Using Smart Watches to Facilitate High Quality Cardiopulmonary Resuscitation for Patients with Cardiac Arrest

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Abstract

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Survival rates for victims of cardiac arrest remain poor worldwide despite medical advancement and technology development. Chest compression quality has been considered the key for patient survival during cardiopulmonary resuscitation (CPR). Past studies have shown that both healthcare professionals and laypersons often perform CPR at inadequate rates and depths. Prior studies also showed that with adequate feedback, CPR quality can be improved and more adherent to the guideline-recommended rate (100 to 120 per minute) and depth (5 to 6 cm).

This dissertation sought to develop a wearable application (app) with real-time feedback mechanism by using a commercially available smartwatch (ASUS ZenWatch 2) to facilitate the delivery of high-quality CPR. First, a systematic review on healthcare applications of smartwatches was conducted by using the “Preferred Reporting Items for Systematic Reviews

and Meta-Analyses (PRISMA)" as the systematic review methodology. After screening 356 articles, 24 were selected for review. The results find that most of the identified smartwatch studies focused on applications involving health monitoring for the elderly (6; 25%), and there is potential for smartwatch use in clinical settings. The second step is to develop a smartwatch app that can accurately estimate the rate and depth of chest compression in real-time, while also providing a user-centered design interface as an assistive device to be used during CPR in clinical settings. By using the sensor data collected from a smartwatch-based accelerometer during chest compressions on a manikin, two novel algorithms capable of estimating chest compression rate and depth were introduced, respectively. The validation study indicates that the developed algorithm based on a smartwatch with a built-in accelerometer is promising. User-centered design was adopted during the user interface development of the prototype and usability testing was conducted for the final app. Finally, to evaluate whether the developed smartwatch app with real-time audiovisual feedback can improve the delivery of high-quality CPR, a total of 80 healthcare professionals were recruited and randomly allocated to either the intervention group wearing a smartwatch with feedback or the control group without a smartwatch. All participants were asked to perform CPR for two minutes, with chest compression and ventilation at a 30:2 ratio. The results show that without feedback chest compressions tend to be too fast and too shallow, and that CPR quality can be improved with the assistance of a smartwatch providing real-time feedback.

This work is a great example of applying modern information technology to improve the quality of healthcare. Although it is a simulation study performed on a manikin, it has substantial potential to be utilized in the clinical settings.

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List of Acronyms and Abbreviations

ACLS	Advanced Cardiovascular Life Support
AHA	American Heart Association
CCD	Chest Compression Depth
CCR	Chest Compression Rate
CDC	Centers for Disease Control and Prevention
CPR	Cardiopulmonary Resuscitation
ECC	Emergency Cardiovascular Care
ED	Emergency Department
EMT	Emergency Medical Technician
ERC	European Resuscitation Council
NTUH	National Taiwan University Hospital
OHCA	Out-of-hospital Cardiac Arrest
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-analysis
SUS	System Usability Scale
UCD	User-Centered Design

DEDICATION

This dissertation is dedicated to my parents, for their love and support throughout my life.

CHAPTER 1. INTRODUCTION

1.1 Motivation

Various wearable devices have emerged to play an important role in the healthcare arena. A wearable device can be defined as a mobile electronic device worn as an accessory or unobtrusively embedded in the user's clothing [1]. With the functionality of intelligent miniaturized biosensors capable of wireless communication, wearable devices are capable of continuously and autonomously transmitting physiologic data in non-invasive ways. They have the potential to provide caregivers with the information they need to improve the quality of health care, change and facilitate clinical workflow, manage and treat patients remotely, collect more and better data, and deliver more meaningful healthcare to patients [2]. As these wearable devices proliferate in the clinical domain, they may transform all phases of the healthcare experience from the initial onset of an acute illness, calling the ambulance, being seen at the Emergency Department (ED), being admitted to the hospital and finally returning home.

For practical use, Zhang's research group noted several key factors that should be incorporated into the development and implementation of wearable devices, including miniaturization, integration, networking, digitalization, and standardization [3]. To be comfortably worn on the body, miniaturization and unobtrusiveness are considered the most important factors to increase compliance for long-term and continuous monitoring [4]. A recent advent to the fast-growing market of wearable devices is the smartwatch. With the design of its miniaturized form factor and intelligent computing technology, a smartwatch can be worn continuously without interrupting the user's daily activity. Although smartphones have become a part of our daily lives and might be considered to be wearable, they most often reside in a pocket or purse. Unlike smartphones, smartwatches can truly be wearable without interrupting our daily lives, and can also act as a readily accessible extension of the smartphone. Because of the proximity to the skin, the smartwatch can also be a source of physiologic data derived directly from the wearer's body [5]. With the potential for widespread adoption in the healthcare sector, smartwatches can contribute to transforming healthcare through innovative technologies.

1.2 Specific Aims and Contribution

Previous healthcare applications in smartwatches focused primarily on the elderly or patients with chronic illnesses. Until recently, there have been few studies focusing on the applications in emergency settings. The goal of this study is to develop a novel application using a smartwatch worn on the rescuers' wrist to facilitate the delivery of high-quality cardiopulmonary resuscitation (CPR) in emergency settings.

The research questions and the specific aims to achieve this goal are:

● **Research Question 1**: What user interface is best suited for the CPR watch to meet the needs of rescuers?

Specific Aim 1: To develop an application (app) for a smartwatch as an assistive device during CPR for healthcare providers through User-Centered Design (UCD) and usability testing.

● **Research question 2**: Is it feasible to use a CPR watch as an assistive device to improve CPR quality?

Specific Aim 2: To conduct a feasibility study by using a smartwatch with the developed app to detect the chest compression rate (CCR) and depth (CCD) with real-time feedback instructions during CPR.

● **Research question 3**: Do rescuers with a CPR watch outperform those without?

Specific Aim 3: To compare the quality of CPR performed by healthcare providers while using the smartwatch with a preinstalled app with traditional resuscitation using a sensorized manikin to simulate the victim of cardiac arrest.

This study developed a novel smartwatch app to facilitate the delivery of high-quality CPR in a simulated cardiac arrest situation for healthcare providers. We found that CPR quality showed significant improvement, in terms of the rate and depth of chest compressions, through the real-time feedback mechanism adopted in the design of a CPR watch. For in-hospital cardiac arrests, healthcare providers can have an additional tool to measure the quality of CPR with feedback instructions. In addition to “professional” mode to be used by healthcare providers, this platform can be easily switched to "hands-only" mode and extended to the prehospital settings. In addition to being utilized by the Emergency Medical Technicians (EMT) during ambulance transfer, it can also be used to guide laypersons for performing bystander-initiated CPR.

1.3 Significance

While there is enormous potential for a smartwatch to improve many aspects of healthcare delivery, there are few applications designed to assist with patients who present as cardiac arrest. During resuscitation, if healthcare providers wear a smartwatch that is capable of providing real-time feedback about the quality of CPR performed, it is possible that physicians will deliver more effective emergency patient care. Such an application can also serve as an assistive device for bystander-initiated CPR. This study generates a novel smartwatch application to facilitate the delivery of high-quality CPR during resuscitation events for healthcare providers through the use of an Android Wear worn on the rescuer’s wrist with a specifically developed UCD interface and real-time feedback mechanism.

A systematic review of research related to smartwatches was conducted to gather the most up-to-date applications in the healthcare domain. In an effort to develop a feedback device to improve CPR quality, current CPR standards, quality measurement, and quality feedback methods were also reviewed and collected as research materials. The development of informatics approaches based on wearable technologies was leveraged to build an interactive smartwatch app for answering questions related to the application of such a device to facilitate the delivery of high-quality CPR. Accordingly, we expect the results will help improve the prognosis of patients suffering from cardiac arrest when successfully implemented for clinical practices.

1.4 Guides for the Reader

This dissertation describes how to develop and utilize a smartwatch app with real-time feedback to facilitate the delivery of high-quality CPR for patients in cardiac arrest. Below is an outline of the contents of each chapter.

● **Chapter 2**: This chapter provides a literature review of current CPR standards and their effects on patient outcomes, methods of measuring the quality of CPR, and reports about feedback devices to improve CPR quality. The results of this review provide abundant resources for research materials.

● **Chapter 3**: This chapter, which is presented in paper 1, describes a systematic review that synthesized research studies involving the use of smartwatch devices for healthcare. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) was chosen as the systematic review methodology. A total of 356 articles were screened and 24 were selected for review. Of the 24 articles selected, most of the identified studies focused on applications involving health monitoring for the elderly (6; 25%). This review highlights that while there is potential for healthcare applications using smartwatch technology, more rigorous studies of their use in clinical settings are needed.

● **Chapter 4**: This chapter discusses the software development of a smartwatch app for feedback instruction during CPR. UCD was adopted as the design methodology, which focuses on maximizing the user experience and suiting specific needs [6]. A usability test was performed on the final product of the smartwatch app by administering the standardized System Usability Scale (SUS) [7]. At the end of this chapter shows the development of a machine learning algorithm for estimating the rate of chest compressions to be adopted on the smartwatch with CPR feedback application.

● **Chapter 5**: This chapter, which is presented in paper 2, describes a novel depth estimation algorithm of chest compression developed for feedback of high-quality CPR using a smartwatch with a built-in accelerometer. Researchers wore an Android Wear smartwatch and performed chest compression-only CPR on a Resusci Anne QCPR training manikin to collect data for model construction. To validate the model, we compared the results of the chest compression depth given by the smartwatch and the reference standard to assess the agreement between the two methods. The results show that there were no differences between the two methods.

● **Chapter 6**: This chapter describes a randomized control simulation study by using a smartwatch with a preinstalled app that provides real-time feedback and discusses how it improves the delivery of high-quality CPR for healthcare professionals. This study, which is the focus of paper 3, shows that without real-time feedback, chest compressions tend to be too fast and too shallow. CPR quality, in terms of rate and depth of compressions, can be improved with the assistance of a smartwatch providing real-time feedback.

● **Chapter 7**: This final chapter summarizes the dissertation findings and conclusions. The study methodologies adopted for this research are described as well as the contributions of the research to the field of biomedical informatics and evidence-based medicine, and how the findings can be extended to future works and used to inform the public of the importance of bystander CPR.

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CHAPTER 2. REVIEW OF LITERATURE

2.1 CPR Standard and Outcome

Prompt administration of high-quality CPR has been considered the most important favorable prognostic factor for patients suffering from cardiac arrest [1]. Since the first CPR guidelines developed in 1966 by the American Heart Association (AHA) and the first mass CPR training held by Dr. Leonard Cobb to serve Seattle and King County in 1972 [2], there have been minor revisions to CPR standards every five years. In 2005, the AHA Guidelines for CPR and Emergency Cardiovascular Care (ECC) were revised and high-quality CPR was first introduced [3]. The guidelines were revised again in 2010 and hands-only CPR was introduced for those who are not familiar, unwilling, untrained, or no longer able to perform the rescue breaths technique. Nowadays, giving continuous chest compression has received attention by media outlets across the world [4]. In the most recently updated 2015 guidelines, the fundamental performance metrics of high-quality CPR remain the same, with an emphasis on compressions of adequate rate and depth, allowing full chest recoil after each compression, minimizing pauses in compressions, and avoiding excessive ventilation [5].

Wide variability has been reported for survival of cardiac arrests after CPR in the literature. In the Resuscitation Outcomes Consortium (ROC) Epistry collected from 139 EMS agencies at 10 ROC sites, survival to discharge from out-of-hospital cardiac arrest (OHCA) in adults ranged from 5.5 to 19.0% (Average 10.4%) [6]. Another major registry that covered more than 40 communities in 23 states, representing 73 EMS agencies and more than 340 hospitals in the United States, the Cardiac Arrest Registry to Enhance Survival (CARES), demonstrated that the overall survival to hospital discharge in all age groups was 9.6% [7]. In terms of Asian people, the Pan Asian Resuscitation Outcomes Study (PAROS) conducted in seven Asian countries showed that survival ranged from 0.5 to 8.5% [8]. For in-hospital settings, based on a study from "Get with the Guidelines-Resuscitation (GWTG-R)", the overall survival to discharge in adults was 16.5% [9]. If in-hospital CPR was initiated in the ED, the survival rate was 23% [10]. Research indicated that the quality of CPR during resuscitation has a significant impact on survival and patient outcomes, whether the CPR is initiated by a layperson in the prehospital environment, by an emergency physician in the ED, or by a caregiver in the inpatient ward [11-14]. However, a large gap exists between current knowledge of CPR quality and its optimal implementation, contributing to preventable deaths attributable to cardiac arrest [1].

2.2 Methods for Measuring CPR Quality

One of the major issues related to CPR quality is monitoring and feedback. As stated by H. James Harrington: "If you can't measure something, you can't improve it." Methods of measuring CPR quality could be broadly categorized into two types, video-recording and time-motion analyses, and an external pad with an accelerometer to measure chest compressions. A review of pertinent studies in this area is discussed below.

2.2.1 Video-recording/Time-motion Analysis

Wang et al. conducted a prospective study to evaluate CPR quality of manual versus mechanical delivery of CPR during ambulance transport in Taipei City. A digital video-recording system was placed in two ambulances and a total of 19 adult non-traumatic OHCA patients were enrolled. Twelve patients were included in the manual CPR group, and seven patients were included in the mechanical group (Thumper). CPR quality, in terms of adequacy of chest compressions, instantaneous compression rates, and unnecessary no-chest compression intervals, was assessed by time-motion analysis of the videos [15]. Although the purpose of this study was to compare CPR quality by different means, it provides a quantitative method to measure CPR quality. However, the method used was a retrospective review of the video rather than real-time monitoring and feedback. Also, they were not able to measure the compression depth.

By using a commercially available electronic device, the Microsoft Kinect with motion-sensing ability, Wattanasoontorn et al. presented a pilot study in developing a Kinect-based system focusing on two key parameters of the CPR procedure: the chest compression rate and correct arm pose, implemented in their existing CPR training system, Life Support Simulation Application (LISSA). They tracked the hand position returned by the skeleton tracking middleware and followed its movement that required no markers. A total of 5 attempts were made, and results showed that their system is able to track the compression rate and evaluate the correct arm position [16].

