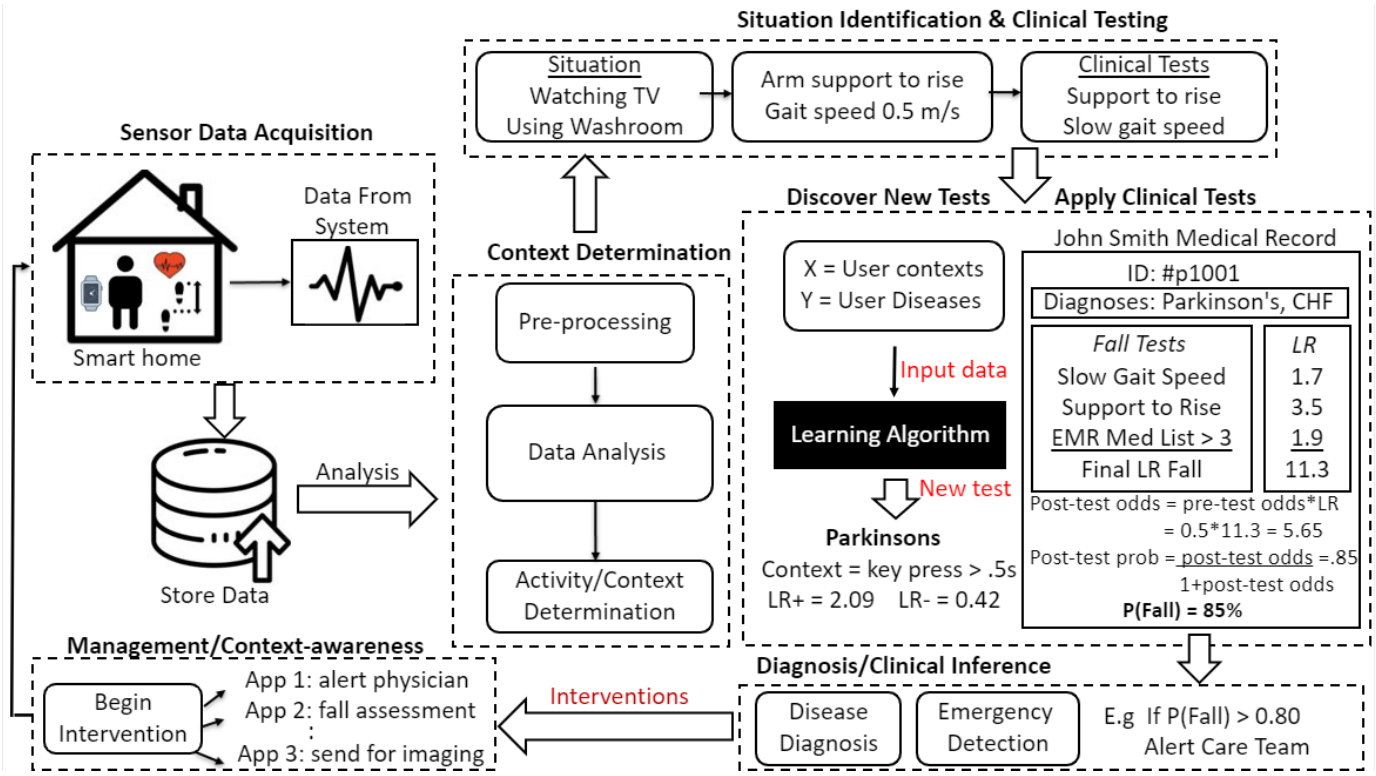

Figure 3.1 Overall Context-Aware Telemedical Framework for Automating Clinical Testing and Diagnoses using Smart Home Technology

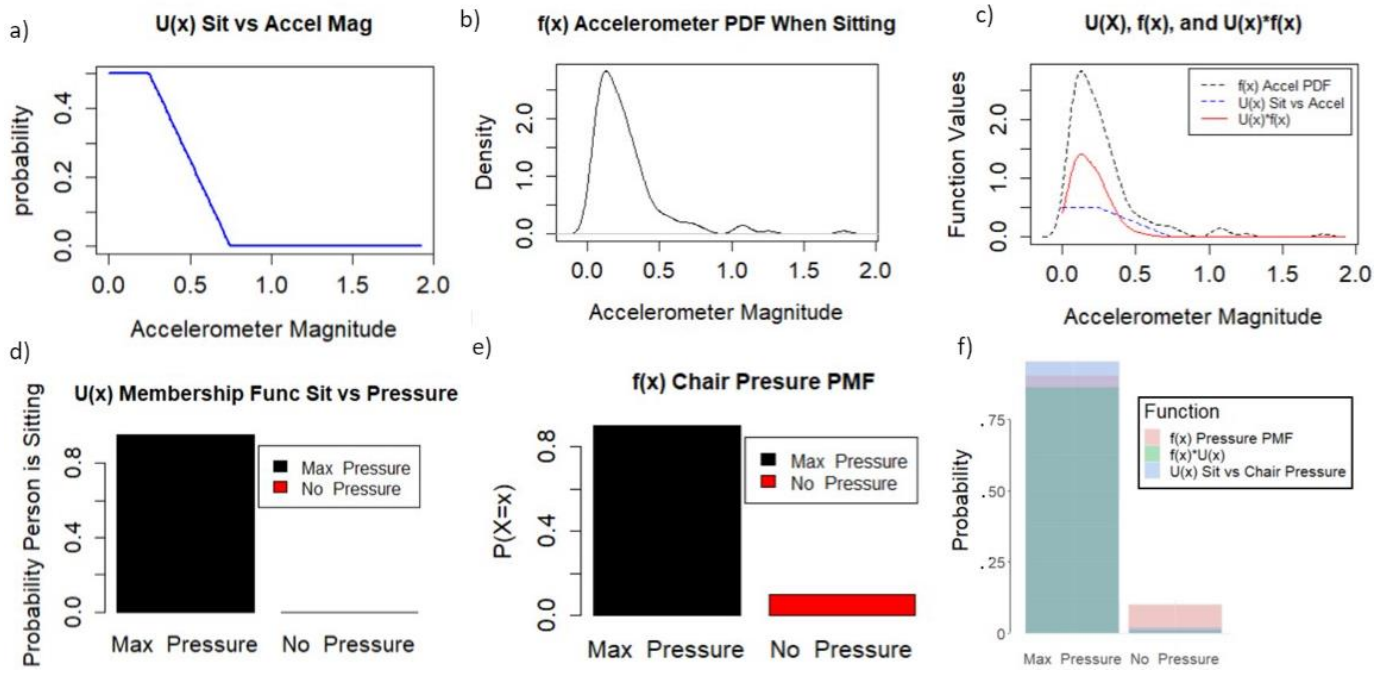

Figure 3.2 Discrete (FSR) and continuous (accelerometer) fuzzy probability calculations to determine the probability of the sitting context from a sensor event. Data shown is between T=0s and the user selecting they left the chair in the android app. a) Membership function for the sitting probability at different accelerometer magnitudes. b) Probability density function for the smartwatch accelerometer data. c) Probability they are sitting based on the data (integral of U(x)f(x) d) Discrete membership function for sitting vs. chair pressure e) Probability mass function for the chair FSR. f) Illustration of how these functions are multiplied to determine the function representing the probability the user is sitting based on the sensor data.

3.2 CONTEXT GENERATION FRAMEWORK AND ALGORITHM

The design of a general architecture/framework for ambient intelligent context-aware telemedical smart-home systems, that is validated in this work, is shown in figure 3.1. First, in the Sensor Data Acquisition module, data from the telemedical system is sent to a cloud database and associated with a user. Once it arrives it is pre-processed, analyzed and used to determine contexts in the Context Determination module (using fuzzy probability in this study) [26]. Next, the contexts probabilities are aggregated in the Situation Identification & Clinical Testing module to determine situations and clinical tests of interest. These clinical tests have known associations with diseases through LRs which multiply onto the individual's pre-test odds of having the disease in the Apply Clinical Tests module to generate post-test odds for the disease. Finally, the post-test odds are converted to a post-test probability. This final probability for the user's chance of having the disease is then compared to thresholds set by healthcare providers in the Diagnosis/Clinical Inference module to determine if their probability for the condition/disease warrants any interventions. Lastly, any software applications relying on data from the telemedical system can retrieve these probabilities to make decisions (e.g trigger intervention) within their applications making the overall system, by definition, context-aware through use of the contextual information.

Through integration with electronic medical records (EMRs), past medical histories' LRs for the given condition can also be used to further improve the user's post-test odds accuracy (e.g., taking more than 4 medications has positive LR for falls implying its more likely). Learning-based approaches can also be utilized to discover new tests/LRs that can be used to modify post-test probabilities in the Discover New Tests module. This is done by determining the sensitivity and specificity of contexts determined by the system for patients' diagnoses using their medical records.

The rest of the paper focuses on demonstrating the use of the framework through a case study where emulated data is used to conduct clinical tests and determine the post-test probabilities a group will fall in 12 months or has Parkinson's. In the present work, the Sensor Data Acquisition module is handled by a smart-home system. The Context Determination module is then used to obtain contexts from the data which are needed to conduct clinical tests for fall and Parkinson's risk. The Situations Identification & Clinical Testing module then runs the tests by modeling known tests as collections of contexts (i.e situations). Lastly, the results of the tests and their LRs are used in the Apply Clinical Tests module to determine the probability they will fall in 12 months or have Parkinson's. Prior to demonstrating this, the theory surrounding how contexts and clinical tests are obtained from sensor data is described in the next section.

3.3 FUZZY PROBABILITY AND CONTEXT ONTOLOGY NETWORKS CLINICAL/SITUATIONAL TEST CALCULATIONS

TABLE 3.1
Notation Used Throughout The Present Work

$P(X_i = C_j)_{s_i,\Delta t_j}$	Probability of context C_j in time period Δt_j according to data from sensor s_i yielding random variable X_i
$P(C_j)_{\Delta t_j}$	Probability of context C_j in time period Δt_j as determined by using all sensors measuring that context in the system
$\mu_{c_{ij}}(x)$	Membership function relating sensor i to context j
Δt_j	Time interval in which context j is being assessed in and that the data was collected
$s_i(x)$	Probability density function for sensor i's data
$P(Situation)_{T_s \leq t \leq}$	The probability a situation occurred between T_s and T_f
T_s	The start time of the first context in a situation
T_f	The final time of the last context in a situation
TP	True positives (sick correctly identified as sick)
TN	True negatives (Healthy correctly identified as healthy)
FP	False positives (healthy incorrectly identified as sick)
FN	False negatives (Sick incorrectly identified as healthy)
P	Total number positive for the condition being tested for
N	Total number that are negative for the condition being tested for
Sens	Sensitivity of the test
Spec	Specificity of the test
$LR+$	Positive likelihood ratio of the test
$LR-$	Negative likelihood ratio of the test
sys	Subscript representing that the value is from the system and differs from the original
$P_t = P_{thresh}$	Threshold error probability after which the system will run the clinical test

To determine the probability that a clinical test's conditions have been met, the probability that the contexts comprising that test occurred are first determined by applying Zadeh's fuzzy probability theory [26]. By building probability density functions (PDF) from sensor data, each context can be determined by leveraging the available sensor data and a fuzzy membership function that describes how each sensor's data relates to the context of interest. A simple example would be a watch accelerometer whose membership function assigns high accelerations a low probability that the user is in the sitting context, as shown in figure 3.2a. The accelerometer readings in 2b are multiplied by the membership function in 2a to yield the function represented by the red curve in 2c, whose integral represents the probability the user is in the sitting context. More formally, the probability of a context is written as

$$P(X_i = C_j)_{s_i,\Delta t_j} = \int_{-\infty}^{\infty} u_{c_{ij}}(x) \cdot s_i(x)_{\Delta t_j} \cdot dx \qquad \text{Equation 3.3}$$

Where $s_i(x)$ is the PDF for sensor i (e.g figure 3.2b), $\mu_{c_{ij}}(x)$ is the membership function relating sensor i to context j (e.g figure 3.2a), and Δt_j is the time interval over which the data was collected, and the

context's probability is valid. A table containing descriptions for this notation and other notation found throughout the paper can be seen in table 3.1.
For sensor data outputs that are discrete/categorical in nature, the PDF (or probability mass function) is described using the Dirac delta function,

$$s_i(x_i)_{\Delta t_j} = \sum_{k=1}^{K} P_k \cdot \delta(x - x_k) \qquad \text{Equation 3.4}$$

Where x_k are the discrete points/categorical outcomes each with a corresponding probability $P_1, \ldots . P_n$ representing how often it occurred during the time interval of interest. The corresponding membership function in this case can either be continuous or discrete, but if it is discrete, it must be defined for each point x_k. Figure 3.2d-f shows an example of this, where a chair pressure sensor has max pressure (x_1) 80% of the time (P_1=0.8) and no pressure (x_2) 20% of the time (P_2=0.2). The membership function in 2d defines a 95% chance the user is sitting when the pressure sensor is at its maximum, and no pressure as a 0% chance of sitting. Figure 3.2f shows the multiplication of the PDF and membership functions, which leads to a 76% (95%*80%) chance of the sitting context. Given that the context/event C_j occurring and its complement ${C_j}^c$ (representing the event not occurring) are disjoint events, meaning the sum of the probabilities is 100%, we have for any sensor event,

$$p(X_i = C_j) = 1 - p(X_i = {C_j}^c) \qquad \text{Equation 3.5}$$

For contexts where only 1 sensor being correct about the context implies it occurred (e.g any chair sensor detecting sitting pressure implies the sitting context) We can write the context probability as

$$\boldsymbol{P(C_j)_{\Delta t_j} = 1 - \prod_{i=1}^{N} P\left(X_i = {C_j}^c\right)_{s_i, \Delta t_j}} \qquad \text{Equation 3.6}$$

Using equation 3.5 , this leads to

$$P(C_j)_{\Delta t_j} = 1 - \prod_{i=1}^{N} \left(1 - P\left(X_i = C_j\right)_{s_i, \Delta t_j}\right) \qquad \text{Equation 3.7}$$

where $P(C_j)_{\Delta t_j}$ is the probability that the context C_j has occurred in the time interval Δt_j based on the set of sensors S available to the telemedical system. Figure 3.3a shows this calculation visually and Figure 3.3b provides a simple graphical example of equation 3.7 relevant to the present work. In this 3-sensor system, the sitting context is measured by a smartwatch accelerometer and 2 pressure sensors on the seats of 2 separate chairs. Even if the accelerometer data is high and chair 1 indicates no pressure, meaning these 2 events are unlikely to indicate the sitting context, the presence of constant applied pressure on chair 2 will dominate equation 3.7 leading to a large value for $P(Sitting)$ (assuming the membership function assigns a probability near 1 for sitting when pressure is detected on the chair). Thus, sitting is highly probable based on the presence of pressure placed on chair 1, regardless of the pressure value on chair 2 and the active accelerometer. If any sensor has a probability near 1.0 for the context of interest, then the multiplicative term in equation 3.7 becomes close to 0 resulting in a probability for the context near 1. This provides a useful way to ascertain the likelihood of a given context from multiple sensors.

For situations, we define these in the usual way as a collection of contexts that together form new meaning [12]. However, we expand on this by formulating them in temporal context networks (figure 3.4a) and by defining their probability of occurring through their sub-contexts. Essentially, we require that each context must occur at a pre-specified point in time relative to another for a situation to occur. The

probability that a given situation has occurred then becomes the simple product of the probabilities that each context has occurred in the chronology specified. This is written as

$$P(Situation)_{T_s \le t \le T_f} = \prod_{j=1}^{M} p(C_j)_{\Delta t_j} \qquad \text{Equation 3.8}$$

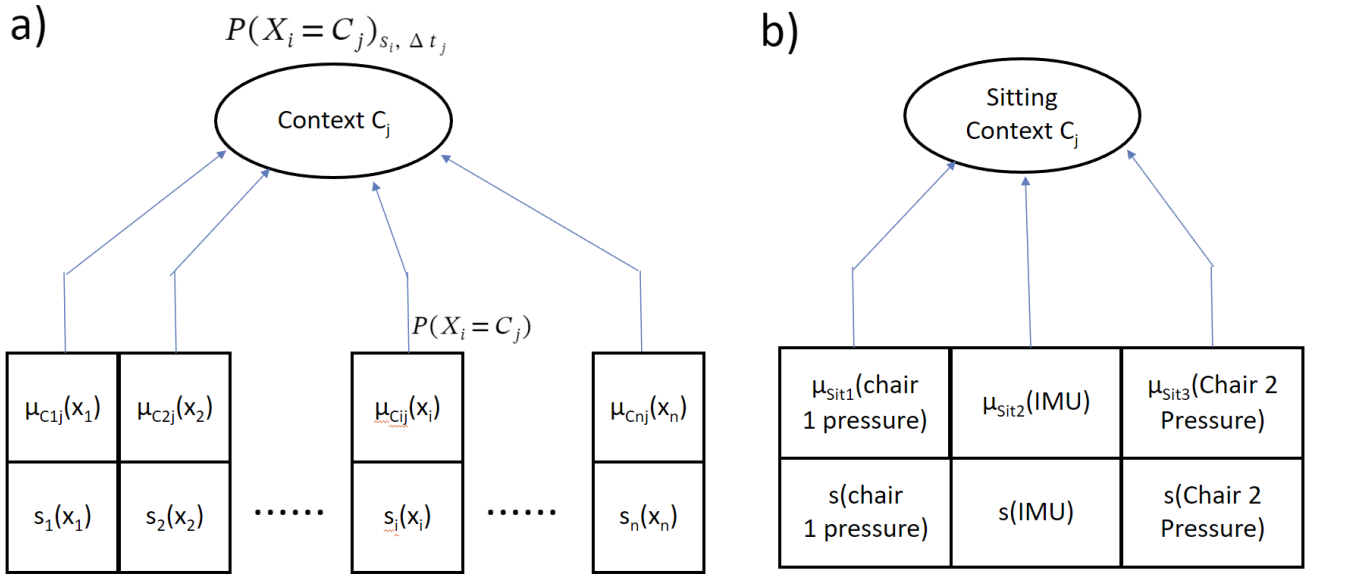

Figure 3.3 Illustration of calculating context probabilities. a) general approach for "n" sensors with probability density functions s(x) formed from their acquired data and membership functions $\mu_{c_{i,j}}(x)$ relating the data to the context. b) Example calculation of determining the sitting context from accelerometer data and pressure sensors on 2 chairs.

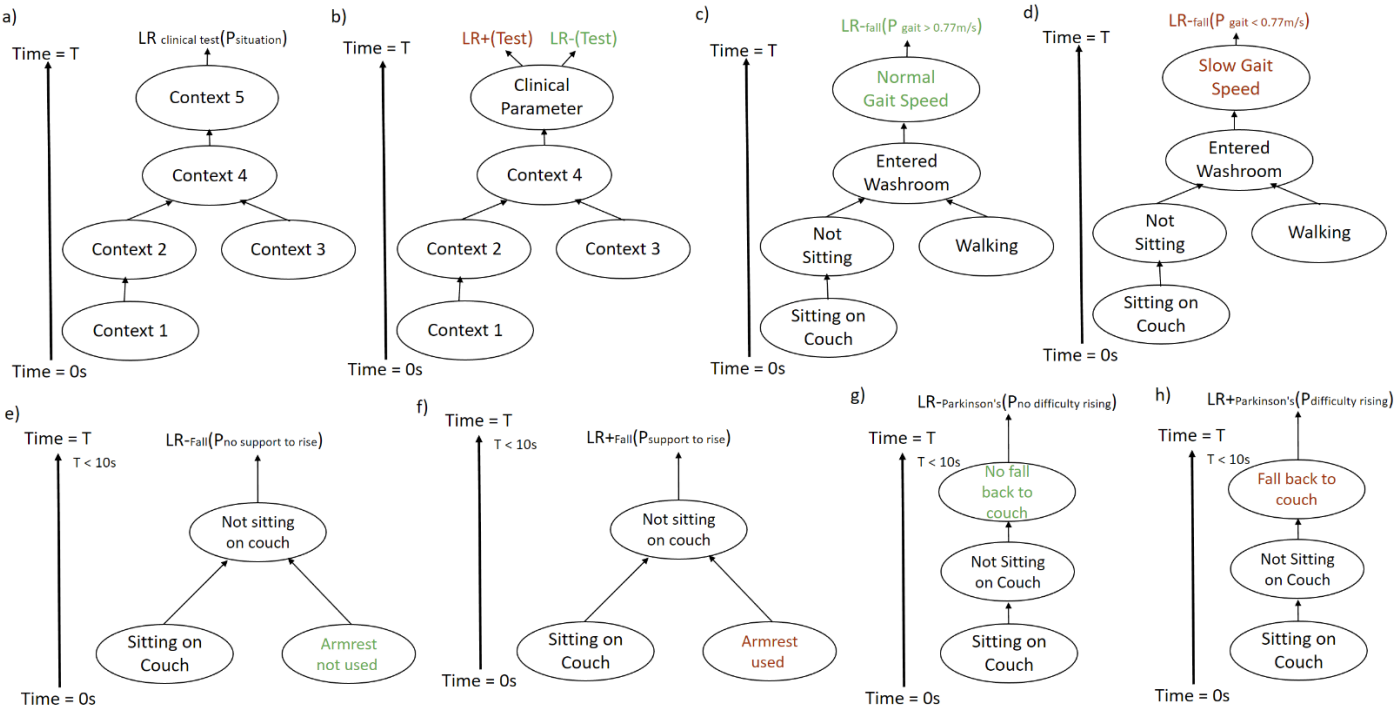

Figure. 3.4 Illustration of using context ontology networks to define situations. a) General framework for determining the probability of a situation from various contexts. b) General framework for determining LR+ and LR- from contexts. c) Example calculation for the clinical test/situation of a normal gait speed and, d) a slow gait speed. e) Context ontology network for assessing fall risk through being negative for

support needed to rise and f) positive for support needed to rise. g) Context ontology network used for assessing Parkinson's risk through being negative for the difficulty rising test and h) positive for the difficulty rising test.

Here, M is the total number of contexts that comprise the situation, $T_s$is the start time of the first context and T_f is the end time of the last context in the temporal context network defining the situation. Using this theory, common clinical tests can be defined as situations based on the sub-contexts that comprise them, as shown in figure 3.4b. To determine if a user is positive or negative for a test, it is broken into the contexts that comprise the test conditions and the context that relates to the clinical parameter being measured in the correct conditions (e.g., gait speed, elevated heart rate, etc.). In the present work, we use this method to conduct two clinical tests for the risk of falling in the next 12 months and one clinical test for assessing the likelihood an older adult has Parkinson's (figure 3.4c-h).

As shown in figure 3.4c-d, gait speed is assessed by measuring the amount of time it takes a user to get from their chair to a washroom, which in the present work is known to be 8.5 meters from the smart-chair. The clinical test/situation is broken into 5 contexts which are sitting initially, then not sitting and walking, followed by walking to the washroom. Lastly, the gait speed (clinical parameter/context) during this room transition, as detected by the IPS, is measured. The probability that this situation was in fact observed is then used to determine the LR of a fall within 12 months by adjusting the normal LRs. The derivation for how this is done is presented in the next section. Gait speeds have been shown to have a positive LR (LR+) of 2.0 and negative LR (LR-) of 0.73 for gait speeds less than and above 0.77 m/s, respectively [27]. Because each test has a clinical parameter of interest, gait speed in this example, there is 1 situation that corresponds to being positive for the test (e.g., gait speed <0.77 m/s, figure 3.4d) and 1 that corresponds to being negative for the test (e.g., gait speed > 0.77 m/s, figure 3.4c). For simplicity, the context that defines the clinical parameter of interest in figure 3.4 and determines if the test result is positive or negative is highlighted in red, and the contexts/conditions that are required before assessing this parameter/context are in black. Because the situation is not guaranteed to have occurred given that each context is a probability based on the sensor data, the LR for the test accepts the probability of the situation as an input so it can be adjusted based on the chance the clinical situation did not occur.

The other test for fall risk shown in figure 3.4e-f assesses whether the user needs to use armrest support to rise (LR+ = 4.3, LR-=-.77) [28]. The last (figure 3.4g-h) test assesses whether an adult has difficulty rising from their seat by determining whether they fall back to the chair during their initial attempt to rise, which has an LR+ and LR- for Parkinson's of 1.9 and 0.58, respectively [29]. These activities are measured by the indoor positioning system, smartwatch, and smart-chair data described in the methods section, and are verified using the ground truth timestamps from a mobile app that the user provides input to. The fuzzy membership functions, sensor data, and time intervals used to determine each context probability, and thus the situation/test probabilities, are also described in the Methods section.

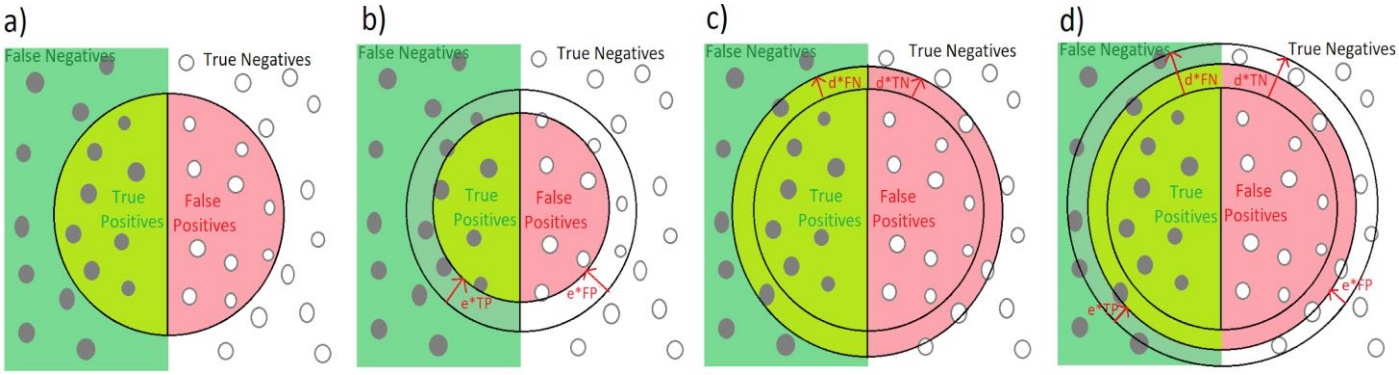

Figure 3.5 Illustration of the outcomes for a clinical test run by a context-aware system and how they relate to sensitivity and specificity. a) outcomes for a clinical test run under normal circumstances. b) Outcome when incorrectly run tests are all negative. c) Outcome when incorrectly run tests are all positive. d) Outcome when incorrectly run tests lead to both positive and negative results.

3.4 ADJUSTING LIKELIHOOD RATIOS DUE TO SITUATIONAL UNCERTAINTY

Although a telemedical system can be used to conduct a clinical test, unlike when a healthcare provider conducts a test the system cannot guarantee the test conditions (e.g user has walked 10 meters for gait speed test) have been met with 100% certainty. Thus, the prognostic value of a test conducted by a telemedical system must be less than its usual value given the system cannot be sure it occurred. It is necessary for those building telemedical systems to determine how to adjust the clinical tests prognostic value to account for these uncertain test conditions, otherwise one would be unable to use the vast number of known clinical tests that ascertain the likelihood a person has a condition or disease. As mentioned earlier (equation 3.1 and 3.2), the pre-test odds a person has a given disease are multiplied by the LR of the test to get their new odds for said disease. It is worth mentioning that the pre-test odds are normally based on epidemiological data (e.g 1% of those 65+ have Parkinson's). Regarding the LR, it is derived by running a test for a given disease on a population and determining the true positives (TP), true negatives (TN), false positives (FP), false negatives (FN), total negatives (N), and total positives (P). Definitions for these terms are provided in table 3.1.

Sensitivity is then defined as TP/P, and specificity as TN/N. Lastly, LR+ and LR- are then defined as

$$LR+ = \frac{sens}{1-spec} \qquad \text{Equation 3.9}$$

$$LR- = \frac{1-sens}{spec} \qquad \text{Equation 3.10}$$

Where LR- is multiplied on to the pre-test odds instead of LR+ if the person has a negative test result. Now, to derive the adjusted LRs, one must investigate how TP, TN, FP, and FN change when the system conducts a test when it should not. Let us call TP_{sys}, FP_{sys}, TN_{sys}, FN_{sys} the true positive, false positive, true negative, and false negative numbers measured by the system. Similarly, the equivalent variables without the "sys" subscript will be the true values unaffected by system measurement uncertainty. The sample space comprising TP, FP, TN and FN under normal circumstances is shown in figure 3.5a. We will also define $LR+_{orig}$ and $LR-_{orig}$ as the tests positive and negative LRs when measured by physicians under normal circumstances and $LR+_{sys}$ and $LR-_{sys}$ as the positive and negative LRs for the test when conducted by the context-aware telemedical system.

Let us assume the system runs a test when it is 95% confident that the situation (P(Situation)) describing the test conditions occurred. This means that on average, 5% of the time, the test will be run at the incorrect time, implying the test results are invalid. Let's call this remaining 5% $P_{thresh} = 1 - P(situation)$. This leads to two possible scenarios: 1) the system runs the test when it should not and obtains a positive result b percent of the time; and 2) the system runs the test when it should not and obtains a negative test result c = 1-b percent of the time. We define $d = P_{thresh} \cdot b$ as the percentage of tests that will incorrectly lead to positive results and $e = P_{situation-thresh} \cdot c$ as the percentage of tests that will incorrectly lead to a negative result. We will first analyze these two scenarios separately and then look at a realistic generalized system where both cases (incorrect positive and negative tests) occur.

First, imagine that the system is used to conduct a clinical test a single time on a sufficiently large population and leads to negative results when triggered incorrectly e percent of the time. Now, in this scenario both the true positives and false positives will decrease by e percent since e percent of the tests will now yield negative results incorrectly. This leads to $TP_{sys} = TP(1-e) = TP - e \cdot TP$ and $FP_{sys} = FP(1-e) = FP - e \cdot FP$. Now, these e percent of newly misclassified true positives who all have a negative result will increase the false negatives leading to $FN_{sys} = FN + e \cdot TP$. Similarly, the e percent of prior false positives will now correctly have a negative result leading to $TN_{sys} = TN + e \cdot FP$. A visualization of this scenario is presented in figure 3.5b. We will now consider the opposite scenario, where the system's incorrect testing d percent of the time only leads to positive test results. Now, it is instead the true negatives and false negatives that decrease by d percent as d percent of tests lead to a positive result. This leads to $TN_{sys} = TN(1-d) = TN - d \cdot TN$ and $FN_{sys} = FN\,(1-d) = FN - d \cdot FN$. Now, these d percent of true negatives, which are incorrectly identified as positive, leads to an increase in the false positive resulting in $FP_{sys} = FP + d \cdot TN$. Similarly, the false negatives correctly identified as true positives now leads to $TP_{sys} = TP + d \cdot FN$ for the systems true positive count (as visualized in figure 3.5c).

In reality, both scenarios occur simultaneously and some proportion e of the system's incorrect tests will lead to classifying users as negative and another proportion d of the system's incorrect tests will lead to classifying user's as positive. Thus, the two scenarios described both occur simultaneously (figure 3.5d) leading to

$$TP_{sys} = TP + d \cdot FN - e \cdot TP \qquad \text{Equation 3.11}$$

$$FP_{sys} = FP + d \cdot TN - e \cdot FP \qquad \text{Equation 3.12}$$

$$TN_{sys} = TN - d \cdot TN + e \cdot FP \qquad \text{Equation 3.13}$$

$$FN_{sys} = FN - d \cdot FN + e \cdot TP \qquad \text{Equation 3.14}$$

Where TP_{sys}, FP_{sys}, TN_{sys} and FN_{sys} have been derived by adding the perturbations the system introduces relative to the usual testing circumstances present in both scenarios. Now, the sensitivity and specificity are derived by using the systems values in place of the original values in their usual formulas,

$$\begin{aligned} sens_{sys} &= \frac{TP_{sys}}{P} = \frac{TP + d \cdot FN - e \cdot TP}{P} \\ &= sens_{orig} + d(1 - sens_{orig}) - e \cdot sens_{orig} \\ &= sens_{orig}(1-e) + d(1 - sens_{orig} \end{aligned} \qquad \text{Equation 3.15}$$

$$spec_{sys} = \frac{TN_{sys}}{N} = \frac{TN - d \cdot TN + e \cdot FP}{N}$$
$$= spec_{orig} - d \cdot spec_{orig} + e(1 - spec_{orig}) \quad \text{Equation 3.16}$$
$$= spec_{orig}(1 - d) + e(1 - spec_{orig})$$

Solving for $LR+_{sys}$and $LR-_{sys}$, we obtain

$$LR+_{sys}(d,e) = \frac{sens_{sys}}{1-spec_{sys}} = \frac{sens_{orig}(1-e)+d(1-sens_{orig})}{1-spec_{orig}(1-d)-e(1-spec_{orig})} \quad \text{Equation 3.17}$$

$$LR-_{sys}(d,e) = \frac{1-sens_{sys}}{spec_{sys}} = \frac{1-sens_{orig}(1-e)-d(1-sens_{orig})}{spec_{orig}(1-d)+e(1-spec_{orig})} \quad \text{Equation 3.18}$$

Looking at the limits, one can see that

$$\lim_{P_{thresh}\to 0} LR+_{sys} = LR+_{orig}$$

$$\lim_{P_{thresh}\to 0} LR-_{sys} = LR-_{orig}.$$

Thus, when the system never runs tests in an incorrect context ($P_{thresh} = 0$) the original LRs are retrieved, as expected. Similarly, taking the limit as $P_{thresh} \to 1$, one can easily show that

$$\lim_{P_{thresh}\to 1} LR-_{sys} = \lim_{P_{thresh}\to 1} LR+_{sys} = 1.$$

As expected, if the system never tests under the correct circumstances neither the positive nor negative LRs have any clinical value in predicting the condition/disease since multiplying the pre-test odds by 1 has no effect. Given it is often not feasible to know the true values of b and c, in the present work we assume that the proportion of tests the system incorrectly classifies as positive, and negative are equal and set $b = c = 0.5$ and $d = e = 0.5P_{thresh}$. As a result, the adjusted LRs for the system considering uncertain conditions can be written as

$$LR+_{sys}(P_{st}) = \frac{sens_{sys}}{1-spec_{sys}} = \frac{sens_{orig}(1-\frac{P_t}{2})+\frac{P_t}{2}(1-sens_{orig})}{1-spec_{orig}(1-\frac{P_t}{2})-\frac{P_t}{2}(1-spec_{orig})} \quad \text{Equation 3.19}$$

$$LR-_{sys}(P_{st}) = \frac{1-sens_{sys}}{spec_{sys}} = \frac{1-sens_{orig}(1-\frac{P_{st}}{2})-\frac{P_{st}}{2}(1-sens_{orig})}{spec_{orig}(1-\frac{P_{st}}{2})+\frac{P_{st}}{2}(1-spec_{orig})} \quad \text{Equation 3.20}$$

Where P_t is an abbreviation for P_{thresh}.

3.5 METHODS

This section is divided into 5 main subsections. The first subsection describes the portable smart-home system, smartwatch, and smart-chair developed to acquire data throughout this study. The next subsection describes the experimental protocol used to collect data with the smart-home system. The third subsection describes how a case study was formulated from the collected data. Next, subsection 4 describes how the data was analyzed to determine the post-test probability a user has of a given condition or disease. Lastly, the final subsection contains a short comment on data availability.