Another group of researchers from Germany used the motion data from a Kinect sensor and the Differential Evolution (DE) optimization algorithm to dynamically fit sinusoidal curves to derive frequency and depth parameters for CPR training. It is intended to be part of a robust and easy-to-use feedback system for CPR training, allowing its use for unsupervised training. Results showed that their system was recognized with a median error of ±2.9 per minute in chest compression frequency (CCF) and ±1.18 cm in chest compression depth (CCD) compared to the reference training mannequin. Although robust CCF quality parameters can be derived from realistic CPR training scenarios, it is not sufficient to achieve a satisfactory result for the prediction of the CCD [17].

2.2.2 Retrospective Analysis Using External Pad with an Accelerometer

To measure the quality of CPR performed by ambulance personnel, 176 adult patients with OHCA treated by paramedics and nurse anesthetists were enrolled in a case series involving several European communities. The defibrillators recorded chest compressions via a sternal pad fitted with an accelerometer. Data from each resuscitation episode were collected and the mean compression rate and depth were calculated [14]. This retrospective analysis of CPR quality during OHCA showed that chest compressions were not delivered successfully half of the time, and most compressions were too shallow [14]. A similar study was conducted by Ayala and colleagues [18]. Again, the method of measuring CPR quality was offline, retrospective, and without a real-time feedback mechanism.

In summary, none of the previous studies described real-time measurement and feedback on CPR quality during resuscitation events.

2.3 Improving CPR Quality by Feedback Devices

In order to improve CPR quality with real-time feedback, researchers around the world have sought to develop a variety of methods to be utilized by professional healthcare providers or laypersons. Through the provision of audio-prompts, Chiang et al. showed that the adherence to current CPR guidelines could be significantly improved in a clinical setting [19]. To improve the quality of dispatcher-assisted chest compression-only CPR, Yang et al. showed that the depth and rate of compressions can be improved by adding interactive video communication to dispatch instructions in cardiac arrest simulations [20]. In a clinical trial conducted by Merchant et al., researchers developed a simple audio program made available for cell phone users, showing an increased quality of bystander CPR with cell telephone aid in a manikin simulation system [21].

In another study conducted by Sakai et al. using a smartphone application program with animation, the number of total chest compressions was significantly higher in the CPR support application group than in the control group in a simulated manikin system [22]. To compare the effects of different CPR prompts and feedback devices on the quality of chest compressions amongst healthcare providers, Yeung et al. conducted a single-blinded, randomized controlled trial comparing a pressure sensor/metronome device (CPREzy), an accelerometer device (Phillips Q-CPR), and a simple metronome on the quality of chest compressions on a manikin by trained rescuers. Although the results showed that CPR feedback devices vary in their ability to improve performance, users preferred the accelerometer and metronome devices over the pressure sensor device [23].

Semeraro et al. developed a Mini-VREM system with specifically designed software to provide audiovisual feedback to improve chest compression during CPR training. This was a randomized crossover pilot study that included a total of 80 participants with 40 in each arm and they compared the chest compression rate and depth between groups. Results showed that CPR performance was significantly better in the intervention group, whether performed by healthcare professionals or by lay people [24]. Although the participants perceived the system to be easy to use with effective feedback, such CPR feedback studies rely on devices with video/motion analysis that can be bulky and difficult to be carried. Currently, they are only used for training purposes, and their applications in real clinical settings remain in doubt.

Although most of the previous studies focused on measuring the rate and depth of chest compressions with real-time feedback in professional or training settings, their practical usage in real-world scenarios demands further investigation in terms of facility settings, portability, and unobtrusiveness. The CPR smartwatch app provides a fascinating idea that can be implemented for both the bystanders in the prehospital conditions and healthcare providers in the professional care settings.

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CHAPTER 3. PAPER 1: HEALTHCARE APPLICATIONS OF SMARTWATCHES: A SYSTEMATIC REVIEW

3.1 Prologue

This dissertation aims to develop a feedback application of smartwatches to assist in the delivery of high-quality CPR for patient with cardiac arrest by using modern information technology. In the remaining chapters the focus will be on how to develop a smartwatch application for a resuscitation event, the most critical and emergent condition in the clinical setting. In this chapter (paper 1), a systemic review of the literature related to smartwatch research in multiple healthcare domains is provided to help gain a comprehensive understanding of current smartwatch applications in the clinical field and their potential limitations. The results will serve as valuable resources for subsequent research. Furthermore, for assistive technologies to be successfully incorporated into current clinical workflow, gaps between the design phase and user experience must be bridged, which is especially important in the case of smartwatches given their small screen size. This systematic review focuses on studies of healthcare applications of smartwatches with relevant user interface design and usability testing.

What follows is a copy of a publication of the results of this systematic review published in "*Applied Clinical Informatics*" (doi: 10.4338/ACI-2016-03-R-0042). The authors had obtained permission (Order Number: 4587100337222) to use this material for the dissertation from the licensed content publisher (Georg Thieme Verlag KG).

3.2 Paper 1 Abstract

Objective: The aim of this systematic review is to synthesize research studies involving the use of smart watch devices for healthcare.

Materials and Methods: The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) was chosen as the systematic review methodology. We searched PubMed, CINAHL Plus, EMBASE, ACM, and IEEE Xplore. In order to include ongoing clinical trials, we also searched ClinicalTrials.gov. Two investigators evaluated the retrieved articles for inclusion. Discrepancies between investigators regarding article inclusion and extracted data were resolved through team discussion.

Results: 356 articles were screened and 24 were selected for review. The most common publication venue was in conference proceedings (13, 54%). The majority of studies were published or presented in 2015 (19, 79%). We identified two registered clinical trials underway. A large proportion of the identified studies focused on applications involving health monitoring for the elderly (6, 25%). Five studies focused on patients with Parkinson's disease and one on cardiac arrest. There were no studies which reported use of usability testing before implementation.

Discussion: Most of the reviewed studies focused on the chronically ill elderly. There was a lack of detailed description of user-centered design or usability testing before implementation. Based on our review, the most commonly used platform in healthcare research was that of the Android Wear. The clinical application of smart watches as assistive devices deserves further attention.

Conclusion: Smart watches are unobtrusive and easy to wear. While smart watch technology supplied with biosensors has potential to be useful in a variety of healthcare applications, rigorous research with their use in clinical settings is needed.

3.3 Paper 1 Full Text

3.3.1 Introduction

●**Background**

There is little doubt that wearable technologies are entering our lives, especially amongst early adopters. Numerous technology companies have invested in developing novel wearable solutions to gain successful access into consumer markets. It was estimated that only1% to2% of individuals in the United States have used a wearable device, but the market is forecasted to be worth $25 billion by 2019 with smart watches taking 60% of market value [1-2].

A wearable device can be defined as a mobile electronic device worn as an accessory or unobtrusively embedded in the user's clothing [3]. Generally, wearable devices adopt the technologies of sophisticated biosensors and wireless data communication that allow the wearer to access and transmit information in all sectors of human endeavor. Given the functionality of miniaturized biosensors capable of wireless communication, these devices are developed to be innovative, non-invasive monitoring technologies for continuous and autonomous transmission of physiological data [4]. As these wearable devices proliferate in the clinical domain, they have the potential to provide caregivers with the information they need to improve the quality of health care, change and facilitate clinical workflow, manage and treat patients remotely, collect greater health data, and deliver more meaningful healthcare to patients [5].

For practical use, Zhang’s research group noted several key factors that should be developed in order to implement wearable devices, including miniaturization, integration, networking, digitalization, and standardization [6]. To be comfortably worn on the body, miniaturization and unobtrusiveness are considered the most important factors that can increase compliance for long-term and continuous monitoring [7]. A recent advent to the fast-growing market of wearable devices is the smart watch. With its miniaturized form factor design and computing technology, a smart watch can be worn continuously without interrupting the user’s daily activity. Although smart phones have become a part of our daily lives and might be considered to be wearable, these devices most often reside in a pocket or purse. Unlike smart phones, smart watches can be truly wearable without interrupting our daily lives, and can also serve as a readily accessible extension of the smart phone [8]. Because of the proximity to the skin, the smart watch can also be a source of physiological data derived directly from the wearer's body [9]. With the potential for widespread adoption in the healthcare sector, smart watches equipped with biosensors have the potential to provide important healthcare information to patients and their providers.

●**<u>Significance</u>**

While there is potential for smart watch technology to gather and display important health data, to our knowledge there has been no systematic review regarding its healthcare application either in the research environment or in clinical practice.

●**<u>Objectives</u>**

In this article, we aim to review the published literature regarding healthcare applications of smart watches and the ongoing research projects that have been registered in the government clinical trials website. We also discuss the potential uses and limitations of smart watches in healthcare settings.

3.3.2 Materials and Methods

●**<u>Literature Search</u>**

We chose the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) as the systematic review methodology [10]. A total of five databases were searched, including PubMed, CINAHL Plus, EMBASE, ACM and IEEE Xplore Digital Library. All databases were searched by using keywords “Smart Watch” or “Smartwatch”, along with the brand names of the most commonly available commercial smart watches. Additionally, searches were conducted on ClinicalTrials.gov to include ongoing registered clinical trials. Although this review focused on healthcare applications, no reference to healthcare or application was included in the search terms to ensure a broad sweep of articles for consideration. The search terms used in PubMed were as follows and were modified to fit specific requirements of each of the databases searched.

("smart watch"[All Fields] OR smartwatch[All Fields]) OR ("Android"[All Fields] AND "Wear"[All Fields]) OR ("Apple"[All Fields] AND "Watch"[All Fields]) OR ("Moto"[All Fields] AND "360"[All Fields]) OR ("Samsung "[All Fields] AND "Gear"[All Fields]) OR ("Pebble "[All Fields] AND "Watch"[All Fields]) OR ("Garmin"[All Fields] NOT ("GPS"[All Fields] OR “Global Positioning System”[All Fields])) NOT ("Comment"[Publication Type] OR "Editorial"[Publication Type] OR “Review”[Publication Type])

We ran our search in December 1, 2015. We did not limit the year in the search terms, since the smart watch and its applications in the healthcare domain are relatively new. Additionally, we conducted a manual review of the citations included in the articles retrieved.

●**Article Selection**

One of the authors conducted an initial screen on the retrieved records. Duplicated articles were eliminated and additional records were excluded after reviewing individual titles and abstracts. A second author then reviewed the included studies. The retrieved full-text articles were evaluated for eligibility by two independent investigators. Reviewers were blinded to each other’s assessments. Discrepancies about article inclusion were then resolved through discussion with other team members. After excluding irrelevant studies, the rest of the studies were selected for final review.

To be included in the final review, studies had to be

(a) Published in peer-reviewed journals either as original articles or as conference proceedings, or be registered as an ongoing study in the official clinical trials website maintained by the National Library of Medicine (NLM) (i.e., ClinicalTrials.gov).

(b) Featuring smart watch or smartwatch as the primary subject of study or a main component of the study methodology.

(c) Targeted toward the clinical application of specific diseases of interest or individuals with specific healthcare demands.

(d) Written in English.

We excluded those articles that were not considered original research, such as letters to the editor, comments, or reviews. Because this review focused on smart watches, wearable wrist devices without the functionality of watches were also excluded. We also excluded smart band devices that solely tracked activity or fitness.

●**Data Extraction**

After the articles were selected for final review, they were randomly assigned to two investigators who extracted data and entered into a free online spreadsheet (Google Sheets). Data extracted included: authors, year of publication, publication type, study design, target population, number of participants, study aims, study intervention, technology-related findings, platform and/or type of smart watch, type of sensors used, and article title. We also extracted information from each article according to whether the study described the use of human-computer interaction, user-centered design, or pre-implementation usability testing as part of their main study interventions or findings. Finally, discrepancies about the contents of the extracted data were resolved through team discussion.

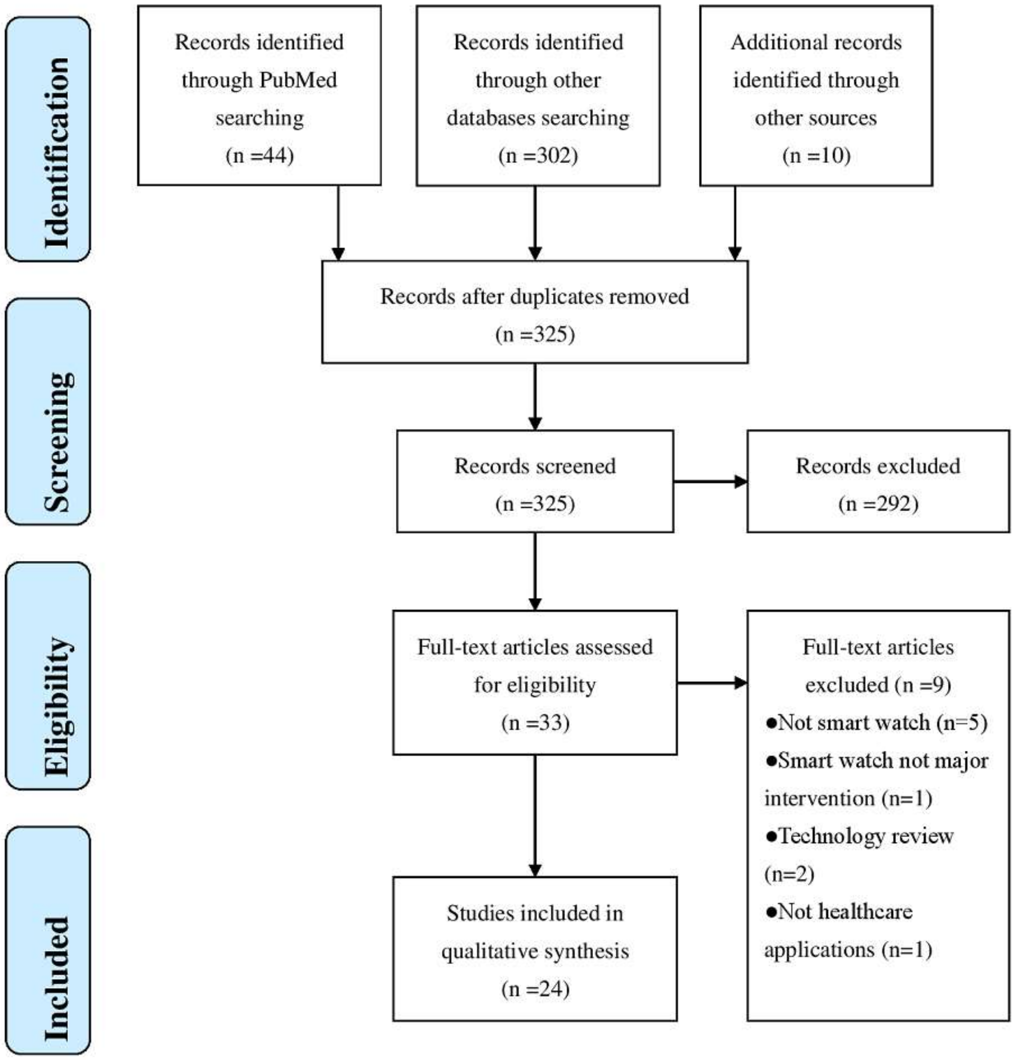


Figure 3.1. The study selection process of the systematic review.

3.3.3 Results

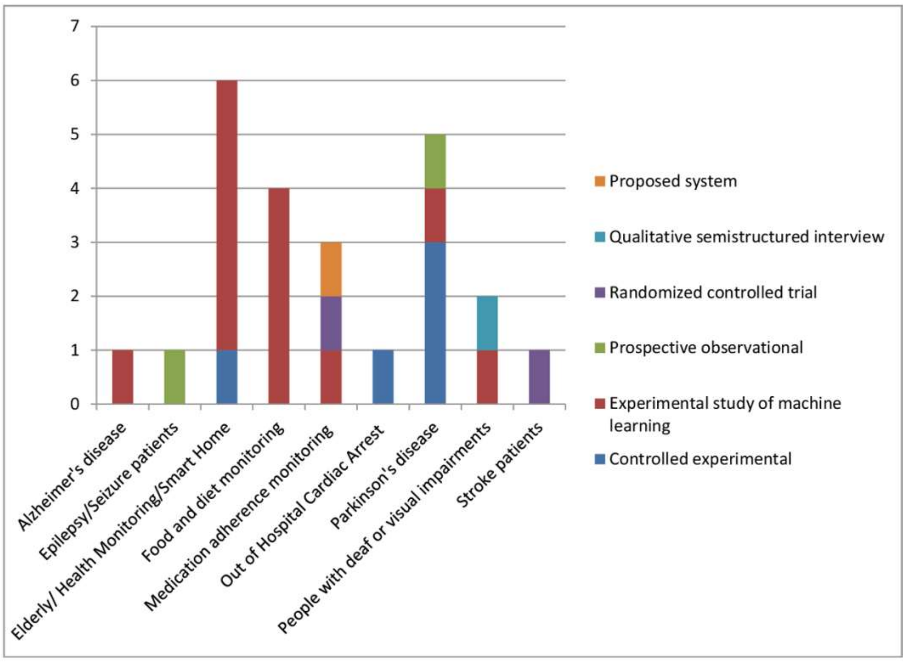
Initially, 356 studies were identified through database searching. After excluding duplicated records, 325 records were eligible for screening. There were 292 records that did not meet our inclusion criteria based on the screen. A total of 33 studies were included to be evaluated for eligibility. Full text records were retrieved and reviewed by two independent assessors. After excluding irrelevant studies, 24 articles were selected for final review, including 7 original studies, 2 conference papers, 13 conference proceedings, and 2 ongoing clinical trials. The study selection process is depicted in **Figure 3.1**. The complete description of the included studies is shown in **Table 3.1**.

Of the 24 records selected, the most common year published, presented, or registered was 2015 (19, 79%), followed by 2014 (4,17%). There was only one article published earlier, in late 2013 (4%). In terms of the publication type, 13 (54%) were published as conference proceedings and seven (29%) as journal articles. With respect to study design, the largest number of studies (13, 54%) utilized experimental designs in which machine learning was used to create annotated datasets for classification or pattern recognition to model a smart watch intervention for a target population, followed by experimental designs with control groups (5, 20%) to investigate the effect of the smart watch intervention on specific outcomes. There were no clinical trials published. However, in ClinicalTrials.gov we identified two studies underway involving smart watches (2, 8%). For studies that have been completed and published, the number of participants or patients ranged from 1 to 143. The highest number of studies were conducted in the USA (10, 42%), followed by three studies in Germany (13%) and two studies in United Kingdom (8%). The remaining nine studies were conducted in different countries around the world.

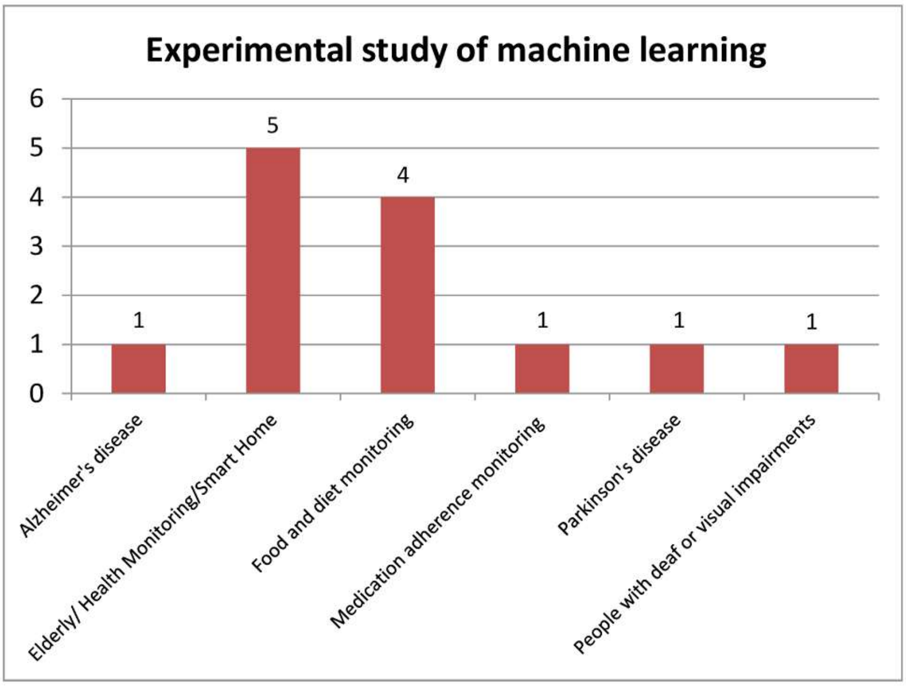
With respect to the target population, six studies (25%) focused on smart watch use among the elderly, either for health monitoring or in a smart home environment, and five studies (21%) focused on patients with Parkinson's disease (PD). The third and fourth largest groups of studies focused on food and diet monitoring (4, 17%) and on medication adherence monitoring in patients with chronic diseases (3, 13%). Although there were dozens of smart watches to choose from, the most commonly used platforms for healthcare research were those involving the Android Wear (11, 46%). Among those, the most commonly used brand was the Samsung Galaxy Gear (6, 25%) followed by the Pebble Smartwatch (4, 17%). Although most studies featured the smart watch as the primary subject of study, seven studies (29%) utilized both a smart watch and a smart phone as main components of the study methodology. Study characteristics, including study design, target population, and platform used, etc., are summarized in **Table 3.2**. Number of publications and types of study design in terms of the target population is shown in **Figure 3.2 (A)**. For the most commonly used study methodology, the experimental study of machine learning, the number of publications with respect to different target population is presented in **Figure 3.2(B)**.

In terms of utilizing the accelerometer or gyroscope functionalities that smart watches general exhibit, most of the selected studies used at least one of these functionalities as the main concept of applications for their studies (16, 67%). Of them, five studies (21%) used the combination of an accelerometer and a gyroscope [11-12, 28-30]. Seven studies did not utilize any sensor in their study intervention [14-15, 18, 23-24, 27, 33]. Instead, smart watches were used as assistive devices for patients with specific needs via their screen or voice as input or reminders. One study utilized physiological sensors to monitor activity in the elderly by recording heart rate and skin temperature [31].

In most of the studies (18, 75%) there was no mention of human-computer interaction, user-centered design, or pre-implementation usability testing as part of their study design or intervention. However, two studies utilized user-centered design during the design phase [15,22]; one study had a brief evaluation of the user interface [27]; and three studies mentioned usability testing in the context of future work [12, 18, 20].



(A)



(B)

Figure 3.2. (A). Number of publications (Y-axis) and types of study design in terms of the target population (X-axis). **(B).**Number of publications (Y-Axis) with respect to different target population (X-axis) for study design using experimental study of machine learning.

Table 3.1. Description of All Articles about Healthcare Related Smart Watch Research.

Author & year	Publication Type	Study Design	Target Population	No. of participants/ patients	Study Aims	Study Intervention	Technology-related findings	Platform/Type of Smart Watch	Type of sensors used
Casilari 2015 [11]	Journal Article	Experimental study of machine learning	Seniors vulnerable to unintentional injuries caused by falls	4 volunteers	To propose and evaluate a fall detection system that benefits from the detection performed by two popular personal devices: a smartphone and a smartwatch (both provided with an embedded accelerometer and a gyroscope).	Participants wearing both devices with diverse fall detection algorithms for fall detection. A fall is only assumed to have occurred if it is simultaneously and independently detected by the two Android devices.	The joint use of the two detection devices increases the system's capability of fall detection.	Android Wear/ LG G Watch R model	Accelerometer and gyroscope
Mortazavi 2015 [12]	Journal Article	Experimental study of machine learning	Health Monitoring (Elderly cancer patients)	20 volunteers	To develop a system to be used in future remote health monitoring systems and by validating the smartwatches' ability to track the posture of users accurately in a laboratory setting.	A pervasive sensing system that could be worn by the user at all times to accurately track the activity levels.	The smartwatch alone can accurately detect posture and transitions between postures.	Android Wear/ Samsung Galaxy Gear	Accelerometer and gyroscope
Patterson 2015 [13]	Journal Article	Prospective observational	Children, adolescents, and young adults being admitted to the Epilepsy Monitoring Unit	143 patients	To assess the sensitivity and reliability of a wrist-worn smart watch monitor to detect various seizure types.	A SmartWatch device that works by continuously monitoring movements and can instantly send alerts to connected caregivers about repetitive, shaking motions.	The SmartWatch detected only 16% of seizures of the total, 31% of the generalized tonic-clonic seizures, and 34% seizures associated with rhythmic arm movements.	The SmartWatch by SmartMonitor	Accelerometer
Kalantarian 2015 [14]	Journal Article	Experimental study of machine learning	People needed food and diet monitoring	10 volunteers	To analyze the overall applicability of a smartwatch based food-intake monitoring method for identification of chews and swallows activity.	A smartwatch device that incorporated audio signal-processing techniques with data recorded using its microphone.	The weighted average precision, recall, and F-Measure from their experiments were 94.7%, 94.4%, and 94.4% respectively.	Android Wear/ Samsung Galaxy Gear	No sensor used

Fardoun 2015 [15]	Journal Article	Experimental study of machine learning	Alzheimer's disease patients	41 patients	The evaluation of a prototypal assistive technology for Alzheimer's disease patients that helps them to remember personal details of familiar people.	A novel assistive software for patients based on face detection and recognition using a smart watch, a smart phone and the cloud environment.	The prototype showed correct results as a personal information system based on face recognition, with some usability problems appeared.	Android Wear/ Samsung Galaxy Gear	No sensor used
Carlson 2014 [16]	Conference Proceedings	Experimental study of machine learning	Smart home system for elderly	1 volunteer	To build a smart home behavioral monitoring system capable of classifying a wide variety of human behavior.	The system used a customized smart watch worn by the user to broadcast data to the wireless sensor network (WSN), where the strength of the radio signal is evaluated at each WSN node to localize the user.	The system is capable of providing accurate localization results in a typical living space.	The smart watch (Chronos, Texas Instruments running custom firmware)	Accelerometer
Wile 2014 [17]	Journal Article	Controlled experimental	Patients with tremor caused by Parkinson disease (PD) or essential tremor (ET)	41 patients	To discriminate PD and ET tremor in a outpatient clinic using a wireless smart watch device.	Recordings were made with a smart watch device on the predominantly affected hand (all patients), and with an analog accelerometer (10 patients) on hands at rest and outstretched. Mean power at the first four harmonics was calculated and used to classify tremor as PD or ET.	The result showed that 80% of patients were correctly classified as having PD or ET (Cohen's kappa = 0.61, SE = 0.14), resulting in a sensitivity of 100% (95% CI 71.33–100%), and a specificity of 64.3% (95% CI 35.2–87.1%) for identifying PD postural tremor.	WIMM One Wearable Android Device (Ca, USA)	Accelerometer
Sailer 2015 [18]	Conference Paper	Randomized controlled trial	Elderly people needed medication monitoring	NA	To investigate on the usage of smart watches as supportive tool to increase medication adherence.	A prototype of a smart watch-based medication reminder applications	Study underway	Samsung Gear S (Tizen OS)	No sensor used
Gazit 2015 [19]	Conference Paper	Controlled experimental	Parkinson's disease patients	9 patients & 7 controls	To evaluate the feasibility and validity of using a commercially available SmartWatch to quantify Parkinson's disease (PD) motor symptoms.	Patients and controls wore the GENEActiv watch on the dominant hand while they performed the Timed Up and Go test and 60s of walking +/- dual tasking (DT). Patients were tested in clinically defined ON and OFF states.	Several measures differed in controls and PD (OFF and ON) and improved in ON, compared to OFF.	GENEActiv watch	Accelerometer