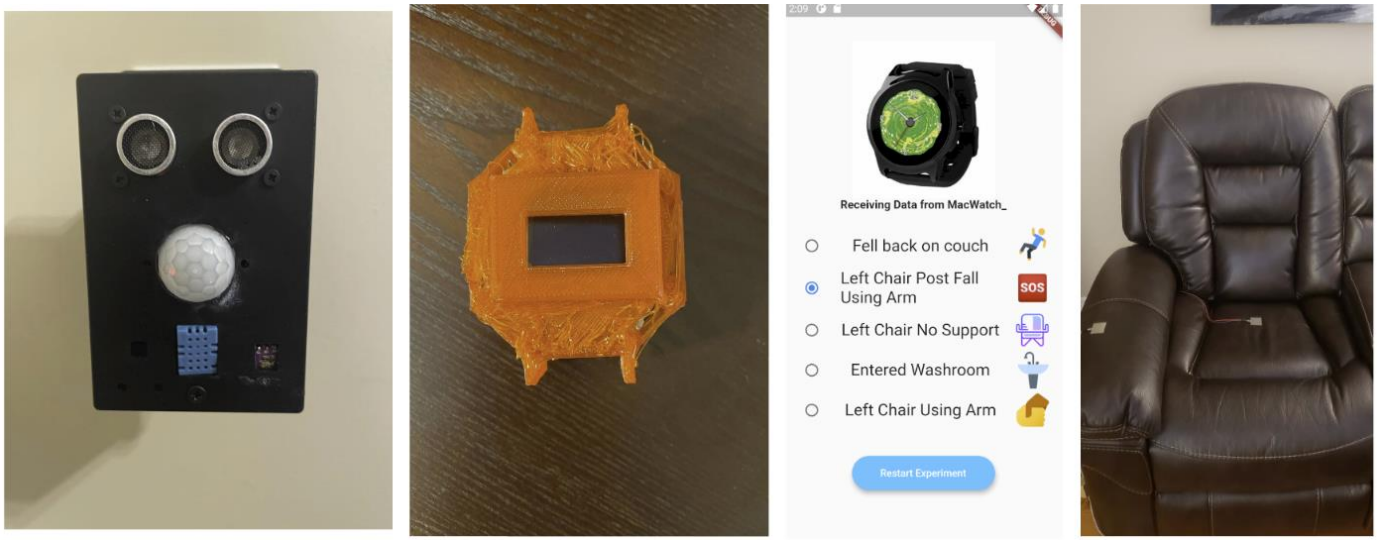

Figure 3.6 Hardware and software used for data collection. a) ESP32 based Indoor positioning beacons. b) Smartwatch for accelerometer data collection and indoor position broadcasting. c) Android application for collecting ground truth data. d) Couch equipped with force sensitive resistors.

3.5.1. Smart-home System/Software: Indoor Positioning System, Smartwatch, and Smart-Chair

The primary data collected via the smart-home system is the user's room location through an indoor positioning system (IPS), movement via a wrist-worn smartwatch, and whether they are in contact with the seat and armrest of the smart-chair. The IPS was constructed by placing a wireless beacon in each room (figure 3.6a). Each beacon is equipped with additional environmental, motion, and light sensor modules. For the contexts used in the present work, only the Bluetooth low energy (BLE) signals from the beacons (broadcasted from the smartwatch) were required during analysis. The BLE sensor stations in each room record the relative signal strength indicator (RSSI) of the machine address associated with the smartwatch and send the data through the ESP-NOW protocol to a master ESP32 device (Espressif Systems, China) located in the living room. The data is then sent to a Raspberry Pi (model 4b) through a serial connection which then assigns the room the user is in to be the room with the beacon that has the strongest RSSI value. This location information is uploaded to a cloud database (Firestore) via Wi-Fi.

The custom-built smartwatch consists of an ESP32 with an OLED display (HTIT-WB32, Heltec, China) and a BNO055 (Adafruit Industries, USA) accelerometer. A 3D printed watch case was made to house the components and secure the watch to the user (figure 3.6b). To ensure the smartwatches data can be stored and sent to the cloud without the home's wireless network, a cross-platform mobile app was developed using Flutter which connects the smartwatch to a smartphone. The device's orientation and linear acceleration along the watches standard cartesian axes (x, y, z) are sent from the smartwatch to the mobile app at 50Hz and then uploaded to Cloud Firestore for analysis after the experiments. Additionally, the mobile app allows the users to enter what they are currently doing during the experiments (figure 3.6c). These entries are time stamped, uploaded to the cloud database, and used as ground truth reference points for when events/contexts occurred. Lastly, the smart-chair (figure 3.6d) consists of one force sensitive resistor (FSR RP-S40-ST, DFRobot, China) attached to the couches base and a second FSR attached to the couch's armrest. The signals from the FSRs are sent to an analog to digital converter (ADS1115, Adafruit Industries, USA) which then sends the result to the Raspberry Pi. The Pi then converts any analog to digital converter (ADC) value greater than 80 percent of the FSRs maximum (22-pound max) to a 1 and uploads the FSR data of the armrest and seat to the cloud database.

3.5.2 Experiment Protocol

Data was collected and generated in house using the IPS system, smartwatch, and smart-chair

during two sets of experiments carried out by volunteers in the smart-home. The experiments were designed to collect the data needed to determine the context/situation probabilities of the clinical tests for slow gait speed, difficulty rising, and support needed to rise. The first set of experiments intended to simulate a healthy mobility unimpaired older adult leaving the couch and walking with a normal gait speed to the washroom. The user begins sitting on the couch and uses the mobile app to select that the experiment has begun. After approximately 1 minute they leave the smart-chair's seat without using the armrest and select that this occurred in the mobile application (figure 3.6c) so that this event's ground truth time can be sent to the cloud database. Lastly, they walk to the washroom at a normal gait speed, select they have arrived in the washroom in the mobile app, and after waiting another 30 seconds they select restart experiment which sends the experiments end time to the cloud. The second set of experiments intended to simulate a mobility impaired adult who has difficulty leaving the smart-chair and walks slowly to the washroom. The only differences relative to the mobility unimpaired experiments are that the user is asked to use the armrest when leaving the chair, to fall back on the chair once right after rising, and then to walk slowly to the washroom when they leave the chair for a second time. Each one of these events is recorded by the user in the mobile app (figure 3.6c) to indicate its time of occurrence. In addition to analyzing the data with ground truth timestamps entered by the user, the analysis was conducted while automating the start and end times of the contexts using the sensor data. For instance, in this case sitting would be assumed to start when pressure on the chair is first detected. This was done to demonstrate that the system could be fully automated.

3.5.3 Case Study

To demonstrate how the framework and system would be used in practice, the 5 mobility impaired and 5 mobility unimpaired experiments were assigned to 10 theoretical older adults. Additionally, to demonstrate the utility of past medical histories (PMH) data, we assigned some hypothetical past medical histories to these adults. Specifically, for fall risk related PMH data a history of using 4 or more medications (LR+ 1.9, LR- .76), having had a stroke (LR+ 3.2, LR- 0.87), or having fallen in the last year (LR+ 2.8, LR- 0.86) were randomly assigned to the theorized older adults [28], [30], [31]. Additionally, a past history of falls was (or was not) assigned to the older adult's given it reduces the odds a user's mobility issues are due to Parkinson's with an LR+ of 0.65 and an LR- of 3.19 [32]. These LRs were also multiplied onto the pre-test odds, however, the LRs were not adjusted given these contexts can be known with certainty.

3.5.4. Data Analysis, Post-Test Probability Determination and Fall/Parkinson's Risk Assessment

Sensor data was downloaded from the cloud and analyzed in R. Code was developed which determines the PDF from the sensor data, creates membership functions, and integrates the multiplication of these functions to determine context and situation probabilities according to equation 3.7 and equation 3.8, respectively. Probability density functions were built via gaussian kernel density estimation and integrals of continuous functions were approximated through adaptive quadrature.

TABLE 3.2
Membership Functions Used to Relate Sensor Data to Contexts and the Time Intervals in which Data was Collected for the Contexts

Context	Data Type	Sensor	Start Auto	End Auto	Start GT	End GT	(x1, y1)	(x2, y2)	Function Type
Sitting	Acceleration	watch	Pressure Detected	No Pressure	Experiment Start	Left Chair	(0.25, 0.5)	(0.75, 0)	Trapezoidal R
Not Sitting	Acceleration	watch	Pressure Detected	No Pressure	Experiment Start	Left Chair	(0.25, .0.0)	(0.75, 0.5)	Trapezoidal L
Sitting	Max Pressure	Chair Seat FSR	Pressure Detected	No Pressure	Experiment Start	Left Chair	(MP, 0.0)	(not MP, 1.0)	Discrete
Walking	Change Location (d)	IPS	No Pressure	Location Change IPS	Left Chair	Entered Washroom	(not CL, 0.0)	(CL, 1.0)	Discrete
Gait Speed	Speed	IPS	No Pressure	Location Change IPS	Left Chair	Entered Washroom	(1.0, 0.77)	(0.0, .77)	Trapezoidal R
Arm Rest Use	Max Pressure	Chair Arm FSR	No Pressure	Start Auto - 5s	Left Chair	Start GT – 5s	(MP, 0.0)	(not MP, 1.0)	Discrete
Second Sit	Max Pressure	Chair Seat FSR	1st No Pressure	2nd Pressure Detect	Fall to Couch	Left Chair Again	(MP, 0.0)	(not MP, 1.0)	Discrete
Enter Washroom	Location	IPS	Location is washroom	Location is washroom	Entered Washroom	Entered Washroom	(not WR, 0.0)	(WR, 1.0)	Discrete

*All time points in the Start GT and End GT column were determined based on users selecting the same text within the mobile application. GT = ground truth, WR = washroom, MP = max pressure, CL = change location

Adjusted LRs were computed in R by using equation 3.17 and equation 3.18. If the probability the user had a positive test was greater than the probability they had a negative outcome for the same test (e.g., 3e probability greater than 3f), then LR+ was used (equation 3.19), otherwise LR- was used (equation 3.20). To determine the post-test probabilities, such as the probability a user will fall in the next 12 months, pre-test probabilities were converted into pre-test odds, multiplied by the relevant LRs for that condition/disease to obtain post-test odds, and then these odds were converted to post-test probabilities, as shown below for a single LR [7].

$$\text{pre-test odds} = \frac{\text{pre-test probability}}{1-\text{pre-test probability}} \quad \text{Equation 3.21}$$

$$\text{post-test odds} = \text{pre-test odds} \cdot LR_{sys-condition} \quad \text{Equation 3.22}$$

$$\text{post-test probability} = \frac{\text{post-test odds}}{1+\text{ post-test odds}} \quad \text{Equation 3.23}$$

Pre-test probabilities were based on epidemiology data as done in a clinical setting. The pre-test probability of falling at least once in 12 months was set to 33% given that studies have indicated this is the fall risk for those over 65 [30]. The probability was then converted into pre-test odds (1:2) and then the probability that the 2 fall risk clinical tests/situations occurred were used to adjust the LRs for the clinical tests prior to using the LRs to get the post-test probabilities. The same procedure was used to determine the post-test probability of Parkinson's using the difficulty rising test with a pre-test probability for Parkinson's of 1% for adults over 65 and 2% for those over 85 [33]. The LRs for Parkinson's and falls for the various medical history data was also multiplied into the pre-test odds prior to calculating the post-test probabilities. After determining the post-test probabilities for Parkinson's and falling within 12 months, a one-sided Wilcoxon Signed Rank Test was used to determine if the post-test probabilities were greater in the mobility impaired group to a statistically significant ($p < 0.05$) degree. Age and past medical history were controlled for by conducting a paired analysis between the two groups where pairs had the same past medical history and age range.

$$\mu_{Trap\text{-}L}(x) = \begin{cases} y1 & x < x1 \\ y1 + (y2-y1)\left(\frac{x-x1}{x2-x1}\right) & x1 \leq x \leq x2 \\ y2 & x > x2 \end{cases}$$

$$\mu_{Trap\text{-}R}(x) = \begin{cases} y1 & x < x1 \\ y1 - (y1-y2)\left(\frac{x-x1}{x2-x1}\right) & x1 \leq x \leq x2 \\ y2 & x > x2 \end{cases}$$

$$\mu_{discrete}(x) = \begin{cases} y1 & x = x1 \\ y2 & x = x2 \end{cases}$$

Figure 3.7 Membership functions used in the study.

The membership functions (defined in figure 3.7) used to relate the sensor data to the contexts of the clinical situations shown in figure 3.4 are described in table 3.2. The relationship between the three function types, (x1, y1), and (x2, y2) from the table are shown below.

Additionally, table 2 describes the time intervals in which the data was collected for each context when automating the time intervals and using the ground truth time intervals based on user input from the mobile application. As an example, for the gait speed clinical test the situation consists of the sitting, not sitting, walking, entered washroom, and slow gait context probabilities (figure 3.4b) and the sitting context was calculated using equation 3.7 with the accelerometer and chair pressure data.

The trapezoidal R membership function for relating gait speed to having a slow gait was set to y=1.0 (100% slow) for values less than or equal to 0.77 m/s and y=0 for values greater than this in accordance with the literature [27]. Since this was a single measurement the PDF used in equation 3.7 was a single termed Dirac delta function which existed at the measured speed (equation 3.4 with 1 term). The support to rise test (figure 3.4e) used the same membership functions, time intervals, and PDFs for the sitting and not sitting context with the addition of the armrest-used context as determined from the pressure sensor on the armrest. Lastly, the difficulty rising test (figure 3.4g) uses the same time interval, PDFs, and membership functions for the initial sitting context. However, the prior tests used the last pressure detection as the beginning of the not sitting context. In this case, the not sitting context interval is measured from the first release of pressure (or mobile app selection) to the first detection of pressure again. The second sitting context's time interval is then between this second pressure time and the time when pressure is released from the sensor, or the user indicated they left the couch again (ground truth case). Falling back to the seat is defined by these events occurring within 10 seconds. In the case of a mobile adult where there is no second sitting event, the system uses data from the 10 seconds following when the user left the seat (automated case), or indicates they have left the seat in the app, to calculate the probability of a second sitting context indicative of difficulty rising.

3.5.5. Data Availability

The data used in this manuscript is included in the supplementary files. Data pertaining to the mobility impaired experiment is in directories with the name "unhealthy" in it whereas the mobility unimpaired directories have the name "healthy". There are 10 directories with data, 1 for each emulated experiment (5 being mobility impaired and 5 mobility unimpaired).

3.6 CASE STUDY

Dr. Smith, a family doctor whose patient population primarily consists of older adults has noticed that approximately a third of older adults in his practice fall within a 12-month timeframe. Many of these fall's lead to hip fractures followed by death within 1-3 years. As a result, Dr. Smith is highly interested in identifying which of his patients are at high risk of falling. In order to identify those at higher risk of falling he asks 5 patients that he suspects to be mobility impaired to use a context-aware telemedical smart home system (CATS) comprising a smartwatch, indoor positioning system, and smart-chair which can conduct common clinical tests that assess fall risk. He also asks 5 patients he suspects to be mobility unimpaired to use the system to test whether it can differentiate between the two groups. The system is linked to Dr. Smith's electronic medical records in order to determine which patients are taking more than 4 medications (LR+ = 1.9), have had a stroke before (LR+=3.2), or have fallen in the last year (LR+=2.4), as these factors also have known LRs for the chance someone over 65 will fall within 12 months [28], [30], [31].

The system also conducts tests for Parkinson's by assessing who has difficulty rising from the smart-chair (LR+=1.9) and who has fallen in the past, as the lack of a fall history has a positive association with Parkinson's (LR+=3.19) [32].

3.7 RESULTS

3.7.1 Fuzzy Probability Calculations

An illustration of using fuzzy probability with sensor data to determine context probabilities is shown in figure 3.2. Here, the maximum pressure on the seat is defined to imply a person is sitting with 95% probability, reduced from 100% used in the study for the purpose of the illustration. Figure 3.2c and 3.2f illustrate how the sensor data (3.5a, 3.5d) is multiplied by the membership functions (3.5b, e) to relate it to the context of interest and obtain a distribution whose integral represents the probability the context occurred (sitting in this case) based on the sensor event.

3.7.2 Situation/Context Probabilities

The mean context probabilities for contexts comprising the 3 clinical situations/tests are shown in table 3.3. Results are divided based on the two groups, namely the experiments emulating mobility impaired and unimpaired adults, and whether the time intervals were determined automatically by the system or based on the ground truth events entered by the user in the smartphone application. For all sets of experiments, the entered washroom context had a probability of 1.0 as the IPS always recorded a transition to the washroom and only contained living room locations prior to this. The average gait speed for the healthy mobile adult experiments using ground truth time points and automated time points was 1.09 m/s (sd 0.08 m/s) and 1.01 m/s (sd 0.25 m/s), respectively, and for the
immobile adult experiments using ground truth time points and automated time points was 0.14 m/s (sd 0.01 m/s) and 0.24 m/s (sd 0.02 m/s), respectively.

TABLE 3.3
Mean Context Probabilities for the Mobile and Immobile Adult Experiments When Automating the Time Intervals and Using the Manually Entered Ground Truth Time Points

	Difficulty Rising Test			Support To Rise Test			Gait Speed Test			
Group	**P(Sit)**	**P(Not Sit)**	**P(Sit Again)**	**P(Sit)**	**P(Arm Rest Use)**	**P(Not Sit)**	**P(Sit)**	**P(Not Sit)**	**P(Walked)**	**P(Slow)**
Mobile GT	0.99 (0.02)	1.00 (0.00)	0.01 (0.00)	0.99 (0.02)	0.00 (0.00)	1.00 (0.00)	0.99 (0.02)	1.00 (0.00)	0.95 (0.10)	0.00 (0.00)
Mobile Auto	0.98 (0.00)	1.00 (0.00)	0.02 (0.00)	1.00 (0.00)	0.00 (0.00)	1.00 (0.00)	0.98 (0.00)	1.00 (0.00)	1.00 (0.00)	0.20 (0.00)
Immobile GT	0.97 (0.02)	1.00 (0.00)	0.96 (0.02)	0.97 (0.02)	0.80 (0.00)	0.97 (0.01)	0.97 (0.02)	0.97 (0.01)	0.80 (0.08)	1.00 (0.00)
Immobile Auto	0.91 (0.05)	1.00 (0.00)	0.94 (0.03)	0.92 (0.05)	1.00 (0.00)	1.00 (0.00)	0.91 (0.05)	1.00 (0.00)	1.00 (0.00)	1.00 (0.00)

*Probabilities are reported as mean (IQR) and LR are reported as mean (standard deviation)

TABLE 3.4
Mean Situation Probabilities for the Clinical Tests and the Resulting Likelihood Ratios

	Difficulty Rising (DR)			Support to Rise (SR)			Slow Gait (SG)		
Group	**P(DR)**	**P(No DR)**	**LR**	**P(SR)**	**P(No SR)**	**LR**	**P(SG)**	**P(No SG)**	**LR**
Mobile GT	0.01 (0.00)	0.99 (0.02)	0.59 (0.01)	0.00 (0.00)	0.99 (0.02)	0.77 (0.00)	0.00 (0.00)	0.95 (0.08)	0.75 (0.03)
Mobile Auto	0.02 (0.00)	0.97 (0.00)	0.60 (0.00)	0.00 (0.00)	1.00 (0.00)	0.77 (0.00)	0.20 (0.00)	0.79 (0.00)	0.74 (0.00)
Immobile GT	0.94 (0.00)	0.04 (0.02)	1.74 (0.01)	0.75 (0.01)	0.19 (0.00)	1.54 (0.03)	0.75 (0.07)	0.00 (0.00)	1.31 (0.13)
Immobile Auto	0.86 (0.01)	0.05 (0.03)	1.55 (0.02)	0.92 (0.05)	0.00 (0.00)	2.38 (0.66)	0.91 (0.05)	0.00 (0.00)	1.66 (0.17)

*Probabilities are reported as mean (IQR) and LR are reported as mean (standard deviation)

3.7.3 Clinical Test/Situation Identification and Adjusted Likelihood Ratios

The individual context probabilities (means listed in 3.2) were used in equation 3.7 to determine the clinical test/situation probabilities that were used as inputs in equation 3.17 and 3.18 to calculate the adjusted LRs. Plots of the adjusted LR+ and LR- for the three clinical tests while varying the situational uncertainty/probability from 0 to 1 are shown in figure 3.8.

The mean situation probabilities and the resulting mean adjusted LRs can be seen in table 3.4. Again, results are divided based on the 2 sets of experiments and whether the time intervals for the contexts were determined automatically or from the events entered by the user on their phone.

3.7.4 Post-Test Probabilities For Fall Risk and Parkinson's

Table 3.5 summarizes the results for the probabilities of each clinical test occurring and the resulting LRs based on these situations probabilities, where the time intervals were determined from the ground truth mobile app data. For each user's clinical test, the LR+ or LR- was selected based on which situation had the highest probability of having occurred. Additionally, elements of the emulated older adult participant's past medical history and their LR for falling in the next 12 months or Parkinson's are shown in the first 4 columns of the table. The second last column of the table is the user's post-test probability of

falling within 12 months determined by multiplying the user's pre-test odds of falling (1:2) by the fall related LRs in the prior columns and then converting these post-test odds to probabilities. The last column is the same procedure but for Parkinson's tests.

Table 3.6 provides the same information, with the difference being that the context and situation probabilities were all calculated while using the sensor data to automate the start and end times of the contexts.

For the one-sided paired Wilcoxon Signed Rank Test investigating whether the post-test probabilities of falling were higher in the mobility impaired group relative to the unimpaired group, the results were statistically significant when using the ground truth timestamps ($p = 0.031$) and automated time stamps ($p = 0.031$). The same analysis investigating if the Parkinson's post-test probabilities were higher yielded statistically significant results when using the ground truth timestamps entered by the user ($p = 0.031$) and automated timestamps determined by the system ($p = 0.029$). No statistically significant differences were observed in the analyses of the post-test probabilities obtained using the automated vs ground truth time intervals for Parkinson's and falling within 12 months.

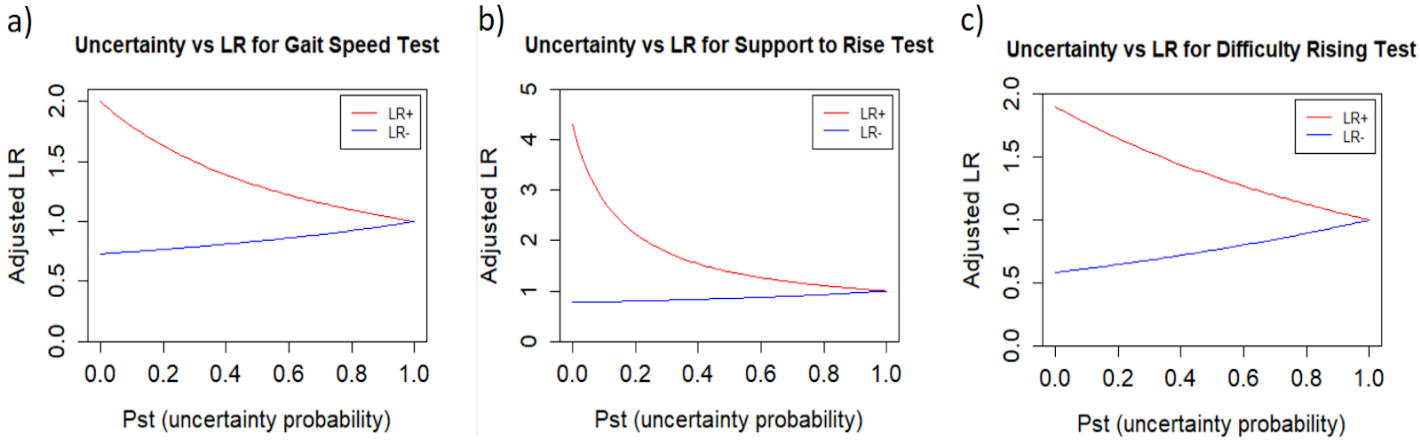

Figure 3.8 Adjusted LRs vs uncertainty level for a) the support to rise fall risk test. b) the slow gait fall risk test. c) the difficulty rising Parkinson's test.

TABLE 3.5
Adjusted LRs and Post Test probability of Falls/Parkinson's for Various Users when Using the Ground truth Data

		Fall						Parkinson's		
Name	**Age**	**LR $_{meds>4}$**	**LR $_{Past\ Stroke}$**	**LR $_{Fall\ Last\ Year}$**	**LR $_{slow\ gait}$**	**LR $_{support\ to\ rise}$**	**Prob (Fall)**	**LR $_{Fall\ History}$**	**LR $_{Difficulty\ Rising}$**	**Prob (Parkinson's)**
John	91	1.90	3.20	2.40	0.77	0.77	0.62	0.65	0.58	0.0076
Jane	72	0.76	3.20	2.40	0.74	0.77	0.39	0.65	0.58	0.0038
Henry	82	0.76	0.87	2.40	0.74	0.77	0.15	0.65	0.59	0.0039
Barry	73	0.76	0.87	0.61	0.77	0.77	0.045	0.65	0.60	0.0039
Sue	86	0.76	0.87	0.61	0.73	0.77	0.17	3.19	0.58	0.036
Kathy	90	1.90	3.20	2.40	1.11	1.40	0.93	0.65	1.72	0.022
Warren	67	0.76	3.20	2.40	1.31	1.37	0.85	0.65	1.73	0.011
Gary	73	0.76	0.87	2.40	1.42	1.06	0.57	0.65	1.70	0.011
Sam	71	0.76	0.87	0.61	1.29	1.40	0.3	0.65	1.81	0.012
Heidi	88	0.76	0.87	0.61	1.43	2.48	0.8	3.19	1.72	0.1

TABLE 3.6
Adjusted LRs and Post Test probability of Falls/Parkinson's for Various Users when Automatically Determining the Contexts/Tests

		Fall						Parkinson's		
Name	**Age**	**LR $_{meds > 4}$**	**LR $_{Past\ Stroke}$**	**LR $_{Fall\ Last\ Year}$**	**LR $_{slow\ gait}$**	**LR $_{support\ to\ rise}$**	**Prob (Fall)**	**LR $_{Fall\ History}$**	**LR $_{Difficulty\ Rising}$**	**Prob (Parkinson's)**
John	91	1.90	3.20	2.40	0.74	0.77	0.71	0.65	0.60	0.0079
Jane	72	0.76	3.20	2.40	0.74	0.77	0.5	0.65	0.60	0.0039
Henry	82	0.76	0.87	2.40	0.74	0.77	0.21	0.65	0.60	0.0039
Barry	73	0.76	0.87	0.61	1.92	0.77	0.15	0.65	0.60	0.0039
Sue	86	0.76	0.87	0.61	0.74	0.77	0.066	3.19	0.61	0.038
Kathy	90	1.90	3.20	2.40	1.76	2.75	0.98	0.65	1.48	0.019
Warren	67	0.76	3.20	2.40	1.59	2.09	0.94	0.65	1.56	0.01
Gary	73	0.76	0.87	2.40	1.79	2.94	0.87	0.65	1.63	0.011
Sam	71	0.76	0.87	0.61	1.59	2.10	0.51	0.65	1.55	0.01
Heidi	88	0.76	0.87	0.61	1.56	2.00	0.49	3.19	1.54	0.091

3.8 DISCUSSION

In this section, we discuss each of the central components of the general framework that allow sensor data to be mapped to clinical tests and ultimately the probability a user has a condition/disease. First, fuzzy probability is discussed, followed by how this is used to obtain context and situation probabilities. Next, the way that clinical tests are modeled as situations is described along with the need to adjust LRs due to situational uncertainty. Following this, the application of these LRs to determine fall and Parkinson's risk is discussed in the context of the experiments. Lastly, how this forms the general framework is described along with some limitations of the framework.

3.8.1 Fuzzy Probability Calculations

The goal of the present work was to develop a framework for telemedical smart-home systems that uses sensor data to quantitatively determine the probability a given user has a certain disease/condition (Parkinson's) or predisposition to a dangerous event (fall). Automatic assessment of older adults physical health is a key area that smart-home systems can contribute to. As outlined in Majumder *et al's* review, many groups have started to build solutions for automatic health assessments [34]. A growing body of literature focuses on using stochastic machine learning techniques to determine user's contexts and diagnose patients based on trained models. However, the present work aims to provide a method of diagnosing conditions by leveraging standard clinical tools (LRs), context-awareness sensing, and situation identification techniques. The motivation behind this is to allow telemedical systems to aid healthcare providers in diagnosing patients without requiring manual labeling of data for training learning models. As demonstrated in figure 3.2, membership functions are required for this fuzzy probability-based method that relates the sensor data to the context of interest. Although the method is deterministic in nature, it assigns probabilities for each context to quantify the level of certainty in each context, similar to many stochastic ML based approaches. For the sitting context, because low accelerometer values are not guaranteed when sitting, we have empirically set the maximum probability of sitting based on low accelerometer readings to 50%. As seen in equation 3.7, the model relies on sensor events that have a high probability of representing the context of interest as any single event with a probability close to 1 will result in a context probability close to 1. Thus, the probability that the user is sitting is dominated by the fact that the chair's pressure sensor is at a maximum (figure 3.2d-f), which can reasonably be assumed to imply the user is sitting, and not solely by the low accelerometer readings (figure 3.2a-c). One contribution of the present work is a

methodology that leverages multiple sensors that provide information on a single context while only needing one sensor to be reasonably certain about the context to obtain a high probability that it occurred. In the future, sensor events of interest and their membership functions will need to be determined in coordination with clinical expertise. For instance, in the case of the gait speed test we created a membership function that defines a slow gait with 100% probability below the 0.77 m/s threshold studied by Luukinen et al. 2 and 0% above this threshold [27]. However, 0.76 m/s and 0.78 m/s likely have similar clinical utility for fall prediction. Thus, clinical expertise will be needed to determine the appropriate way to transition between slow and normal gaits such that this can be reflected in the membership function relating speed to whether one is positive or negative for the slow gait test.

3.8.2 Situation/Context Probabilities

Situations are typically defined as collections of contexts that have spatiotemporal relationships which can be used to understand more complex events. Here, we have modeled clinical tests as situations within spatiotemporally defined context networks, where each context can be inferred from simple sensor events. Since certain test conditions must be met prior to performing the test, the difference between being positive (LR+) or negative (LR-) for the test is usually a single context or clinical parameter of interest (e.g., gait speed). For clinical tests with predefined contexts/conditions, such as gait speed for fall risk assessment, the use of specification-based approaches is more appropriate than asking a learned model to infer the relationship between the contexts and the outcome. Since the relationship between the parameter being measured by the sensors and outcome is known, there is nothing to be learned, especially if the relationship between said parameter and the sensor data is obvious. For instance, only measurements of the users' distance traversed over a specified time interval are needed to measure self-selected gait speed. Thus, we assume that a chair seat that begins to have pressure applied implies the user is sitting and that a change in location according to our IPS implies the user has left the chair. Here, the distance from the chair to the washroom is known in advance via the home's floorplan so gait speed is easily determined without learning models using the time (and distance) it took to move from the chair to a new room. Evidently, specification-based approaches are the logical solution for conducting already known clinical tests that can be determined through easily measured contexts. Although various specification-based context-awareness techniques exist, to the best of our knowledge, these methods do not return probabilities for contexts which makes understanding the true likelihood of a situation/clinical test difficult to determine. A possible exception may be the application of Dempster-Shafer theory which returns ranges of probabilities. However, various researchers raised issues with its rules for combining evidence, including Zadeh whose theory the current approach is based on [36]. Thus, we have developed a specification-based context determination model along with fuzzy probability context networks for situation identification in order to utilize sensor data to obtain context/situation probabilities.

Unlike many stochastic ML based approaches to context determination, the fuzzy probability-based method developed in the present work is deterministic in that no models need to be trained which leads to the same outcome for a set of inputs to the algorithm. The methodology does provide a probability for each context similar to what can be derived from ML methods such as neural networks, random forests, support vector machines, etcetera. There are two main advantages to this approach that are worth highlighting. Firstly, in order to identify new contexts, one does not need to gather training data, spend time labeling it, and then build models. Instead, membership functions need to be paired with sensors that can provide information on the likelihood of the context. This is more scalable for adding additional contexts over time as it is not practical to collect training data for every user context. A second advantage, which was a primary consideration when choosing a deterministic method, was the lack of adoption of ML based methods in clinical practice. Issues have been identified within the current evidence-based medicine approach to providing care surrounding difficulty justifying decisions to patients when the path between their data/circumstances and the decision cannot be clearly identified due to algorithmic complexity [16]-[18]. Deterministic methods provide a clear and reproducible route between the users' data and the

diagnosis, thus, adoption by healthcare providers should be less problematic, especially when the method is paired with standard clinical diagnostic tools such as post-test probabilities derived from LRs of known clinical tests.

3.8.3 Clinical Test/Situation Identification And Adjusted Likelihood Ratios

Since ground truth data is not available for telemedical systems when human observers are not present, and thus whether an event occurred or not cannot be known for certain, it is pivotal that whether a clinical event, context, or situation occurs be a probability based on sensor data. Additionally, it is important that tests run based on more certain contexts have a higher prognostic value than those run under less certain test conditions. This posed an interesting question for how to treat the LRs of clinical tests/situations given the conditions of the test cannot be guaranteed in the absence of a human observer. We have demonstrated that by considering how patients would be misclassified as a function of the probabilistic uncertainty that defines the number of incorrect tests, adjusted LRs for each clinical test can be derived. The results are logical as figure 3.7 shows that when there is no uncertainty the LR clinical utility/value is equivalent to those measured by clinicians under normal circumstances. Thus, they are at a maximum in the case of LR+ and minimum in the case of LR-. As the level of uncertainty approaches 100 percent, the LR+ ratios decrease and approach 1 while the LR- ratios increase and approach 1. This is also a logical result as the test provides no clinical utility or change to the post-test probability when there is no certainty it occurred. For the purpose of this work, we assumed that each incorrect test misclassified users as positive or negative at equal rates (c = d), however, certain sensor events and situations may misclassify users as positive or negative at different rates. Adjusting the LRs also helps reduce false positives in the absence of a human-run test, as the clinical utility of a test run by a telemedical system can only be equal to or less than that run by a healthcare provider that can ensure the contexts have occurred.

3.8.4 Post-Test Probabilities for Fall Risk And Parkinson's

To demonstrate that the entire system can be automated, we conducted an analysis where the start and end time of each context was based on various sensor events instead of the ground truth inputs from the users.. The post-test probabilities for falls and Parkinson's when automating the results (table 3.6) still led to significant differences between the mobility impaired and mobility unimpaired groups, demonstrating that the system can operate autonomously to identify high and low risk users.

As different experiments lead to different sensor PDFs, the clinical test LRs for each experiment (shown in table 3.5 and 3.6 for different users) fall at different locations on the adjusted LR curves. By utilizing standard clinical tools, namely multiplying the pre-test odds for a condition (given by epidemiological data) by the adjusted LRs of validated clinical tests, the system can determine the post-test probability of a user having a condition/disease without requiring training data. Each user in table 3.5 and 3.6 has their LRs relating to falls multiplied by their pre-test odds to easily determine their post-test odds, and thus post-test probability, as seen in the last column. The same logic is applied to determine their post-test odds for Parkinson's, which in this case is only based on the difficulty rising situation and having a history of falls. In all mobility impaired experiments, the system correctly identified the arm rest was used to rise and that walking was slowed given these experiments are positive for the support to rise and gait speed test. Additionally, the probability of having Parkinson's or falling within 12 months was greater in the mobility impaired group to a statistically significant degree, confirming the system could distinguish between the two groups/experiments. Integration of telemedical systems with EMRs further enhances the clinical utility of the framework by leveraging user's past medical histories (table columns 3-6), which often have their own predictive ability for a condition. In this sense, the system mimics how physicians leverage information obtained through medical histories to qualitatively assess the probability of various disease outcomes. Thus, the presented framework successfully integrates past medical history (PMH) to make clinical decisions. To our knowledge, this is the first general framework to link sensor data acquisition to

the post-test probability of any condition/disease using validated clinical test's LRs and past medical histories.

3.8.5 Context-Aware Telemedical Smart Home Framework

Although the fuzzy probability theory presented here is one method of determining context/situation probabilities for adjusting LR and calculating post-test probabilities, we have left this out of our general framework shown in figure 3.1. Future groups may determine their own specification-based method of relating sensor data to context probabilities and thus clinical test/situation probabilities. Thus, the framework as presented leaves room for this. However, the clinical test/situation probabilities determined after sensor data acquisition and processing can still be used to determine adjusted LRs, calculate post-test probabilities for conditions, and set intervention thresholds based on the post-test probabilities. This framework represents the crux of what was done in the present work, as senor data was acquired, used to determine contexts, translated into situations that represented clinical tests, and then the outcomes of these tests were used in conjunction with medical histories to determine the probability of outcomes such as Parkinson's or falling. Generally, when the system is triggered to intervene due to the clinical test outcomes/situations, this decision is sent to other applications that interface with the telemedical system causing changes to occur, thus making the overall system context aware. As identified by other researchers, this autonomic decision-making system's goal is not to replace medical specialists, but to perform time consuming tasks such as regularly conducting these clinical tests so older adults can age at home comfortably [37].

We have separated the roles of specification and learning-based approaches in telemedical systems within the framework and identified them as complementary, not competing, techniques. Whereas specification-based situation identification techniques are used to conduct clinically validated tests in the Apply Clinical Tests module (figure 3.1), as demonstrated in this work, learning-based approaches are used to discover new clinical tests (Discover New Tests module) by identifying how contexts obtained by the system relate to conditions/diseases. For instance, the system may collect contexts relating to users' typing habits and a learning-based approach may discover that slow typing is sensitive and specific for diagnosing Parkinson's. The keyboard stroke example provided in figure 3.1 is based on typing features used in studies which have successfully combined keyboard and phone interaction features to obtain a sensitivity and specificity of over 70% for Parkinson's diagnosis in data collected from patients remotely[38]–[40]. As systems identify collections of contexts via specification-based approaches, like fuzzy probability theory, the relationship between these contexts and the likelihood of having a disease can be determined through learning-based approaches like neural networks that use patient outcomes found in EMRs, to relate the contexts to various conditions. LRs can then be derived from the tests sensitivity and specificity which can be used to adjust the post-test probability that patients have a disease along with the specification-based test results. We believe this framework is advantageous as clinicians can easily interpret the test results since the specification approach uses currently conducted clinical tests.

3.8.6 Limitations and Future Directions

To demonstrate the frameworks use within a practical context, the data was assigned to hypothetical older adults with varying medical histories and turned into a case study. In this study, Dr. Smith sent 10 of his patients the system, 5 of which were suspected to be mobility impaired. The system was able to conduct clinical tests and send Dr. Smith a report on all 10 patients. Dr. Smith was then able to determine which patients are at high risk for having Parkinson's or falling so he could act early to improve his patients' outcomes. This represents the end goal of the system/framework, which is to help healthcare providers pre-emptively detect possible adverse events and diseases.

One limitation of this approach is that the LRs used to generate the probabilities for the conditions/diseases are assumed to independently predict the outcome of interest, whereas this is likely not the case in some scenarios. For instance, although taking 4 meds is likely independent of having a slow

gait, there is likely some overlap between those who have a slow gait and those that need support to rise. Thus, future work will need to either calculate the joint LRs when patients are positive for potentially related tests, only use the test with the highest LR when tests are not believed to be independent or set intervention thresholds when multiple potentially related tests are positive. The latter approach is likely best and clinical expertise will be needed to determine intervention thresholds that would benefit healthcare providers. As an example, Al-Ama recommended a fall intervention program when post-test probabilities for a fall within 12 months exceeded 50% in their case study depicting a user who was at risk of falling due to self-reported mobility problems and benzodiazepine-use [41]. Future work will aim to pilot the system in a retirement home to compare the post-test probabilities determined by the smart-home system in a real world setting to those determined by physicians.

3.9 CONCLUSION

Telemedical and smart-home systems for remote monitoring and aging-in-place have become a prominent area of research over the last decade due to rapid advancements in IoT technology. However, a general model that uses these systems to conduct clinical tests and quantifies the probability patients have a given condition has not been well-defined. In the present work, a new specification-based context identification technique was developed using fuzzy probability theory to determine the probability a given context or situation occurred based on multiple sources of sensor data. Clinical tests with known associations (through LRs) with Parkinson's and falling were then modeled as situations so they could be conducted on different participants whose data was obtained within our smart-home system. The participants were separated into a mobility impaired and mobility unimpaired group for a case study, and assigned past medical histories to show how systems can use this info to further adjust post-test probabilities. Through this study, we were able to show that the system could differentiate a high and low risk Parkinson's and falls group.

Normally, the results of the clinical tests LR's would be applied directly to the pre-test odds for the users (which were based on epidemiological data) to obtain the probability they have each condition. However, a method for reducing the LRs of clinical tests measured by telemedical systems was derived to account for probabilistic uncertainty in the test's conditions/contexts. This is significant as it should allow systems to utilize known tests to aid in diagnosis, instead of needing to derive new tests or predict diseases from learning based models, which differs from what is done in actual medical practice. . In the future, physician guidance will be needed to determine the specific probability for each condition that an intervention should be triggered. Additionally, a conservative approach to combining LR's of different clinical tests may be needed as it is possible some tests are not fully independent.

To our knowledge, this is the first general framework for telemedical systems to use sensor data and context-aware computing to conduct clinical tests to quantitatively determine the probability an adult has a given condition/disease. Our hope is that this will set the foundation for future work focusing on providing disease probabilities through clinical test automation for healthcare providers using current clinical knowledge.

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Author Contributions

MZ developed the algorithm, designed, and performed the experiments, analyzed the data, and wrote the paper. GG analyzed the data and edited the paper. QF created the concept, planned, and supervised the study, analyzed the data, and wrote and edited the paper.

References

[1] G. D. Abowd, A. K. Dey, P. J. Brown, N. Davies, M. Smith, and P. Steggles, "Towards a Better Understanding of Context and Context-Awareness," in *Handheld and Ubiquitous Computing*, 1999, pp. 304–307.

[2] P. Greenland *et al.*, "Resting heart rate is a risk factor for cardiovascular and noncardiovascular mortality: the Chicago Heart Association Detection Project in Industry," *Am. J. Epidemiol.*, vol. 149, no. 9, pp. 853–862, May 1999.

[3] B. Slovis, "Wells' Criteria for Pulmonary Embolism," MDCalc. https://www.mdcalc.com/calc/115/wells-criteria-pulmonary-embolism (accessed Oct. 12, 2022).

[4] B. Slovis, "Wells' Criteria for DVT," MDCalc. https://www.mdcalc.com/calc/362/wells-criteria-dvt (accessed Oct. 12, 2022).

[5] F. Lamontagne, D. A. Harrison, and K. M. Rowan, "qSOFA for Identifying Sepsis Among Patients With Infection," JAMA: the journal of the American Medical Association, vol. 317, no. 3. pp. 267–268, Jan. 17, 2017.

[6] B. E. Backus et al., "Chest pain in the emergency room: a multicenter validation of the HEART Score," Crit. Pathw. Cardiol., vol. 9, no. 3, pp. 164–169, Sep. 2010.

[7] R. Parikh, S. Parikh, E. Arun, and R. Thomas, "Likelihood ratios: clinical application in day-to-day practice," Indian J. Ophthalmol., vol. 57, no. 3, pp. 217–221, May 2009.

[8] "A survey on health monitoring systems for health smart homes," Int. J. Ind. Ergon., vol. 66, pp. 26–56, Jul. 2018.

[9] N. Bricon-Souf and C. R. Newman, "Context awareness in health care: a review," *Int. J. Med. Inform.*, vol. 76, no. 1, pp. 2–12, Jan. 2007.

[10] K. Yin *et al.*, "Context-Aware Systems for Chronic Disease Patients: Scoping Review," *J. Med. Internet Res.*, vol. 21, no. 6, p. e10896, Jun. 2019.

[11] N. Singh and U. Varshney, "Medication adherence: A method for designing context-aware reminders," *Int. J. Med. Inform.*, vol. 132, p. 103980, Dec. 2019.

[12] J. Ye, S. Dobson, and S. McKeever, "Situation identification techniques in pervasive computing: A review," *Pervasive Mob. Comput.*, vol. 8, no. 1, pp. 36–66, Feb. 2012.

[13] T. Nef *et al.*, "Evaluation of Three State-of-the-Art Classifiers for Recognition of Activities of Daily Living from Smart Home Ambient Data," *Sensors* , vol. 15, no. 5, pp. 11725–11740, May 2015.

[14] K. Avgerinakis, A. Briassouli, and I. Kompatsiaris, "Recognition of Activities of Daily Living for Smart Home Environments," in *2013 9th International Conference on Intelligent Environments*, Jul. 2013, pp. 173–180.

[15] S. Das *et al.*, "Toyota smarthome: Real-world activities of daily living," in *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 2019, pp. 833–842.

[16] B. Chin-Yee and R. Upshur, "The Impact of Artificial Intelligence on Clinical Judgment: A Briefing Document," 2020, [Online]. Available: http://www.ams-inc.on.ca/wp-content/uploads/2020/02/The-Impact-of-AI-on-clinical-judgement.pdf

[17] I. Masic, M. Miokovic, and B. Muhamedagic, "Evidence Based Medicine - New Approaches and Challenges," *Acta Informatica Medica*, vol. 16, no. 4. p. 219, 2008. doi: 10.5455/aim.2008.16.219-225.

[18] B. Heinrichs and S. B. Eickhoff, "Your evidence? Machine learning algorithms for medical diagnosis and prediction," *Hum. Brain Mapp.*, vol. 41, no. 6, pp. 1435–1444, Apr. 2020.

[19] H. Zheng, H. Wang, and N. Black, "Human Activity Detection in Smart Home Environment with Self-Adaptive Neural Networks," 2008 IEEE International Conference on Networking, Sensing and Control. 2008. doi: 10.1109/icnsc.2008.4525459.

[20] A. Fleury, M. Vacher, and N. Noury, "SVM-based multimodal classification of activities of daily living in Health Smart Homes: sensors, algorithms, and first experimental results," IEEE Trans. Inf. Technol. Biomed., vol. 14, no. 2, pp. 274–283, Mar. 2010.

[21] T. Nef et al., "Evaluation of Three State-of-the-Art Classifiers for Recognition of Activities of Daily Living from Smart Home Ambient Data," Sensors , vol. 15, no. 5, pp. 11725–11740, May 2015.

[22] A. Lakehal, A. Alti, and P. Roose, "Real-time ontology-based context-aware situation reasoning framework in pervasive computing," Multimed. Tools Appl., vol. 81, no. 11, pp. 14913–14957, Feb. 2022.

[23] S. McGee, W. B. Abernethy III, and D. L. Simel, "Is this patient hypovolemic?," *JAMA*, vol. 281, no. 11, pp. 1022–1029, 1999.

[24] S. W. Loke, "Representing and reasoning with situations for context-aware pervasive computing: a logic programming perspective," *Knowl. Eng. Rev.*, vol. 19, no. 3, p. 213, 2004.

[25] J. C. Augusto, J. Liu, P. McCullagh, H. Wang, and J.-B. Yang, "Management of Uncertainty and Spatio-Temporal Aspects for Monitoring and Diagnosis in a Smart Home," *null*, vol. 1, no. 4, pp. 361–378, Dec. 2008.

[26] L. A. Zadeh, "Probability measures of Fuzzy events," J. Math. Anal. Appl., vol. 23, no. 2, pp. 421–427, Aug. 1968.

[27] H. Luukinen, K. Koski, P. Laippala, and S. L. Kivelä, "Predictors for recurrent falls among the home-dwelling elderly," *Scand. J. Prim. Health Care*, vol. 13, no. 4, pp. 294–299, Dec. 1995.

[28] A. J. Campbell, M. J. Borrie, and G. F. Spears, "Risk factors for falls in a community-based

prospective study of people 70 years and older," *J. Gerontol.*, vol. 44, no. 4, pp. M112–7, Jul. 1989.

[29] J. Duarte and L. E. Clavería, "de Pedro--Cuesta J, Sempere AP, Coria F, Calne DB. Screening Parkinson's disease: a validated questionnaire of high specificity and sensitivity," *Mov. Disord.*, vol. 10, pp. 643–649, 1995.

[30] D. A. Ganz, Y. Bao, P. G. Shekelle, and L. Z. Rubenstein, "Will my patient fall?," JAMA, vol. 297, no. 1, pp. 77–86, Jan. 2007.

[31] L. W. Chu, I. Chi, and A. Y. Y. Chiu, "Incidence and predictors of falls in the Chinese elderly," Ann. Acad. Med. Singapore, vol. 34, no. 1, pp. 60–72, Jan. 2005.

[32] G. K. Wenning, Y. Ben-Shlomo, A. Hughes, S. E. Daniel, A. Lees, and N. P. Quinn, "What clinical features are most useful to distinguish definite multiple system atrophy from Parkinson's disease?," J. Neurol. Neurosurg. Psychiatry, vol. 68, no. 4, pp. 434–440, Apr. 2000.

[33] G. Rao et al., "Does this patient have Parkinson disease?," JAMA, vol. 289, no. 3, pp. 347–353, Jan. 2003.

[34] Majumder, Sumit, et al. "Smart homes for elderly healthcare—Recent advances and research challenges." *Sensors* 17.11: 2496, 2017.

[35] L. A. Zadeh, "On the validity of Dempster's rule of combination," Univ. of California, Berkeley, Memo M79/24, 1979.

[36] P. C. Cheeseman, "In Defense of Probability," in *IJCAI*, 1985, vol. 85, pp. 1002–1009.

[37] Deen, M. Jamal. "Information and communications technologies for elderly ubiquitous healthcare in a smart home." *Personal and Ubiquitous Computing* 19.3: 573-599, 2015

[38] D. Iakovakis *et al.*, "Screening of Parkinsonian subtle fine-motor impairment from touchscreen typing via deep learning," *Scientific Reports*, vol. 10, no. 1. 2020. doi: 10.1038/s41598-020-69369-1.

[39] T. Arroyo-Gallego *et al.*, "Detecting Motor Impairment in Early Parkinson's Disease via Natural Typing Interaction With Keyboards: Validation of the neuroQWERTY Approach in an Uncontrolled At-Home Setting," *Journal of Medical Internet Research*, vol. 20, no. 3. p. e89, 2018. doi: 10.2196/jmir.9462.

[40] D. Iakovakis, S. Hadjidimitriou, V. Charisis, S. Bostantzopoulou, Z. Katsarou, and L. J. Hadjileontiadis, "Touchscreen typing-pattern analysis for detecting fine motor skills decline in early-stage Parkinson's disease," *Scientific Reports*, vol. 8, no. 1. 2018. doi: 10.1038/s41598-018-25999-0.

[41] T. Al-Aama. "Falls in the elderly: spectrum and prevention." Canadian Family Physician vol 57, pp. 771-776, July 2011.

Introduction to Chapter 4

After building the system and developing the general framework, chapter 4 focuses on applying the framework to build a context-aware application, meaning an application that adapts based on the measured contexts. Although in chapter 3 the general framework includes the system being triggered in response to contexts, little emphasis is placed on the context-awareness element of the system. Thus, in the following chapter a context-aware emergency system is built to demonstrate the systems use in building context-aware applications that truly adapt to context. Additionally, it was important to demonstrate the importance of context for ruling out false positives and building more intelligent applications. We originally understood that a context unaware system would have difficulty differentiating between some benign and dangerous heart rates, such as a user with a heart rate of 160 beats per minute due to working out, versus having their heart rate elevated to 160 due to an arrythmia. We wanted to demonstrate that by applying contexts such as the user's mobility level, we could prevent the system from falsely triggering an emergency alert due to an elevated heart rate that is appropriate for the activity level. It was deemed important to formalize this notion of understanding physiological data within its context, thus, chapter 4 places some emphasis on adapting prior context-aware frameworks to build a context-aware medical framework. The emergency system built uses the theory developed in the prior chapter. Namely, the situations that define the emergencies are mapped to the spatiotemporal context networks defined in chapter 3, where each context is determined using fuzzy probability.

My contribution was adapting the smart home system to stream and process data in real-time, developing the desktop application which allows healthcare providers to adjust the alarm settings, designing the experiments that compared the context-aware versus context-unaware alarms, and writing the manuscript. Guha Ganesh helped develop the smart home beacons by changing the hardware from Raspberry Pi's to lower cost ESP32s. Dr. Qiyin Fang supervised the study and edited the manuscript. The significance of the present work is in demonstrating that context is required to rule out false positives in emergency systems, and identifying the need to classify physiological data within its context for context-aware medical system frameworks.

Chapter 4

Low-Cost Portable Smart Home System for Context-Aware Medical Applications and its use in Building Intelligent Life Alert Systems

Michael Zon[1,2], Guha Ganesh[1], Qiyin Fang[1,3]
[1]McMaster University, School of Biomedical Engineering, Hamilton, ON,
[2]Michael G. DeGroote School of Medicine, Hamilton, ON,
[3]McMaster University, Department of Engineering Physics, Hamilton, ON,

Contents of Paper II

Abstract

Objective: The objective of the present work is to develop a framework for analyzing physiological data from telemedical systems within its context and to use this framework to build an automated emergency response system. **Methods:** A portable smart home system was built that leverages an indoor positioning system and smart watch to communicate to a healthcare desktop application where healthcare providers can stream patients data, view historical averages, and set emergency alarms. To integrate context, emergency scenarios were defined as situations and modeled through temporal context networks that identify the events which must occur for a situation to be considered an emergency. Individual contexts were determined using fuzzy probability theory and the probability an emergency occurred was determined through the probabilities of the individual contexts. Context-aware alarms that considered the time of day, location, and activity levels were tested against context-unaware alarms (which do not use activity, location, and time) for detecting abnormal bouts of immobility and inappropriately elevated heart rates. Experiments were conducted where users increased their heart rate through exercise and emulated sleeping at night in order to test the alarms. **Results:** The context-unaware alarm triggered an emergency when the users heart rate was elevated during exercise, and the context-aware alarm was not triggered since the active context was detected. The context-unaware alarm triggered while the user emulated sleeping, and the context-aware alarm was not triggered because the time of day was within sleeping hours and the location of the user was their bedroom. A context-awareness sensing framework for medical systems was developed that requires physiological data to be classified according to its context in order to rule out false positives. **Conclusions:** The present work demonstrates how medical data can be classified according to its context and how context surrounding physiological data is required to rule out false positives and automate emergency systems. **Significance:** The framework presented represents an important step towards allowing telemedical systems to automate tasks for healthcare providers by developing a medical context-awareness framework that subcategorizes physiological data according to its context. It also shows how this framework can be used to build useful applications such as an emergency alarm system.

4.1 INTRODUCTION

4.1.1 Wearables and Smart Home Technology in Healthcare

Smart home technology is a growing industry projected to penetrate approximately 43.4% - 52.4% of homes in North America by 2024 [1]. Although multiple definitions for smart homes have been proposed, a smart home is generally considered any home with interconnected devices and services that perform actions to improve users' quality of life [2]. The increased use of smart home technology for remote monitoring and diagnosis has led to the advent of the Health Smart Home subsector within the smart home space. Health smart homes focus on residents' health status and include any primary residence equipped with communicating devices that control the physical environment, track the residents' health, and monitor their surroundings. [3] To date, the vast majority of medically-oriented smart home research has focused on identifying falls/emergencies, activities of daily living, and Parkinson's in older adults [4]–[10]. Results from small (n=103) clinical trials using typing data from smart home technologies to detect Parkinson's have been extremely promising, given a reported sensitivity and specificity for Parkinson's diagnosis of 96% and 97%, respectively [11]. This is especially promising given that nearly half (47%) of Parkinson's diagnoses made in a primary care setting are incorrect [12]. Parkinson's diagnoses are likely to be smart home technologies' initial medical success given that tremors which manifest themselves in patients' hands are easily detected by low-cost accelerometers present in wrist-worn smartwatches or mobile phones [13]–[15]. The integration of wearable devices within smart home systems, such as the smartwatches used in many of these Parkinson's studies, has paved the way for new medical applications, which monitor mobility and patients' vitals to detect medical anomalies. For instance, many of the current fall-detection systems utilize similar wearable devices that contain accelerometers, barometers, and other low-cost sensors to detect falls through sudden drastic changes in elevation [6], [16], [17]. Additionally, the WATCH AF clinical trial demonstrated that commercial smartwatches can be used in hospitalized patients to detect dangerous arrhythmias, like atrial fibrillation, from PPG data with high sensitivity (93.7%), specificity (98.2%) and accuracy (96.1%) [18]. Emergency response systems, however, have had less success in automatically detecting similar crises outside of clinical settings, as they lack the necessary contextual information surrounding the collected vitals data to automatically detect medical emergencies. For instance, without understanding user context, these systems cannot determine whether an abnormally high heart rate determined from PPG data is exercise induced or from a dangerous arrhythmia. As a result, current emergency systems require users to be able to call for help via a button, which is a less than ideal solution in an emergency [19], [20].

4.1.2 Context-awareness Sensing and Patient-Centered Smart Home Technology

Contextualizing health data within medical applications is pivotal to developing successful emergency and telemedical systems. Even the context surrounding basic vitals measurements is key to diagnosing conditions such as hypertension, hypovolemia through orthostatic vitals, and arrhythmias. For instance, prior to measuring blood pressure (BP), medical professionals ensure that a patient's prior context does not include coffee or cigarette consumption within the previous 30 minutes, and that the patient has been sitting for at least 5 minutes. Regardless of whether these conditions are met, the current context, namely having one's blood pressure checked by a physician, is in itself known to raise BP enough to warrant naming the phenomenon the White Coat Effect [21]. As a result, hypertension diagnosis most often relies upon measurements from outside of a clinic, since the context of the in-clinic measurements is known to provide inaccurate readings [22].

Blood pressure is not the only vital that relies on context to provide clinically useful information. Heart rates greater than 100 bpm when at rest are considered a risk factor for ischemic stroke (Relative

Risk = 2.03) or may be indicative of a dangerous arrhythmia, but is appropriate when exercising. Physicians even take advantage of changes in context to make diagnoses, as a change in heart rate greater than 30 bpm when transitioning from sitting to standing is considered to be a possible indicator of hypovolemia [23]. Without considering context, telemedical systems cannot hope to differentiate between abnormal heart rates indicative of arrhythmias or hypovolemia, and an equivalent elevated heart rate due to exercise.

Even though physicians regularly assess health data within its current context, there is an unfortunate lack of literature on the use of context-awareness sensing, which integrates aspects of the person, place, time, and prior events, in telehealth systems [24]. The limited prior research in this area has focused on using context to decide when to send medical data to healthcare providers and the application of simple thresholds to inform providers when medical data is outside of the physiologically normal range [25], [26]. However, prior research has not investigated how intelligent systems can utilize context, such as location and time, to correctly subcategorize the same set of vitals/mobility data obtained from telemedical systems into normal and dangerous in order to build novel medical applications. Furthermore, the ability of context-aware vitals to reduce false positives in these applications, a known issue in new healthcare applications due to increased healthcare provider workload, is also unexplored [27]. Presumably, the lack of context assigned to data collected via telehealth systems is one reason why no automated emergency systems for arrhythmias and falls are available to date, and that current systems usually rely on the user's calling for help.

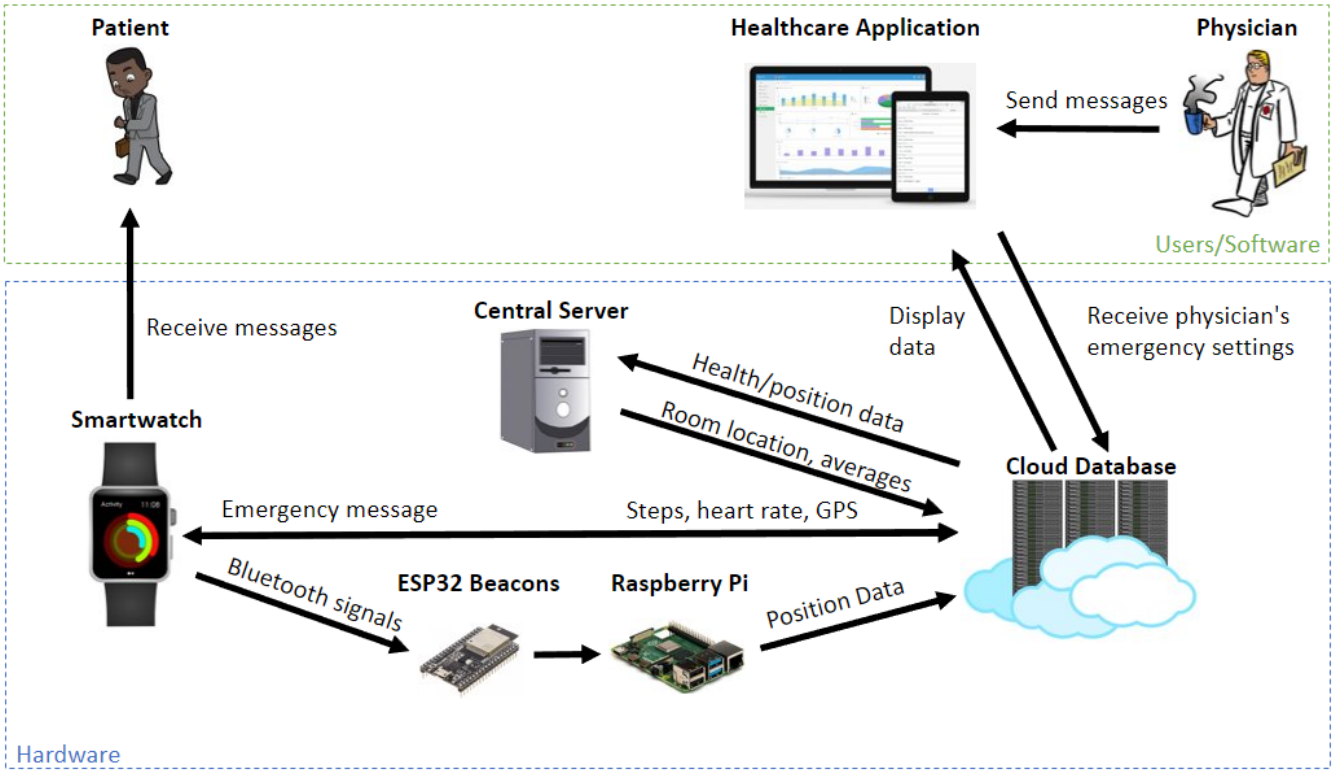

Figure 4.1 Overview of the portable smart home system and the communication between its components.

4.2 OBJECTIVES

The present work seeks to develop a framework for how telehealth systems can utilize context-awareness sensing when assessing physiological data to build novel medical applications (i.e. automated emergency systems), make context-dependent diagnoses, and reduce false positive alerts. First, we update

Musamba and Nyongesa's context-aware computing framework with a healthcare-specific component that subcategorizes physiological data according to its context [28]. Next, we utilize this framework to categorize mobility and heart rate data from a programmed smartwatch according to the contexts of room location, activity levels, and the time of day, provided from our indoor positioning system. Fuzzy probability and spatiotemporal context networks are then used to model dangerous vs. benign cardiac and mobility data, and demonstrate how context is needed to differentiate correct and incorrect medical decisions from the same physiological data within the emergency response system presented here. These context-informed decisions allow us to build an automated medical emergency system that does not rely on user input to identify emergencies and can be updated in real-time by healthcare providers through a cloud-based IoT infrastructure.

4.3 MATERIALS AND METHODS

4.3.1 System Architecture and Overview

The primary components of the system are a programmable Android-based smartwatch, ESP32 microcontrollers, a Raspberry Pi computer, a central server for processing the data, and a NoSQL cloud database for hosting the data. An overview of the system's architecture and the interaction between its various components is presented in Figure 4.1. The smartwatch sensors collect medically relevant data from the patient (mobility and heart rate) and emit bluetooth signals to the ESP32 microcontrollers. The ESP32 microcontroller then sends the bluetooth relative signal strength indicator (RSSI) to a master ESP32 using the ESP now protocol. The master ESP32 then sends this information to a Wifi-enabled Rasberry Pi, which determines the users' position and uploads it to a cloud database. One ESP32 computer is present in each room in order to determine whether a patient is located in that room based on the maximum received signal strength index (through RSSI) among the devices at each point in time.

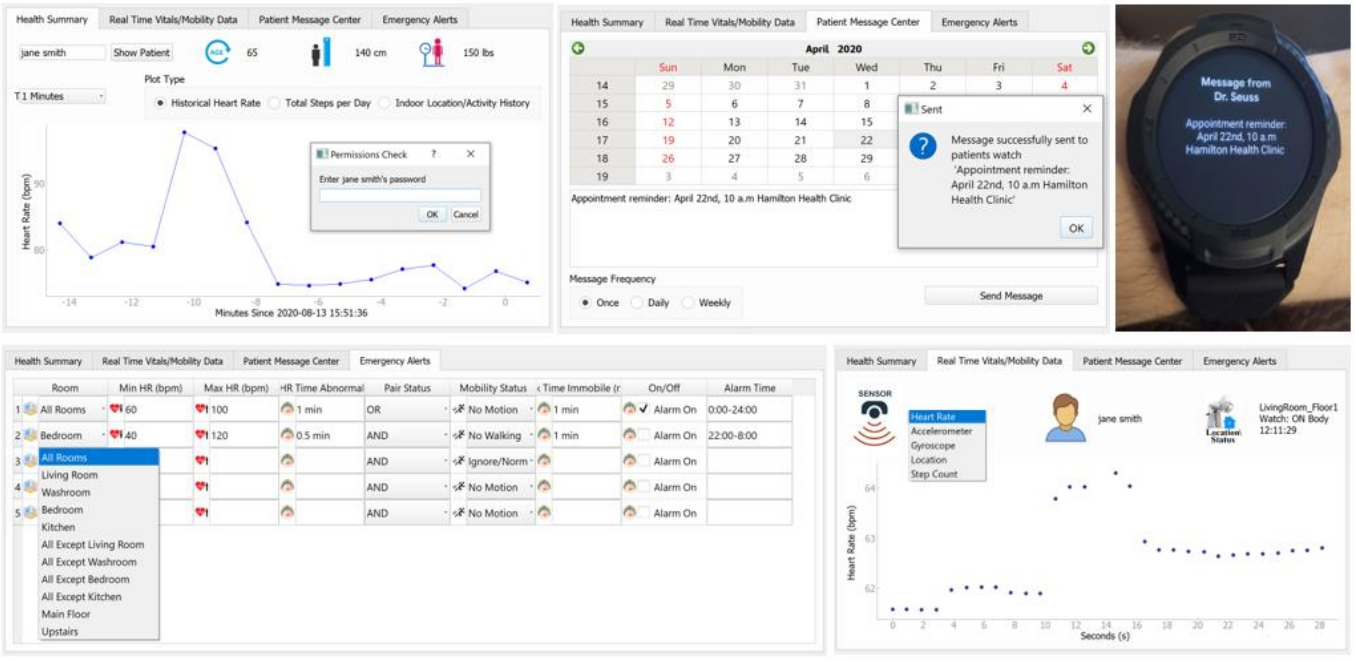

Figure 4.2 Healthcare application. a) Historical health data and patient look-up. b) Patient message center. c) Watch receiving a message from the patient message center. d) Tab to input emergency alert settings. e) Real-time data streaming

Sensor data is uploaded to a cloud database through Wi-Fi via the smartwatch, with the exception of the users' room location, which is uploaded through Wi-Fi via the Raspberry Pi. The central server code running on a computer reads the cloud data for each patient every 15 seconds, computes historical averages for each patient (e.g mean heart rate in the last 24 hours), and writes the results into the cloud database. Healthcare providers can stream sensor data in real-time, view a patient's historical averages, or send messages to a chosen user's smartwatch through a standalone desktop application that reads/writes to the cloud database (Figure 4.2). Each context-aware medical application is present as a different tab within the healthcare provider's app. Input provided by the applications' users is used to inform the conditions under which the server code detects an emergency (e.g what heart rate to trigger an emergency), communicate with the patient's watch, or trigger another component of the smart home system. Technical details regarding the hardware/software implementation, and how users are automatically registered within the system through the watch application, can be found in the appendix at the end of the present work.

4.3.2 Spatiotemporal Context Networks for Dangerous Cardiac Events and Fuzzy Probability

In order to categorize the physiological data according to context, fuzzy probability theory was used to determine the probability that users were in the resting vs. active state and normal vs. tachycardic state. The discrete fuzzy function describing the active vs. resting state as a function of the smartwatches' step count data is shown in Figure 4.3a). No steps recorded is assumed to imply a resting state, whereas steps being recorded implies an active state. The fuzzy function describing the immobile vs not immobile state as a function of accelerometer readings is shown in 4.3b. Accelerometer readings at less then 0.1 m/s^2 is assumed to imply immobility. Lastly, the tachycardic state as a function of heart rate is shown in Figure 4.3c, where a heart rate over 100 beats per minute is defined as tachycardic in accordance with standard clinical guidelines. Using Zadeh's fuzzy probability theory, the probability that a user is in a given context at a given time period is determined through the integral of the product of the probability density function (PDF) representing the physiological data and the fuzzy function describing the relationship between this data and the contexts that can be predicted with it.

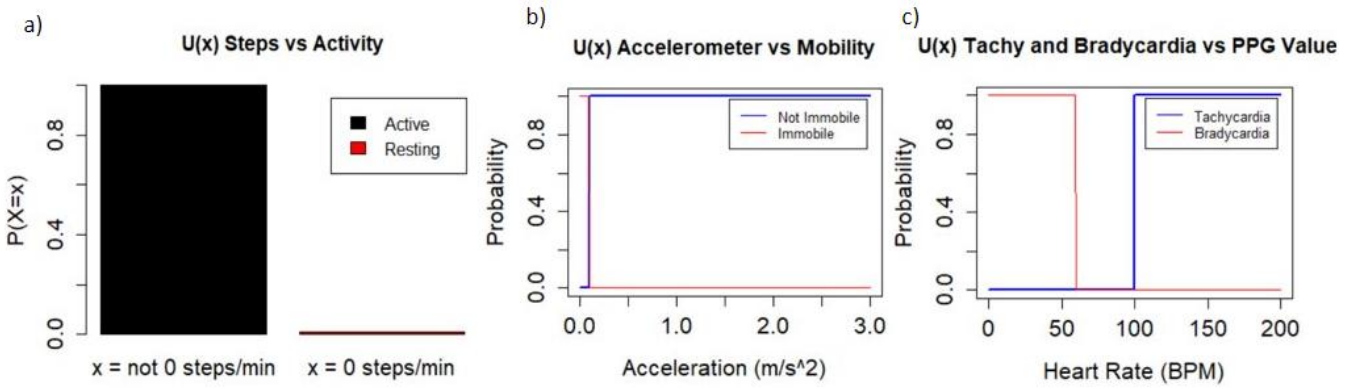

Figure 4.3 a) Membership function for activity level versus step count rate. b) Membership function for immobile or not immobile versus accelerometer readings. c) Membership function for bradycardia and tachycardia versus PPG readings.

$$P(X_i = C_j)_{s_i,\Delta t_j} = \int_{-\infty}^{\infty} \mu_{c_{ij}}(x) \cdot s_i(x)_{\Delta t_j} \cdot dx \qquad \text{Equation 4.1}$$

Where X_i is the random variable describing the outputs for sensor s_i that is mapped to the context C_j by the membership function $\mu_{c_{ij}}$, and Δt_j is the time over which the data was collected for context j.