Ahanathapillai 2015 [20]	Journal Article	Experimental study of machine learning	Smart home system for elderly	30 volunteers	To develop assistive technology for older people using low cost, off-the-shelf devices to provide affordable in-home unobtrusive monitoring and web communications.	The Unobtrusive Smart Environments for Independent Living (USEFIL) project includes a wrist wearable unit and other specific devices with communication backend.	The wrist wearable unit offers an excellent and minimally intrusive way to monitor a person's well-being by the various health indicators extracted from its inbuilt sensors.	The Z1 smartwatch	Accelerometer
Gruenerbl 2015 [21]	Conference Proceedings	Controlled experimental	Patients with Out of Hospital Cardiac Arrest (OHCA)	41 volunteers	To evaluate the CPR watch application using frequency and compression depth as the main quantitative indicators in three modalities.	Using the accelerator of the Smart-Watch, a CPR feedback application was developed with three screen-based feedback functionalities including frequency, depth, and counting.	The evaluation demonstrated that the Smart Watch feedback system provided a significant improvement in the participant performance.	Android Wear/ LG G Watch R model	Accelerometer
Porzi 2013 [22]	Conference Proceedings	Experimental study of machine learning	People with Visual Impairments	15 volunteers	To develop a system based on the combination of a mobile phone and a smart watch for gesture control, for assisting low vision people during daily life activities.	The signals of the smartwatch's integrated accelerometers are used as input to a robust user-independent gesture recognition algorithm runs on the mobile phone.	The implemented algorithm running on a Sony Xperia Z smartphone achieves a better processing time to recognize a single gesture, making it suitable for the use in the proposed application.	Android Wear/ Sony SmartWatch	Accelerometer
Mielke 2015 [23]	Conference Proceedings	Qualitative semistructured interview	Deaf people	6 patients	To find out about the users' needs and expectations of deaf people being interviewed.	A Wizard of Oz experiment was implemented to simulate the environmental sound alert application. Whenever the wizard heard one of four sounds he triggered the application at the watch using a Bluetooth connected smartphone. Then the watch showed the notification associated with the sound.	The use of a smartwatch as an environmental sound alert was appreciated by all participants of the interview, and such a device would be a valuable aid in their daily life.	Android Wear/ LG G Watch	No sensor used

Dubey 2015 [24]	Conference Proceedings	Controlled experimental	Parkinson's disease patients with voice and speech disorders	3 patients & 3 controls	To assess the performance of the smartwatch with EchoWear technology compared with traditional speech recording methods in a controlled acoustic environment.	A smartwatch-based system (EchoWear) was developed to collect data on various attributes of speech exercises performed by patients with PD outside of the clinic. The performance of EchoWear data were validated using healthy adults as controls.	The results suggest that EchoWear data were comparable to data collected using traditional speech recording methods. The data support EchoWear as a reliable framework to collect speech data from inhome speech exercises.	Android wear/ Asus Zenwatch	No sensor used
Lee 2015 [25]	Conference Proceedings	Experimental study of machine learning	Smart home system for elderly	3 volunteers	To propose a home occupant tracking system that uses a smartphone and an off-the-shelf smartwatch without additional infrastructure.	The system uses a smartphone to obtain location information and a smartwatch to record activity fingerprints for inferring a user's location. A hidden Markov model using the relationship between home activities and the room's location was designed.	Extensive experiments showed that the system tracks the location of users with 87% accuracy, even when there is no manual training for activities.	Android Wear/ Samsung Galaxy Gear	Accelerometer
Thomaz 2015 [26]	Conference Proceedings	Experimental study of machine learning	People needed food and diet monitoring	28 volunteers	To develop and evaluate a practical solution for eating moment detection with wrist-mounted inertial sensors.	Participants wore a smartwatch and data were trained in laboratory first and two evaluation plans were conducted in-the-wild, including 7 participants over the course of one day, and a naturalistic study with one participant over a month.	The system recognized eating moments in two free-living condition studies, with F scores of 76.1% (66.7% Precision, 88.8% Recall), and 71.3% (65.2% Precision, 78.6% Recall).	Pebble smartwatch	Accelerometer
Maglogiannis 2014 [27]	Conference Proceedings	Proposed system	Patients with chronic illnesses needed medication monitoring	1 patient	To present a multimodal electronic reminder system that supports the use of smart devices and utilizes the recently introduced Pebble smartwatch.	By using PC or android device to create the reminders and store in a Cloud infrastuture, reminder notification are pushed to the smartwatch with audio and visual alerts. Other registered users can use a web application and create or update reminders.	The system provides an easy and automated method of measuring patient nonadherence by self-reports via smartwatch. A study of the system in practice shall be conducted in order to verify expected results in patient adherence and test the reliability of the system's adherence reports.	Pebble smartwatch	No sensor used

Sen 2015 [28]	Conference Proceedings	Experimental study of machine learning	People needed food and diet monitoring	6 volunteers	To explore how far the multiple sensors (accelerometer and gyroscope) on a wristworn smartwatch can help to automatically infer both such gestural and dietary context.	The inertial sensors on the smartwatch was used to identify an eating gesture, and the series of all such gestures that define a complete eating episode. Additionally, camera on the watch was activated to capture the plate's content and offline image analysis techniques was used to automatically identify the type and the quantity of the food.	The experiments indicate that the detection of eating activity can be reliably achieved using a smartwatch and that, at certain points in a person's eating gesture, the smartwatch camera can provide useful and un-occluded view of the food content.	Android Wear/ Samsung Galaxy Gear	Accelerometer and gyroscope
Sanders 2014 [29]	Conference Proceedings	Experimental study of machine learning	Parkinson's disease patients	10 volunteers	The study aims were to quantify the advantages of using multi-modal monitoring to detect the signs of PD, and to determine if the PD signs could be assessed without prior knowledge of an individual's activity type.	The subjects were instrumented with the remote monitoring system consisting of a belt mounted smartphone and a watch. Data were colletced from the accelerometers and gyroscope while the subjects moved normally or while simulating PD symptoms of bradykinesia, tremor, and postural instability.	The average discrimination accuracy between parkinsonian and normal conditions was 0.88. Additionally, individual symptoms of the disease could be accurately detected in > 0.8 of cases.	Linux/ Texas Instruments EZ430-Chronos watch	Accelerometer and gyroscope
Kalantarian 2015 [30]	Conference Proceedings	Experimental study of machine learning	Patients with chronic illnesses needed medication monitoring	17 volunteers	To propose a smartwatch-based system for detecting adherence to prescription medication based the identification of several motions using the built-in triaxial accelerometers and gyroscopes.	Training data was collected from five subjects wearing the watch on their dominant hand and were asked to open the pill bottle. The results were used to formulate the algorithm constraints, which were then tested on the remaining subjects. An online survey was also conducted for the Survey of drug taking habits.	The system is able to detect the act of twisting the cap of a medicine bottle open, and the removal of a tablet or pill by pouring the pill into the palm of the hand. The online survey suggested that some individuals will need to adapt their watch usage in order to recognize the motions suggested.	Android Wear/ Samsung Galaxy Gear	Accelerometer and gyroscope

Jovanov 2015 [31]	Conference Proceedings	Controlled experimental	Health Monitoring	1 volunteer	To present analysis of use and reliability of continuous physiological measurements of Basis watch and comparison with the standard polysomnographic monitoring systems.	Continuous monitoring using the smartwatch during 122 days, or 173,410 measurements was analyzed. Physiological measurements are validated with two standard monitors Zephyr Bioharness 3 and polysomnographic monitor SOMNOscreen+ during sleep.	Preliminary results indicate that the physiological monitoring performance of existing smartwatches provides sufficient performance for longitudinal monitoring of health status and analysis of health and wellness trends.	Basis Peak Smartwatch	Heart rate and temperature sensors
Ye 2015 [32]	Conference Proceedings	Experimental study of machine learning	People needed food and diet monitoring	10 volunteers	To propose a method of automatic eating detection in detecting chewing motion using a head-mount accelerometer and in detecting hand-to-mouth gestures using a wrist-worn accelerometer during eating activities.	A Google Glass and a Pebble Watch with pre-installed apps and an Android Phone with a data assembling app were provided to each participant. The acceleration data on Pebble and Glass were continuously sampled at 50Hz and transmitted to the phone through Bluetooth. Eating activity was detected using three popular classification algorithms.	Combining the features from both devices can achieve 97% cross-person eating detection accuracy and the average error when predicting duration of eating meals was only 105 seconds.	Pebble smartwatch	Accelerometer
Steins 2015 [33]	Study registered in ClinicalTrials.gov	Randomized controlled trial	Patients admitted for acute/sub-acute in-patient neurorehabilitation of a first stroke	200 patients (Estimated)	To determine the effect of augmented activity feedback by smart watches to support in-patient stroke rehabilitation.	Participants will wear a smart watch every weekday during in-patient rehabilitation to monitor activity levels while receiving their usual care. Augmented feedback will be provided by the smart watch. For participants assigned to the control group, the smart watch will not provide any activity feedback.	No Study Results Posted	Smart Watches	No sensor used

Faber 2015 [34]	Study registered in ClinicalTrials.gov	Prospective observational	Parkinson's disease patients	1000 patients (Estimated)	To evaluate the feasibility and compliance of usage of wearable sensors in PD patients in real life. Moreover, an explorative analysis concerning activity level, medication intake and mood will be done.	Participants will wear a set of medical devices (Pebble Smartwatch, fall detector) and they will use a smartphone with the Fox Insight App (Android app), 24/7, during 13 weeks. Primary measures of interest are: 1) physical activity, falls and tremor, measured by the axial accelerometers embedded in the Pebble watch and fall detector; and 2) medication intake and mood reports measured by patients' self report in the Android app.	No Study Results Posted	Pebble smartwatch	Accelerometer

Table 3.2. Characteristic of Selected Articles.

Categories		N=24 (100%)
Years Published	2013	1 (4%)
	2014	4 (17%)
	2015	19 (79%)
Publication Type	Journal Article	7 (29%)
	Conference Paper	2 (8%)
	Conference Proceedings	13 (54%)
	Study registered in ClinicalTrials.gov	2 (8%)
Study Design	Controlled experimental	5 (20%)
	Experimental study of machine learning	13 (54%)
	Prospective observational	2 (8%)
	Randomized controlled trial	2 (8%)
	Proposed system	1 (4%)
	Qualitative semistructured interview	1 (4%)
Target Population	Elderly/ Health Monitoring/Smart Home	6 (25%)
	Epilepsy/Seizure patients	1 (4%)
	Alzheimer's disease	1 (4%)
	Out of Hospital Cardiac Arrest	1 (4%)
	People with deaf or visual impairments	2 (8%)
	Parkinson's disease	5 (21%)
	Stroke patients	1 (4%)
	Food and diet monitoring	4 (17%)
	Medication adherence monitoring	3 (13%)
Platform/Smart Watch	Android Wear	11 (46%)
	Pebble Smartwatch	4 (17%)
	Others	9 (38%)
Locations of the Study	United States	10 (42%)
	Germany	3 (13%)
	United Kingdom	2 (8%)
	Others	9 (38%)

3.3.4 Discussion

Our review of the literature revealed that, since late 2013, there were 24 studies involving smart watches in healthcare applications that met our inclusion criteria. Given their recent appearance on the commercial market, it is not surprising that the majority of these studies were published in 2015. This review discloses a wide variation in study design and target population. As shown in

Figure 2 (A) and **2 (B),** the number of publications in terms of the study design and target population reflect the heterogeneity of using smart watch in healthcare. In the following discussion, we will examine the platform used, other related technologies, target population, usability testing, study design and their potential bias, and type of sensors used.

Based on our review, the platform most commonly used in healthcare research was that of the Android Wear, and there was no research utilizing that of the Apple Watch, which is not surprising since the first Android Wear started shipping in July 2014, whereas the Apple Watch was not available until April 10, 2015. While our study was designed to review the literature on healthcare applications of smart watches, a large amount of selected studies utilized the combination of a smart watch and a smart phone [11, 15, 22, 25, 27, 29, 34]. Although the smart watch has emerged as a standalone computing device intended to be used by the wearers with or without the concomitant use of a smart phone, currently most smart watches rely on a smart phone to assist their computing or connection abilities. Perhaps because smart phones are so prevalent today, some researchers chose to conduct research based on the combination of a smart phone and a smart watch, or compare usage between the two. With the launching of the Apple Watch OS 2.0 and a later version having native apps support (that can run on the watch itself instead of the iPhone), and with the Android Wear, which can now work on its own with cellular support via 4G connectivity [35-36]. It is possible that wearable smart watches will become a reality for content providers and therefore an opportunity for healthcare applications.

One study used a multimodal approach, including a wrist worn smart watch, a Microsoft Kinect, and other devices, to act as an assistive technology for activity monitoring in the elderly [20]. Microsoft Kinect was developed for gaming purpose, however, developers have recognized that the motion sensing camera has potential for healthcare applications, due to its ability to track movements in three-dimensional (3D) space and to Kinect's open software development kit [37]. In the literature, there are several studies that utilized Kinect to assist the diagnosis or monitoring disease activity for movement disorders especially in PD [38-42]. A performance comparison of Kinect and smart watches demands further investigation.

Smart watches are being used as a platform for a variety of healthcare applications. Based on our review, the most common healthcare applications using smart watches focused on health monitoring or smart home environment for the elderly [11-12,16, 20, 25-26]. Another major application is with chronically ill patients needing medication adherence monitoring [18,27,30]. This focus is particularly relevant since the United States is projected to experience rapid growth in its older population in the next four decades [43], which will increase demand for chronic care. According to a report released by Centers for Disease Control and Prevention (CDC), approximately 80% of older adults have one chronic condition, and 50% have at least two [44]. As seniors live longer, technology may become an indispensable aspect of modern life. There are a number of care issues related to seniors, individuals with disabilities, and their caregivers throughout the aging process, which can potentially benefit from technology. Among them, fall detection and prevention, chronic disease management, and medication management are the leading three identified by the Aging Services Technology Study [45].