For instance, if the smartwatch records a heart rate over 100 bpm, then the fuzzy function in 4.3c describes the data as tachycardic. If the smartwatch only records heart rates over 100 bpm over a given period of time, then the integration of the multiplication of the PDF of heart rates and fuzzy function will lead to a 100% probability of the tachycardia context for the user in this period. Step count and raw accelerometer readings are used with the fuzzy functions in Figure 4.3a and 4.3b in the same manner to determine the probability that the user is active, resting, or immobile.

The emergency situations can be modeled through context networks as shown in Figure 4.4. The probability of the situation being an emergency is a simple multiplication of the probability of the contexts in the network having occurred in the order specified by the context network within the time of day the contexts are relevant, as shown on the vertical time axis. For instance, in Figure 4.4a, the probability of an abnormal tachycardic event is the probability that the user was not active at any point in the day and that their heart rate was above 100 bpm during this same time period. The exact length of time that the inactive and elevated heart rate context need to occur for can be varied by healthcare providers within the desktop application (Figure 4.2d). The situation in 4.4b models an emergency detected due to an abnormal bout of immobility outside of sleeping hours. Lastly, 4.4c and 4.4d monitor for abnormal heart rates during sleep. More details on using sensor data to determine contexts and situation probabilities can be found in our prior work (see Chapter 3)

4.3.3 Context-Aware Emergency Alert System Implementation

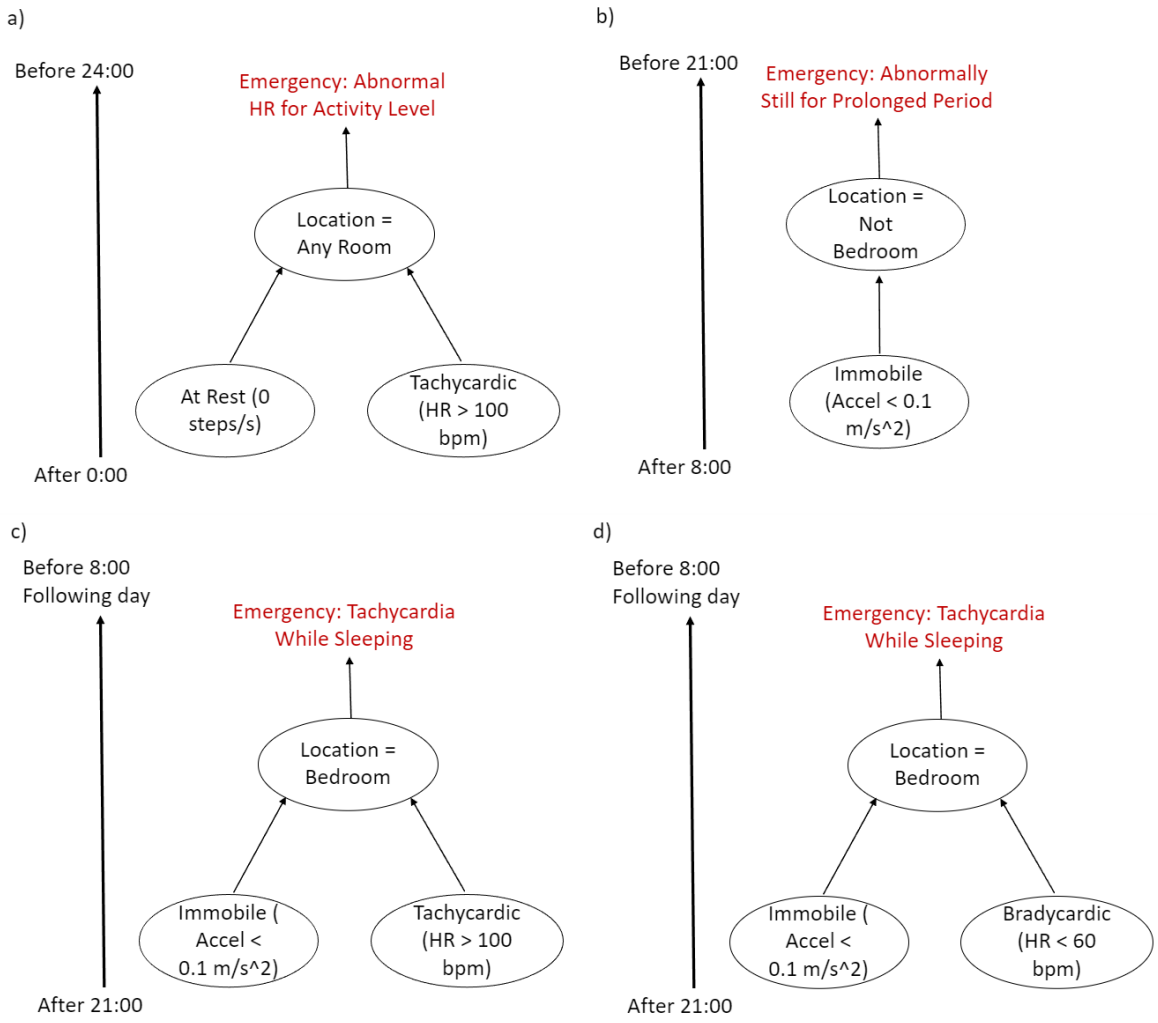

Figure 4.4 Situation networks for emergency alarms. a) General tachycardia alarm. b) Immobility alarm. c) Alarm for elevated heart rate during sleep. d) Alarm for abnormally low heart rate during sleep.

The emergency alert system uses the smartwatches' inertial measurement unit (accelerometer, gyroscope, and magnetometer) and optical PPG sensor to monitor the users' mobility and heart rate, respectively. Bradycardia, tachycardia, and complete immobility are considered dangerous events that trigger the emergency system. After a username and password are entered by a study participant during the watch application's start-up procedure, the user is registered within the database's emergency section. Healthcare providers have control over the parameters shown in Figure 4.2d, which dictate if a situation is an emergency. More specifically, the minimum and maximum allowable heart rate, how long the user's heart rate can be above or below these thresholds, how long a user can be immobile, and what locations and times of day these conditions are considered abnormal are set by health care providers (HCP)/administrators through the desktop application. These settings are then sent to the cloud database and stored as emergency conditions for the chosen user. Whether both heart rate and immobility abnormalities must be present, or one will suffice, and whether the system should trigger based on complete immobility or a lack of walking are also set through the desktop application (fig 4.5a mobility status column). After the alarm conditions are set, the user's smartwatch reads these settings from the database and constantly samples its inertial measurement unit and PPG sensor to calculate the probability

of the activity, mobility, and tachycardic/bradycardic contexts (Figure 4.3 and equation 4.1) to see if the situation has occurred with 100% probability (i.e. all contexts have data above or below the threshold for the time specified). If the conditions set within the desktop application are met and thus confirm that the situation has occurred, the watch sends an emergency alert to the patient's subsection of the cloud database, which is then received by the central server code. The server then checks the context of this emergency alert by determining whether the current room location and time of day match the conditions set by the HCP for that alarm. If the patient is in the room associated with the alarm at the correct time, an emergency notification is sent to the cloud database which is subsequently read by both the desktop app and the patient's smartwatch (Figure 4.5b). The patient is notified via the smartwatch that help is on the way and asked to confirm whether they need help or this is a false alarm (Figure 4.5c). If they select the false alarm option, the response is written to the cloud database, and the desktop app is informed that the patient has deemed the emergency a false alarm (Figure 4.5d).

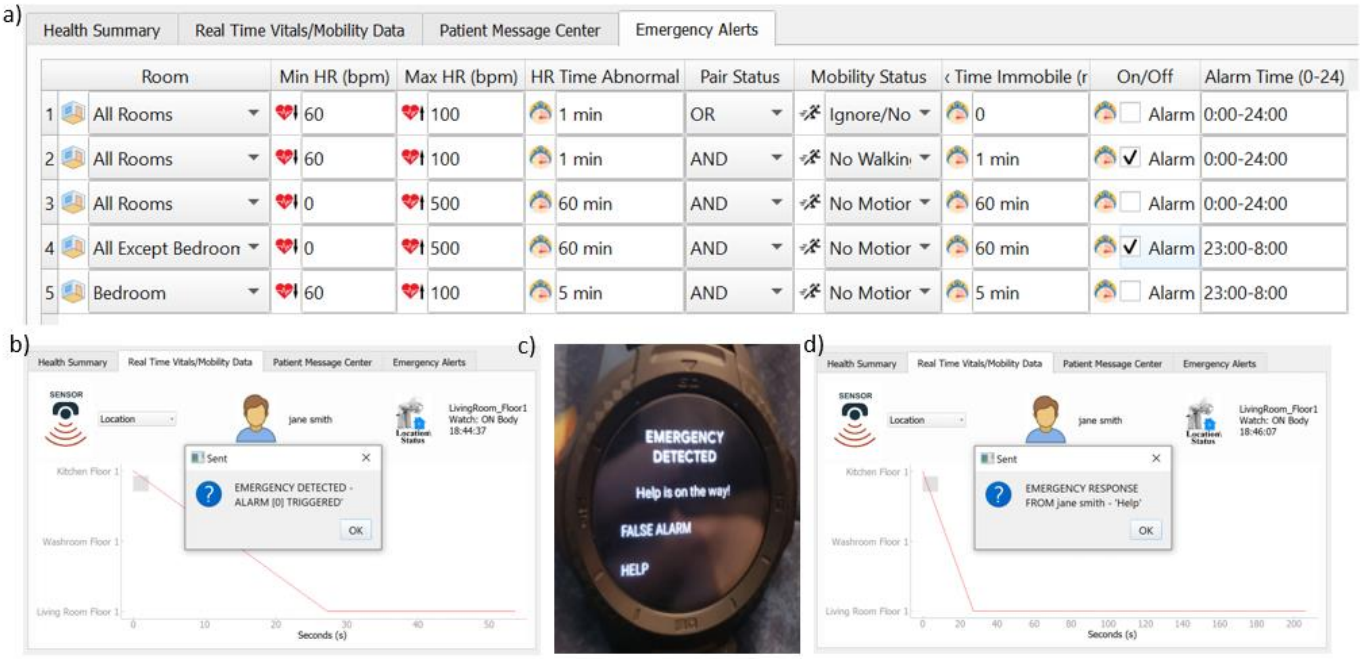

Figure 4.5 a) Emergency alert settings for the alarms based on mobility status. b) Alarm being triggered based on location, immobility, time of day, and heart rate requirements being met. c) Patient's watch being prompted for feedback to inform them of the alright and confirm if it is an emergency. d) Response from patient being relayed to the healthcare provider via the desktop application. Note that the check-boxed alarms are the context-unaware ones used on one of the watches and the unchecked alarms are the context-aware alarms set on the other watch.

4.3.4 Validation of Context Requirements for Automated Emergency Systems

Emergency alarms were programmed on the watches through the context-aware emergency system in the desktop application. Alarms without context provided by user location, mobility status, and time of day were tested against alarms that utilized context, specifically those shown in Figure 4.4c and 4.4d, in order to validate the requirement of context in automating emergency alert systems. First, a context-unaware watch was set with an emergency alarm that was programmed to trigger in any room where heart rate falls below 60 (bradycardia), or above 100 (tachycardia) and is sustained for at least 1 minute (Figure

4.5a, first row). The participant then wore a second context-aware watch, which had an alarm set to trigger on the same heart rate conditions, but to avoid being triggered if the active state was recognized (figure 4.4a, requirement for rest, alarm set in second row of figure 4.5d). The participant was then asked to exercise by jogging for 2 minutes. Next, the context-unaware watch was set to trigger on abnormal bouts of complete immobility lasting over 1 hour (Figure 4.5d, row 3). The context-aware watch was then set to trigger on the same long bouts of immobility, but not in the bedroom nor between the hours of 11 p.m. and 8 a.m. when the participant sleeps (Figure 4.4b; setting shown in Figure 4.5d, row 4). The participant was then asked to sleep with the watches on. The tachycardia and bradycardia night time alarms (Figure 4.4c and 4.4d) were also programmed onto the context-aware watch (settings shown in row 5 of 4.5d). However, this was just to illustrate the situation networks could be programmed through the application as artificially raising or lowering the users heart rate without activity level changes would require pharmacological intervention.

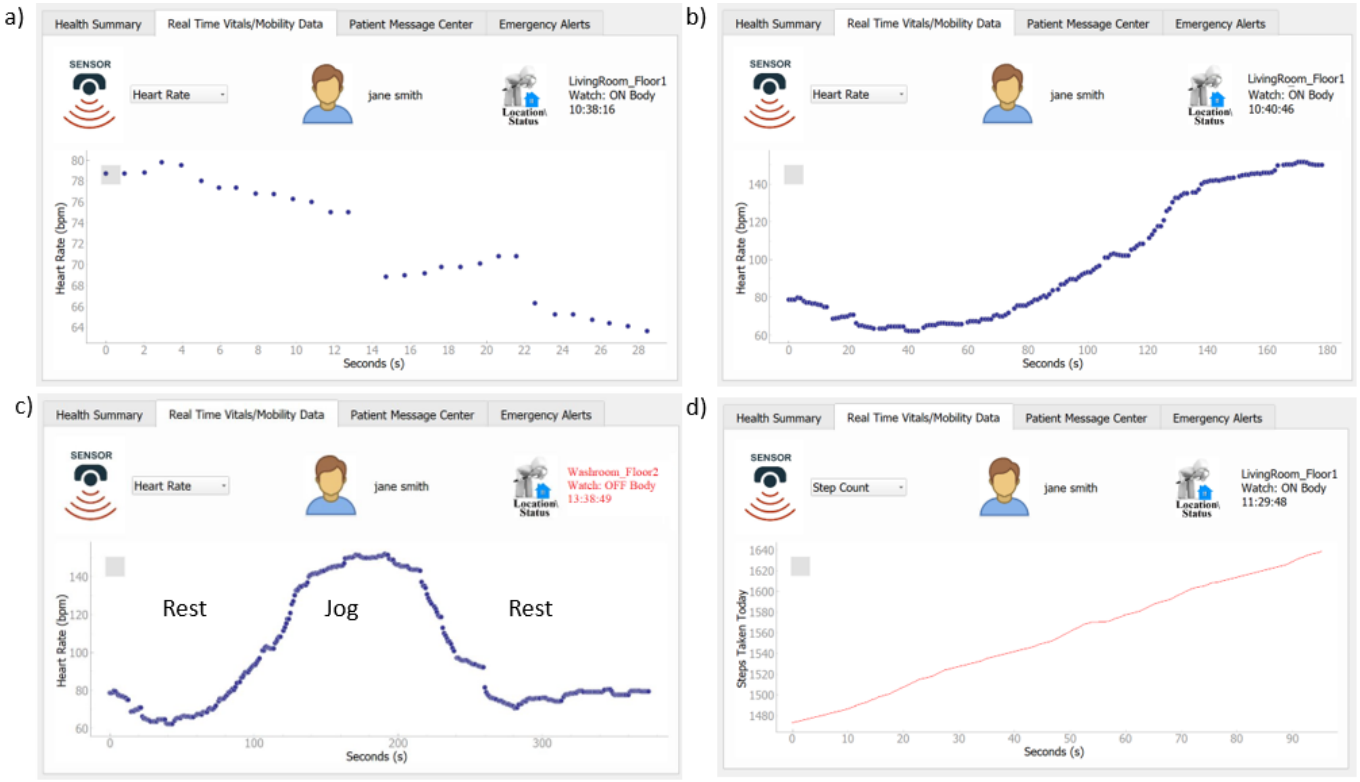

Figure 4.6 Realtime streaming data for a participant. a) Heart rate at rest. b) Heart rate going from rest to a jogging state. c) Heart rate when going from rest to jogging and back to rest, followed by the watch being removed. d) Step count changes over 100 seconds of the jogging period. 15

4.4 RESULTS

4.4.1 Real-time Data Streaming

The location, heart rate, and step count results for a user during the emergency alarm testing can be seen in Figure 4.6. Figure 4.6a-c shows the participants' heart rate when going from rest, to jogging, and then back to rest. Figures 4.6d shows the participants' step count over the jogging period. The participants' removal of the smartwatch was noted by the system, as can be seen by the OFF_body status in Figure 4.6c.

4.4.2 Context-Aware Vitals Framework

The context-aware vitals framework, which is an expansion on Bardram and Hansen's work, [29] put into a flow diagram by Musumba and Nyongesa, [28] is shown in Figure 4.7. The general framework section represents elements that are similar across general context-aware frameworks taken from Musumba and Nyongesa's diagram. The middle section, labeled context-aware medical systems, is unique to medical applications of context-aware systems. To start, sensors – such as the smartwatch and indoor position system present in this work, collect data such as heart rate, accelerometer, and position readings. Next, this data is used to calculate features (e.g steps from the accelerometer data). After this, the data is used to understand the users' context. The medical data is then subcategorized according to the context it was collected in, to conduct clinical tests that require certain contexts to be met. For instance, as in this work, abnormally high heart rates are assessed in a resting context to rule out sinus tachycardia. Lastly, the outcome of the clinical tests are used to understand the users' relative risk or post-test probabilities for conditions via likelihood ratios and inputted into applications which make decisions based on the findings from the users. An illustration of the aforementioned process of determining post-test probabilities based on contexts and sensor data can be found in our prior work (see Chapter 3).

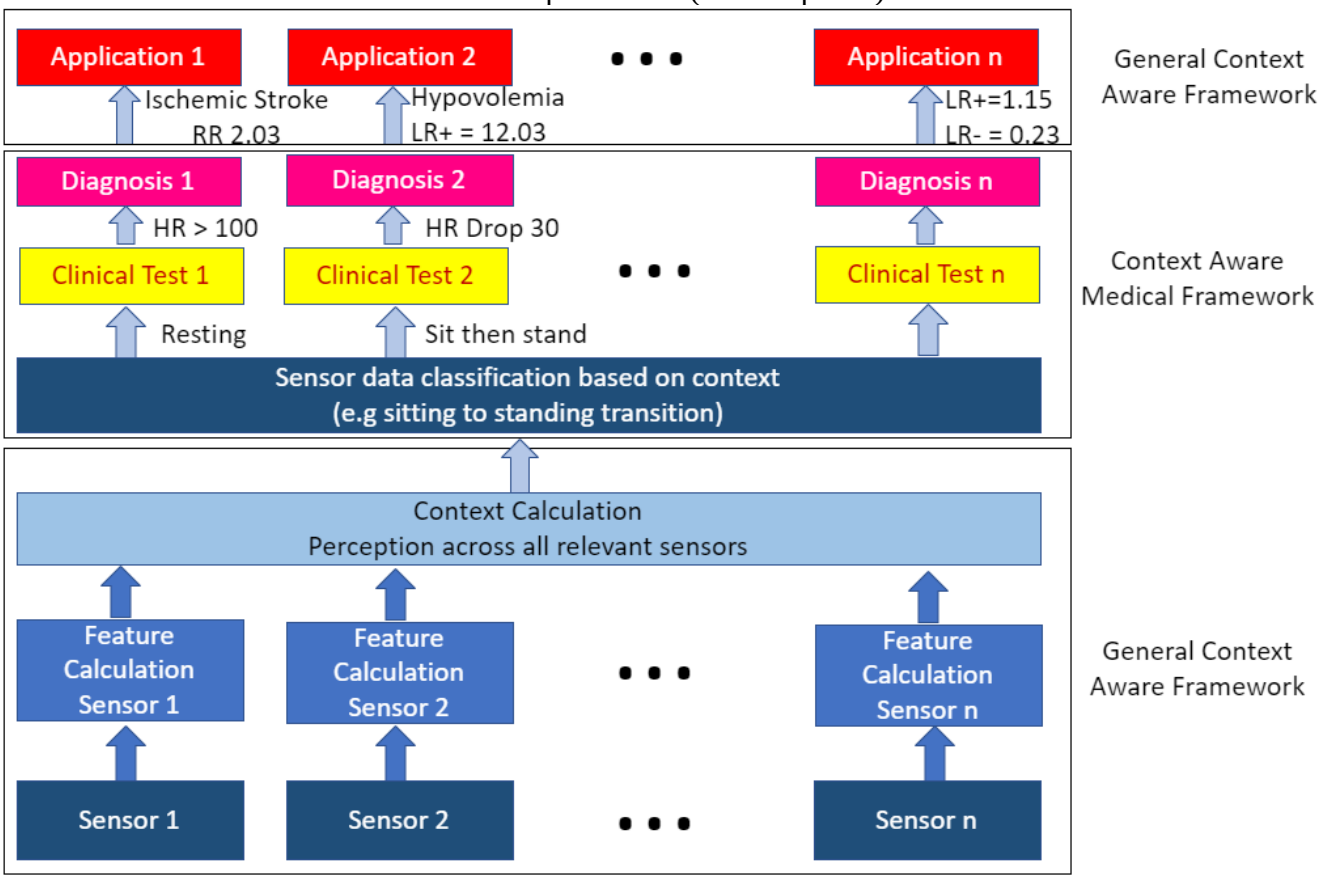

Figure 4.7 Context-aware medical systems framework.

4.4.3 Context-Aware Emergency Alert System

Results from the trial with the context-unaware and context-aware alarms that triggered on bradycardia or tachycardia are shown in Figure 4.8. After 1 minute of sinus tachycardia during the active state, the context-unaware alarm was triggered (Figure 4.8a), whereas the context-aware alarm on the other arm that does not trigger during the active state was not triggered (Figure 4.8b). The results of the second set of alarms, that triggered on complete immobility, are shown in Figure 4.8c and 4.8d. The context-unaware alarm (Figure 4.8c) triggered after 1 hour of immobility, thus interrupting the participants' rest. The context-aware alarm did not trigger in the same setting, as the location of the user was the bedroom (Figure 4.8d).

Figure 4.8 Context-aware vs context-unaware alarms. a) context-unaware alarm triggering on sinus tachycardia. b) context-aware alarm not triggering on sinus tachycardia c) context-unaware alarm triggering on immobility in the bedroom at night. d) context-aware alarm not triggering in the bedroom at night (same data as c).

4.5 DISCUSSION

4.5.1 Principal Findings

The present work focused on adding medical system-specific considerations to previous frameworks for context-aware systems and demonstrated the application of the modified framework to developing emergency systems that are better able to rule out false positives using contextual data. This framework is an expansion of Musumba and Nyongesa's work with an additional consideration for medical systems where physiological data is classified according to its context [28]. In this framework, sensor data is used to calculate different features, which are then used to determine the contexts. As an example, the accelerometer data of the smartwatch may be used to determine the step count feature, which is then used to determine whether the person is at rest or is mobile. In the general non-medical context-aware framework shown in Musumba and Nyongesa's work, the contexts are sent to a context provision module, which then gives the context to the correct applications so they can make decisions accordingly. In the medical context-aware framework, there is an extra step where the sensors collecting physiological data need to have their data classified based on the context it was measured in. This is because the normality of physiological parameters varies within a given context, which necessitates classifying them based on the context they are measured in. For instance, without knowing if a user is active or not it is inappropriate to classify an elevated heart rate as abnormal or benign (e.g. exercise-induced sinus tachycardia). Additionally, during many clinical tests, physicians use physiological changes during context changes to assess a patient's health. As an example, orthostatic vitals are measured by asking the user to transition from a sitting context to a standing context and are used to assess possible hypovolemia due to

gastrointestinal bleeds or other causes [30]. Given that medical practitioners assess physiological data both within a given context and when context changes occur, the context-aware medical framework has been adjusted to reflect this healthcare specific consideration.

To demonstrate how this framework can be useful we built a context-aware emergency system into our health smart home desktop application that can be programmed by healthcare providers to trigger on certain context conditions. The general context-aware smart home application contains a tab for looking at historical data (Figure 4.2a), real-time data streaming (Figure 4.6), sending messages to the patients' watch (Figure 4.2c), and programming context-aware alarms (Figure 4.5a). Each tab represents an application that may or may not utilize context. For the present work we added an alarm system that does utilize context to allow healthcare providers to trigger alarms that look for abnormal mobility or heart rates while considering the users' location, time of day, and activity levels. To demonstrate the usefulness of this in ruling out false positives, we compared alarms set on a context-unaware and context-aware watch, worn simultaneously by a user. The first set of alarms was programmed to identify abnormally high heart rates. As shown in Figure 4.8a, the context-unaware alarm mistakes sinus tachycardia due to exercise as a dangerous event. However, the context-aware alarm (Figure 4.8b) is able to rule out this false positive by considering that the user is active and thus the heart rate is appropriately elevated. In the future, additional parameters can be added so that abnormal heart rates (HR) are triggered if the HR surpasses what is expected for each activity level. The second set of alarms focused on identifying abnormal bouts of immobility lasting over 1 hour, which could be due to several events, such as an undetected fall or inability to get up from a given position. Again, the context-unaware alarm was unable to rule out normal situations such as a user sleeping in a bedroom (Figure 4.8c). In contrast, the context-aware alarm (Figure 4.8d) was able to rule out this benign situation by considering the time of day (daytime hours) and location (not bedroom) in which the alarm should trigger.

We hypothesize that lack of context within emergency alert systems is likely why, to our knowledge, no automated emergency alert system like the one presented in this work exists to date. As a result, current systems require users to call for help, which may not be possible during a medical emergency. Considering context allows systems to differentiate normal and abnormal medical data that would otherwise appear the same to telemedical systems, thus allowing us to build an automated emergency system. Low-cost automated systems are a necessity as manually spot-checking vitals is not a practical alternative. This is evident given that postoperative hypotension after abdominal surgery is missed in about half of the total cases in general hospital wards and mortality in these wards from cardiorespiratory events is significantly worse (40% mortality) than in ICUs where vitals are automatically monitored by expensive equipment [31], [32]. Thus, successful integration of automated context-aware emergency systems within hospitals holds great promise for improving patient outcomes.

4.6 CONCLUSIONS

As IoT technology becomes more ubiquitous, the cost and complexity of IoT systems has decreased such that remote monitoring smart home systems can be compact, affordable and simple enough to be installed independently by the average consumer. The portable smart home system developed in the present work can be installed by older adults in a matter of minutes and is a cost effective (~$150 watch plus $50 Raspberry Pi and $20 beacons for each room) smart home solution that only relies on open-source electronic devices to reach a price point comparable to most consumer electronics. By uploading user data to cloud databases through Wi-Fi, sensor data from multiple patients containing mobility, heart rate, and location can be remotely viewed by HCPs in real-time. Additionally, by transmitting Bluetooth signals from wearable devices, users' locations within buildings can be ascertained and used to assign context to their medical data. We demonstrate the necessity for context by showing that automated emergency

systems need basic contextual information such as location, activity, and time of day to rule out many false positives. We also created a context-aware medical systems framework by updating past general frameworks, so that physiological data can be differentiated according to its context, as is required for the context-aware emergency system presented here and for various context-dependent diagnoses. Future work will aim to pilot our context-aware emergency system in an assisted living facility or hospital to detect medical emergencies.

Appendix

The smartwatch code was developed in Java (AndroidStudio version 4.0.1) and executed on a Ticwatch (Mobvoi, Ticwatch s2). During the watch application's start-up procedure (Figure 4.3a), a username is requested which is used to create a new patient entry within Google's NoSQL Cloud Firestore database. The information requested at start-up (username, password, age, weight and height) , along with the sensor data, is then stored in the users' subsection of the applications database. Within the app, the username is converted to a unique UUID and then the first 4 bytes (8 characters) of this UUID are replaced with a fixed character sequence. The final UUID (fixed plus unique part) is broadcasted over Bluetooth from the smartwatch, and thn Python code (version 3.7) on the ESP32s present in each room of the home searches for the fixed character sequence. When the character sequence is found by the ESP32, the received signal strength indicator (RSSI) of the Bluetooth parcel containing the fixed and unique sequence is recorded and sent to the ESP32 connected to the Raspberry Pi. The Raspberry Pi then uses the unique part of the UUID to upload the RSSI value to the patient's data collection within the cloud database, and a "room_location" parameter in the Raspberry Pi python code ensures the signal of each ESP32 is associated with the correct room. This "room_location" parameter (e.g room_location = kitchen) is the only thing unique between the ESP32s and dictates which rooms' outlet the ESP32 is plugged into. Bluetooth signals are sampled at 1 Hz on the ESP32 and data is uploaded to the cloud every 5 seconds. The remaining data, namely the accelerometer, gyroscope, heart rate, step count, step detector, and off-body detector data, is collected on the watch and uploaded to Cloud Firestore every 15 seconds. All data points collected by the sensors and uploaded by the watch or Pi to the cloud are uploaded with an associated epoch timestamp. Server-side code written in Python runs continuously on a central computer and uses the RSSI values from the ESP32s located throughout the patients' home to determine which room users are located in. The final room location, and historical averages computed by the server, is uploaded to the cloud database for use in the desktop executable app developed using PyQt5.

References

[1] "Smart Home - United States | Statista Market Forecast," *Statista*. https://www.statista.com/outlook/279/smart home (accessed Jul. 28, 2020).

[2] R. J. Robles and T.-H. Kim, "Applications, systems and methods in smart home technology: A," *Int. Journal of Advanced Science And Technology*, vol. 15, pp. 37–48, 2010.

[3] B. Wollschlaeger and K. Kabitzsch, "Navigating the Jungle of Assistance Systems: A Comparison of Standards for Assistance Functionality," *Proceedings of the 12th International Joint Conference on Biomedical Engineering Systems and Technologies*. 2019. doi: 10.5220/0007397903590366.

[4] M. Yu, A. Rhuma, S. M. Naqvi, L. Wang, and J. Chambers, "A posture recognition based fall detection system for monitoring an elderly person in a smart home environment," *IEEE Trans. Inf. Technol. Biomed.*, vol. 16, no. 6, pp. 1274–1286, Nov. 2012.

[5] S. Greene, H. Thapliyal, and D. Carpenter, "IoT-Based Fall Detection for Smart Home Environments," in *2016 IEEE International Symposium on Nanoelectronic and Information Systems (iNIS)*, Dec. 2016, pp. 23–28.

[6] D. Sprute, A. Pörtner, A. Weinitschke, and M. König, "Smart Fall: Accelerometer-Based Fall Detection in a Smart Home Environment," in *Inclusive Smart Cities and e-Health*, 2015, pp. 194–205.

[7] K. Avgerinakis, A. Briassouli, and I. Kompatsiaris, "Recognition of Activities of Daily Living for Smart Home Environments," in *2013 9th International Conference on Intelligent Environments*, Jul. 2013, pp. 173–180.

[8] X. H. B. Le, M. Di Mascolo, A. Gouin, and N. Noury, "Health smart home for elders - a tool for automatic recognition of activities of daily living," *Conf. Proc. IEEE Eng. Med. Biol. Soc.*, vol. 2008, pp. 3316–3319, 2008.

[9] C. Azefack *et al.*, "Data-Driven Modeling and Simulation of Daily Activity Patterns of Elderlies Living in a Smart Home," *2019 Winter Simulation Conference (WSC)*. 2019. doi: 10.1109/wsc40007.2019.9004910.

[10] A. M. Anter and Z. Zhang, "E-Health Parkinson Disease Diagnosis in Smart Home Based on Hybrid Intelligence Optimization Model," in *Proceedings of the International Conference on Advanced Intelligent Systems and Informatics 2019*, 2020, pp. 156–165.

[11] W. R. Adams, "High-accuracy detection of early Parkinson's Disease using multiple characteristics of finger movement while typing," *PLoS One*, vol. 12, no. 11, p. e0188226, Nov. 2017.

[12] F. L. Pagan, "Improving outcomes through early diagnosis of Parkinson's disease," *Am. J. Manag. Care*, vol. 18, no. 7 Suppl, pp. S176–82, Sep. 2012.

[13] R. López-Blanco *et al.*, "Smartwatch for the analysis of rest tremor in patients with Parkinson's disease," *J. Neurol. Sci.*, vol. 401, pp. 37–42, Jun. 2019.

[14] W. Wang, L. Xie, and X. Wang, "Tremor detection using smartphone-based acoustic sensing," in *Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2017 ACM International Symposium on Wearable Computers*, Maui, Hawaii, Sep. 2017, pp. 309–312.

[15] N. Kostikis, D. Hristu-Varsakelis, M. Arnaoutoglou, and C. Kotsavasiloglou, "Smartphone-based evaluation of parkinsonian hand tremor: quantitative measurements vs clinical assessment scores," *Conf. Proc. IEEE Eng. Med. Biol. Soc.*, vol. 2014, pp. 906–909, 2014.

[16] P. Jatesiktat and Wei Tech Ang, "An elderly fall detection using a wrist-worn accelerometer and barometer," *Conf. Proc. IEEE Eng. Med. Biol. Soc.*, vol. 2017, pp. 125–130, Jul. 2017.

[17] G. Cola, M. Avvenuti, P. Piazza, and A. Vecchio, "Fall Detection Using a Head-Worn Barometer," in *Wireless Mobile Communication and Healthcare*, 2017, pp. 217–224.

[18] M. Dörr *et al.*, "The WATCH AF Trial: SmartWATCHes for Detection of Atrial Fibrillation," *JACC Clin Electrophysiol*, vol. 5, no. 2, pp. 199–208, Feb. 2019.

[19] A. S. Dibner, "Personal Emergency Response Systems: Communication Technology Aids Elderly and Their Families," *J. Appl. Gerontol.*, vol. 9, no. 4, pp. 504–510, Dec. 1990.

[20] R. Stokke, "The Personal Emergency Response System as a Technology Innovation in Primary Health Care Services: An Integrative Review," *J. Med. Internet Res.*, vol. 18, no. 7, p. e187, Jul. 2016.

[21] M. R. Pioli, A. M. Ritter, A. P. de Faria, and R. Modolo, "White coat syndrome and its variations: differences and clinical impact," *Integr. Blood Press. Control*, vol. 11, pp. 73–79, Nov. 2018.

[22] "Screening for High Blood Pressure in Adults: Recommendation Statement," *Am. Fam. Physician*, vol. 93, no. 4, pp. 300–302, Feb. 2016.

[23] G. Jacob, D. Robertson, R. Mosqueda-Garcia, A. C. Ertl, R. M. Robertson, and I. Biaggioni, "Hypovolemia in syncope and orthostatic intolerance role of the renin-angiotensin system," *Am. J. Med.*, vol. 103, no. 2, pp. 128–133, Aug. 1997.

[24] Ö. Yürür, C. H. Liu, Z. Sheng, V. C. M. Leung, W. Moreno, and K. K. Leung, "Context-awareness for mobile sensing: A survey and future directions," *IEEE Communications Surveys & Tutorials*, vol. 18, no. 1, pp. 68–93, 2014.

[25] J. O'Donoghue and J. Herbert, "Data management system: A context aware architecture for pervasive patient monitoring," 2005. [Online]. Available: http://www.cs.ucc.ie/~herbert/pubs/ICOST2005.pdf

[26] S. Chang, R. Chiang, S. Wu, and W. Chang, "A Context-Aware, Interactive M-Health System for Diabetics," *IT Prof.*, vol. 18, no. 3, pp. 14–22, May 2016.

[27] O. M. Cho, H. Kim, Y. W. Lee, and I. Cho, "Clinical Alarms in Intensive Care Units: Perceived Obstacles of Alarm Management and Alarm Fatigue in Nurses," *Healthc. Inform. Res.*, vol. 22, no. 1, pp. 46–53, Jan. 2016.

[28] G. W. Musumba and H. O. Nyongesa, "Context awareness in mobile computing: A review," *International Journal of Machine Learning and Applications*, vol. 2, no. 1, p. 5, May 2013.

[29] J. E. Bardram and T. R. Hansen, "Context-Based Workplace Awareness," *Comput. Support. Coop. Work*, vol. 19, no. 2, pp. 105–138, Apr. 2010.

[30] S. McGee, W. B. Abernethy III, and D. L. Simel, "Is this patient hypovolemic?," *JAMA*, vol. 281, no. 11, pp. 1022–1029, 1999.

[31] A. K. Khanna, P. Hoppe, and B. Saugel, "Automated continuous noninvasive ward monitoring: future directions and challenges," *Crit. Care*, vol. 23, no. 1, p. 194, May 2019.

[32] A. Turan *et al.*, "Incidence, Severity, and Detection of Blood Pressure Perturbations after Abdominal Surgery: A Prospective Blinded Observational Study," *Anesthesiology*, vol. 130, no. 4, pp. 550–559, Apr. 2019.

Introduction to Chapter 5

After identifying significant medical contexts, using them to build a context-aware medical system and framework for safe aging in place, and demonstrating its use in a context-aware (emergency) application, the final objective was to evaluate the system in data collected from older adults. The goal was to demonstrate that the system is viable in a small study population and that it can be used to identify some clinically relevant situations and behaviours in older adults. To do this, the system was sent to 6 participants who used the system for 1 month or more. Data from the system was used to calculate the average probability, and accuracy, for several contexts and these contexts were then used to build situations. Additionally, a sub analysis was conducted on 2 older adults living in the same home to demonstrate that information pertaining to how they spend time in their home, and when they may be located in rooms together, can be determined. The fuzzy probability approach to context determination derived in chapter 3 (and used in chapter 4) is utilized to demonstrate it can successfully be used on data acquired from older adults with the system. Given a future direction of work is to test the hypothesis that wandering behaviour exhibited by older adults within their home can be indicative of cognitive decline, one of the situations of interest was whether we could capture transitions between rooms in the home. Additionally, whether users are starting or ending their day was investigated as this may represent a useful time to que older adults to take their medications.

My contribution was building the systems sent to participants, writing the REB application, enlisting participants, identifying useful contexts that can be obtained from the system, and writing the R code that processed and analyzed the study data. Guha Ganesh helped build the systems hardware and designed the plastic enclosures that housed the hardware. Ishita Paliwal helped enroll and obtain consent from participants. Dr. Qiyin Fang supervised the study, coordinated with Age-Well/Mira to recruit participants, and reviewed the manuscript. The significance of the present work is in demonstrating that the smart home system and theory described in this thesis can be used to autonomously determine some simple but clinically useful contexts without the need for ground truth data.

Chapter 5

Autonomous Context Detection for Safe Aging in Place using Fuzzy Probability and Context-Aware Smart Home Technology

Michael Zon[1,2], Guha Ganesh[1], Qiying Fang[1,3]
[1]McMaster University, School of Biomedical Engineering, Hamilton, ON,
[2]Michael G. DeGroote School of Medicine, Hamilton, ON,
[3]McMaster University, Department of Engineering Physics, Hamilton, ON,

Contents of Paper III

ABSTRACT

Objective: Machine learning based context/activity recognition within older adults homes has been a prominent area of research given the amount that can be understood about one's health from their activity levels and their proficiency in completing activities of daily living. However, manually labeling datasets to build activity recognition models is time consuming and impractical for each new environment of interest. The present work seeks to validate a context detection method within older adults homes which does not rely on training data. *Methods:* A smart home system built in a lab consisting of an indoor positioning system and smartwatch was sent to multiple older adults. Mobility data from the smartwatch and location/motion sensing data from the smart home devices was analyzed using fuzzy probability to determine contexts autonomously. The system's accuracy for detecting contexts, and situations composed of those contexts, was determined by investigating its ability to successfully measure contexts in circumstances where that context could reasonably be assumed to have occurred based on other sensor events. *Results:* The accuracy (acc) for measuring the contexts and probability (prob) they occurred was assessed. These contexts were walking/mobile (acc 100%, prob 1.0), resting/immobile (acc 100%, prob 0.99), being present in a room (acc 71%, prob 0.84), arriving in a new room (acc 92%, prob 0.96), and equipping the watch in the morning (acc 100%, prob 1.0). The situations that were assessed based on these contexts were users' room transitions (74% accuracy, prob 0.8), resting in a room (acc 79%, prob 0.78), starting the day (acc 96%, prob 1.0), ending the day (acc 91%, prob 1.0), and sleep/resting duration over night (acc 89%, prob 1.0). *Conclusions:* The present work demonstrates that certain contexts and activities can be determined autonomously through specification-based approaches without requiring ground truth data to train machine learning models. *Significance:* Determining contexts autonomously will allow researchers to detect activities/contexts in new environments without collecting training data, which is likely required to implement remote monitoring systems in older adults homes to promote safe aging in place. High certainty autonomously determined contexts may also be used as the ground truth for training machine learning models so that learning based approaches can be applied in new environments without requiring ground truth data collection.

5.1 INTRODUCTION

Throughout the globe, increases in life expectancy are leading to increased healthcare costs for first world nations given the larger percentage of older adults with chronic conditions requiring care [1]–[3]. In addition to the desire of older adults to live independently at home, living in retirement homes is costly for both healthcare systems and patients [4]. For these two reasons, there has been a large emphasis on taking actions which will prolong the amount of time older adults can live independently at home. Unfortunately, it is impractical to regularly visit and assess each older adult at their home to pre-emptively detect declines in mobility and diagnose/prevent diseases. However, as demonstrated by Musich et al., who showed reduced costs from patients who did receive regular health screenings, pre-emptive detection of mobility decline/disease and prevention efforts is pivotal for decreasing healthcare costs [5]. To this end, much attention has been given to smart home systems. These systems can persist within older adult homes to regularly assess their health and mobility status similar to regular screening programs, and facilitate early intervention when problems are detected [6]–[8]. Additionally, many systems have focused on using Markov models or machine learning to recognize activities of daily living via training data and understand which adults are at risk for events like falls based on activity decline [9], [10]. Given the strong link between in home location and the specific activity a user is conducting, a major component of many of these remote monitoring systems has been indoor positioning detection through either Wi-Fi, BLE, of RFID tagging of the user [11], [12].

Although much progress has been made towards telemedical remote monitoring smart home systems, there are still several challenges for these systems to provide useful data so they can be adopted by users and healthcare providers. For one, ease of use and simple setup for older adults is pivotal for adoption, yet many systems require older adults to interact with hardware or software they may be unfamiliar with.[13] Another issue is the reliance on ground truth data to build machine learning models to predict activities/contexts. Many groups collect data over a period of time and require someone to annotate the data to then build models which can predict activities from future data [9], [10]. However, this is an impractical approach given that there is no guarantee that the models will extrapolate to data from a different user in a different building with the same accuracy, and there are too many total activities to label data for each one. Thus, a method of automatically detecting contexts/activities without ground truth data is needed. Lastly, although an increasing number of systems have started to discuss context-awareness, many of these remote monitoring applications still do not leverage contextual data [14]. This is problematic given that physiological parameters have different meanings within different contexts, which must be understood to correctly inform medical decisions. For instance, a heart rate of 160 BPM can either indicate a user is exercising at 6 pm, which may be obvious if their location context is a local gym, or it could indicate a dangerous arrhythmia if they are stationary in their bed at 4 a.m.

The objective of the present work is to build a context-aware remote monitoring system that is easy for older adults to use, can detect activities without requiring ground truth data, and leverages context to better understand the meaning of user data. First, we built a plug and play indoor positioning system, paired with a smartwatch, that can be sent to older adults and installed without assistance to obtain mobility/physiological data. We then built and tested a remote calibration procedure with older adults to obtain room level localization so we could understand user's contexts within their home. Next, we demonstrate the validity of this approach by testing its accuracy on some ground truth location data in the older adults' homes. Lastly, we analyze the users smartwatch and location data using fuzzy probability to understand their context without ground truth data [15]. Early results for detecting contexts and situations (which are collections of contexts) autonomously using the system are then shown to demonstrate the practicality of determining contexts autonomously.

5.2 METHODS

5.2.1 System Architecture

A smart home system was built and shipped to older adults who then set up the system in their home. A full description of the hardware and software for the system can be found in our past works (see Chapter 3). Briefly, the hardware of the system consists of ESP32 based beacons that are placed in multiple rooms, a programmed android smartwatch, and a Raspberry Pi. Each ESP32 beacon is connected to a humidity, ultrasonic, passive infrared, and photoelectric sensor, and then relays data from these sensors to a master ESP32. Additionally, Bluetooth signals from the user's smartwatch are collected by the ESP32 beacons and sent to the master ESP32. This master ESP32 then relays the data through a serial connection to a Wi-Fi enabled Raspberry Pi computer which then stores the data locally and uploads the data to a cloud database (Google Cloud Firestore). The smartwatch was a TicWatch S2 and custom software was developed in Android Studio that broadcasts Bluetooth signals and stores accelerometer, gyroscope, heart rate, and step count data locally.

5.2.2 Pilot Study Details

To assess the feasibility of the system a longitudinal study was carried out on a small number of older adults. The only eligibility criteria was that older adults were 60 years of age or older and spoke English. The study was approved by the Hamilton Integrated Research Ethics Board and participants' verbal consent was provided before sending them the systems. Participants were asked which rooms they would permit having a beacon in, and access was requested for the kitchen, living room, master bedroom, and master washroom. For homes with 2 stories, beacons were always situated on both the main and upstairs floor. Setup instructions were included with the system, and aside from this the team was not involved in setup. The instructions asked participants to plug the beacons into specific rooms, to wear the smartwatch throughout the day with the custom application we developed turned on, and to plug the ethernet cable from the Raspberry Pi into their router in order to provide the system with internet connectivity. The full Research Ethics Board protocol describing the study details, setup procedure, consent, and devices is attached to the appendix of this thesis.

5.2.3 System Control and Calibration

In order to adjust the parameters of the system, cloud functions on the python code controlling the system would listen to cloud directories for changes to file parameters. This allowed for remote rebooting of the system and increasing the frequency that the system writes data to the cloud. To calibrate the system, participants were called and instructed to stand in 3 positions within each room in their home. These positions were the middle of the room, midway between the room's middle and an entrance, and at the location they are most frequently located within that room. A remote calibration script was written in python that reads the relative signal strength indicator (RSSI) values each beacon is receiving from the watch, and then stores these values for the user's location at each position. The result of this was a set of files that represent the signal strength that each beacon receives while the user is in multiple positions within each room in their home. Note that data is collected for rooms that do not have beacons in order to detect user location in all rooms as opposed to just those that contain beacons.

The Bluetooth low energy (BLE) data collected during calibration was used to determine the user's location throughout the duration of the study. Let $C_{p,i}$ represent the RSSI strength at a calibration point p in some room, from beacon i. Let $S(t)_i$ be the RSSI strength of a point during the study at time t for beacon i. In order to figure out the room r that the user is in at a given point of time based on the signals from each

beacon, the Euclidean distance from each calibration point at each point in time is determined. Then, the current room is taken to be the room that the calibration point with the minimum Euclidean distance from the current RSSI readings was obtained in. More precisely, we obtain $L(p,t)$ representing the Euclidean distance from the users current position at time t to each calibration point p for the N calibration points and M beacons (in a home) as follows

$$L_p(t) = \sum_{i=1}^{M} \sqrt{(S(t)_i - C_{p,i})^2} \qquad \text{Equation 5.1}$$

Then, $L(t) = min_p \sum_{p=1}^{N} L_p(t)$ gives the location of the user at time t. Since multiple calibration points p are gathered within each room, but for the purposes of this study only the specific room they are in is of interest, the room r that point p was collected in is assumed to be the user's location at time t.

5.2.4 Calibration Data Validation

In order to test whether the calibration data could accurately predict the room users were situated in, we used ground truth data where the user's location was known to determine the accuracy that the right room was selected. More specifically, we removed each calibration point and calculated the user's location with the remaining calibration points. We assessed the average accuracy of the system in selecting the correct room for the subset of rooms that had beacons, and the subset of rooms without beacons, in order to see if results varied drastically based on the presence of a beacon.

The calculation of location is based on the method described in 5.2.3, and the percent of locations that were correctly determined were calculated for 4 different homes that the 6 participants lived in. The total rooms in each home, and which ones had a beacon, can be seen in table 5.1. Additionally, the signal strength of beacons near the smartwatch were compared to those that were further to verify there was increased signal strength closer to the beacons. This was done by comparing the signal strengths from beacons in the same room as the user to those in the other rooms via a Wilcoxon signed rank test. A p-value under 0.01 was taken to be a statistically significant difference. Additionally, to assess the mean signal strength in rooms with and without beacons, the mean and standard deviation of the signal strengths for each home were determined for rooms with and without beacons. Then, a meta-estimate for the mean signal strength with and without beacons was determined from the individual estimates (and their associated standard deviations) via the survcomp package in R using a random effects model.

TABLE 5.1
Beacon Locations in Homes used for Calibration Data Validation

Beacon Count	Users	Floors	Total Rooms	Rooms with Beacons	Rooms without Beacons
5	1	3	13	Family F1 Kitchen F1 Living F1 Basement Main F0 Master Bathroom F2	Bathroom F1 Bathroom F2 Dining Room F1 Guest One F2 Guest Two F2 Laundry F0 Master Bedroom F2 Storage F0 TV Room F2
4	2	3	14	Basement Main F0 Family Room F1 Kitchen F1 Master Bedroom F2	TV Room F1 Dining Room F1 Family Room F1 Guest Room One F2 Guest Room Two F2 Kitchen F1 Laundry Room F0 Master Bedroom F2 Master Bathroom F2 Bathroom F1 Bathroom F2 Bathroom F0 Office F1
4	2	1	5	Bedroom F1 Den F1 Kitchen F1 Living F1	Washroom F1
4	1	3	11	Basement Main F0 Kitchen F1 TV Room F1 Master Bedroom F2	Backyard F1 Dining Room F1 Guest Room One F2 Guest Room Two F2 Living Room F1 Bathroom F1 Bathroom F2

- F0 = basement, F1 = main floor 1, F2 = upstairs

5.2.5 Context Determination via Membership Functions and Fuzzy Probability

Using Zadeh's fuzzy probability theory, the probability that a user is in a given context in a specified time period was determined [15]. The context was computed as the integral of the product of the probability density function (PDF) representing the physiological data and the fuzzy membership function describing the relationship between this data and the contexts that can be predicted with it. The calculation is shown in equation 5.2 as

$$P(X_i = C_j)_{s_i,\Delta t_j} = \int_{-\infty}^{\infty} \mu_{c_{ij}}(x) \cdot s_i(x)_{\Delta t_j} \cdot dx \quad \text{Equation 5.2}$$

Where $X_i$is the random variable describing the outputs for sensor $s_i$that is mapped to the context $C_j$by the membership function $\mu_{c_{ij}}$, and $\Delta t_j$is the time over which the data was collected. For sensor data outputs that are discrete/categorical in nature (e.g step detected vs not detected) the PDF (or probability mass function in the discrete case) is described using the dirac delta function

$$s_i(x_i)_{\Delta t_j} = \sum_{k=1}^{K} P_k \cdot \delta(x - x_k) \quad \text{Equation 5.3}$$

Where $\vec{x} = \{x_1, x_2, \ldots\ldots x_K\}$ are the discrete points/categorical outcomes, each with a corresponding probability $P_1, \ldots\ldots P_n$of occurring. In the case of multiple sensors which are conditionally independent and measuring the same context , the different sensors can be leveraged to gain increased understanding about the context using the below formula.

$$P(C_j)_{\Delta t_j} = 1 - p(C_j{}^c)_{\Delta t_j} = 1 - \prod_{i=1}^{N} P\left(X_i = C_j{}^c\right)_{s_i,\Delta t_j}$$

$$= 1 - \prod_{i=1}^{N} \left(1 - P(X_i = C_j)_{s_i,\Delta t_j}\right) \quad \text{Equation 5.4}$$

Where $p(C_j)_{t_{s_j} \le t \le t_{f_j}}$ is the probability that the context C_j has occurred in the time interval $t_{s_j} \le t \le t_{f_j}$based on the set of sensors S available to the telemedical system.

Using the above method for context determination a few key contexts were determined. The 5 contexts of interest were whether the user is in a room or not, whether they are stepping/mobile, whether they are immobile, whether they are putting the watch on, and whether they are taking the watch off. Table 5.2 shows the contexts, sensor data used, membership function values, and the type of membership function used. For the discrete functions, (x1, y1) and (x2, y2) represent the two points used for the trapezoidal L function. The transition to a probability of 0 from 1 occurs at the x2 value. Since a normal person is assumed to be stationary the majority of the time in their home, the value for $\Delta|RSSI|$ under which users were assumed to be at rest was taken to be 1.5 times the mean $\Delta|RSSI|$ obtained from 1 million samples. The cut off point at which users were assumed to be moving (x2) was taken to be 2 standard deviations past the mean of 3.27. An illustration of a discrete and continuous case using data from one of the participants is shown in figure 5.1 (and in Chapter 3), where membership functions are used to determine context probabilities. To determine the final mean probabilities for each context, the mean probability and standard deviation for measuring that context in each individual participant was determined. Following this, the mean probability and mean standard deviation for each context probability was calculated by taking the average of the individual participants' context probability means and standard deviations. Accuracies are reported as the total number of detections for the contexts of interest over the total instances they should have been measured according to the number of times the watch was removed.

TABLE 5.2
Contexts Determined and Their Membership Functions

Context	Data/Sensor	Membership function x1 & x2 variable	(x1, y1 = probability1)	(x2, y2 = probability2)	Function Type
In/Out Room	RSSI from Watch BLE	location	(L(t) = room, 1)	(L(t) != Room, 0)	Discrete
Resting/Immobile	RSSI from Watch BLE	Delta |RSSI|	(6.9, 1)	(10.5, 0)	Trapezoidal L
Resting/Immobile	Watch step count via accelerometer	Delta steps	(0, 1)	(>0, 0)	Discrete
Watch Removed	Optical PPG from watch	Change in On body status of smartwatch	(0, 0)	(-1, 1)	Discrete
Watch Put On	Optical PPG from watch	Change in On body status of smartwatch	(0, 0)	(1, 1)	Discrete
Stepping/Mobile	Watch step count via accelerometer	Delta Steps	(0, 0)	(>0, 1)	Discrete

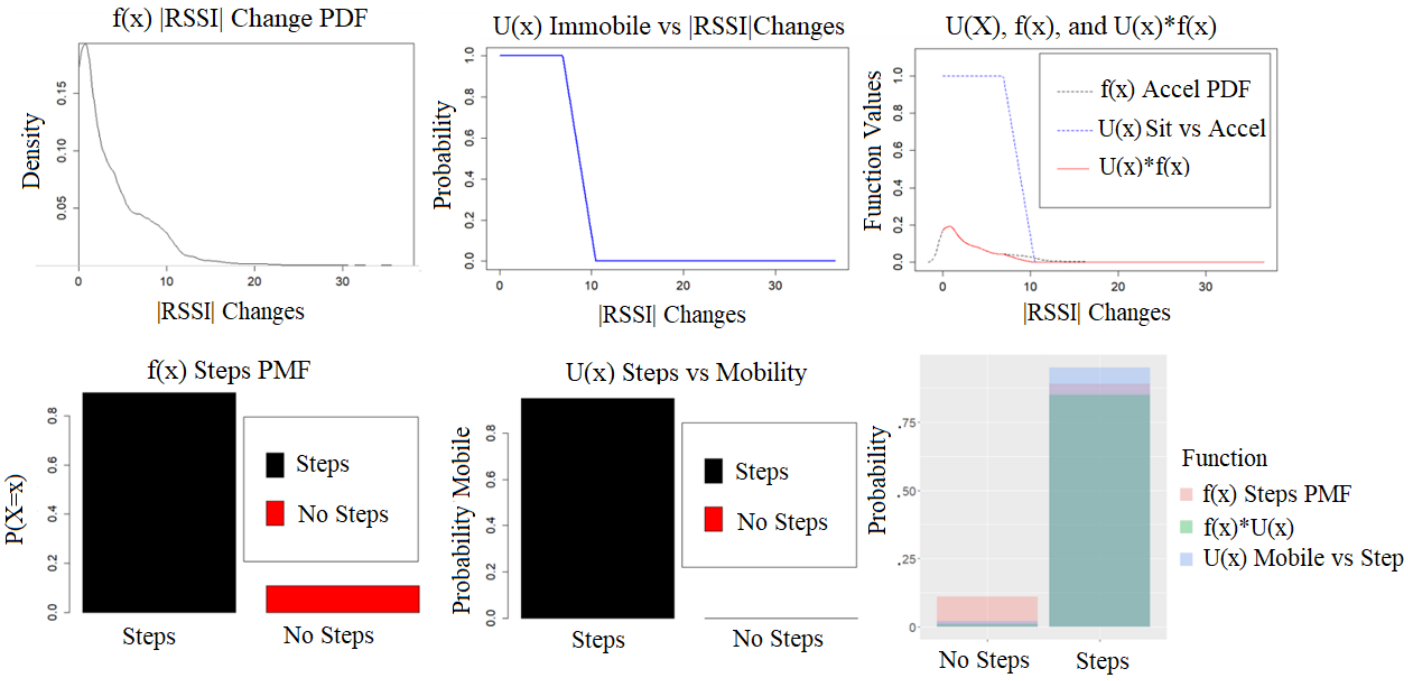

Figure 5.1 Discrete (Steps) and continuous (|RSSI| change) fuzzy probability calculations to determine the probability of the mobility context from a sensor event. a) Probability density function for the change in RSSI magnitude. b) membership function describing whether users are immobile based on the magnitude of the RSSI change. c) illustration of how these functions are multiplied to determine the function with an area under the curve that represents the probability the user is immobile based on the sensor data. d) Probability mass function for the instance steps were and were not detected. e) discrete membership function for whether users are mobile vs step detection. f) Probability they are mobile (green bar) based on the integral of U(x)f(x).

In order to calculate the accuracy of detecting the contexts we need to know how many times each context will occur during each day. However, it is not possible to know the total number of instances that some of the contexts in table 5.2 will occur on a daily basis (e.g cannot assume how many times a person will be in each room each day). Thus, to mitigate this issue we instead focused on measuring these contexts in a situation where we could be fairly certain they occurred, and then we calculated the accuracy based on the total times the context was detected divided by the total instances of the situation where the context should occur. The situation used to define the total instances of the contexts in Table 5.3 was when the user took off the watch. At this point, we could be confident that the watch is stationary in a room until it is put back on, the user must exist in a different room at some prior time, the user must take steps to move from the prior room to the final room they take the watch off in, and that time without motion in the prior room is time where they are immobile prior to transitioning to the final room. A full list of the assumptions made is shown in Table 5.3. By assuming these contexts exist around the event of the watch being removed, we could reasonably assume the total instances that these contexts occurred and then calculate accuracy based on the number of times the context was detected (where detection is considered a probability greater than 70% of the context occurring based on equation 5.1). Thus, accuracy for contexts that were assumed to have occurred around this event was defined as the total instances that context was measured around the (watch removal) event divided by the total number of instances the watch removal event occurred. To determine the final mean probabilities for each context, the mean probability and standard deviation for measuring that context in each individual participant when the contexts were detected was determined. Following this, the mean probability and mean standard deviation for each context probability was calculated by taking the average of the individual participants' contexts probability means and standard deviations.

TABLE 5.3
Assumptions Surrounding Accuracy Assessment for Autonomously Determined Contexts

Context	Assumption
In Room 1	The user is located in a room aside from the one they take the watch off in at some point before taking the watch off
In Room 2	The user must take steps to move from the room they are in prior to removing the watch to the room they remove the watch in
Stepping/Mobile	Steps will be detected at some point before the user reaches room 2 from room 1
Resting/Immobile	If the user is in 1 room and they are not stepping and/or the change in BLE is extremely small, they are inactive in that room
Watch Removed	The onBody status indicator of the smartwatch is accurate and a value of 0 means the watch has been removed
Watch put on	The onBody status indicator of the smartwatch is accurate and a value of 1 means the watch has been put on

5.2.6 Situation Determination via Spatiotemporal Context Networks

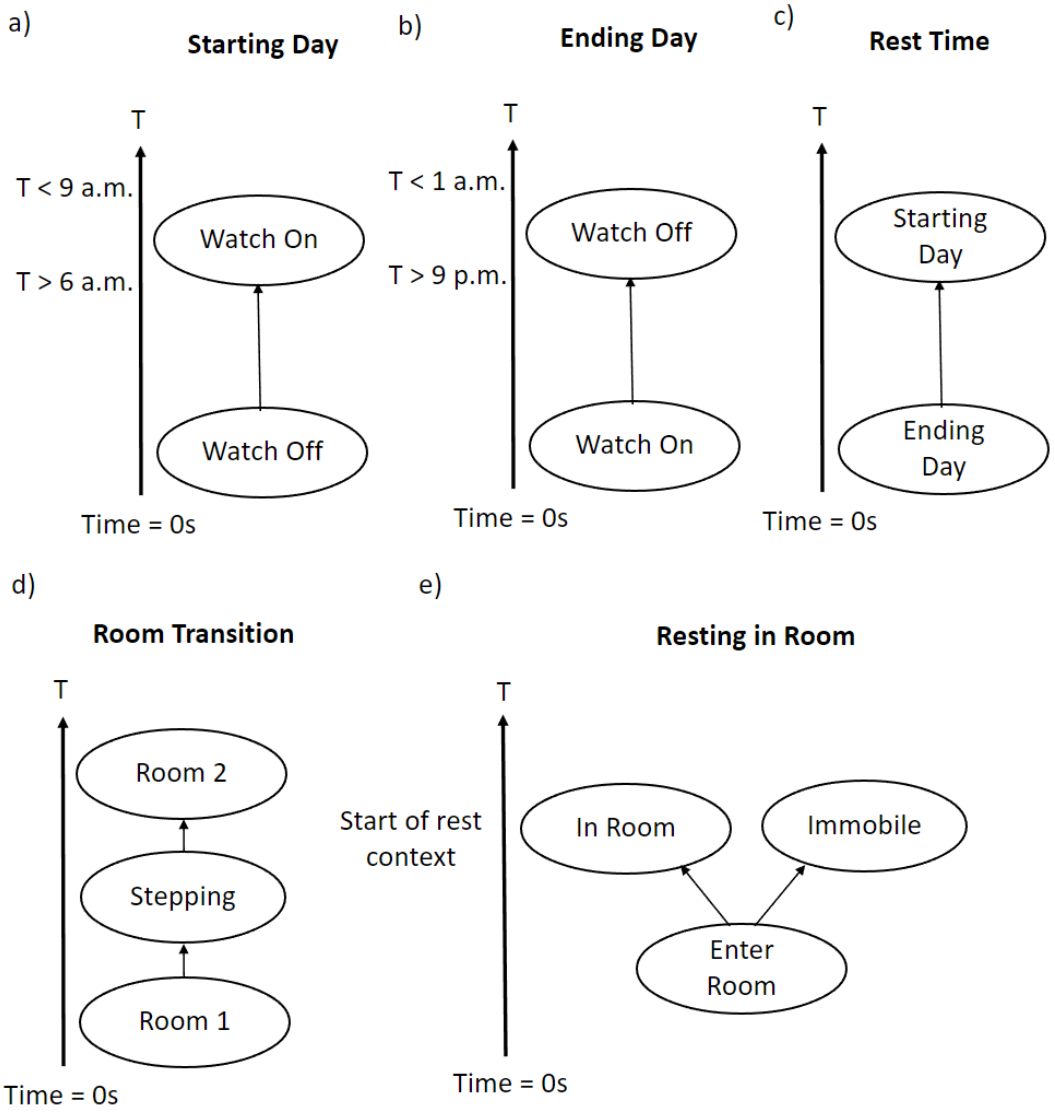

Figure 5.2 Situations determined based on the measured contexts. a) When the user starts their day. b) When the user ends their day. c) Rest time of the user from going to sleep to waking in the morning. d) Room transition of the user in their home. e) User at rest in a room in their home.

$$P(Situation)_{T_s \le t \le T_f} = \prod_{j=1}^{M} p(C_j)_{\Delta t_j}$$

Equation 5.5

$$= \prod_{j=1}^{M} \left(1 - \prod_{i=1}^{N} \left(1 - P(X_i = C_j)_{s_i, \Delta t_j}\right)\right)$$	
$$= \prod_{j=1}^{M} \left(1 - \prod_{i=1}^{N} \left(1 - \int_{-\infty}^{\infty} \mu_{c_{ij}}(x) \cdot s_i(x)_{\Delta t_j} \cdot dx\right)\right)$$	Equation 5.6

Using the contexts of the user, we can establish situations that represent a collection of contexts that together form new meaning.[16] Situations are defined as temporal context networks whose probability of occurring is based on the probability of each context that defines the situation. Each context must occur at a pre-specified point in time relative to another in order for a situation to occur since the situation's meaning can change based on the order. The probability that a given situation has occurred then becomes the simple product of the probabilities that each context has occurred in the chronology specified. This is written as

Where M is the total number of contexts that comprise the situation, $T_s = min\{t_{s_1}, t_{s_2}, \ldots, t_{s_M}\}$is the start time of the first context and $T_f = min\{t_{f_1}, t_{f_2}, \ldots, t_{f_M}\}$ is the end time of the last context in the temporal context network defining the situation. Using this approach, common situations can be defined based on the sub contexts described in table 5.3, as shown in figure 5.2. As before, the assumptions required for the situations are the same as those required for contexts in table 5.2 since the situations are made up of those contexts. Thus, accuracy is reported for the situations given we have reasonable grounds to believe the events must have occurred in the prescribed time frames before and after the watch was taken off based on the assumptions in table 5.3. If any of the contexts defining the situation are not detected, then the situation is assumed to not have occurred or been detected. Additionally, a probability of over 70% according to formula 5.5 is counted as successful detection, whereas less than this is counted as a missed detection. Accuracies are reported as the total number of detections for the situations of interest over the total instances they should have been measured according to the number of times the watch was removed. To determine the final mean probabilities for each situation, the mean probability and standard deviation for measuring that situation in each individual participant when the contexts were detected was determined. Following this, the mean probability and mean standard deviation for each situation probability was calculated by taking the average of the individual participants' situation probability means and standard deviations.

5.2.7 Participant Demographics, Compliance and Step Data Validation

The only criteria for study participation was that the participant was 60 years of age or older. Of the 6 participants 4 were female and 2 were male. Participants were asked about the comfortability of the smartwatch and whether they would continue using the system in a post-study interview. In order to determine user compliance, after the watches were returned the optical PPG sensor which reports when the watch was on or off was used to calculate the total time users wore the watch. Users were not asked to wear the watch when sleeping so the expected percentage of time they wear the watch is expected to be around 66% when fully compliant.

Watch step data for the TicWatch S2 used in the present study was validated by a collaborator and compared to the Actigraph gold standard (Dr. Marla Beauchamp's group, results have not been published yet). A group of 21 participants were asked to take 50-100 steps with both the TicWatch and ActiGraph equipped on their wrist. Participants recorded their start and end time along with their total step count. The

TicWatch step count was then compared to the ActiGraph and participant recorded step count. A t-test using the difference in the participants recording and the ActiGraph reading, and the participants recording and the TicWatch S2 reading, was done to see if one device was statistically more accurate than the other.

5.2.8 Case Study in a 2 Participant Home on Functional Areas and Kitchen Activity

A sub analysis was conducted on 2 participants living together to compare and observe the amount of time they spent in different functional areas within their home at different points in the day. Using equation 5.1, their location versus time was determined over the study. Next, the amount of time spent in each room at various points in the day was determined by adding up the amount of time spent in each room at different time intervals. More specifically, each day was split into eight 3-hour time intervals starting from midnight in order to observer differences between the morning, midday, and evening periods. Following this, for each 24-hour period the amount of time spent in each room within the 3-hour time intervals was determined. Two heatmaps were then generated for each participant to visualize and compare their data over the same time period. The first heatmap showed their time spent in each functional area over 1 day, where the columns represent each 3-hour time interval, and the rows are the different functional areas. The second heatmap looked at the participants behaviour on a 1-week basis by determining their time spent in each functional area over 24-hour periods instead of 3-hour periods. A heatmap with each functional area as the rows, and each day as the columns, was then generated to observe and compare the 2 participants behaviours over the course of the same 1 week period.

To investigate a single functional area in more depth and compare IPS location data to other sensor data, kitchen activity as determined by the IPS system and passive infrared (PIR) sensor were compared. For the 2-participant home, PIR sensor triggering times in the kitchen throughout the study were determined. Following this, 45 seconds of BLE data before and after this time was obtained for each participant. The location of each participant according to this data subset was then calculated using equation 5.1, and whether the participant was in the kitchen was determined. The total number of times the PIR was triggered each day, total number of instances each participant was in the kitchen during the PIR triggering events, and the total number of instances both participants were found in the kitchen during PIR triggering was then plotted. A Pearson correlation coefficient was calculated between the number of times the PIR was triggered in the kitchen and the number of times participant one was found in the kitchen that day in the same time intervals. The same analysis was also done for participant two. Additionally, a Pearson correlation coefficient was also calculated between the number of times the PIR was triggered in the kitchen and the number of times either participant was found in the kitchen that day in the same time intervals. For each Pearson correlation coefficient, a P-value was determined and taken to be significant at a value of less than 0.05.

5.3 RESULTS

5.3.1 Calibration Validation and BLE RSSI Versus Proximity

The mean RSSI of the beacons that were in the same room as the watch was -74.3 (SD 2.7), whereas the mean RSSI of the beacons in rooms the watch was not present was -88.8 (SD 2.5). This difference was significant according to the Wilcoxon signed rank test comparing the two groups ($p < 0.01$).

For the leave one calibration point out approach to validating room detection accuracy, the overall accuracy in predicting the correct room the user was in was 81.5%. Sub setting this into rooms that did have a beacon and rooms that did not, the accuracy for predicting rooms without beacons was 87.3% and the accuracy for predicting rooms that did have beacons was 76.7%.

5.3.2 Context Determination and Accuracy

TABLE 5.4
Context Accuracy and Probabilities

Context	Measured	Total	Data Time Interval	Accuracy (%)	Average Probability	SD probability
In/Out room (Second last room)	116	164	T2 = Last step before watch removed T1 = T2 - 5 minutes	71	0.84	0.14
In/Out Room (Final Room)	151	164	T1 = Last step before watch removed T2 = T1 + 5 minutes	92	0.96	0.1
Resting/Immobile (using step data)	164	164	T2 = first time room differs from final room before watch removed T1 = T2 - 5 minutes	100	0.99	0.01
Resting/Immobile (using RSSI data)	164	164	T2 = First time before watches final room when removed T1 = T2 - 20 minutes	100	0.99	0.003
(Last) Watch* Removed	164	164	T1 = T2 = Instant watch was removed	NA	NA	NA
First Watch Put On	164	164	T1 = T2 = first watch status update after watch removed	100	1	0
Mobile	164	164	T1 = T2 = instant steps detected before final room	100	1	0

*T1 = start time for context, T2 = end time for context

Table 5.4 shows the accuracy in detecting the contexts for the contexts that were assumed to have occurred each time the watch was removed in the evening. A total of 165 measurements are assumed to have occurred based on 165 watch removal events over 398 days worth of data from the 6 participants. For the 6 participants, the number of instances for each context based on removing the watch (and thus situations) were 15, 15, 17, 20, 42 and 56.