Fall detection for elderly adults has been playing an important role in smart home environment [46]. Thousands of research articles have been published in the literature, and a variety of products are available on the market for automatic fall monitoring. Although existing fall detection studies have been conducted with different sensor positions, the devices are usually placed on both the upper and lower body, and the most common device placement position is the waist [47]. With the advent of smart watches characterized by miniaturization and unobtrusiveness, wide applications of fall detection algorithm in such devices are possible in the future. Nevertheless, use of a wearable fall detection devices by older adults in real world settings demands further research and improvement in accuracy [48].

Another category of research found on this review is related to smart watch applications in patients with neurologic diseases, including PD, Alzheimer's disease, epilepsy, and stroke [13,15,17,19,24,29,33,34]. Neurologic diseases are amongst the major causes of disabilities, and those coping with these disabilities may benefit from assistive technology using smart watches. These studies used a variety of study designs and interventions utilizing smart watches, including those intended to: help Alzheimer patients recognize familiar people, enable analysis and diagnosis of tremors, detect types of seizures in children and young adults, assist PD patients with voice and speech disorders, and assess symptoms and motor signs of PD. In the two ongoing clinical trials, researchers are testing the use of smart watches for monitoring activity feedback during in-patient stroke rehabilitation, and for monitoring physical activity (including falls and tremor) in PD patients [33-34]. In one of the larger clinical studies by Patterson [13] the use of a smartwatch to detect seizures had disappointing results, suggesting that while their use in laboratory settings holds promise, further development and evaluation in clinical settings are needed.

For assistive technologies to be successfully implemented into the current workflow, gaps between design phase and user experience must be bridged. This is especially important in the case of smart watches given their small screen size. Another focus from this review emphasizes the importance of enhancing the user experience through usability testing, to evaluate a product before implementation. However, only two studies utilized user-centered design in design phase, and only one study described a user interface evaluation [15, 22, 27]. No studies followed rigorous usability testing guidelines [49]. Usability testing has been used to evaluate a variety of assistive devices, however, this testing often excluded individuals with disabilities [50]. Among the selected articles, two studies focused on groups of people with special needs, including patients with visual or hearing impairment [22-23]. Both of these studies utilized a combined smart watch - smart phone system. One aimed to develop a system for gesture control in assisting low vision people during daily life; the other was designed to identify the needs and expectations of deaf people related to using the smartwatch as an environmental sound alert. It will be important to consider user-centered design and usability testing in future trials.

Although most of the studies we identified focused on health monitoring and patients with chronic illnesses, one study aimed to help patients experiencing out-of-hospital cardiac arrest (OHCA). Gruenerbl et al. developed a Cardiopulmonary Resuscitation (CPR) feedback application for a smart watch, designed to allow untrained bystanders to perform CPR correctly in emergencies [21]. Using the accelerometer of the smart watch, a CPR application was developed to provide real time feedback during chest compression CPR with three screen-based feedback functionalities: frequency, depth, and counting. This study enrolled a total of 41 participants to perform CPR in manikins. Using the smart watch for assistance was significantly associated with increased rate and depth of chest compression, although the findings were not as promising as desired in terms of high quality CPR [51]. The application developed by Gruenerbl and colleagues did provide a brand new concept of using smart watches to assist bystander CPR, however, it provided only on-screen reminders without audio and vibration feedback. Furthermore, there was no usability testing on the product.

In this review, more than half (13, 54%) of the selected studies adopted a quantitative approach by using experimental design of machine learning. Since most smart watches exhibit an accelerometer and a gyroscope, it is possible to utilize the motion detection sensors for different patient populations. As a form of artificial intelligence, machine learning involved the training of a computer based on data collected from prior examples [52]. For healthcare applications using smart watches via machine learning approaches, health related data can be collected and combined with appropriate algorithms to provide valuable results. Such data collecting process constitutes what Simon called "the sciences of the artificial" [53], and experimentation is the alternative way for learning algorithms to formalize complex analysis when theoretical evidence is lacking. As Langley wrote in his influential editorial entitled "Machine Learning as an Experimental Science" in the journal Machine Learning, an experiment involves systematically varying one or more independent variables and examining their effect on some dependent variables [54]. In order to improve the performance of dependent measures, a machine learning experiment requires a number of observations made under different conditions [55]. As shown in **Figure 2(B),** motion detection using smart watches and machine learning can be found in a variety of healthcare applications including elderly health monitoring or smart home, food and diet monitoring, medication adherence monitoring, and movement disorders. Experiments have to be conducted to collect annotated datasets for training purpose. Based on our review, all selected articles rely on supervised machine learning algorithms for the tasks of classification or pattern recognition, and most studies chose N-fold cross validation. Threats to validity include small sample size, classifiers used, and lack of testing with alternative datasets.

Although a detailed discussion is beyond the scope of this review, there are a variety of factors that may affect performance measures in healthcare applications using smart watches and machine learning algorithms. In particular, the use of sensors and the related performance measures may be of interest to some of our readers. With respect to types of sensors used in the included studies, 67% of studies used at least one sensor and 21% used the combination of an accelerometer and a gyroscope. An accelerometer is a sensor which measures acceleration in the 3D coordinate system and a gyroscope detects rotation. Theoretically, the combination use of both sensors can increase the accuracy of motion detection in selected target population. Empirically, Alias et al. showed significant results using both gyroscope and accelerometer sensors with some filters in a stabilized and moving platform application [56]. Due to the heterogeneity of selected studies, however, there is currently insufficient evidence to draw any relevant conclusion regarding the performance of the combined sensors use. Expanded experimental studies are needed.

In sum, the impact of the smart watch in real world clinical practice or even emergency settings has yet to be determined. For smart watches to be commonly used in the clinical arena, researchers will need to adopt more rigorous study designs and conduct usability testing before full implementation of smart watches technologies into clinical settings.

3.3.5 Limitations

The smart watch is not a new concept, however with the advent of Android Wear and Apple Watch it has attracted wide attention. Research articles regarding healthcare applications of smart watches are scarce, based on our search of the literature. In order to expand the range of our review, we searched all pertinent databases available, and we included studies presented in medical conferences, as well as ongoing clinical trials. In the search terms, we used smart watch or smartwatch as the main keywords to ensure a broader coverage of articles to be considered for inclusion. Due to the heterogeneous nature of different databases, the quality of the included studies varied greatly. Nevertheless, this review highlights that while there is potential for healthcare applications using smart watch technology, more rigorous studies of their use in clinical settings is needed.

3.3.6 Conclusions

Smart watches exhibit the advantages of small form factor and can be wrapped on the wrist for daily wear. Although the reported use of smart watch applications for patients with chronic diseases appear promising, we found only one study focused on managing patients in critical or emergency conditions. In order for these devices to gain wide acceptance by health professionals, rigorous research on their accuracy, completeness and effect on workflow should be conducted before smart watch applications are integrated into clinical practice. User studies to investigate ideal functionality, user interface design and usability for a variety of clinical and patient settings are needed. Further research is required to understand the impact of smart watch applications on clinical practice.

3.4 Concluding Remarks

This chapter provides a literature review of smartwatch applications in healthcare domain. The results show that a large proportion of the identified studies focused on applications involving health monitoring for the chronically ill elderly. Based on this review, few studies utilized UCD or user interface evaluation in the design phase. There was a lack of detailed description of UCD or usability testing before implementation. To develop an assistive device with a good understanding of healthcare provider needs that fits in with the clinical workflow, it is necessary to consider UCD in the design phase and usability test before conducting the experiment in the clinical settings.

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CHAPTER 4. THE DEVELOPMENT OF A SMARTWATCH APP FOR CPR

4.1 Introduction

The overarching goal of this dissertation research is to develop and test an application for smartwatches to improve CPR quality in patients with cardiac arrest either in prehospital, emergency, or inpatient settings for healthcare providers. Chapter 2 reviewed the current CPR standard and surveyed the up-to-date research works or products of how to measure the quality of CPR and provide feedback. The literature review described in Chapter 3 synthesized research studies involving the use of smartwatch devices for healthcare and confirmed the potential of smartwatches in the clinical setting. Within the context of developing the application for a smartwatch to provide feedback on CPR quality, the addressed research question for aim 1 of this dissertation was: "What user interface is best suited for the CPR watch to meet the needs of rescuers?"

The first specific aim of this study was: to develop an application (app) for a smartwatch as an assistive device during CPR for healthcare providers through UCD and usability testing. To answer the question, we used a commercially available Android Wear, the ASUS ZenWatch 2 (model WI501Q, Taipei, Taiwan), as the main part of our system architecture. By using UCD methodology with the focus on maximizing the user experience and suiting specific needs in clinical settings [1], the interface of for the smartwatch app was developed for use by healthcare providers to improve the CPR quality. A brief usability test was also administered using the standardized System Usability Scale [2].

In this chapter, the system architecture of the application is described, including the wearable (smartwatch) and mobile (smartphone) applications. In addition, a novel CCR estimation algorithm based on a smartwatch with a built-in accelerator was introduced. For depth detection, another CCD estimation algorithm will be introduced in the next chapter (Chapter 5).

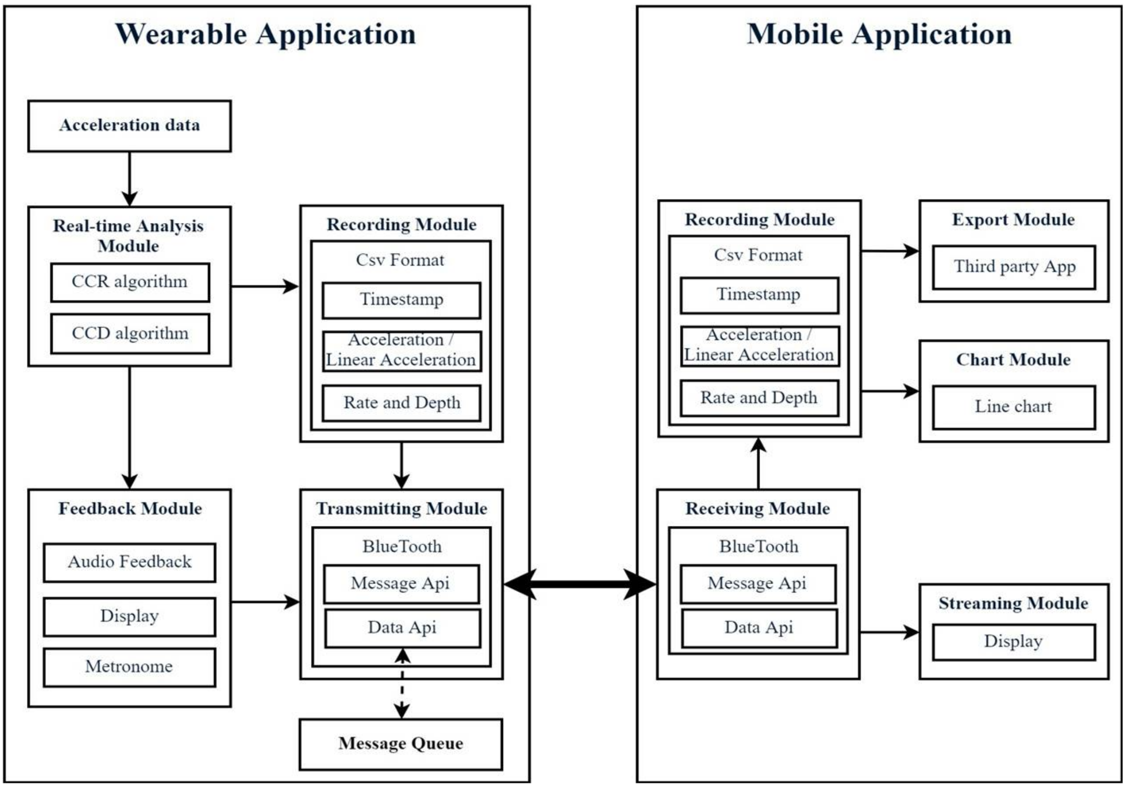


Figure 4.1. The system architecture.

4.2 System Architecture

Figure 4.1 shows the system architecture and the data flow of the two applications, the wearable (smartwatch) application and the mobile (smartphone) application, connected by Bluetooth after pairing. The wearable application is the main focus of this study, which detects the CCR/CCD and provides real-time feedback while worn on the wrist by rescuers. In this design, the wearable application can actually be used as a standalone application. If connected with a smartwatch application, a smartphone can stream the records of CCR and CCD, export records to another computer, and check the CPR performance from the records.

The wearable application and mobile application were developed using Android Studio (Google, United States; JetBrains, Czech Republic) 3.0.1 with Java SE Development Kit (JDK) 1.8.0_152. In this study, a mobile device running Android 5.0 (API Level 21) or higher is required, and currently it supports up to the newest Android 8.1 (API Level 27). For the wearable application, it supports both Wear 1.x and 2.x, but a smartwatch with a speaker is recommended because of the application is a real-time audiovisual feedback device in this study.