5.3.3 Situation Determination and Accuracy

TABLE 5.5
Situation Accuracy and Probabilities

Situation	Contexts	Measured Occurrences	Total Measurement	Accuracy (%)	Average Probability	SD probability
Room Transition	1. Second last room 2. stepping/ mobile 3. Final room	122	164	74	0.80	0.18
Starting Day	1. Watch put on 2. T > 6 a.m 3. T < 11 a.m	158	164	96	1	0
Ending Day	1. Watch removed 2. T > 8 p.m. & T < 1 a.m.	150	164	91	1	0
Resting in Room	1. Resting/ immobile (steps) 2. second last room	129	164	79	0.78	0.23
Rest Time Evening to Morning	1. Ending day 2. Starting day	146	164	89	1	0

The accuracy and average probability for the situations described in figure 5.2 are shown in table 5.5.

5.3.4 Participant Demographics, Compliance and Step Data Validation

TABLE 5.6
Participant Info and Compliance

Sex	Age	Watch on Time (Days)	Watch Off Time (Days)	On Time/Total Time	Watch Size an Issue	Willing to Continue	Pre-existing Conditions
Female	62	113.7	55.92	0.67	Yes	Yes	None
Male	75	48.01	121.67	0.28	Yes	Yes	Alzheimer's
Male	72	42.44	143.50	0.23	Yes	No	None
Female	71	52.7	36.22	0.59	Yes	No	Peripheral Arterial Disease
Female	66	21.6	21.1	0.51	No	Yes	Osteoarthritis
Female	72	45.46	11.57	0.80	No	Yes	Macular Degeneration

Information pertaining to the age, sex, and pre-existing conditions of the participants can be seen in Table 5.6. Additionally, the duration that the patients were and were not wearing the watch is shown. 4 out of the 6 participants reported the watch was too large and the mean percentage of time participants were wearing the watch was 51% (SD 22%). The TicWatch S2 recorded 6.6 steps less than the participants recorded on average, whereas the ActiGraph recorded 32.7 less steps. The difference between these two means was significant in a Student's t-test at $p=2.8 \times 10^{-6}$.

5.3.5 Case Study in a 2 Participant Home on Functional Areas and Kitchen Activity

Figure 5.3a shows participant one's amount of time spent in each room for each 3-hour time interval over 1 day. Figure 5.3b contains the same information but for the other participant living in the home. Figure 5.3c contains the heatmap showing participant one's time spent in each functional area over 24-hour periods over the course of a week. Figure 5.3d contains the same information for participant 2, who also lives in the home.

A plot of the number of times the PIR sensor was triggered in the kitchen each day is shown in

figure 5.4. One can see how many times participant one and two were located in the kitchen according to the IPS (figure 5.4a), and how many times both participants were found together in the kitchen (figure 5.4b). The Pearson correlation coefficient (r) between the PIR kitchen triggering and participant one's kitchen instances was 0.57 and statistically significant ($p = 4 \times 10^{-6}$). The Pearson correlation coefficient (r) between the PIR kitchen triggering and participant two's kitchen instances was 0.36 and statistically significant with a P-value of $p = 7 \times 10^{-3}$. Lastly, the Pearson correlation coefficient (r) between participant one's kitchen instances and participant two's kitchen instances was 0.39 and statistically significant ($p = 3 \times 10^{-3}$).

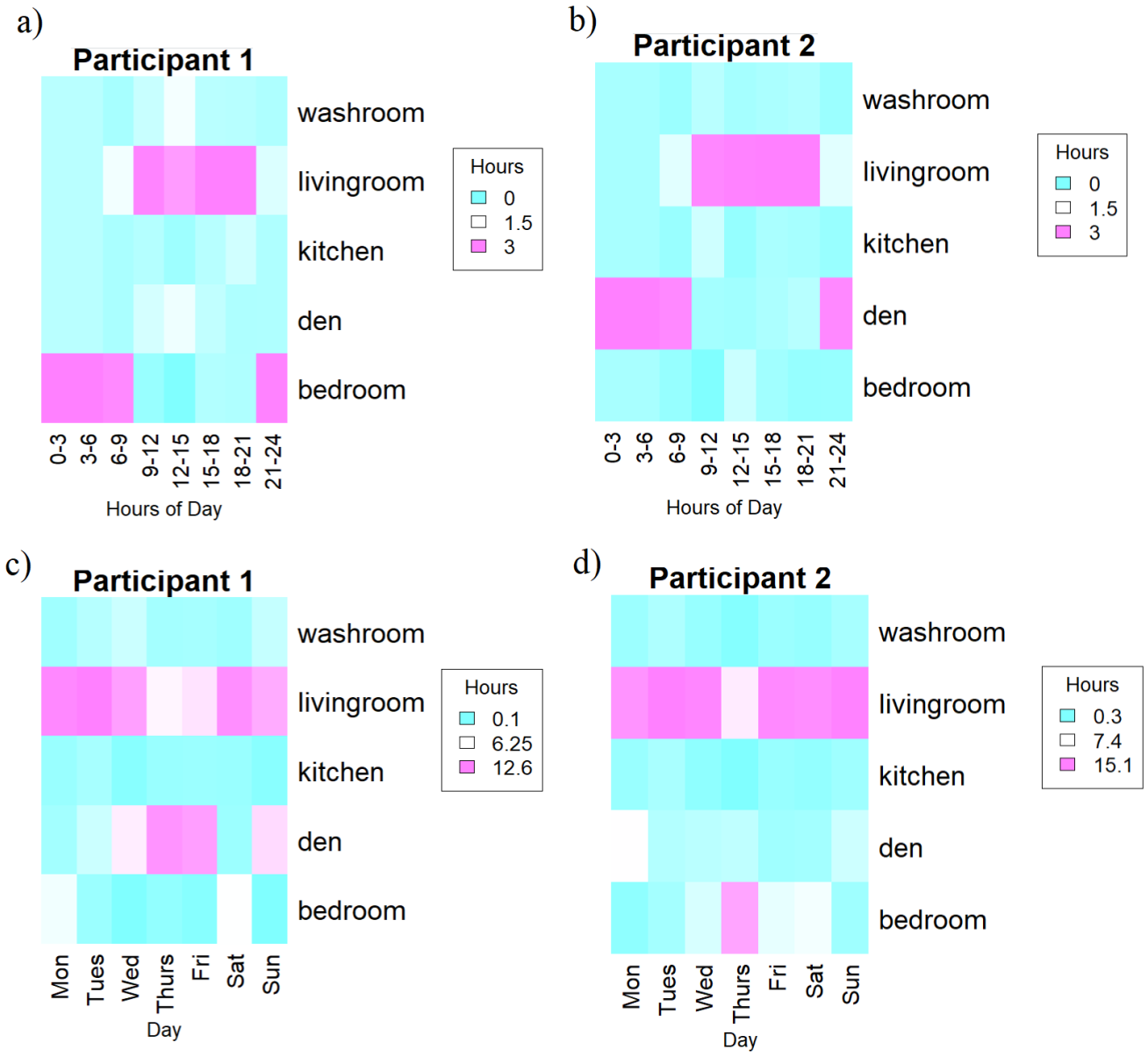

Figure 5.3 Visualization of the time spent by two participants that live together in various areas of their home. a) Participant 1's time spent throughout their home in a 24 hour period. b) Participant 2's time spent throughout their home in the same 24 hour interval. c) Participant 1's time spent throughout their home over the course of a week. d) Participant 2's time spent throughout their home over the same week.

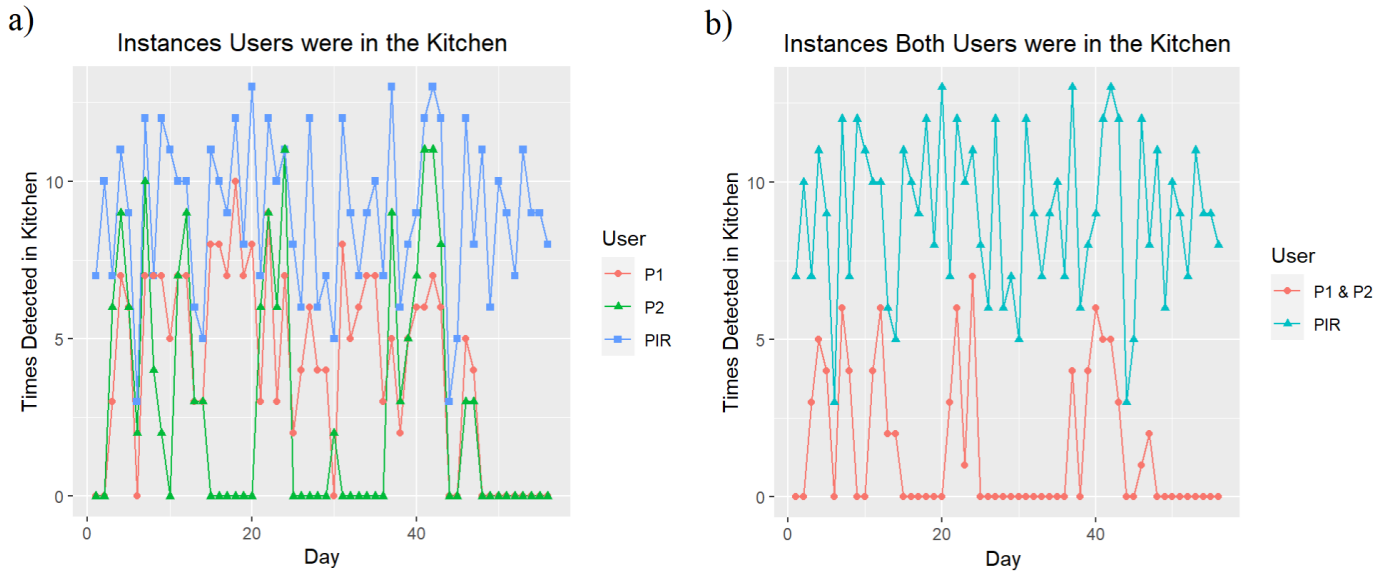

Figure 5.4 a) Plot showing the total number of times the PIR sensor in the kitchen was triggered each day and how many times participant 1 (P1) and participant 2 (P2) were located in the kitchen according to the IPS during this time b) Plot showing the total number of times the PIR sensor in the kitchen was triggered each day and how many times participant 1 and participant 2 were located in the kitchen together at this time according to the IPS.

5.4 DISCUSSION

The present work sought to demonstrate that some clinically relevant contexts can be determined autonomously without training models from ground truth data obtained by manual data curation. Given that manual labeling of ground truth data is not practical in each participant's home, an alternative method of understanding the total instances of each context and assessing accuracy is needed. The current approach determines context accuracy by measuring contexts that must have occurred around known events that could be measured with higher certainty, such as the watch being removed in the evening. Then, the accuracy for detecting these contexts was based on the total number of times the context was measured before/after the known event relative to the total number of times the known event occurred. We chose to base our total measurements around the event of the user removing their watch in the evening given we could be certain the watch was stationary in a single room once it was removed, and that the user must have been in another room at some time before this. We were able to show that the system is reasonably accurate at detecting contexts that logically follow from this watch removal event, such as placing the watch back on, being present in a room before and after the watch is removed, and being mobile or at rest. Using these contexts, we could then similarly understand some situations with reasonable accuracy, such as the approximate rest time of the user, when they started and ended their day, whether they were resting in a room, etc. It was assumed that the time between the watch being removed and then being put on 6 or more hours later in the morning was a proxy for their total rest time. However, it is not guaranteed the user goes to sleep right when they take their watch off or puts it back on right away in the morning so this likely serves more as a rough estimate of their morning to evening routine.

We choose to focus on simple contexts to prove this concept, however, simple contexts and situations like the approximate time older adults start and end their day can be useful for applications. For instance, many groups have focused on building smart-pill boxes that remind patients when to take their medications,[17]–[19] and have demonstrated improved performance of context-aware prompting for medication [20], [21]. Thus, detection of the starting day and ending day situations may be useful for

context-aware prompting of patients to take medications through the watches user interface. There is also ample evidence that older adults with cognitive impairment and dementia often exhibit seamlessly aimless or disoriented ambulation within facilities, often referred to as wandering behavior [22], [23]. Thus, we focused on the room transition situation in hopes of understanding older adults trajectories in their homes to eventually try to detect wandering behavior and early signs of dementia. Lastly, the resting in room situation, immobile context, and step data from the system can be used to understand an older adult's activity levels. These are highly relevant contexts for understanding an older adult's health, as demonstrated by a recent meta-analysis from Cunningham et al. of activity levels and health outcomes. Through this meta-analysis they demonstrated that physically inactive older adults have an increased risk of all-cause mortality, cardiovascular mortality, falls/fractures, cognitive decline, and dementia. Ideally, monitoring for declines in mobility/activity related contexts can allow for the identification of high-risk individuals. By identifying these individuals prior to late-stage mobility decline, early intervention through exercise programs can be used to reduce falls and all-cause mortality in order to promote safe-aging in place [24], [25].

In order to investigate how the IPS system and other sensor data could work together, we correlated the number of instances the kitchen PIR was triggered with the number of instances the IPS system detected the participants in the kitchen around the triggering time. This was done as part of a sub-analysis that focused on 2 participants living in the same household, as we wanted to determine if we could observe shared behaviours between the two participants. We were able to observe some joint kitchen activity between the married couple, as there was a statistically significant and moderate correlation ($r=0.39$) between the number of instances they were both found in the kitchen each day around PIR triggering. This can also be observed in figure 5.4 as the plot shows many instances where both participants are in the kitchen when the PIR is triggered. Additionally, the correlation between both participants kitchen instances per day and the PIR triggering was also statistically significant, and had a moderately strong correlation in the case of participant one ($r = 0.57$). The stronger correlation of participant one aligns with the results shown in the heatmaps in figure 5.3, as participant one is observed to spend more time in the kitchen over the 1-week interval shown (5.9 hours vs 4.7 hours for participant two). Aside from this, the heatmaps are mostly useful to visualize differences in the two participants time spent in different areas throughout their home. Figure 5.3a and 5.3b allow one to understand how their time spent varies at different points in the day, whereas 5.3c and 5.3d provide a more longitudinal overview by providing a visual method of assessing behaviours seen across a 1-week span.

Although accuracy can be assigned to many contexts with some light assumptions, other contexts, such as whether participants entered a specific room or not, are difficult to assess the accuracy of. Despite measuring a user's location with the indoor positioning system, we cannot assume the total instances that they enter a room such as the kitchen. In the future, higher certainty events, such as a measurement from a sensor that detects the fridge opening/closing, will be needed to design a subset of kitchen visits that are known to occur. Using these known events, we can then similarly assign an accuracy to other measurements that indicate the user was in the kitchen, such as measurements from the indoor positioning system or motion sensor. High certainty sensor measurements may provide a means to assess the accuracy of the indoor positioning system in new environments. Additionally, the measured use of appliances may also serve as a method to calibrate the IPS system. For instance, if there was no kitchen beacon one would still expect the position of a user living alone to register that they are in the kitchen each time the stove was used or the fridge was opened, and one could use these sensor events to calibrate what signals from the beacons are representative of the user being located in the kitchen. This would replace the current calibration procedure we used, where the participant was asked to stand at various points in their home while we collected signals from all the beacons. Indeed, many groups have begun exploring self-calibrating systems and other calibration free approaches given this is a more viable long-term solution for new environments [26]–[28]. Preliminary results for detecting location were reasonable as the accuracy in

detecting the user was 81.5%, however, being able to collect calibration points more regularly through the systems other sensor events should lead to better results. We chose to test the system with a smaller number of beacons (usually 4) in participants' homes. However, for homes with many rooms the signal strength at the 4 beacons is often similar for two rooms given they may be equidistant from each beacon. Thus, to improve the indoor positioning systems accuracy more beacons will need to be assigned to participants in the future.

It is clear from the post-study interview that many participants (4 of 6) found the smartwatch too bulky and uncomfortable. Furthermore, the participants that were not willing to continue with the study said they would continue if a smaller watch was used. Given the smartwatch software works on any android smartwatch, a smaller android device can easily be selected in the future. However, these other devices should be tested to confirm the step counter is accurate. This appears to be the case for the TicWatch S2 given it's step count results were closer to participants' ground truth measures than the ActiGraph (gold standard). Despite issues with the size of the watch, participants still wore the watch 51% of the time. This is reasonable compliance given that most users sleep without their watch for 8 hours a day such that one would expect 66% at best.

Although sufficient samples per participant were collected to have confidence in the results, the total number of participants was still small and future work will be needed to assess differences that may be observed between participants. The preliminary study results are promising for autonomous context detection for remote monitoring systems. Aside from it being impractical to collect and label training data for each medical context of interest, there is no guarantee that learning algorithms built from data in one home or clinical setting will achieve the same accuracy on new users or in new environments. Thus, practical solutions to autonomously determining contexts are needed to avoid retraining in each new environment (or assuming the same accuracy in the new environment if one does not retrain). Furthermore, high certainty contexts determined autonomously can be used as ground truth events to allow training of algorithms in new environments, which may serve as a middle ground that leverages learning based approaches along with the practicality of specification-based approaches, such as the one described in this work. For instance, a system may label the ground truth for a watch's accelerometer data as sitting when a chair pressure sensor surpasses 100 pounds. Following this, one can train a personalized algorithm that detects sitting for that user using smartwatch accelerometer data in any environment, without needing to label the sitting context's ground truth manually. Similar approaches have begun to be employed, such as in Cruciani et al's. work, where accelerometer and GPS data is used to label sitting, walking, standing, and running. Results are promising as the weakly supervised approach obtains a 74% accuracy, which is only 13% less than the dataset where the ground truth is labeled manually [29]. Many groups are exploring ways of automatically labeling data given this provides a means of training models in multiple environments without relabeling each time, which is not practical to do in each new setting [30], [31]. Creative ways of reducing activity/context recognition's requirement of obtaining ground truth data will allow researchers to spend more time focusing on solving medical challenges through remote monitoring technology and less time annotating datasets.

5.5 CONCLUSION

In conclusion, we piloted our context-aware smart home system in older adults' homes and demonstrated its ability to autonomously determine contexts. Additionally, assessments of the systems accuracy for determining room locations within homes were promising for both rooms with and without our beacon devices. Situations composed of contexts measured by the system were also determined autonomously to demonstrate clinically relevant information (e.g bouts of immobility, the time users start/end the day, etcetera) could be established.

Autonomous context detection via remote monitoring systems serves as an alternative approach to laborious labeling of ground truth data for each environment, which may not be practical for each clinical setting of interest. Future work will focus on establishing additional contexts in more participants and demonstrating how high certainty autonomously determined contexts can be used as ground truth data for learning based approaches.

References

[1] T. M. Dall, P. D. Gallo, R. Chakrabarti, T. West, A. P. Semilla, and M. V. Storm, "An Aging Population And Growing Disease Burden Will Require ALarge And Specialized Health Care Workforce By 2025," *Health Aff.*, vol. 32, no. 11, pp. 2013–2020, Nov. 2013.

[2] M. Caley and K. Sidhu, "Estimating the future healthcare costs of an aging population in the UK: expansion of morbidity and the need for preventative care," *J. Public Health* , vol. 33, no. 1, pp. 117–122, Mar. 2011.

[3] E. L. Schneider and J. M. Guralnik, "The aging of America. Impact on health care costs," *JAMA*, vol. 263, no. 17, pp. 2335–2340, May 1990.

[4] T. Bond and D. Doonan, "The Growing Burden of Retirement," *National Institute on Retirement Security. Available online: https://www. nirsonline. org/reports/growingburden/(accessed on 30 July 2021)*, 2020, [Online]. Available: https://www.nirsonline.org/wp-content/uploads/2020/09/The-Growing-Burden-of-Retirement.pdf

[5] S. Musich, S. Wang, K. Hawkins, and A. Klemes, "The Impact of Personalized Preventive Care on Health Care Quality, Utilization, and Expenditures," *Population Health Management*, vol. 19, no. 6. pp. 389–397, 2016. doi: 10.1089/pop.2015.0171.

[6] A. Alberdi *et al.*, "Smart Home-Based Prediction of Multidomain Symptoms Related to Alzheimer's Disease," *IEEE J Biomed Health Inform*, vol. 22, no. 6, pp. 1720–1731, Nov. 2018.

[7] M. N. Mohammed, S. F. Desyansah, S. Al-Zubaidi, and E. Yusuf, "An internet of things-based smart homes and healthcare monitoring and management system," in *Journal of Physics: Conference Series*, 2020, vol. 1450, p. 012079.

[8] A. Alberdi Aramendi, A. Weakley, A. Aztiria Goenaga, M. Schmitter-Edgecombe, and D. J. Cook, "Automatic assessment of functional health decline in older adults based on smart home data," *J. Biomed. Inform.*, vol. 81, pp. 119–130, May 2018.

[9] V. Bianchi, M. Bassoli, G. Lombardo, P. Fornacciari, M. Mordonini, and I. De Munari, "IoT Wearable Sensor and Deep Learning: An Integrated Approach for Personalized Human Activity Recognition in a Smart Home Environment," *IEEE Internet of Things Journal*, vol. 6, no. 5, pp. 8553–8562, Oct. 2019.

[10] G. Singla, D. J. Cook, and M. Schmitter-Edgecombe, "Incorporating temporal reasoning into activity recognition for smart home residents," in *Proceedings of the AAAI workshop on spatial and temporal reasoning*, 2008, pp. 53–61.

[11] A. Filippoupolitis, W. Oliff, B. Takand, and G. Loukas, "Location-Enhanced Activity Recognition in Indoor Environments Using Off the Shelf Smart Watch Technology and BLE Beacons," *Sensors* , vol. 17, no. 6, May 2017, doi: 10.3390/s17061230.

[12] J. D. Ceron, D. M. López, F. Kluge, and B. M. Eskofier, "Framework for Simultaneous Indoor Localization, Mapping, and Human Activity Recognition in Ambient Assisted Living Scenarios," *Sensors* , vol. 22, no. 9, p. 3364, Apr. 2022.

[13] M. Tacken, F. Marcellini, H. Mollenkopf, I. Ruoppila, and Z. Széman, "Use and acceptance of new technology by older people. Findings of the international MOBILATE survey: 'Enhancing mobility in later life,'" *Gerontechnology*, vol. 3, no. 3. 2005. doi: 10.4017/gt.2005.03.03.002.00.

[14] S. Chang, R. Chiang, S. Wu, and W. Chang, "A Context-Aware, Interactive M-Health System for Diabetics," *IT Prof.*, vol. 18, no. 3, pp. 14–22, May 2016.

[15] L. A. Zadeh, "Probability measures of Fuzzy events," *J. Math. Anal. Appl.*, vol. 23, no. 2, pp. 421–427, Aug. 1968.

[16] J. Ye, S. Dobson, and S. McKeever, "Situation identification techniques in pervasive computing: A review," *Pervasive Mob. Comput.*, vol. 8, no. 1, pp. 36–66, Feb. 2012.

[17] D. S. A. Minaam and M. Abd-ELfattah, "Smart drugs:Improving healthcare using Smart Pill Box for Medicine Reminder and Monitoring System," *Future Computing and Informatics Journal*, vol. 3, no. 2. pp. 443–456, 2018. doi: 10.1016/j.fcij.2018.11.008.

[18] S. Shinde, T. Kadaskar, P. Patil, and R. Barathe, "A smart pill box with remind and consumption using IOT," *Int Res J Eng Technol*, vol. 4, no. 12, pp. 152–154, 2017.

[19] P. K. N. J. Najeeb, A. Rimna, K. P. Safa, M. Silvana, and T. K. Adarsh, "Pill Care-The Smart Pill Box with Remind, Authenticate and Confirmation Function," *2018 International Conference on Emerging Trends and Innovations In Engineering And Technological Research (ICETIETR)*. 2018. doi: 10.1109/icetietr.2018.8529030.

[20] M. Lim, J.-H. Choi, S.-L. Bang, D.-H. Kim, and S.-J. Park, "Design of a context-aware model to enhance medication adherence," *Conf. Proc. IEEE Eng. Med. Biol. Soc.*, vol. 2009, pp. 5147–5150, 2009.

[21] T. L. Hayes *et al.*, "A study of medication-taking and unobtrusive, intelligent reminding," *Telemed. J. E. Health.*, vol. 15, no. 8, pp. 770–776, Oct. 2009.

[22] G. Cipriani, C. Lucetti, A. Nuti, and S. Danti, "Wandering and dementia," *Psychogeriatrics*, vol. 14, no. 2, pp. 135–142, Jun. 2014.

[23] T. Hope, J. Keene, R. H. McShane, C. G. Fairburn, K. Gedling, and R. Jacoby, "Wandering in dementia: a longitudinal study," *Int. Psychogeriatr.*, vol. 13, no. 2, pp. 137–147, Jun. 2001.

[24] Thomas, Mackintosh, and Halbert, "Does the 'Otago exercise programme'reduce mortality and falls in older adults?: a systematic review and meta-analysis," *Age Ageing*, [Online]. Available: https://academic.oup.com/ageing/article-abstract/39/6/681/9467

[25] P. de Souto Barreto, Y. Rolland, B. Vellas, and M. Maltais, "Association of Long-term Exercise Training With Risk of Falls, Fractures, Hospitalizations, and Mortality in Older Adults: A Systematic Review and Meta-analysis," *JAMA Intern. Med.*, vol. 179, no. 3, pp. 394–405, Mar. 2019.

[26] A. K. M. M. Hossain and W.-S. Soh, "A survey of calibration-free indoor positioning systems," *Comput. Commun.*, vol. 66, pp. 1–13, Jul. 2015.

[27] M. Cypriani, P. Canalda, and F. Spies, "OwlPS: A Self-calibrated Fingerprint-Based Wi-Fi Positioning System," in *Evaluating AAL Systems Through Competitive Benchmarking. Indoor Localization and Tracking*, 2012, pp. 36–51.

[28] C. Luo, H. Hong, M. C. Chan, J. Li, X. Zhang, and Z. Ming, "MPiLoc: Self-Calibrating Multi-Floor Indoor Localization Exploiting Participatory Sensing," *IEEE Trans. Mob. Comput.*, vol. 17, no. 1, pp. 141–154, Jan. 2018.

[29] F. Cruciani, I. Cleland, K. Synnes, and J. Hallberg, "Personalized Online Training for Physical Activity monitoring using weak labels," in *2018 IEEE International Conference on Pervasive*

Computing and Communications Workshops (PerCom Workshops), Mar. 2018, pp. 567–572.

[30] F. Cruciani, I. Cleland, C. Nugent, P. McCullagh, K. Synnes, and J. Hallberg, "Automatic Annotation for Human Activity Recognition in Free Living Using a Smartphone," *Sensors* , vol. 18, no. 7, Jul. 2018, doi: 10.3390/s18072203.

[31] J. Biswas *et al.*, "Activity Recognition in Assisted Living Facilities with Incremental, Approximate Ground Truth," in *Inclusive Smart Cities and e-Health*, 2015, pp. 103–115.

Chapter 6

Conclusions and Next Steps

6.1 SUMMARY

The present work described a framework for building context-aware telemedical systems to promote safe aging in place through the pre-emptive detection of diseases and adverse medical events. In this dissertation, the framework was applied in the context of smart home technology given one's primary residence represents a practical location for monitoring health trends in older adults. Theory was developed to autonomously determine contexts/situations from sensor data and map these situations to known clinical tests to establish post-test probabilities describing an individual's chance for various conditions/events. Additionally, the need for context in emergency systems was presented along with a revised context-awareness framework which categorized physiological data according to its context. Lastly, the system's ability to autonomously establish contexts in older adults' homes was demonstrated in a pilot study for validation purposes.

A systematic review was provided in **Chapter 2** to determine the most significant medical contexts needed in context-aware medical systems, along with what context determination algorithms are most used. We sought to provide researchers with a list of context-aware medical systems being used by medical professionals and then developed subdomains for context-aware medical applications. Location, time of day, patient history, and mobility were identified as key medical contexts and used to inform design decisions for our smart home system. No common context-determination method was seen across systems which led to the need to develop our own generalized method of determining contexts.

The context-aware telemedical framework, smart home system, and theory for autonomously determining contexts and using them to assign probabilities of adverse medical events to users was provided in **Chapter 3**. Fuzzy probability was utilized to define a general way of determining contexts from sensor data, and situations/clinical tests were modeled through spatiotemporal context networks, where spatiotemporal refers to the technique's emphasis on the order that contexts occur and the location they occur in. Traditional approaches to establishing the probability a patient has a condition/disease from the likelihood ratios of clinical tests were integrated into the framework. This was done to ensure that the framework used tools for pre-emptive detection of adverse medical events that healthcare providers already leverage. A method to adjust the prognostic value of clinical tests based on uncertainty in the systems data was derived to ensure the post-test probability of a user having a condition reflects the probability that the system measured the required contexts. Emulated experiments of mobility impaired vs unimpaired individuals showed the framework and smart home system could be used to identify those at high risk for falling in 12 months and having Parkinson's.

Chapter 4 demonstrated an application of the framework to build a context-aware application, namely an emergency detection system. A desktop application was built that communicated healthcare providers' preferred alarm settings to the smart home system and then context-aware versus context-unaware alarms were compared to show the need for context to avoid false positives. It was demonstrated that context-unaware alarms could not be used to monitor dangerously high heart rates due to their inability to rule out sinus tachycardia from events like exercising. This led to an update of Musumba and Nyongesa context-awareness framework[1], which summarized Bardram and Hansen's work[2], that categorized

physiological data according to its context for context-aware medical systems. This allows for healthcare providers and the system to understand if the data is normal given the user's current activity/context.

Finally, this work concludes with a pilot study using the smart home system and framework in older adults' homes, as described in **Chapter 5**. An REB application was submitted and accepted which allowed us to build up to 30 systems to collect data and determine contexts using data from older adults. The study is ongoing and what is presented in Chapter 5 are preliminary results demonstrating that the smart home system and framework can be used to determine contexts such as whether an older adult is immobile, mobile, transitioning in their home, ending or starting their day, etc.

6.2 DISCUSSION AND FUTURE DEVELOPMENTS

The discussion in this chapter focuses on the relationship between chapters 2-5 and their position on the roadmap (figure 1.1) that describes a practical context-aware telemedical system for safe aging in place. The future developments section focuses on what remains to be completed within the roadmap, and the next logical steps for the present work.

6.2.1 Discussion

Initially, the motivation for this work began with the notion of building a smart home system to promote safe-aging in place through understanding of older adults' mobility levels and activities. Activity recognition in smart home environments in particular has become a prevalent research area as various groups attempt to collect information pertaining to older adults' instrumental activities of daily living (IADLs)[3], [4] as a proxy for understanding their health [5]. Recent trends in context-awareness sensing in the field of computer science had just begun to appear within medical systems, and it was understood that context would be important for our smart home system (and telemedical systems in general) given many clinical tests have specific contextual requirements (e.g sitting during blood pressure assessment) [6].

Prior to building a context-aware smart home, we sought to determine which contexts were most relevant for medical systems based on current trends so we could prioritize them in our system. Additionally, we wanted to know what approaches most groups were using for context determination. Through the systematic review, we were able to ascertain that time of day, location, and past medical history were highly relevant contexts that needed to be included within our system and framework. Surprisingly though, there did not appear to be a standard method for determining contexts. Reviews focusing on context determination separated methodologies into specification and learning based approaches, however, both had their limitations [7]. Learning based approaches suffered from the need to manually label training data and build ML models that may not have the same accuracy in new environments. Specification based approaches did not require training data but lacked a way to quantify the certainty in the contexts they measured. As a result, the decision was made to develop a new generalized context determination approach that combined spatio-temporal logic[8], [9] and fuzzy logic[10] from specification based approaches, but quantified the probability the contexts took place as in many learning based approaches.

Chapter 3 presents the generalized context determination theory whose development was necessitated by the lack of standard context algorithms found in the prior chapter's review. Having understood that location and mobility were pivotal contexts we built a smart watch based smart home system that could detect a user's location in their home through Bluetooth low energy (BLE) signals broadcasted by the smartwatch. As demonstrated in the section of the appendix describing the systems accuracy in detecting users within rooms, the system is quite accurate with a 96% detection accuracy when

each room contains a beacon. This is relevant given many of the locations results, such as whether the user is in the living room or washroom, are used in chapter 3 to conduct clinical tests (e.g gait speed test based on the time to transition from living room to washroom). The watch also recorded mobility and step counts through accelerometer data, which was another priority of ours given the known relationship between mobility decline and many age related diseases [11]–[13]. As the overlaying goal was to promote safe-aging in place through pre-emptive detection of adverse events/disease, a way to translate the sensor data and contexts into useful clinical information was required. Using artificial intelligence based approaches (e.g neural networks, random forest, etc) has become quite common in research for detecting aging related conditions[14], [15], however, the lack of interpretability of these approaches has seemed to preclude their use in clinical environments. It appears that clinicians who base decisions on clinical logic have not been willing to trust decisions to black box algorithms, regardless of the high cited accuracy in predicting various conditions. Additionally, collecting training data on each condition/event of interest seemed unnecessarily burdensome if it could be avoided. Thus, we looked towards standard clinical methods of assigning probabilities of outcomes to people via tests that have likelihood ratios with known impacts on the outcomes probability [16]. The advantage of this being that the framework would not need data from multiple users who have the disease of interest for training and would also use an approach that is already accepted by healthcare providers. Surprisingly, this had not been done in any systems found in our review, or outside our review to the best of our knowledge. Modeling clinical tests through spatiotemporal context networks proved simple, and thankfully many contexts (e.g gait speed) were simple to obtain when using fuzzy probability with the systems sensor data. However, it was challenging to determine how to reduce the prognostic value of the clinical test given a test's original prognostic value was from situations that were known to have occurred with 100% certainty, which could not also be assumed to be the case with our system. Thus, a method to adjust the likelihood ratios (LRs) of tests in light of context uncertainty was derived, with results logically leading to no prognostic value for the test (LR=1) in the limit of 0% certainty it occurred. This completed the framework and allowed us to demonstrate its utility in assigning post-test probabilities to emulated users for falling and Parkinson's. These two conditions were selected given that over 6,600 older adults are diagnosed with Parkinson's each year, and falls cause over 85% of seniors' injury related hospitalizations in Canada, illustrating the large benefit that would come from pre-emptive detection of both these conditions [17], [18].

After completing the framework, the next logical step was to demonstrate how it could be used to build context-aware applications. It became apparent that Musumba and Nyongesa context-awareness framework[1], which summarized Bardram and Hansen's work[2] work on context-aware systems, needed to be updated for context-aware medical systems given that physiological data has different meanings in different contexts. This phenomenon has been known in medical settings for some time, for instance, even blood pressure measurements within an outpatient setting are known to be unreliable relative to at home measurements (a phenomenon called whitecoat syndrome) [19]. Heart rate can also be misleading without context given dangerously high levels are normal with extreme activity increases. To demonstrate the notion that context was required by useful systems, and that the framework could create context-aware applications, we built a context-aware emergency alert system and compared context-aware alarms to context-unaware alarms. We demonstrated the need for context in an emergency system by showing that we could prevent false positive alarms (which occurred in the context-unaware alarms) by ruling out high heart rates during bouts of elevated activity levels. Additionally, we showed the systems software application could respond to context to become context-aware. Finally, we updated the context-aware systems framework[1], [2] for context-aware medical systems to deal with changes in physiological data that occur in different contexts.

Having demonstrated the system's/framework's ability to create context-aware applications, the final step was to begin trialing the system in older adults homes to establish our system works in a clinically relevant setting. After completing an REB we built 10 systems and shipped them to older adults

for data collection. As the strength in our current approach was the lack of training data needed, an approach to measuring the accuracy of context measurements without training data was desired to validate the method in a practical manner. Thus, similar to how we focused on easily confirmable clinically relevant contexts (e.g large force on couch implying sitting/immobile with high likelihood), we chose to focus on using high certainty contexts for validation. By leveraging the fact we could depend on the participants to take the watch off at night we were able to determine the systems accuracy for measuring key contexts that we knew existed around this event. The study is in its early stages, and other contexts will be added to the analysis in the future. Other remaining work for the study, and on the research roadmap, will be discussed in the Future Directions section.

Significant contributions have been made to the field of context-aware medical systems, especially pertaining to pre-emptive detection of medical conditions for safe aging in place applications. The systematic review of context-aware medical systems provides researchers with insights into what contexts have been most useful in the small number of systems which have found use in clinical settings. The lack of standardization across context detection techniques in the resulting studies also brings attention to the need for more general approaches in context-aware medical systems. The framework presented in Chapter 3 is this work's primary contribution, having provided a generalized approach to move from sensor data to context detection, and then model clinical tests through context networks to apply them to older adults for pre-emptive detection of disease. Whereas many approaches rely on machine learning models and require extensive labeling of training data[20]–[22] , the present work provides an autonomous context detection method and utilizes standard clinical tools to quantify the probability an individual is at risk for an event/disease. A generalized approach to assign probabilities for conditions using standard clinical tools and likelihood ratios by remote monitoring systems has not been done to the best of our knowledge, and is significant given it represents a method for remote monitoring systems to quantify older adults chance for various diseases/outcomes using a clinically established approach. Additionally, it is unclear whether artificial intelligence (AI) based diagnosis (in its current state) will be accepted in clinical practice due to a lack of clarity in how the algorithm makes decisions, and this methodology provides an alternative to AI based diagnosis. Furthermore, the derivation for reducing the prognostic value of clinical tests based on the probability the test occurred allows researchers to use established relationships between tests and diseases in telemedical systems by providing a means to reduce known likelihood ratios that map the test to the disease of interest. The demonstration in chapter 4 of the ability for context-aware alarms to rule out false positives is useful. However, the more important contribution is likely the natural progression of context-aware systems framework to context-aware medical systems by classifying physiological data according to the context it was measured in. This will promote analyzing vitals and medical data within their context so systems can differentiate benign situations like exercise induced sinus tachycardia from dangerous situations like an atrial fibrillation with the same heart rate. Lastly, the preliminary results demonstrating that contexts can be autonomously measured in older adults' homes via data collected in a clinically relevant setting is significant given that many studies have relied on labeling data to build models to establish activities/contexts [20]–[23]. This is an important step forward for telemedical systems focused on pre-emptive detection of events/diseases as it is unlikely to be practical to label data for each new clinical environment a system is used in (e.g primary residence, ICU, emergency room, etc). Even if researchers choose to avoid labeling training data by assuming the prior models will work, they will still likely need to label data to validate that the old model's predictions are correct in the new setting. Hopefully, the present work's focus on autonomous context detection techniques will shift attention away from methods that require significant resource allocation to labeling data or lead to using autonomously labeled high certainty contexts as ground truth data.

6.2.2 Future Developments

The work presented in this thesis primarily focused on modules 1 (system development), 2 (context determination), 3 (situation identification), and 4b (application of clinical tests), while presenting demonstrations of module 5 (diagnosis and clinical inference) and module 6 (management/context-awareness). However, much remains to be done before this system and methodology can be used in practice, and parts of modules remain to be started.

Preliminary results in older adults' homes have been presented. However, more participants are required, and additional contexts should be assessed, in order to better understand the accuracy of the system in context determination. Clinical tests for fall risk (i.e gait speed) should be conducted in the pilot study using spatiotemporal context networks and the post-test probability of falling for participants according to the system should be compared to fall questionnaire data to validate the approach. The relationship between the test and fall outcomes has already been established[24], so one would expect to see the LR in the study participants approach the values from the literature as more participants were added. For the system to be useful for healthcare providers, clinicians should be consulted to determine what post-test probability for each condition would warrant an alert (module 5). Ideally, this alert would be sent to their usual medical record software, as shown in the roadmap, to ensure remote monitoring systems were properly integrated into older adults' current care system. The final test of the system for each disease/event would then be a randomized control trial where groups above the desired post-test probability according to the system received an intervention and success would be reduced outcomes or disease progression in the intervention group relative to the control. This would satisfy the long-term goal of this technology for promoting sage aging in place through early intervention, as there would be sufficient evidence to suggest reduced adverse outcomes above an intervention threshold detected by the system in various diseases or preventable medical events (e.g falls).

Regarding the actual technology, the systems hardware would benefit from a lower power design with intermittent sampling[25] to allow multiple battery powered beacons to be added to the system that are not constrained to wall outlets within the participants home. This would improve the user experience and allow the devices to be spread across any desired location instead of placed only where an outlet is present. Additionally, many participants felt that the watch was too bulky. Thus, the smartwatch software should be uploaded to a smaller sized android watch to increase user satisfaction and compliance. Software wise, the data should be made accessible to older adults, who then should be able to delete their data and add/revoke access to various healthcare providers as they desire. Data security for smart home and wearable systems has been identified as a primary research challenge given the sensitive nature of peoples medical information [26]. Blockchain technology may be a logical fit here as it provides a decentralized way to share asymmetrically encrypted data with new identities without the need to communicate or share a key in advance [27]. Many groups have already begun to investigate the security advantages of blockchain technology for smart home systems[28]–[30], and open source standardized modules for data access control such as OpenZeppelin's[31] *AccessControl* modules already exist on the Ethereum blockchain and have recently seen some use from medical researchers [32]. Of course, the system would need to be made HIPAA compliant, which on-chain user authentication and data access controls should help with. Software packages and architectures should also be developed for the system in order to standardize and simplify the process of converting raw sensor data into contexts via membership functions and determining the probabilities of situations.

Regarding the fuzzy probability-based context determination algorithm, it should be adapted to consider variability and margins of error in sensor measurements. This can be captured quite well by adjusting the values of the sensor according to the manufacturers error prior to using them to form the probability density function that is part of the context calculation (Equation 5.2). The direction of the adjustment should be in the direction that decreases the likelihood of the context according to what would

decrease the membership function. This can be summarized by the following adaptation to equation 5.2 shown below

$$argmin_{\delta\epsilon\{-1,1\}} P(X_i = C_j)_{s_i,\Delta t_j} = \int_{-\infty}^{\infty} \mu_{c_{ij}}(x) \cdot s_i(x - \delta * E)_{\Delta t_j} \cdot dx \qquad \text{Equation 6.1}$$

Where E is the error in the sensor measurement and gamma is the direction of the adaptation to the values. The $argmin$ ensures the error is properly integrated such that it reduces the contexts probability instead of increases it. For instance, if one was basing the probability of standing on barometer readings then the readings would be decreased given that higher values imply standing instead of sitting. Note that a similar approach of adapting the values within equation 5.2 could be used to adjust for other forms of sensor error or variability. Using this approach, the uncertainty will be propagated properly through each context and any situations that are comprised of the contexts.

Lastly, this work did not touch upon module 4b of the research roadmap which describes the discovery and eventual application of new clinical tests composed of system measured contexts. An example is provided in figure 4b that is inspired from numerous studies that have combined keyboard and phone interaction features to obtain a sensitivity and specificity of over 70% for Parkinson's diagnosis in data collected from patients remotely [33]–[35]. By linking multiple older adults' diagnoses (outcome variable) to the contexts collected (predictors), learning algorithms can be used to identify which contexts predict which diagnoses and the result can be used in module 4a to better estimate post-test probabilities for the outcome. Of course, this would likely require significant integration of telemedical systems in standard clinical practices given multiple older adults' outcomes according to their EMRs would be required in conjunction with their pooled system/context data.

6.2.3 Conclusions

In conclusion, the present work contributes to the development of context-aware telemedical systems for safe aging in place through the development and validation of a framework for pre-emptive detection of adverse medical events. The framework was applied to emulated data to demonstrate its ability to establish post-test probabilities for falls and Parkinson's, and then piloted on older adults to demonstrate autonomous context collection. A systematic review of clinically used context-aware medical systems was shown in **Chapter 2**. In **Chapter 3,** the smart home system was built and the framework for pre-emptive detection of medical events via post-test probabilities was demonstrated. **Chapter 4** presented the system's use in emergency detection for building a context-aware application, as well as the revised context-aware medical systems framework that classifies physiological data within its context. Lastly, **Chapter 5** presents autonomously determined contexts from preliminary data obtained from a pilot study of the system in older adults homes. Additional work to establish other contexts autonomously, and conduct fall related tests, is ongoing. Progress has been made towards promoting safe-aging in place through context-aware telemedical systems, and the future is promising for developing proactive, instead of reactive, healthcare systems. As context-awareness is a prerequisite for ambient intelligent medical systems[36], it will be interesting to see how personalized ambient intelligent systems begin to impact healthcare following the successful integration of context-awareness into healthcare monitoring.

REFERENCES

[1] G. W. Musumba and H. O. Nyongesa, "Context awareness in mobile computing: A review," *International Journal of Machine Learning and Applications*, vol. 2, no. 1, p. 5, May 2013.

[2] J. E. Bardram and T. R. Hansen, "Context-Based Workplace Awareness," *Comput. Support. Coop. Work*, vol. 19, no. 2, pp. 105–138, Apr. 2010.

[3] K. Avgerinakis, A. Briassouli, and I. Kompatsiaris, "Recognition of Activities of Daily Living for Smart Home Environments," in *2013 9th International Conference on Intelligent Environments*, Jul. 2013, pp. 173–180.

[4] T. Nef *et al.*, "Evaluation of Three State-of-the-Art Classifiers for Recognition of Activities of Daily Living from Smart Home Ambient Data," *Sensors* , vol. 15, no. 5, pp. 11725–11740, May 2015.

[5] E. Füzéki and W. Banzer, "Activities of Daily Living and Health," *Public Health Forum*, vol. 21, no. 2, pp. 4.e1–4.e4, Jun. 2013.

[6] E. O'Brien *et al.*, "Practice guidelines of the European Society of Hypertension for clinic, ambulatory and self blood pressure measurement," *J. Hypertens.*, vol. 23, no. 4, pp. 697–701, Apr. 2005.

[7] J. Ye, S. Dobson, and S. McKeever, "Situation identification techniques in pervasive computing: A review," *Pervasive Mob. Comput.*, vol. 8, no. 1, pp. 36–66, Feb. 2012.

[8] J. C. Augusto, J. Liu, P. McCullagh, H. Wang, and J.-B. Yang, "Management of Uncertainty and Spatio-Temporal Aspects for Monitoring and Diagnosis in a Smart Home," *null*, vol. 1, no. 4, pp. 361–378, Dec. 2008.

[9] B. Gottfried, H. W. Guesgen, and S. Hübner, "Spatiotemporal Reasoning for Smart Homes," in *Designing Smart Homes: The Role of Artificial Intelligence*, J. C. Augusto and C. D. Nugent, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2006, pp. 16–34.

[10] L. A. Zadeh, "Fuzzy sets," *Information and Control*, vol. 8, no. 3. pp. 338–353, 1965. doi: 10.1016/s0019-9958(65)90241-x.

[11] B. Yoon *et al.*, "Balance and Mobility Performance Along the Alzheimer's Disease Spectrum," *J. Alzheimers. Dis.*, vol. 73, no. 2, pp. 633–644, 2020.

[12] N. M. F. Sousa and R. C. Macedo, "Relationship between cognitive performance and mobility in patients with Parkinson's disease: A cross-sectional study," *Dement Neuropsychol*, vol. 13, no. 4, pp. 403–409, Oct. 2019.

[13] O. Hardiman, L. H. van den Berg, and M. C. Kiernan, "Clinical diagnosis and management of amyotrophic lateral sclerosis," *Nat. Rev. Neurol.*, vol. 7, no. 11, pp. 639–649, Oct. 2011.

[14] J. Mei, C. Desrosiers, and J. Frasnelli, "Machine Learning for the Diagnosis of Parkinson's Disease: A Review of Literature," *Front. Aging Neurosci.*, vol. 13, p. 633752, May 2021.

[15] M. Tanveer *et al.*, "Machine learning techniques for the diagnosis of Alzheimer's disease," *ACM trans. multimed. comput. commun. appl.*, vol. 16, no. 1s, pp. 1–35, Apr. 2020.

[16] A. K. Akobeng, "Understanding diagnostic tests 2: likelihood ratios, pre- and post-test probabilities and their use in clinical practice," *Acta Paediatr.*, vol. 96, no. 4, pp. 487–491, Apr. 2007.

[17] “Parkinson’s disease.” https://www.ucb-canada.ca/en/Patients/Conditions/Parkinson-s-Disease (accessed May 06, 2022).

[18] Public Health Agency of Canada, “Seniors’ Falls in Canada - Infographic,” Jan. 15, 2015. https://www.canada.ca/en/public-health/services/health-promotion/aging-seniors/publications/publications-general-public/seniors-falls-canada-second-report/seniors-falls-canada-infographic.html (accessed May 06, 2022).

[19] M. R. Pioli, A. M. Ritter, A. P. de Faria, and R. Modolo, “White coat syndrome and its variations: differences and clinical impact,” *Integr. Blood Press. Control*, vol. 11, pp. 73–79, Nov. 2018.

[20] T. L. M. van Kasteren, G. Englebienne, and B. J. A. Kröse, “Activity recognition using semi-Markov models on real world smart home datasets,” *J. Ambient Intell. Smart Environ.*, vol. 2, no. 3, pp. 311–325, 2010.

[21] S. Azzi, A. Bouzouane, S. Giroux, C. Dallaire, and B. Bouchard, “Human activity recognition in big data smart home context,” in *2014 IEEE International Conference on Big Data (Big Data)*, Oct. 2014, pp. 1–8.

[22] V. Bianchi, M. Bassoli, G. Lombardo, P. Fornacciari, M. Mordonini, and I. De Munari, “IoT Wearable Sensor and Deep Learning: An Integrated Approach for Personalized Human Activity Recognition in a Smart Home Environment,” *IEEE Internet of Things Journal*, vol. 6, no. 5, pp. 8553–8562, Oct. 2019.

[23] V. Radu *et al.*, “Multimodal Deep Learning for Activity and Context Recognition,” *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, vol. 1, no. 4, pp. 1–27, Jan. 2018.

[24] D. A. Ganz, Y. Bao, P. G. Shekelle, and L. Z. Rubenstein, “Will my patient fall?,” *JAMA*, vol. 297, no. 1, pp. 77–86, Jan. 2007.

[25] M. López *et al.*, “Software management of power consumption in WSN based on duty cycle algorithms,” in *Eurocon 2013*, Jul. 2013, pp. 399–406.

[26] Majumder, Sumit, Tapas Mondal, and M. Jamal Deen. "Wearable sensors for remote health monitoring." *Sensors* 17.1 (2017): 130.

[27] Z. Zheng, S. Xie, H. Dai, X. Chen, and H. Wang, “An Overview of Blockchain Technology: Architecture, Consensus, and Future Trends,” in *2017 IEEE International Congress on Big Data (BigData Congress)*, Jun. 2017, pp. 557–564.

[27] S. Arif, M. Arif Khan, S. U. Rehman, M. A. Kabir, and M. Imran, “Investigating Smart Home Security: Is Blockchain the Answer?,” *IEEE Access*, vol. 8. pp. 117802–117816, 2020. doi: 10.1109/access.2020.3004662.

[28] A. Dorri, S. S. Kanhere, R. Jurdak, and P. Gauravaram, “Blockchain for IoT security and privacy: The case study of a smart home,” in *2017 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*, Mar. 2017, pp. 618–623.

[29] T. L. N. Dang and M. S. Nguyen, "An Approach to Data Privacy in Smart Home using Blockchain Technology," in *2018 International Conference on Advanced Computing and Applications (ACOMP)*, Nov. 2018, pp. 58–64.

[30] "OpenZeppelin," *OpenZeppelin*. https://openzeppelin.com/ (accessed May 06, 2022).

[31] A. Peyvandi, B. Majidi, S. Peyvandi, and J. Patra, "Computer-Aided-Diagnosis as a Service on Decentralized Medical Cloud for Efficient and Rapid Emergency Response Intelligence," *New Gener Comput*, vol. 39, no. 3–4, pp. 677–700, Jun. 2021.

[32] D. Iakovakis *et al.*, "Screening of Parkinsonian subtle fine-motor impairment from touchscreen typing via deep learning," *Scientific Reports*, vol. 10, no. 1. 2020. doi: 10.1038/s41598-020-69369-1.

[33] T. Arroyo-Gallego *et al.*, "Detecting Motor Impairment in Early Parkinson's Disease via Natural Typing Interaction With Keyboards: Validation of the neuroQWERTY Approach in an Uncontrolled At-Home Setting," *Journal of Medical Internet Research*, vol. 20, no. 3. p. e89, 2018. doi: 10.2196/jmir.9462.

[34] D. Iakovakis, S. Hadjidimitriou, V. Charisis, S. Bostantzopoulou, Z. Katsarou, and L. J. Hadjileontiadis, "Touchscreen typing-pattern analysis for detecting fine motor skills decline in early-stage Parkinson's disease," *Scientific Reports*, vol. 8, no. 1. 2018. doi: 10.1038/s41598-018-25999-0.

[35] G. Acampora, D. J. Cook, P. Rashidi, and A. V. Vasilakos, "A Survey on Ambient Intelligence in Healthcare," *Proceedings of the IEEE*, vol. 101, no. 12. pp. 2470–2494, 2013. doi: 10.1109/jproc.2013.2262913.

Appendix

Introduction to IPS Characterization Paper

The following paper describes and characterizes the IPS system used throughout this thesis. A detailed description of the hardware used in the system is presented. Additionally, schematics of the flowof information throughout the system are described. After describing the system, tests are conducted to assess the stability of the RSSI readings obtained from two separate devices (a BLE tag and smartwatch) in a residential home and our group's smart home. Two devices and locations are tested in order to determine if the results appear consistent when using different broadcasting signals and home setups. Additionally, tests are conducted to determine if the system can accurately predict the location of the user within the homes. This is highly relevant to the present thesis given results are often based on knowing the location of the users from the IPS system. Results are promising as the system had a 96% accuracy at detecting room location for rooms containing beacons.

Contents of Paper

Compact Bluetooth Low Energy based Indoor Positioning System for Smart Home's

Michael Zon[1,2], Guha Ganesh[1], Qiying Fang[1,3]
[1]McMaster University, School of Biomedical Engineering, Hamilton, ON,
[2]Michael G. DeGroote School of Medicine, Hamilton, ON,
[3]McMaster University, Department of Engineering Physics, Hamilton, ON,

Abstract— Objective: **Indoor positioning system's (IPS) are part of the internet of things (IoT). In this work, we designed an IPS that requires little prior knowledge of its location of integration and allows the end-user to self-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 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 backup motion sensor, 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 RSSI values proved to be a highly accurate method of correlating distance using BLE signal strength. The use of PIR motion and ultrasonic sensors as backup presence detectors provided improved validity when compared with existing indoor positioning systems. Significance: The ease of use and modular design of this IPS makes it an ideal choice for implementation in larger scale smart healthcare monitoring systems.**

I. 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. 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 extremely 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. Specifically, the use of indoor tracking would be highly beneficial for Alzheimer's and Dementia patients who have a history of getting lost. 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 IPS' 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 IPS' are optimized to determine position at almost the centimetre level which makes them ideal for indoor tracking applications.

The two main types of IPS' 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]. This approach led to a higher degree of precision and accuracy. The IPS developed in this paper 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 very 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. 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.

II. SYSTEM DESIGN

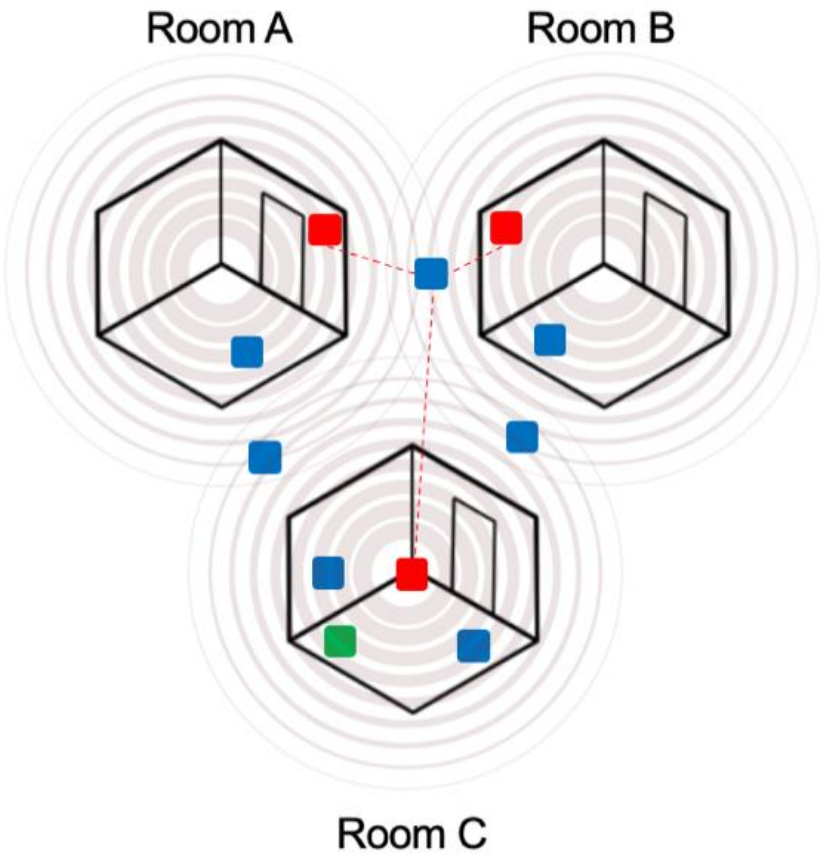

Fig. 1: IPS System level design diagram, Red: Ambient beacon, Green: Raspberry Pi based Hub Module, Blue: BLE tag (iTag's and smartwatches)

A. Hardware and Electrical

The overall hardware system consists of three major components: sensors, microcontrollers and BLE devices. The sensors and microcontrollers are physically connected to each other whereas the BLE

devices are 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. Fig. 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.

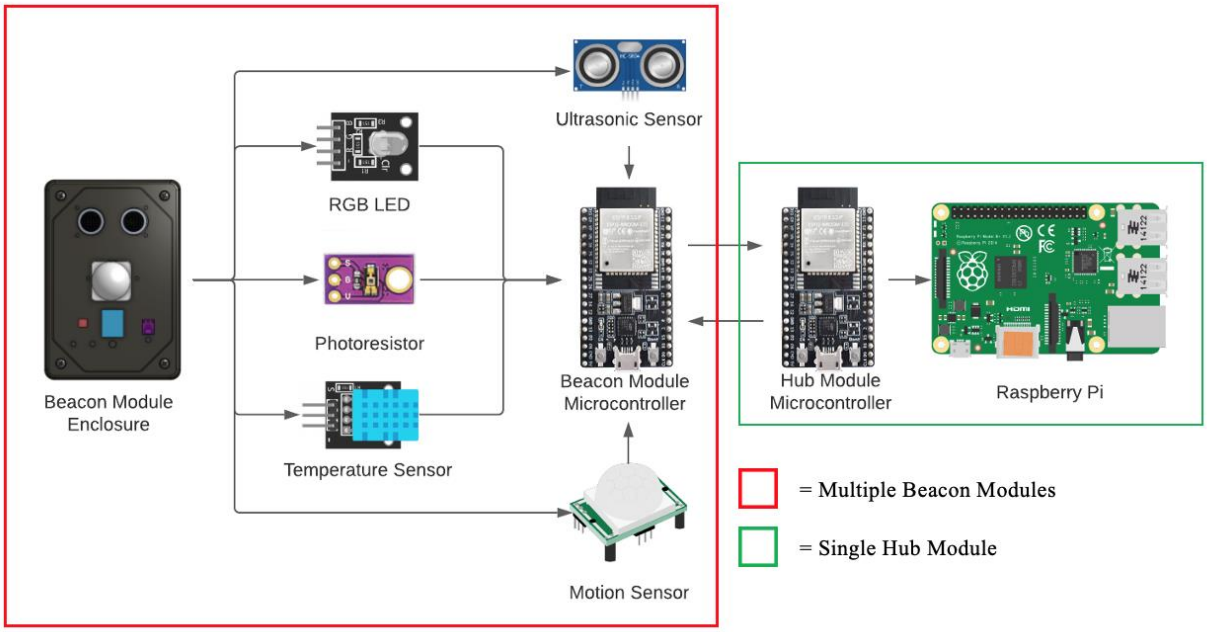

Fig. 2: Hardware Flow Diagram, Red: Beacon Module Component Composition, Green: Hub Module Component Composition

B. 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 Fig. 3.

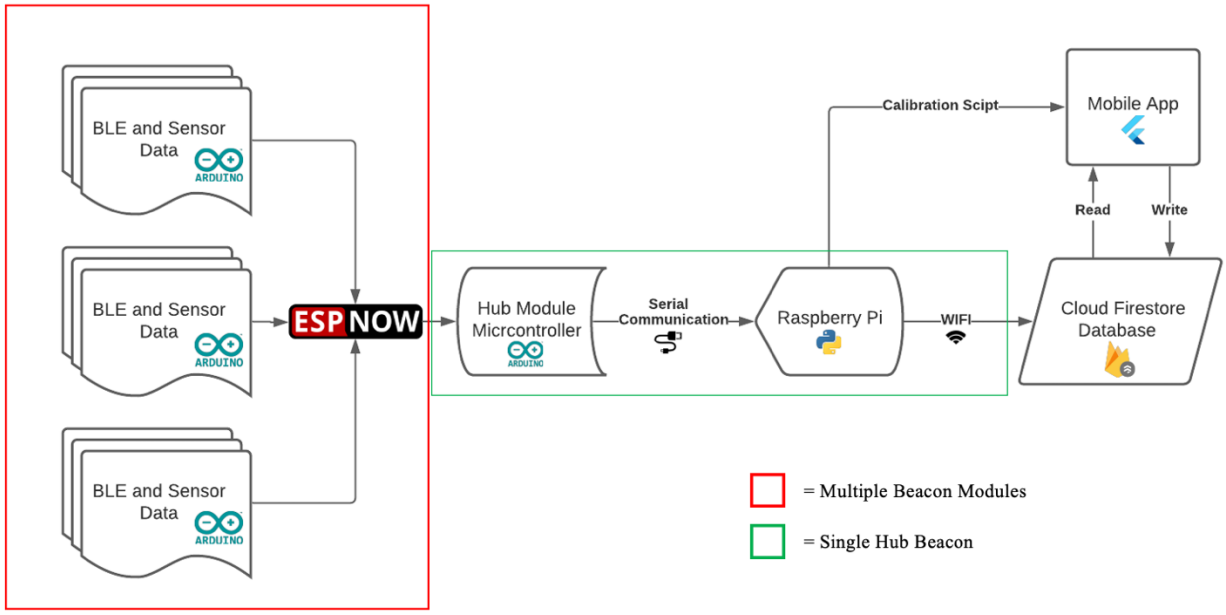

Fig. 3: Software and Data Transfer Flow Chart, Red: Beacon module sensor and BLE data communication pathway from rooms to the hub module, Green: Hub module post processing data management, allocation, and calibration process pathway

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 IPS' 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.

C. 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 Fig. 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.

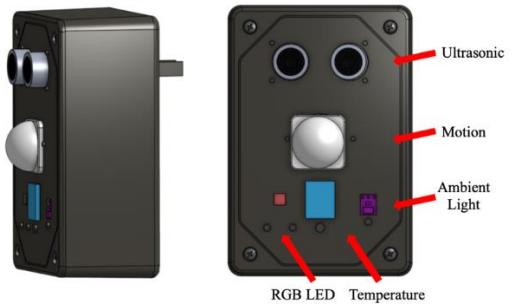

Fig. 4a: Beacon Module Enclosure with Labelled External Sensors

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.

I. METHODS

A. 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 I. 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 I
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

B. 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.

$$Distance = 10^{\frac{(Measured\ Power - RSSI)}{10 \times N}} \quad (1)$$

C. 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.

D. 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.

E. 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.

F. 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.

G. 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.

H. 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].

$$y_n = w \times x_n + (1 - w) \times y_{n-1} \quad (2)$$

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%.

I. RESULTS

A. RSSI Fluctuation and Filtering

Fig. 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 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 Fig. 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.

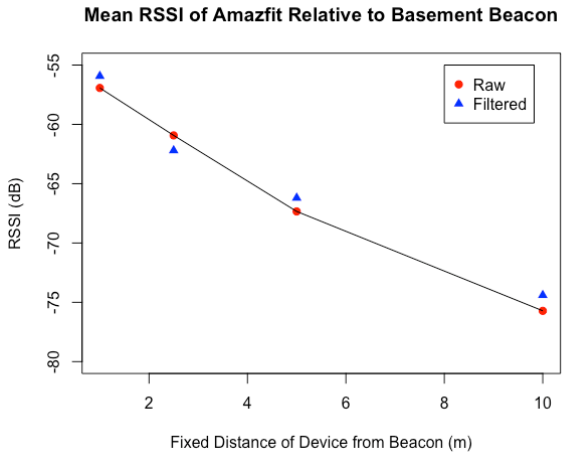

Fig 5a: Mean Measured RSSI at Fixed Distances (1, 2.5, 5 and 10m) in the Smart Home Basement

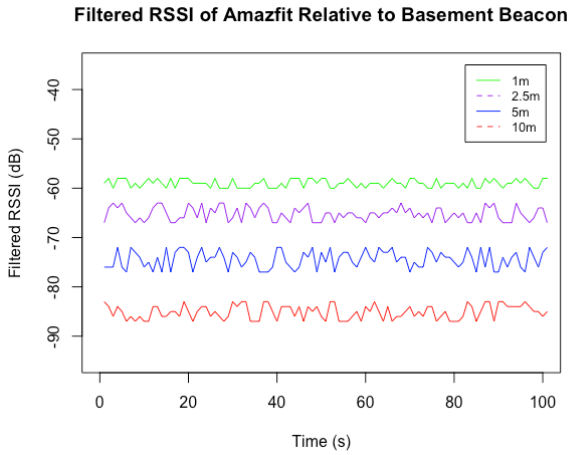

Fig. 5b: Filtered RSSI at Fixed Distances (1, 2.5, 5 and 10m) in the Smart Home Basement

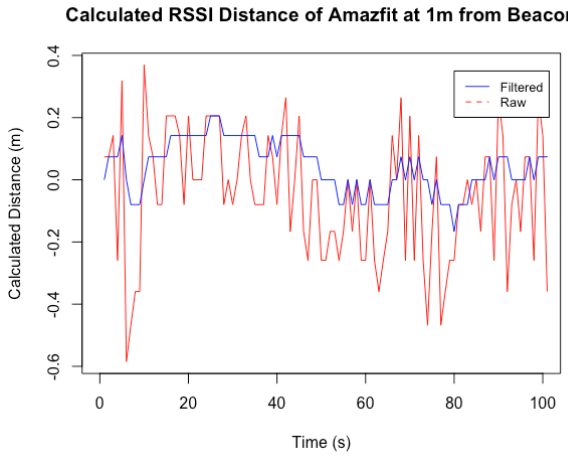

Fig. 5c: Calculated RSSI based Distance Measurements of Amazfit Smartwatch at a fixed 1m relative to the IPS Beacon in the Smart Home Basement

B. 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 Fig 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 II. 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.

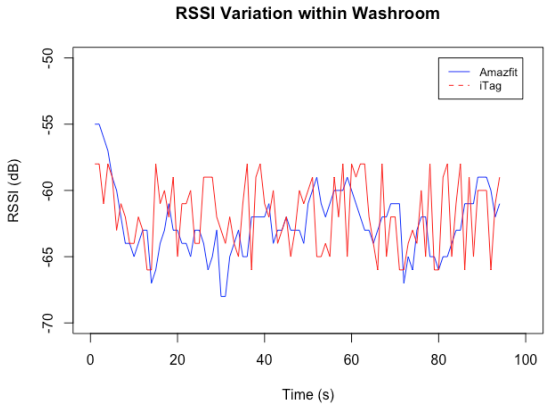

Fig. 6a: Measured RSSI vs Time in the Residential Home Washroom

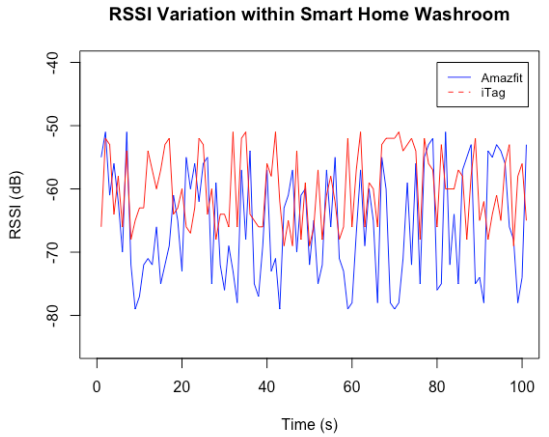

Fig. 6b: Measured RSSI vs Time in the McMaster Smart Home Washroom

TABLE II
RSSI Signal Properties of the Amazfit Smartwatch and iTag from RSSI Variation Testing

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

C. Location vs Ground Truth

Mobile app entries and IPS determined locations were compared and the detection results are displayed in Table III.

The IPS achieved a calculated percentage accuracy of 96.7% in the residential home and 95.33% in the smart home.

TABLE III
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

D. Sensor Based Room Detection

Mobile app entries and recorded sensor values were compared, and the detection results are displayed in Table IV. 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 IV
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

E. 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 V. 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 V
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

F. 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 Fig. 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 Fig. 7b. The RMS curve follows an exponential growth between 0-20 weight % and then steadily increases.

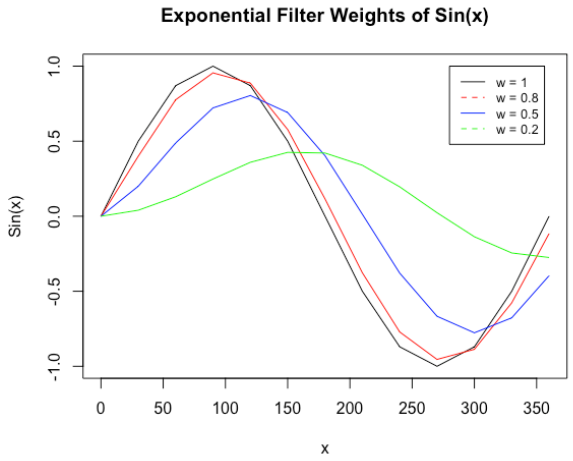

Fig. 7a: Exponential Filtered Sin(x) Function at Varying Weight Factors

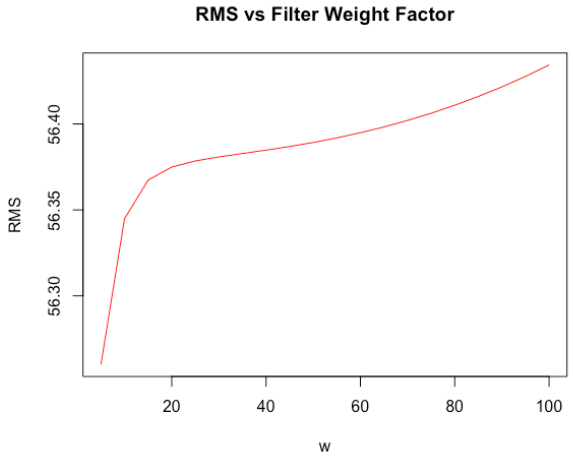

Fig. 7b: RMS value as a function of Weight Factor for the RSSI Stability Dataset (1m)

I. DISCUSSION

A. 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.

B. 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 Fig. 5c. When the exponential filter is applied to the raw values, determining the relative distance of a device is significantly easier as shown in Fig. 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. Fig. 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.