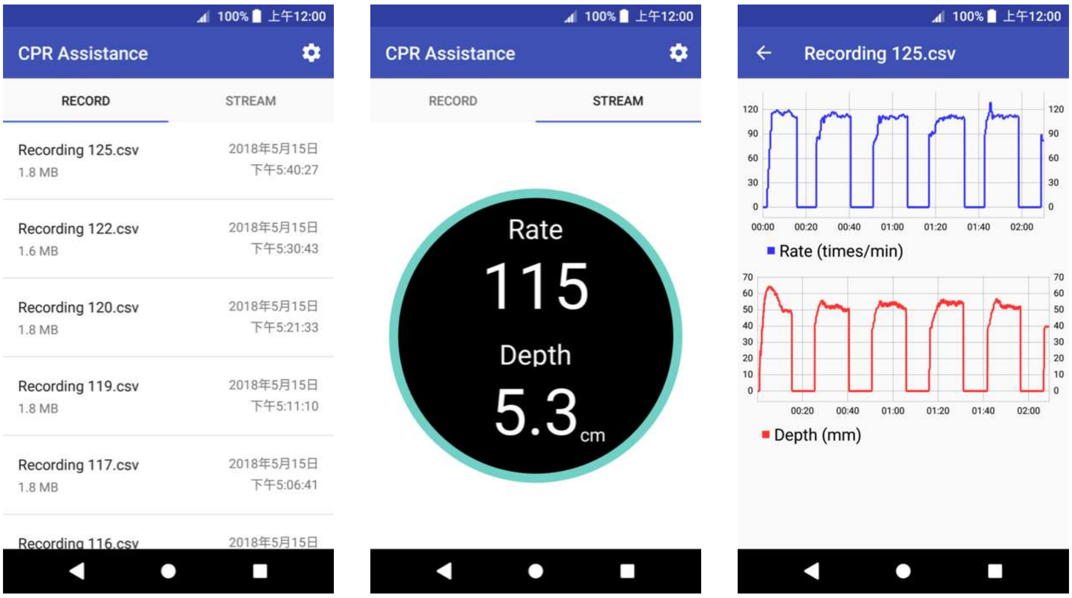


Figure 4.2. Screenshots from the mobile application.

4.2.1 The Mobile Application

In this study, the mobile application is deployed on the SONY Xperia XZ Premium, with Android 8.0.0 (API Level 26) and Google Play service 12.6.85. We implemented the Wearable Listener Service in the receiving module to listen for the message received and data changed from the wearable. The message received event is used for receiving real-time streaming data, and the received data are then broadcasted to the streaming module for displaying. On the other hand, data changed event is used for receiving the recorded CSV files, which are saved to the device storage. Syncing mechanisms are mentioned in the next section. Additionally, the mobile application has a chart module that plots the recorded data of each session on the line chart, and an export module that allows users to share the recorded file using third party applications. Screenshots of the developed mobile application are shown in **Figure 4.2**.

4.2.2 The Wearable Application

In this study, the wearable application was deployed on the ASUS (Taipei, Taiwan) ZenWatch2 Model WI501Q, with Android 7.1.1 (API Level 25), Wear OS2.12.0 and Google Play Service 12.6.85. The real-time analysis module continuously receives the acceleration data and calculates the CCR and the CCD using the algorithms discussed in **Section 4.4** and **Chapter 5**. The display function (user interface) of the feedback module shows the real-time estimated CCR and CCD on the watch screen with a 5Hz refresh rate.

The estimated values of CCR and CCD are sent to the transmitting module and delivered to the mobile application if any mobile smartphone is connected. For the purpose of real-time streaming, the Wearable's Message Send Method was used to transmit the data to the mobile node. If the Android system cannot immediately deliver the message, the message will be dropped to avoid streaming data that are delayed for long periods. This only happens when the smartwatch is too far from the mobile phone, or during a partial disconnection or interruption of the signal between the two devices. The feedback module is also comprised of an audio module that gives verbal commands to help rescuers better adhere to the guideline-recommended rate (100-120 min-1) and depth (50-60 mm) of high-quality CPR. The detailed audio feedback mechanism is described in **Chapter 6** (paper 3).

During the chest compression session, the recording module continuously writes the received 3-axis acceleration data, corresponding timestamp, and calculated rate and depth to a temporary CSV file in the smartwatch. After the session is finished, the recorded file is sent to the transmitting module for synchronizing. If the Android system cannot immediately deliver the messages, the messages are buffered and synced when the connection between the two devices is re-established. Furthermore, we convert the file to a byte stream and create the Asset for transferring. Assets automatically handle caching of data to prevent retransmission and to conserve Bluetooth bandwidth, and can be larger than the limitation of the data item (100 KB).

4.3 User-Centered Design (UCD) of the Wearable (Smartwatch) App

Based on the users' (healthcare providers or laypersons) specific purpose, the user interface of a smartwatch app was designed using UCD techniques with the active involvement of users for a clear understanding of user and task requirements, iterative design and evaluation, and a multi-disciplinary approach [1]. During CPR, one should push on the patient's chest to achieve the goal of providing effective chest compressions of adequate rate (with the target of 100-120 compressions per minute) and depth (5-6 cm for adults) with minimal interruptions to victims of cardiac arrest [3]. User interfaces for wearable apps differ significantly from those built for handheld devices. Apps for wearables should follow the design principles of Apple Watch, or Android Wear and implement the recommended UI patterns, which ensure a consistent user experience across apps that are optimized for the wearables. To make the best use of the wearables, automatic audio feedback instruction was integrated into the UI design of the wearable devices with the built-in speaker.

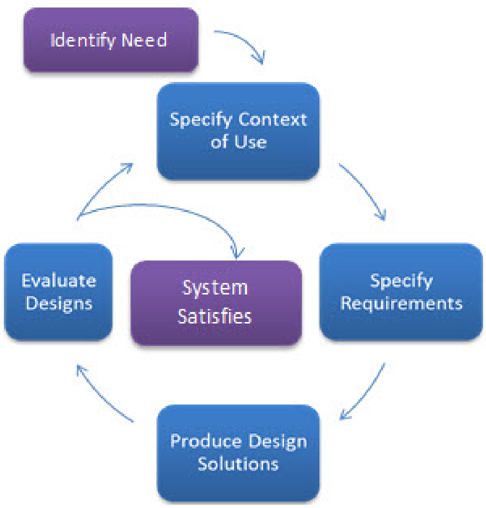


Figure 4.3. The general phases of the UCD process [4].

4.3.1 The Design Process

This study follows the general phases of the UCD process addressed by usability.gov and illustrated in **Figure 4.3** [4].

●**Specify the context of use**: Identify the people (healthcare providers or laypersons) who will use the product, what they will use it for (for gaining feedback), and under what conditions they will use it (during CPR).

●**Specify requirements**: Identify the user goals (to improve CPR quality).

●**Produce design solutions**: This part of the process was done from a rough concept to complete design, and the results are described in **Section 4.3.3.**

●**Evaluate designs**: Evaluation - through usability testing with actual users (to be discussed in **Section 4.3.2)**.

Five participants (two ED physicians and three ED nurses) were enrolled for the design phase and another twelve participants (three ED physicians and nine ED nurses) for the usability testing. The iterative UCD process included 10 interviews (two for each participant) involving 5 participants and one usability testing involving another twelve participants for the final results. The semi-structured interviews were conducted with representative end users (ED professionals) to test the prototype of a smartwatch app that aims at improving the delivery of CPR quality for victims of cardiac arrest. Interview questions were developed based on discussions with senior ED physicians and nurses. The first interview had four sections focused on participant demographics, prior CPR experiences, user preferences and expectations for feedback devices during CPR, and perceptions of using the smartwatch as a CPR feedback device. The second interview focused on the perceptions of the smartwatch app for CPR feedback and how to improve it by presenting some of the smartwatch prototypes we developed. Data were analyzed using the ethnographic approach for qualitative data analysis and interview transcripts were evaluated to identify emerging themes. There were four thematic categories identified by this qualitative approach (**Table 4.1**). This initial user research provided the necessary evidence for the conceptualization and final product of the app, which was subsequently used in usability testing. This UCD process explored the intuitiveness of the app and identified user preferences and expectations. The final design of the smartwatch app ensured that functionality was aligned with clinical needs and practitioners' preferences.

Table 4.1. The identified thematic categories.

Thematic categories	Description
Perceptions of feedback devices use during CPR	Will it be too bulky to be used? It must be very expensive. Interruption on clinical workflow.
Perceived time spent on setting the devices	How long will it take to set up the device? Will it delay the completion of my work? Any extra time for documentation needed?
Smartwatch usability issues	The screen size is too small and difficult to read during chest compression. Information displays should be the simpler the better. The speaker volume should be increased. Metronome tempo can be set at 110 to gain adequate guidance in rate. The feedback interval can be adjusted at 3 seconds to avoid annoying influence.
Influence of smartwatch use on CPR quality	This app is well suited for CPR training. I am excited to see its clinical application in the future.

4.3.2 The Usability Testing

We measured usability by 12 participants who accessed the product of the smartwatch app by administering the standardized System Usability Scale (SUS) [2]. SUS is a validated composite measure, which is scored from 0 to 100, with higher scores representing greater usability (**Figure 4.4**). The smartwatch app scored 76.3 (SD 5.6), indicating good usability [5].

Participant Name: ______________ Dept: ________________ Date: ___/___/___

System Usability Scale

Instructions: For each of the following statements, mark one box that best describes your reactions to the website *today*.

		Strongly Disagree				Strongly Agree
1.	I think that I would like to use this app frequently.	☐	☐	☐	☐	☐
2.	I found this app unnecessarily complex.	☐	☐	☐	☐	☐
3.	I thought this app was easy to use.	☐	☐	☐	☐	☐
4.	I think that I would need assistance to be able to use this app.	☐	☐	☐	☐	☐
5.	I found the various functions in this app were well integrated.	☐	☐	☐	☐	☐
6.	I thought there was too much inconsistency in this app.	☐	☐	☐	☐	☐
7.	I would imagine that most people would learn to use this app very quickly.	☐	☐	☐	☐	☐
8.	I found this app very cumbersome/awkward to use.	☐	☐	☐	☐	☐
9.	I felt very confident using this app.	☐	☐	☐	☐	☐
10.	I needed to learn a lot of things before I could get going with this app.	☐	☐	☐	☐	☐

Figure 4.4. Usability testing administered using the System Usability Scale.

4.3.3 The Results of the User Interface

The storyboard of the wearable application is shown in **Figure 4.5** and the description of each page is shown in **Table 4.2**.

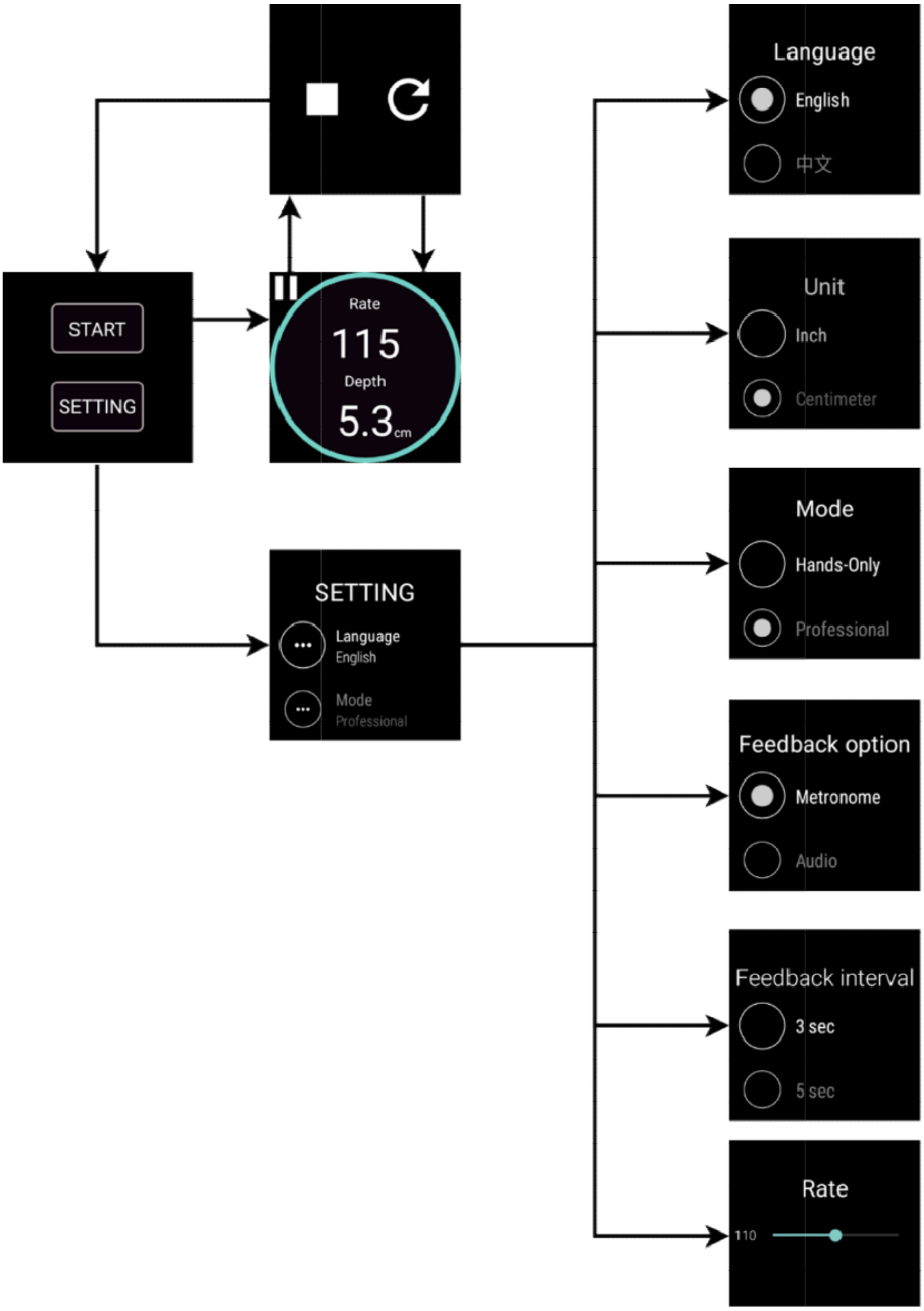
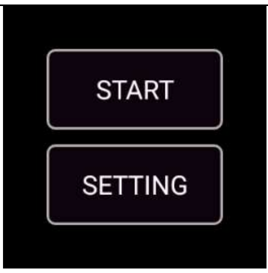
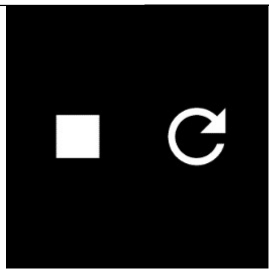
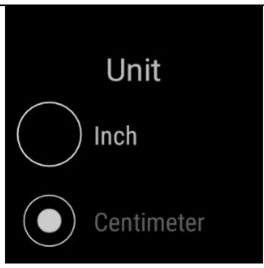
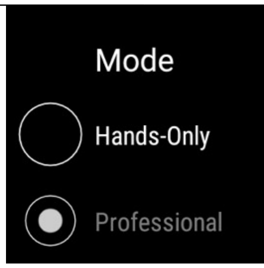
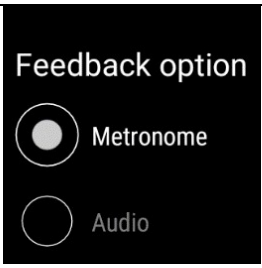
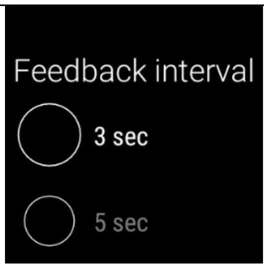
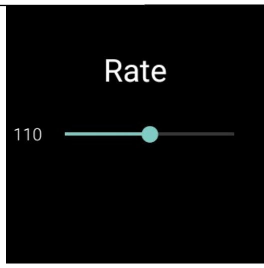


Figure 4.5. The storyboard of the wearable (smartwatch) application.

Table 4.2. Wearable application description.

		
The starting page of the application. Users can start directly or go to the setting page.	The main page during chest compression shows the calculated CCR and CCD in real-time.	When the left top button of the main page is pressed, the user can choose to resume or stop the session.
		
Language settings: English and Mandarin Chinese.	Unit settings: Decide the unit used on the main page, either inch or centimeter.	Mode settings: Hands-only (chest compression-only) mode, or Professional mode, which includes rescue breathing at a 30:2 compression-ventilation ratio.
		
Feedback option: Define how the app provides feedback, including a metronome, audio feedback, or both.	Feedback interval settings: 3 sec, 5 sec, or 10 sec. The default value is 3 sec.	Rate settings: Define the metronome rate, from 100 to 120. The default value is 110.

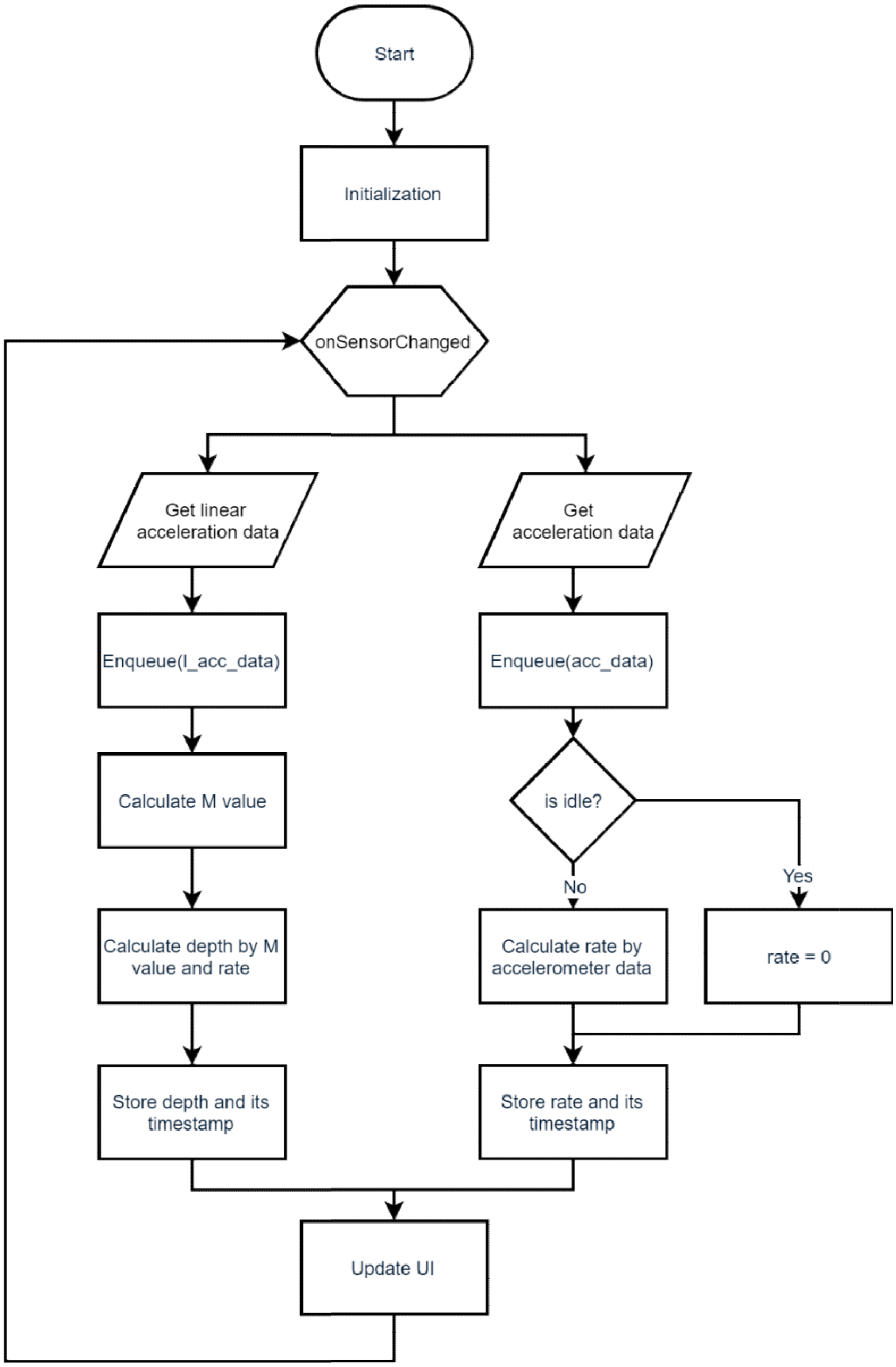


Figure 4.6. Sensor data acquisition flow chart.

4.4 The Rate Estimation Algorithm of Chest Compression

To implement a smartwatch-based device for providing effective feedback instructions during CPR, it is important to develop robust algorithms by using sensor data collected from an accelerometer that can accurately measure CCR/CCD in real-time during chest compressions. In this study, two different algorithms based on a smartwatch with a built-in accelerator are introduced for the estimation of CCR and CCD, respectively. For CCD detection, a novel algorithm for CCD estimation will be introduced in the next chapter (**Chapter 5**), with a detailed description in experimental design and data collection for validation. In this chapter, only the CCR estimation algorithm we developed will be described.

4.4.1 The Mathematical Model

The wearable application receives the acceleration data from the smartwatch-based accelerometer at a sampling frequency of 100 Hz. The accelerometer will return three values $a_x(t), a_y(t), a_z(t)$, denoted as the acceleration of the x-axis, y-axis, and z-axis, respectively. After eliminating gravitational influence, the processed acceleration values (a') data are then stored into a queue, which will be used for real-time CCR and CCD estimation. Finally, the display screen is updated based on the estimated CCR and CCD and, waiting for the next data change event. The whole data flow chart is shown in **Figure 4.6**.

4.4.2 The Rate Estimation Algorithm

●**<u>Data capturing</u>**: The acceleration sensors return three-dimensional arrays of sensor values for each Sensor Event as mentioned in **Section 4.2.2**. Data are captured every 0.025 seconds and returned as values in three coordinate axes, denoted as

$$a_x(t), a_y(t), a_z(t)$$

●**Data pretreatment using Moving Average Method**: We define the magnitude of the acceleration data at timestamp ***t*** as:

$$a(t) = a_x(t)^2 + a_y(t)^2 + a_z(t)^2$$

These values are then smoothed using the moving average technique, which are then used to remove the short-term fluctuations and maintain the long-term trends of the time series. The smoothed data at timestamp ***t*** can be calculated using the equation:

$$a'(t) = \frac{\sum_{i=0}^{n} a(t-i)}{n}, with\ n\ \in integer$$

Where *n* is the window size and can be set as 3 to 7 (we set *n* = 5 in the final algorithm).

●**Peak detection and the endpoint estimation**: The proposed CCR algorithm uses peak detection to estimate the end point of each chest decompression when the timestamp ***t*** satisfies all of the rules:

Rule 1: $a(t_1) < threshold_{min}$
Rule 2: $a(t_2) > threshold_{max}$
Rule 3: $a(t) < threshold_{min}$
Rule 4: $t - t_{prev} > 333(ms)$

For t1<t2<t, we assign $t_{current} = t$

Here $threshold_{min}$ is used for deciding the start and end timestamps of the chest compression, and $threshold_{max}$ is used for examining if the amplitude of the smoothed acceleration is large enough to be treated as the chest compression action.

Rules 1-3 are used to find the corresponding smoothed linear acceleration signal for each chest compression, and rule 4 is considered the real situation that rescuers are performing CPR at the nearly impossible rate of greater than 180 times/min, so a chest compression should have at least a 333 ms duration. **Figure 4.7** shows a real case for endpoint estimation, where the red points are our estimated end point of each compression.

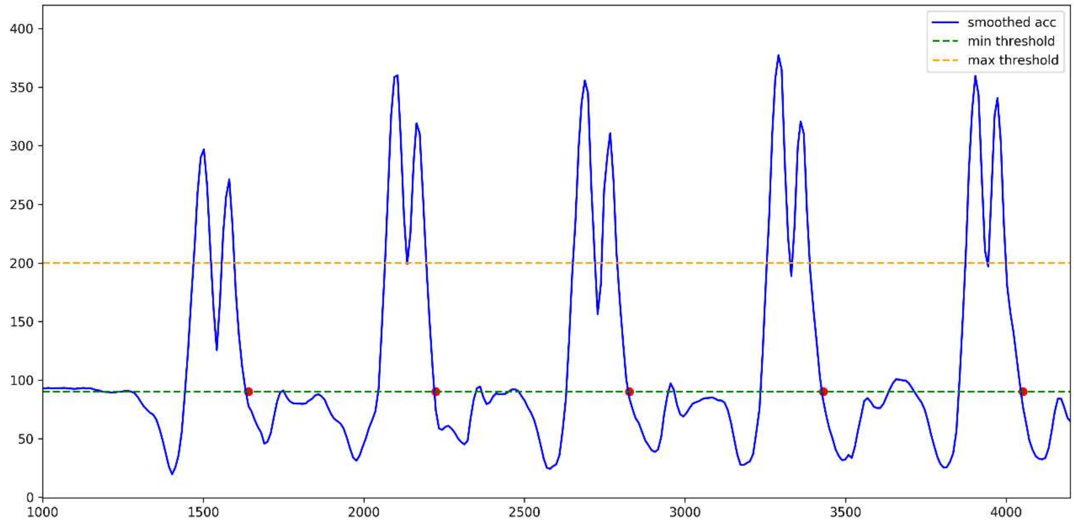


Figure 4.7. Peak detection and the endpoint estimation for each chest compression.

●**<u>Model building by machine learning</u>**: The values of $threshold_{max}$ and $threshold_{min}$ are trained by one of the supervised machine learning methods (Artificial Neural Networks), with minimizing the following mean absolute percentage error (MAPE) loss function:

$$\sum_{t=1}^{t} \frac{|rate(t) - Manikin(t)|}{Manikin(t)}$$

Finally, CCR is estimated using the following equation:

$$rate_{current} = \frac{60.0}{t_{current} - t_{prev}}$$

We also propose a fault-tolerant equation to avoid suddenly high or low estimations, which fixes the $rate_{current}$ when the predicted rate follows:

$if\ (90 \leq rate_{avg} \leq 130)\ and\ (rate_{current} > 140\ or\ rate_{current} < 80)$

$and\ |rate_{new} - rate_{avg}| \leq 25$

$$then\ rate_{current} = \frac{rate_{current} + rate_{prev}}{2},$$

Where $rate_{avg}$ means the average rate during the last four compressions, and $rate_{prev}$ means the previous CCR estimation.

4.4.3 Evaluation of the Rate Estimation Model

To construct the rate estimation algorithm and validate the model, researchers (wearing a smartwatch with accelerometer) performed the chest compression-only CPR experiment on the Resusci Anne QCPR training manikin (as a reference standard). The experimental design is described in detail in **Chapter 5**. The training data set comprised of 28 two-minute sessions performed by 6 healthcare providers in our team, with a total of 5,482 compressions. For validation, we collected a total of 3,978 compressions performed by another two researchers. **Table 4.3** shows the distribution comparison between training and validation sets. **Figure 4.8** shows the global error distribution between the estimated CCR and the reference standard. The absolute error of more than 95% compressions was below 6, as shown in **Figure 4.9**, the Cumulative Distribution Function (CDF) of the absolute error in CCR.

Table 4.3. The data distribution comparison of chest compression rate collected for training and validation sets.

		Training set (n=5,482)	Validation set (n=3,978)
CCR (min^{-1})	Mean ± SD	114.1± 17.0	110.7± 15.9
	IQR	97.1-131.1	94.8-126.6

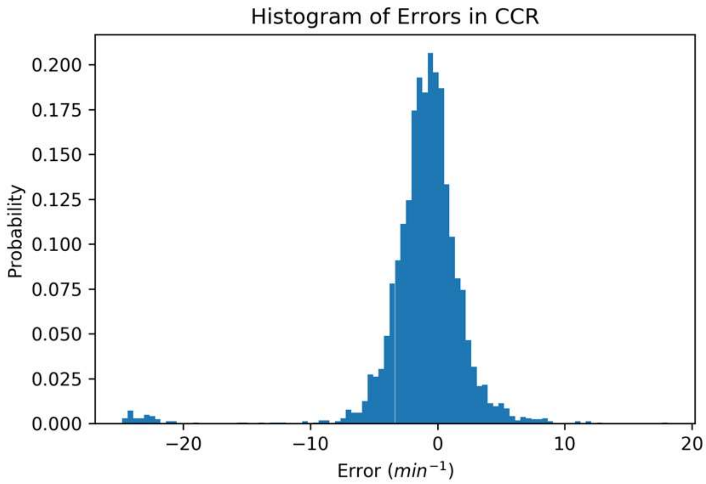


Figure 4.8. The histogram of error of chest compression rate between the estimated model and the reference standard.