C. 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 II. 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.

D. Location vs 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 IPS' 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.

E. 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.

F. 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.

G. 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 IPS's ability to accurately detect rooms. From Fig. 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.

I. 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.

I. REFERENCES

[1] N. Mohsin et al, "Study of activity tracking through Bluetooth LOW Energy-based network," *Journal of Sensors*, vol. 2019, pp. 1–21, 2019.

[2] R. Giuliano et al, "Indoor localization system based on Bluetooth low energy for Museum Applications," *Electronics*, vol. 9, no. 6, p. 1055, 2020.

[3] D. Hango. “Support received by caregivers in Canada.” *Statistics Canada,* Ottawa, ON, 2020. Available: https://www150.statcan.gc.ca/n1/pub/75-006-x/2020001/article/00001-eng.htm.

[4] Pascacio et al, J. Collaborative Indoor Positioning Systems: A Systematic Review. Sensors 2021, 21, 1002. https://doi.org/10.3390/s21031002

[5] H.-P. Bernhard et al, “Work-in-progress: Rssi-based presence detection in industrial wireless sensor networks,” *2020 16th IEEE International Conference on Factory Communication Systems (WFCS)*, 2020.

[6] A. A. Nazari Shirehjini and S. Shirmohammadi, “Improving accuracy and robustness IN HF-RFID-Based indoor positioning With Kalman filtering and Tukey Smoothing,” *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 11, pp. 9190–9202, 2020.

[7] Katja Streich, Indoor Navigation & Indoor Positioning Using Bluetooth,” *infsoft Blog*, 30-Apr-2020. [Online]. Available: https://www.infsoft.com/blog/indoor-navigation-indoor-positioning-using-bluetooth.

[8] Mokhtari et al, 2018. Multi-Residential Activity Labelling in Smart Homes with Wearable Tags Using BLE Technology. *Sensors*, 18(3), p.908.

[9] A. Noertjahyana, I. A. Wijayanto, and J. Andjarwirawan, “Development of Mobile Indoor Positioning System Application Using Android and Bluetooth Low Energy with Trilateration Method,” *2017 International Conference on Soft Computing, Intelligent System and Information Technology (ICSIIT)*, 2017.

[10] A. Thaljaoui et al, “BLE localization using RSSI measurements and iRingLA,” *2015 IEEE International Conference on Industrial Technology (ICIT)*, 2015.

[11] G. Li et al, “Indoor Positioning Algorithm Based on the Improved RSSI Distance Model,” *Sensors*, vol. 18, no. 9, p. 2820, 2018.

[12] Espressif Systems, *ESP*. [Online]. Available: https://www.espressif.com/en/products/software/esp-now/overview.

[13] Contreras, D.; Castro, M.; De la Torre, D.S. Performance evaluation of Bluetooth low energy in indoor positioning systems. Trans. Emerg. Telecommun. Technol. 2014, 28, e2864.

[14] Z. Ma et al, "A BLE RSSI ranking based indoor positioning system for generic smartphones," *2017 Wireless Telecommunications Symposium (WTS)*, 2017.

[15] J.-H. Hauer, A. Willig, and A. Wolisz, "Mitigating the Effects of RF Interference through RSSI-Based Error Recovery," *Lecture Notes in Computer Science*, pp. 224–239, 2010.

[16] T. Van Haute et al, "Performance analysis of multiple Indoor Positioning Systems in a healthcare environment," *International Journal of Health Geographics*, vol. 15, no. 1, 2016.

Scoping Review Protocol

1. Review title:

Context Aware Computing Systems in Healthcare: A scoping review protocol

2. Anticipated or actual start date:

26 April 2021

3. Anticipated completion date:

July 23 2021

4. Stage of review at time of this submission:

Data extraction

5. Named contact:

Michael Zon

6. Named contact email:

zonm@mcmaster.ca

7. Named contact address:

1280 Main St W, Hamilton, ON L8S 4L8

8. Named contact phone number:

905-525-9140 ext. 24227

9. Organisational affiliation of the review:

McMaster University

10. Review team members and their organisational affiliations:

Title	First Name	Last Name	Affiliation
	Michael	Zon	Department of Medicine, Faculty of Health Sciences McMaster University, Hamilton, Ontario, Canada Department of Biomedical Engineering, Faculty of Engineering, McMaster University, Hamilton, Ontario, Canada
	Guha	Ganesh	Department of Biomedical Engineering, Faculty of Engineering, McMaster University, Hamilton, Ontario, Canada
Dr.	Qiyin	Fang	Department of Engineering Physics, Faculty of Engineering, McMaster University, Hamilton, Ontario, Canada

Department of Electrical & Computer Engineering, Faculty of Engineering, McMaster University, Hamilton, Ontario, Canada
School of Interdisciplinary Science, Faculty of Science, McMaster University, Hamilton, Ontario, Canada

11. Funding sources/sponsors:

McMaster Institute for Research on Aging (MIRA) and Natural Sciences and Engineering Research Council of Canada

12. Conflicts of interest:

There are no known conflicts of interest.

13. Review question(s):

The objective of this scoping review is to determine what medical context aware systems are currently being used by healthcare providers and patients. As this goal is focused on broadly identifying what exists within the literature at present, the review question lends itself well to a scoping review. Although a review of context aware systems in healthcare has been conducted in the past, systems that are currently being used by patients/healthcare providers were not identified. This is likely largely due to a lack of applications past the prototype stage at the time of the last review.

A secondary objective is to identify which contexts are being used by these systems and to find themes/categories for the context aware applications that are identified throughout the review. An adapted PICO framework for the research question is provided below.

14. Literature search:

Standard scoping review methodology will be used and reporting of results will follow established guidelines.[1, 2] A systematic literature search will be piloted on Medline using the broad search concepts of “context-aware*”, “health”, and “patient”, with relevant key terms nested under each concept. The process of search design will be iterative. Over a series of piloting cycles, a workable final search will be obtained that will be adapted to other search databases. Searches will be assessed based on whether they yield a hand-selected list of key studies that are deemed to fit the research question. The databases that will be searched are SpringerLink, EBSCO, PubMed, IEEE Xplore, Wiley, ScienceDirect, and ACM. The search interval was from the earliest data available on the database to May 2021 and only published peer reviewed journal articles were considered. This was done to ensure only quality systems and study designs/methods that have been reviewed by experts are included, thus giving a more accurate representation of the state of context aware systems in healthcare. Rayyann.ai , will be used to detect duplicates and keep track of references.

15. URL to search strategy:

An example search for PubMed yielding 404 results from 1981 to May 1, 2021 is shown below.

(("context$aware*"[Title/Abstract] OR "situation$aware*"[Title/Abstract]) AND ((health*[Title/Abstract] OR medic*[Title/Abstract] OR hospital*[Title/Abstract] OR well*[Title/Abstract] OR diagnos*[Title/Abstract] OR detect*[Title/Abstract] OR clinic*[Title/Abstract] OR condition[Title/Abstract])) AND (patient*[Title/Abstract] OR doctor*[Title/Abstract] OR nurse*[Title/Abstract] OR elder*[Title/Abstract] OR participant[Title/Abstract] OR physician*[Title/Abstract]))

https://pubmed.ncbi.nlm.nih.gov/?term=%28%28%22context%24aware*%22%5BTitle%2FAbstract%5D+OR+%22situation%24aware*%22%5BTitle%2FAbstract%5D%29+AND+%28%28health*%5BTitle%2FAbstract%5D+OR+medic*%5BTitle%2FAbstract%5D+OR+hospital*%5BTitle%2FAbstract%5D+OR+well*%5BTitle%2FAbstract%5D+OR+diagnos*%5BTitle%2FAbstract%5D+OR+detect*%5BTitle%2FAbstract%5D+OR+clinic*%5BTitle%2FAbstract%5D+OR+condition%5BTitle%2FAbstract%5D%29%29+AND+%28patient*%5BTitle%2FAbstract%5D+OR+doctor*%5BTitle%2FAbstract%5D+OR+nurse*%5BTitle%2FAbstract%5D+OR+elder*%5BTitle%2FAbstract%5D+OR+participant%5BTitle%2FAbstract%5D+OR+physician*%5BTitle%2FAbstract%5D%29%29&filter=pubt.journalarticle

16. Condition or domain being studied:

Context aware systems; healthcare; applications used by patients; applications used by healthcare providers; Non lab prototypes

17. Participants/population:

Healthcare providers, caregivers, and patients of any age

18. Intervention(s)/exposure(s):

Context aware technologies, defined as systems where the applications have the “ability to adapt to changing circumstances and respond according to the context of use (J. Kjeldskov, M. Skov, Supporting work activities in healthcare by mobile electronic patient records, in: Proceedings of the 6th Asia–Pacific Conference on Human–Computer Interaction, APCHI 2004, Rotorva, New Zealand, 2004). Context is defined in the usual way, by Dey, as “any information that can be used to characterize the situation of entities (i.e. whether a person, place or object) that are considered relevant to the interaction between a user and an application, including the user and the application themselves.” (A. Dey, G. Abowd, D. Salber, A conceptual framework and toolkit for supporting the rapid prototyping of context-aware applications in special issue on context-aware c) We further define the technology/intervention by focusing only on those applications with a medical focus which have been used by patients to help manage their disease or healthcare providers to help with their workflow or management of patients conditions. Thus, lab prototypes that have not been used by patients/healthcare providers are excluded.

19. Comparator(s)/control(s):

Any comparator.

20. Types of study to be included initially:

All studies featuring primary data will be included. Systematic reviews were eligible and will be evaluated for any missing references but will not be extracted.

21. Context:

Studies with technology field tested in patients within their homes/daily lives or location of treatment, and those used by healthcare providers in their work environment.

22. Primary outcome(s):

Any outcome relevant to improving the quality of life of patients or their management by healthcare providers.

23. Secondary outcome(s):

N/A

24. Data extraction (selection and coding):

Selection – two screeners will independently evaluate eligibility criteria for both title and abstract and for full text citations at each stage of the screening process. Screening software (Rayyan.ai) will be piloted on a randomly-selected subset of references to ensure consistency between screeners prior to using the software to screen all studies returned from the search. Level of agreement (kappa score) will be evaluated to assess level of agreement between screeners.

Extraction – A standardized form will be generated using excel for data abstraction. We will abstract general characteristics of studies such as the sample size, setting, eligibility criteria, participant description, contexts used, technology used, and funding source. Additionally, the TIDieR checklist will be adapted for extracting information about the characteristics of how the context-aware technology was used to assist healthcare providers or patients.[2]

25. Risk of bias (quality) assessment:

Studies will not be assessed for risk of bias as per the Preferred Reporting Items for Systematic Reviews and Meta-Analysis: extension for Scoping Reviews (PRISMA-ScR) guidelines.[3]

26. Strategy for data synthesis:

The findings of this scoping review will be summarized and presented in tables. The resulting papers will be analyzed according to the contexts used, technology present, and type of application the context aware system was used. The purpose of each study's context-aware system wi be described along with the current state of the technology (e.g large field test or early testing by patients/healthcare providers). Areas that could benefit from potential future research and gaps in the current literature will be identified.

27. Analysis of subgroups or subsets:

Context aware applications categorized/analyzed by application type

28. Type of review:

Scoping review

29. Language:

English

30. Country:

All countries

31. Other registration details:

N/A

32. Reference and/or URL for published protocol:

N/A

33. Dissemination plans:

Dissemination of the findings of this review will be in the form of a published manuscript.

34. Keywords:

Context aware; situation aware; healthcare; telemedical systems; patient; healthcare provider

35. Details of any existing review of the same topic by the same authors:

N/A

36. Current review status:

Ongoing

37. Any additional information:

N/A

38. Details of final report/publication(s):

N/A

References

1. Aromataris E, Munn Z (Editors). *JBI Manual for Evidence Synthesis*. JBI; 2020. Available from https://synthesismanual.jbi.global. doi: 10.46658/JBIMES-20-01Tricco AC,

2. Hoffmann TC, Glasziou PP, Milne R, et al. Better reporting of interventions: template for intervention description and replication (TIDieR) checklist and guide. *BMJ*. 2014;348:g1687. doi: 10.1136/bmj.g1687

3. Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA Extension for Scoping Reviews (PRISMAScR): Checklist and Explanation. *Ann Intern Med.* 2018;169:467–473. doi: 10.7326/M18-0850.

Research Ethics Board Application Protocol

The following protocol was submitted and approved by the research ethics board so that the pilot study could commence. It contains details about the equipment, items sent to participants, device installation, inclusion and exclusion criteria, and some survey data collected from the participants. The description of how the data analysis will be conducted is not relevant to the present thesis. Additionally, of the devices described only the Raspberry Pi, ESP32 Devkit, and TicWatch were used in the present work.

Smart Homes Ageing and Monitoring: Indoor Positioning System Pilot Clinical Trial

1. Introduction

Canada's demographic continues to shift to an older average age requiring increased health care expenditure to maintain our populations health[1]. Given the limited resources of our publicly funded system, new technologies will be required to ensure adequate treatment of our increasing elderly patient population with a similar number of healthcare providers. Recent studies suggest that declining mobility is an early predictor of disability[2,3] cognitive decline[4,5], and falls leading to hospitalization[6,7]. Thus, technology that can detect early mobility decline is essential to early intervention targeted at reducing costly visits to emergency due to falls. Additionally, preventing falls is pivotal to keeping our older population safe given fractures induced by falls have been shown to result in death within 1 year in 10-20% of individuals over the age of 65[8].

Studies have shown that many of the clinical measures used to assess mobility do not correlate well with functional performance of elderly individuals and fall risk[9]. This is likely because these tests are point of care measurements and do not reflect the environmental challenges older adults have in their home (e.g number of stairs)[8]. Research on indoor position systems that track adults' trajectories within the home have shown promising results for assessing the true mobility performance of older adults, especially when paired with other sensor data from wearable smartwatches such as step count[10]. Additionally, many of these systems have demonstrated that increasing variability in the paths taken by adults between rooms can be indicative of cognitive decline[11]. However, these systems are often too complex for the average older adult making installation within many adults' homes too time consuming to permit large scale trials. Furthermore, prior systems are expensive and have not focused on transmitting data in real time for diagnosing early mobility decline[12].

The primary aim of this pilot study is to assess the feasibility of implementing our low-cost and simple to install indoor positioning system that can monitor the position, step count, heart rate and distance travelled of older adults withing their home. This indoor positioning system has been developed by students in Dr. Fang's group in McMaster University's Biomedical Engineering Department. It has been developed by programming open-source microcontrollers/sensors that are spread across homes which record Bluetooth signals sent from devices worn by older adults (e.g., a smartwatch). Thus, although the individual sensors are not proprietary the software and system as a whole is proprietary technology owned by McMaster University. A survey will be used to evaluate users experience with our system. Additionally, results from this pilot study will be used to determine whether our system is in fact easy to install, does not inconvenience older adults, and provides reliable position and step count data in real-time.

2. Methods

2.1 Participants

The number of participants will be kept to a minimum as the primary objective of this pilot study is to assess the feasibility of implementing our system and to ensure it is convenient for older adults. Thus, we will recruit 30 participants for the primary residence based smart-home study in order to ensure any results from our survey or data across participants have a reasonable likelihood of being normally distributed.[13] We will also recruit 10 participants to run simulated tests with our system to investigate the accuracy of the positioning system and collected heart rate data. One target source for volunteers will be upper-level engineering students in the Engineering Physics program as they will have the capability of operating the devices when doing real time call sessions.

All study participants will be required to provide informed verbal consent before participating. Inclusion criteria for the primary residence-based study will consist of any adult 60 years or older with no known history of cognitive deficits. For the simulated tests of the system, 10 healthy and willing participants of age 18 or over will be recruited. Volunteers will be recruited via advertisements across centers throughout Hamilton (library, hospitals, community centers) and word of mouth. Upon recruitment, basic information will be collected over the phone such as the number of stairs within their home and the number of rooms in their home, since each room will need a device.

2.3 Instruments

2.3.1 Bluetooth Tag iTag or nut

The iTag and Nut are cheap Bluetooth tags that can be carried by people in order to broadcast a Bluetooth ID to surrounding devices. The tag has been used in various indoor positioning systems and will be attached to a necklace to be worn by the participants. This will allow the participants to broadcast an anonymized Bluetooth ID to the other components in our system which will then determine their position. In addition to the

provided tags, users may choose to use their own Bluetooth tag (ex. Tile, nut, eddystone, etc.) but will need to provide the tag's MAC ID prior to installation.

2.3.2 ESP32 DevkitC sensor station

The ESP32 DevkitC is an open-source low cost-programmable microcontroller with built in Wi-Fi and Bluetooth capabilities. This system on a chip has been used in various medical grade applications, including those localizing the position of adults. One ESP32 will be encased in plastic to form a sensor station that compactly fits into a box and then plugged into the outlet of each room in the participant's home. The strength of the signal emanating from the Bluetooth tag attached to the user that is recorded by the ESP32 sensor station will be used later to determine the room the participant is in. Additionally, the sensor station will have ultrasonic and passive infrared sensors to detect users entering the room to confirm the Bluetooth based method is correct about their location. A humidity temperature will also be present in the box to understand how the environment effects the devices temperature. The signal strength data will be sent to a Raspberry Pi device over Bluetooth so all ESP32 signals are located on a single device allowing them to be compared to determine the participant's room location.2.3.3 Raspberry Pi.

The Raspberry Pi is a palm sized open-source computing platform that utilizes a Linux operating system. It functions as a full desktop computer and has been used in several smart-home remote monitoring applications. For our study, the Raspberry Pi will be used to put all the ESP32 signals from the different rooms within the participants home on a single device where it can be compared. Additionally, the Raspberry Pis will also collect Bluetooth signals to improve the accuracy of the indoor positioning system within its room. The room with an ESP32 that recorded the largest signal strength for 8 of the last

10 seconds will be assumed to be the room the user is located in. This final location of the user will then be encrypted according to the Advanced Encryption Standard (AES) set forth by the U.S National Institute of Standards and Technology and sent to a Google Cloud Firestore database. Our central server at McMaster campus will then read the data from the Cloud database, decrypt it, and then delete it from the cloud. Thus, user data will only be present online in an encrypted state (not interpretable by 3rd parties) for less than 1 minute prior to being deleted from this online database. Additionally, the cloud Firestore database is not accessible to third parties as access is asymmetrically RSA encrypted, requiring a private key located in a locked room within our labs facilities to be accessed. Thus, user data is doubly encrypted, once through RSA encryption then again through AES encryption. This same locked room holds the AES keys to decrypt the users' data and these keys will never be transferred through an online medium. Note that all data throughout this study which is transferred online follows this twice encrypted protocol.

2.3.4 Polar M600 and TickWatchS2

The Polar M600 and TicWatchS2 WearOS based smartwatches compatible with the open-source android programming environment. Using this open-source platform, the devices will be programmed to provide timestamped step count and heart rate data. This data will not leave the device and instead will be AES encrypted and removed later to compare with the positioning data via the timestamps.

2.3.5 Fossil Gen 5 smartwatch

The Fossil Gen 5 smartwatch is another WearOS based watch compatible with the open-source android programming environment. The device will be programmed to provide timestamped step count and heart rate data using the same software that is on the Polar M600 and TicWatch S2. Initial tests seem to indicate this device provides more accurate

heart rate data than the other 2 devices, but less accurate step count information. Thus, it will also be tested throughout the project. Like the other devices, data will not leave the device and instead will be AES encrypted and removed later to compare with the positioning data via the timestamps.

2.3.6 Custom Built Smartwatch

Our lab has manufactured our own smartwatch in order to collect the raw optical PPG data associated with the heart rate data from commercial watches (e.g Polar M600). Additionally, our watch has sensors to investigate falls (barometer) and temperature (IR sensor). This watch will only be used in the simulated tests to explore the accuracy of its data collection and compare it to commercial smartwatches. The watch will not be used within users' primary residencies and will be tested for periods less than 1 day at a time. Data from these watches during simulated experiments will be AES encrypted, sent through WiFi to a secure Cloud Firestore database, downloaded off this server onto our encrypted desktop hosted at McMaster, and then deleted from the online database.

As a backup option to the secure Cloud Firestore file transfer method, we will also develop a secured e-mail program in the R-Pi to send the files through encrypted e-mail to a secured McMaster e-mail address specifically for this study.

2.3.7 Bell Turbo Stick

In order to send the encrypted position/mobility data to our secure server a reliable internet connection will be required. The Bell Turbo stick is a USB compatible device that provides a continuous connection to Bell's network. The turbo stick will be plugged into the Raspberry Pi, providing a continuous internet connection that does not rely on the internet of the participants. Thus, many of the technological challenges involving difficulties with older adults in setting up devices with Wi-Fi requirements will be avoided.

2.3.8 Desktop Database

The users' location determined on our Raspberry Pi device will be sent to a secure database hosted on one of our labs computers in a locked room at McMaster University. A password protected location on this computer will host all the AES encrypted data from this trial. Data will only be decrypted during analysis, thus effectively leaving the data to appear as random sequences of numbers to anyone who does manage to bypass the password to the database.

2.4 Device Usage Protocol

Participants will take home 1 ESP32 senor station for each room in their home, 1 Raspberry Pi, a Bell turbo stick, 1 android smartwatch, and 1 necklace with a Bluetooth tag. They will receive an instruction manual that asks them to plug 1 ESP32 based sensor station into the wall outlet of each room and to place the Raspberry Pi, with its Bell Turbo Stick, in the living room or plugged into their router. After this, they will be asked to wear the necklace throughout the day over the 3-month span of this pilot study and to wear a smartwatch with our custom software. They will be asked to charge the devices anytime they run out of battery. Additionally, 10 participants will be asked to use the devices over a shorter period to help calibrate the system and assess the accuracy of the data.

The smartwatches heart rate and step count data will be compared to the positioning data to determine if the results are reasonable. For instance, steps should increase proportionally to the number of room transitions detected by the system and heart rate should increase when participants transition from one floor to another. The shorter 10 person simulated experiment will aim to confirm this relationship prior to sending the 30-person cohort of older adults their devices.

2.5 Device Usage Log and Satisfaction Survey

2.5 Data Collection Sheets: demographic/medical info, device satisfaction and shortened PASE

Data Collection Sheets

Title of Study: _____

1. **DEMOGRAPHIC AND MEDICAL INFORMATION**

a. Sex: Male/Female Age (years): _____ Height (cm): _____ Weight (kg): _____

Use of Gait Aid:

☐ Yes ☐ No Specify:_____

If yes: In home / Community / Both?

Balance/Falls History:

Self-reported difficulty with balance? ☐ Yes ☐ No

A near fall in the last 12 months? ☐ Never ☐ Seldom ☐ Often ☐ Very Often

"We all fall from time to time. A fall would be when you find yourself suddenly on the ground, without intending to get there, after you were in either a lying, sitting or standing position. How many times in the past year did you fall?"

Have you had any falls in the last year? ☐ Yes ☐ No

If yes, how many? _____

Major Co-Morbidities: (circle)

Vision	Gastrointestinal	Musculoskeletal	Neurological	Cardiac/Cardiovascular
-Macular degeneration -Cataracts -Glaucoma	-Bowel incontinence -Urinary incontinence	-Osteoarthritis -Osteoporosis	-Memory problem -Dementia or Alzheimer's disease -Multiple	-Heart disease (incl CHF) -Peripheral arterial disease -Hypertension/ High blood pressure

Mental Health	**Respiratory**	**Other**	sclerosis -Epilepsy -Stroke/CVA Ministroke/TIA - Traumatic Brain Injury -Parkinsonism	-Angina -Heart attack/MI -Aortic Valve Stenosis
-Anxiety disorder -Mood disorder -Clinical depression -Depression questionnaire	-Asthma -COPD -Bronchitis -Emphysema	-Kidney disease/failure -Diabetes -Cancer		

2. SENSOR PLACEMENT

Did you find the pendant inconvenient to use?

☐ Very inconvenient ☐ somewhat inconvenient ☐ convenient ☐ Very convenient

Did you find the smartwatch inconvenient to use?

☐ Very inconvenient ☐ somewhat inconvenient ☐ convenient ☐ Very convenient

Were the ESP32 devices and Raspberry Pi's an inconvenience to you throughout the study?

☐ Very inconvenient ☐ somewhat inconvenient ☐ convenient ☐ Very convenient

What was your overall level of user satisfaction with the devices?

☐ Very dissatisfied ☐ dissatisfied ☐ satisfied ☐ Very satisfied

Would you be willing to use this technology in the future in collaboration with health professionals for early diagnosis of disability/disease?

☐ yes ☐ no

Which devices would you use in the future?

Bluetooth Necklace □ Polar Watch □ ESP32 □ Raspberry Pi □

Why?

How difficult would it be for you to remember to use the necklace everyday?

Very difficult □ Difficult □ Neutral □ Easy □ Very easy □

How difficult would it be for you to remember to use the watch everyday?

Very difficult □ Difficult □ Neutral □ Easy □ Very easy □

Did the devices interfere with your daily routine?

No effect □ Minor effect □ Neutral □ Moderate effect □ Major effect □

Which devices interfered with your daily routine?

_____

Ask participants to elaborate on their answer and ask why they chose that option.

What did you not like about the technology?

_____

_____

_____

_____

How would you improve the technology so it was more convenient for you?

_____

_____

_____

_____

Shortened Physical Activity Scale for the Elderly (PASE)

Instructions:

Please complete this questionnaire by either circling the correct response or filling in the blank. Here is an example:

During the past 7 days, how often have you seen the sun?
[1] NEVER
[2] SELDOM (1-2 DAYS)
[3] SOMETIMES (3-4 DAYS)
[4] OFTEN (5-7 DAYS)

Answer all items as accurately as possible. All information is strictly confidential.

Leisure Time Activity

1. Over the past 7 days, how often did you participate in sitting activities such as reading, watching TV, or doing handcrafts?
[1] NEVER (go to question 2)
[2] SELDOM (1-2 DAYS) (go to question 1a. and 1b.)
[3] SOMETIMES (3-4 DAYS) (go to question 1a. and 1b.)
[4] OFTEN (5-7 DAYS) (go to question 1a. and 1b.)

1a. What were these activities? (open end question)

1b. On average, how many hours did you engage in these sitting activities?
[1] Less than 1 hour
[2] 1 but less than 2 hours
[3] 2 - 4 hours
[4] More than 4 hours

2. Over the past 7 days, how often did you take a walk outside your home or yard for any reason? For example, for fun or exercise, walking to work, walking the dog, etc.
[1] NEVER (go to question 3)
[2] SELDOM (1-2 DAYS) (go to question 2a.)
[3] SOMETIMES (3-4 DAYS) (go to question 2a.)
[4] OFTEN (5-7 DAYS) (go to question 2a.)

2a. On average, how many hours per day did you spend walking?
[1] Less than 1 hour
[2] 1 but less than 2 hours

[3] 2 - 4 hours
[4] More than 4 hours

3) Over the past 7 days, how often did you take a walk outside your home or yard for any reason? For example, for fun or exercise, walking to work, walking the dog, etc.

(1) NEVER (go to question 3)
(2) SELDOM (1-2 DAYS)
(3) SOMETIMES (3-4 DAYS)
(4) OFTEN (5-7 DAYS)

3a. On average, how many hours per day did you spend walking?
(1) Less than 1 hour
(2) 1 - 2 hours
(3) 2 - 4 hours
(4) More than 4 hours

4) Over the past 7 days, how often did you do any exercises specifically to increase muscle strength and endurance, such as lifting weights or pushups, etc.?

(5) NEVER (go to question 5)
(6) SELDOM (1-2 DAYS)
(7) SOMETIMES (3-4 DAYS)
(8) OFTEN (5-7 DAYS)

4a. On average, how many hours per day did you spend walking?
(5) Less than 1 hour
(6) 1 - 2 hours
(7) 2 - 4 hours
(8) More than 4 hours

5) Over the past 7 days, how often did you engage in sport and recreational activities such as jogging, swimming, cycling, singles tennis, aerobic dance, skiing (downhill or cross-country) or other similar activities?

(9) NEVER (skip 5a)
(10) SELDOM (1-2 DAYS)
(11) SOMETIMES (3-4 DAYS)
(12) OFTEN (5-7 DAYS)

5a. On average, how many hours per day did you spend walking?
(9) Less than 1 hour
(10) 1 - 2 hours
(11) 2 - 4 hours
(12) More than 4 hours

4. Activity Difficulty Level Assessment

1. **Do you use a walking aid?**

a. yes
b. No

2. **If you do use a walking aid, what kind do you use?**

_____

3. **Do you have difficulty in walking 0.5 km?**

c. No difficulty
d. Some difficulty
e. I find it difficult
f. Need the help of another person for this distance
g. Unable to manage even with help

4. **Do you have difficulty in walking 2 km?**

a. No difficulty
b. Some difficulty
c. I find it difficult
d. Need the help of another person for this distance
e. Unable to manage even with help

5. **Do you have difficulty in climbing up one flight of stairs?**

a. No difficulty
b. Some difficulty
c. I find it difficult
d. Need the help of another person for this distance
e. Unable to manage even with help

Study ID: _____ Date: _____

2.6 Procedures

Two graduate students and an undergraduate student researcher assistant will perform the initial calibration in the McMaster SHAPE facility. They have all been properly trained and approved for on campus research activities during COVID-19, including PPE use and physical distancing.

Ten participants will be asked to move between rooms in their own home and wear a smartwatch for 1 week in order to calibrate the system and asses its accuracy prior to the larger cohort study. Additionally, they will be asked to wear our custom smartwatch for 1 week to assess its data's accuracy relative to the commercial smartwatch solutions. After the indoor positioning system has been calibrated and tested, 30 older adults will be sent devices for use in their home. These adults will be instructed to plug in the ESP32 and Raspberry Pi devices and then wear the Bluetooth tag and smartwatch for a period of 3 months. The smartwatch will be worn on the non-dominant wrist and the Bluetooth tag will be attached to a necklace. After the study, participants will answer survey questions during a phone call that are primarily targeted at understanding if the devices were an inconvenience for them, how the system can be made more convenient for them, and what they did not like about the system. A few questions on the physical activity scale for the elderly (PASE), co-morbidity information, and fall related questions will be asked as these reduced mobility and balance issues have been shown to affect step counts on activity trackers. The mobility questions of the survey will also be completed over the phone during the initial recruitment interview. If the participant prefers and has access,

we will also offer a video call option through Zoom. After the pilot study ends, participants will mail the devices back in an envelope we have given them that is addressed to McMaster University. They will also complete the survey one more time over a phone call to assess for changes in the responses/mobility over the study and consistency in their responses. Mail will be used to assess the feasibility of contactless delivery/pickup of the system and to ensure participant safety during the pandemic.

2.7 Data Analysis

Participants indoor activity will be broken into periods where no steps were detected and they are presumably at rest, and periods where there is an increase in step counts. Periods where no room transitions take place and times transitions do take place will also be determined from the data. All 4 groups timescale will be converted to minutes for that day. An intraclass correlation coefficient (ICC) will then be calculated between the watch step count and room transition times, and the times where transitions and steps were not recorded. An ICC greater than 0.75 will be considered excellent, 0.60–0.74 good, 0.40–0.59 fair and less than 0.40 poor[14]. The absence of reflected light from the heart rate sensor will be used to determine when participants were using the watch or not and intervals they were not will be removed from the analysis. A paired t-test will also be used to compare the heart rates obtained when participants are stationary, versus the heart rates obtained when they are transitioning between rooms or upstairs.

The results of the survey questions will be aggregated to determine older adults' overall satisfaction with the system. We will also calculate a point biserial correlation coefficient between the survey questions pertaining to mobility and the total number of step counts and total number of room transitions. Most importantly, the written responses will

carefully be reviewed to determine how we can make the system more convenient to use for older adults. Feedback will then be integrated in order to improve the system and test it in a larger cohort.

References

1. Anderson GF, Hussey PS. Population Aging: A Comparison Among Industrialized Countries: Populations around the world are growing older, but the trends are not cause for despair. *Health Affairs*. 2000;19(3):191-203. doi:10.1377/hlthaff.19.3.191

2. Fried LP, Young Y, Rubin G, Bandeen-Roche K. Self-reported preclinical disability identifies older women with early declines in performance and early disease. *Journal of Clinical Epidemiology*. 2001;54(9):889-901. doi:10.1016/S0895-4356(01)00357-2

3. Rantanen T. Promoting Mobility in Older People. *J Prev Med Public Health*. 2013;46(Suppl 1):S50-S54. doi:10.3961/jpmph.2013.46.S.S50

4. Montero-Odasso M, Verghese J, Beauchet O, Hausdorff JM. Gait and Cognition: A Complementary Approach to Understanding Brain Function and the Risk of Falling. *J Am Geriatr Soc*. 2012;60(11):2127-2136. doi:10.1111/j.1532-5415.2012.04209.x

5. Verghese J, Wang C, Lipton RB, Holtzer R, Xue X. Quantitative gait dysfunction and risk of cognitive decline and dementia. *Journal of Neurology, Neurosurgery & Psychiatry*. 2007;78(9):929-935. doi:10.1136/jnnp.2006.106914

6. Tromp AM, Pluijm SMF, Smit JH, Deeg DJH, Bouter LM, Lips P. Fall-risk screening test. *Journal of Clinical Epidemiology*. 2001;54(8):837-844. doi:10.1016/S0895-4356(01)00349-3

7. Bridenbaugh SA, Kressig RW. Laboratory Review: The Role of Gait Analysis in Seniors' Mobility and Fall Prevention. *Gerontology*. 2011;57(3):256-264. doi:10.1159/000322194

8. Rubenstein LZ. Falls in older people: epidemiology, risk factors and strategies for prevention. *Age and Ageing*. 2006;35(suppl_2):ii37-ii41. doi:10.1093/ageing/afl084

9. Brusse KJ, Zimdars S, Zalewski KR, Steffen TM. Testing Functional Performance in People With Parkinson Disease. *Physical Therapy*. 2005;85(2):134-141. doi:10.1093/ptj/85.2.134

10. Konstantinidis EI, Bamidis PD. Density based clustering on indoor kinect location tracking: A new way to exploit active and healthy aging living lab datasets. *2015 IEEE*

15th International Conference on Bioinformatics and Bioengineering (BIBE). Published online November 2015:1-6. doi:10.1109/BIBE.2015.7367714

11. Kearns WD, Nams VO, Fozard JL. Tortuosity in Movement Paths Is Related to Cognitive Impairment: Wireless Fractal Estimation in Assisted Living Facility Residents. *Methods Inf Med*. 2010;49(06):592-598. doi:10.3414/ME09-01-0079

12. Yasir M, Ho S-W, Vellambi BN. Indoor Position Tracking Using Multiple Optical Receivers. *J Lightwave Technol*. 2016;34(4):1166-1176. doi:10.1109/JLT.2015.2507182

13. Chan Y. Biostatistics 101: data presentation. *Singapore Medical Journal*. 2003;44(6):280-285.

14. Welton T, Kent DA, Auer DP, Dineen RA. Reproducibility of Graph-Theoretic Brain Network Metrics: A Systematic Review. *Brain Connectivity*. 2015;5(4):193-202. doi:10.1089/brain.2014.0313