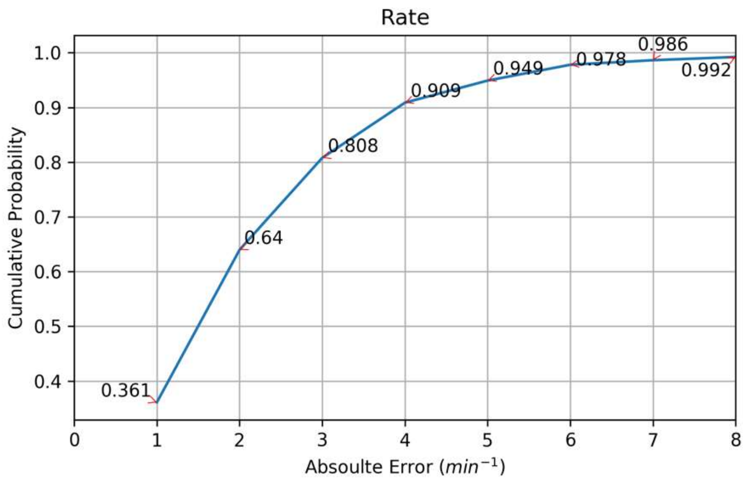


Figure 4.9. The Cumulative Distribution Function (CDF) of absolute error in chest compression rate (CCR).

4.5 References

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CHAPTER 5. PAPER 2: A NOVEL DEPTH ESTIMATION ALGORITHM OF CHEST COMPRESSION FOR FEEDBACK OF HIGH-QUALITY CARDIOPULMONARY RESUSCITATION BASED ON A SMARTWATCH

5.1 Prologue

Chapter 4 provided a description of the system architecture of a smartwatch-based feedback system to assist the delivery of high-quality CPR by using the UCD design methodology for the display module of the smartwatch, and a new chest compression rate (CCR) estimation algorithm using a machine learning method by collecting sensor data from the accelerometer of a smartwatch. As compared to rate estimation, chest compression depth (CCD) is a relatively difficult task characterized by computational complexity and error accumulation due to the nature of the accelerometer that may be influenced by environmental noise and gravity. This chapter introduces a relatively simple and effective method of real-time CCD estimation algorithm, which can be used in an accelerometer-based smartwatch as an assistive device to improve CPR quality. To answer the research question for aim 2: "Is it feasible to use a CPR watch as an assistive device to improve CPR quality?" A validation experiment was conducted to examine the accuracy of depth estimation for this algorithm.

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5.2 Paper 2 Abstract

Introduction: High-quality cardiopulmonary resuscitation (CPR) is a key factor affecting cardiac arrest survival. Accurate monitoring and real-time feedback are emphasized to improve CPR quality. The purpose of this study was to develop and validate a novel depth estimation algorithm based on a smartwatch equipped with a built-in accelerometer for feedback instructions during CPR.

Methods: For data collection and model building, researchers wore an Android Wear smartwatch and performed chest compression-only CPR on a Resusci Anne QCPR training manikin. We developed an algorithm based on the assumptions that 1) maximal acceleration measured by the smartwatch accelerometer and the chest compression depth (CCD) are positively correlated and 2) the magnitude of acceleration at a specific time point and interval is correlated with its neighboring points. We defined a statistic value *M* as a function of time and the magnitude of maximal acceleration. We labeled and processed collected data and determined the relationship between *M* value, compression rate and CCD. We built a model accordingly, and developed a smartwatch app capable of detecting CCD. For validation, researchers wore a smartwatch with the preinstalled app and performed chest compression-only CPR on the manikin at target sessions. We compared the CCD results given by the smartwatch and the reference using the Wilcoxon Signed Rank Test (WSRT), and used Bland-Altman (BA) analysis to assess the agreement between the two methods.

Results: We analyzed a total of 3,978 compressions that covered the target rate of 80-140/min and CCD of 4-7 cm. WSRT showed that there was no significant difference between the two methods (P=0.084). By BA analysis the mean of differences was 0.003 and the bias between the two methods was not significant (95% CI: -0.079 to 0.085).

Conclusion: Our study indicates that the algorithm developed for estimating CCD based on a smartwatch with a built-in accelerometer is promising. Further studies will be conducted to evaluate its application for CPR training and clinical practice.

5.3 Paper 2 Full Text

5.3.1 Introduction

In addition to early recognition of the event and immediate activation of the emergency response system, one of the important favorable prognostic factors for patients suffering from cardiac arrest is the provision of high quality Cardiopulmonary Resuscitation (CPR) in a timely manner [1]. After the first CPR guidelines were developed in 1966 by American Heart Association (AHA) [2], revisions have been made to the CPR standards every five years. In 2005, the AHA Guidelines for CPR and Emergency Cardiovascular Care (ECC) were revised and high quality CPR was first introduced [3]. The guidelines were revised in 2010 and chest compression-only CPR was introduced for those who are not familiar, unwilling, untrained or unable to perform the rescue breaths technique. In the most updated 2015 AHA and European Resuscitation Council (ERC) guidelines, the fundamental performance metrics of high quality CPR remain the same, with an emphasis on compressions of an adequate rate at 100 to 120/min and depth at 5 cm (2 inches) to 6 cm (2.4 inches), allowing full chest recoil after each compression, minimizing pauses in compressions, and avoiding excessive ventilation [4, 5].

There has been wide variability of survival for cardiac arrests published in the literature, but the overall reported survival rate remains poor [6-10]. Research findings have shown that the quality of CPR during resuscitation has a significant impact on survival and patient outcomes, whether CPR is initiated by a layperson in the prehospital environment, an emergency physician in the emergency department (ED), or a clinician in the inpatient ward [11-14]. To improve CPR quality and patient outcomes, accurate monitoring and real-time feedback are important for both laypersons and professional rescuers performing CPR on suspected victims of cardiac arrest. Researchers around the world have sought to develop methods that professional healthcare providers or laypersons can utilize to improve CPR quality. For example, Chiang et al. showed that a feedback device using audio-prompts improved adherence to current CPR guidelines in a clinical setting [15]. Yeung et al. conducted a single blinded, randomized controlled trial to compare the effect of three CPR prompt and feedback devices on quality of chest compressions on a manikin amongst healthcare providers. Although the results showed that CPR feedback devices vary in their ability to improve performance, users preferred the accelerometer and metronome devices over the pressure sensor device [16].

The concept of using accelerometer-equipped consumer electronics to help bystander initiated CPR is not new. Semeraro et al. developed an iPhone app, the iCPR, to facilitate CPR training for both laypersons and healthcare professionals. Participants using iCPR performed better than a control group, and were able to maintain chest compression toward the desired rate of 100 per minute according to guidelines at that time [17]. Zoll Medical Corporation developed an app, the PocketCPR, which can be installed in an iPhone or an Android smart phone to provide real-time feedback and instructions for bystander-initiated CPR [18]. Currently the app is used for training and practice purposes only. The major drawback of this type of application is that rescuers have to hold the smart phone in order to activate its feedback mechanism during CPR. This can be cumbersome and may hinder its practice use in real world settings.

Various wearable devices have emerged to play an important role in the current healthcare arena. A recent advent to this fast-growing market of wearable devices is the smartwatch. A smartwatch can be worn without interrupting our daily lives and can act as a readily available extension of the smart phone. Recently there were two published studies that focused on using smartwatches to facilitate the delivery of high quality CPR. Gruenerbl et al. developed a CPR feedback app for a smartwatch with a built-in accelerator (LG G Watch R model based on Android Wear) to facilitate untrained bystanders performing CPR correctly on manikins [19]. Using the smartwatch for assisting CPR was significantly associated with increased rate and depth of chest compression, although only approximately half of 41 study participants managed to stay within the recommended rate and depth ranges for high quality CPR. The authors also did not reveal a detailed algorithm explaining their development of the app, and the application provided only on-screen reminders without audio or vibration feedback. Another study conducted by a Korean group of researchers developed a similar smartwatch (Galaxy Gear Live) app for assisting with CPR on manikins. A randomized controlled trial demonstrated that the proportion of accurate chest compression depth (CCD) in the intervention group using the smartwatch app was significantly higher than that in the control group. However, the mean compression depth and rate and the proportion of complete chest decompressions did not differ significantly between the two groups [20].

To successfully implement accelerometer-based devices for providing effective feedback instructions during CPR, we believe that it is important to develop robust algorithms for real-time and accurate measurement of CCD during chest compressions. The algorithm currently used in the literature and real world products relies mainly on double integration of the acceleration, which is characterized by computational complexity and error accumulation due to the nature of the accelerometer that may be influenced by variable sampling rate, environmental noise, and earth gravity [21-25]. In this study, we introduce a novel real-time CCD estimation algorithm, which is a relatively simple and effective method that can be used in an accelerometer-based smartwatch as an assistive device to improve CPR quality. We also conduct a validation experiment to examine the accuracy of depth estimation for our algorithm.

5.3.2 Materials and Methods

【A】Equipment and Data Collection Software

During the chest compression data collection process, we used a Resusci Anne QCPR training manikin (Laerdal Medical, Stavanger, Norway) to simulate an adult cardiac arrest victim. Researchers wore the ASUS ZenWatch 2 model WI501Q (Asus, Taipei, Taiwan), one of the major commercially available smartwatches of Android Wear with a built-in accelerometer and speakers, while performing chest compression-only CPR on the manikin. We used SensorsApi (Google, Menlo Park, California) to collect real time sensor data generated by the accelerometer on the smartwatch, and used Microsoft Excel 2007 (Microsoft, Redmond, Washington, USA) to process the data. We recorded and analyzed the corresponding rate and depth data of chest compression on the manikin using Laerdal PC SkillReporting software (Laerdal Medical, Stavanger, Norway). Finally, we used the fit command in Gnuplot (ver. 4.2) to fit a function to a set of collected data points for CCD estimation (details described below) [26].

【B】Depth Estimation Algorithm Based on the Smartwatch with an Accelerometer

(B-1) The sensor values of the smartwatch accelerometer

We used the accelerometer in the smartwatch to detect the acceleration values. The accelerometer will return 3 values $a_x(t), a_y(t), a_z(t)$ denoted as the acceleration of the x-axis, y-axis, and z-axis, respectively. To eliminate gravitational influence, the acceleration in the direction of the gravity a' can be calculated using the following formula:

$$a' = \vec{a} \cdot \hat{g} - \vec{g} = \frac{1}{\sqrt{g_x^2 + g_y^2 + g_z^2}} \left(a_x g_x + a_y g_y + a_z g_z\right) - \sqrt{g_x^2 + g_y^2 + g_z^2}$$

Where g denotes the gravity.

(B-2) Assumptions

We developed the CCD estimation algorithm based on two assumptions:

● the magnitude of acceleration and CCD are positively correlated.

● the magnitude of acceleration at a specific time point during a specific time interval correlates with its neighboring points.

We defined a statistic value *M*, which is the summation of acceleration square divided by the number of time point t' during a specific time interval, as the following formula:

$$M(t) = \sum_{0 \le t - t' \le T} \frac{a'^2(t')}{\#t'}$$

Where T is a user-defined time constant that was set as 3 seconds in our algorithm.

(B-3) Model Building Process

For model building, researchers (wearing a smartwatch with accelerometer) performed the chest compression-only CPR experiment on the Resusci Anne QCPR training manikin (as a reference standard). The experimental design is described in detail in section 2.3. We downloaded the depth (CCD) and rate data from the manikin and labeled with the corresponding M-value that recorded and processed from the smartwatch at each timestamp.

M	$rate$	$depth$
M_1	$rate_1$	$depth_1$
M_2	$rate_2$	$depth_2$
...	...	...
M_n	$rate_n$	$depth_n$

We used a polynomial (as a function of M and rate) to predict the CCD in the form of:

$$\text{CCD}\ predicted(M, rate) = aM^2 + b(M)(rate) + c(rate)^2 + dM + e(rate) + f$$

Where a, b, c, d, e, f are real-number coefficients.

A set of data $(M, rate, CCD)$ can be collected and a, b, c, d, e, f can be found by using Gnuplot with the fit command [26].

Finally, a smartwatch app capable of detecting CCD can be developed according to the aforementioned polynomial if we know the corresponding M value and rate in each timestamp.

For model construction, data were collected and labeled as described below.

【C】Experimental Design for Data Collection and Labeling

CPR experiments were conducted to collect and label data to fit the above described model. Two researchers acted as rescuers and performed chest compression-only CPR on a Resusci Anne QCPR training manikin placed on hard, uncarpeted floor with kneeling position. Each researcher performed nine target sessions (a total of 18 sessions) of 2-minute uninterrupted chest compression-only CPR, with different combinations of target rate (80-100, 101-120, 121-140 per minute) and depths (4-5, 5-6, 6-7 cm). We asked the researchers to deliver the desired target rate and depth during each session with the help of the on-screen information provided by the Resusci Anne. The recorded data were processed using Microsoft Excel 2007 (Microsoft, Redmond, Washington, USA) and analyzed using SPSS statistical software for Windows (Release 17.0, SPSS Inc., Chicago, IL, USA).

During the labeling process for model fitting, we recorded the values of acceleration during chest compressions from the smartwatch. We calculated the relevant *M* values and labeled their corresponding depth and rate according to the records from the reference (Resusci Anne). We collected a set of data (*M*, rate, CCD), fed it into the polynomial function, and found the coefficients (a, b, c, d, e, f) using Gnuplot with the fit command [26]. We developed a smartwatch app capable of detecting CCD accordingly.

【D】Model Validation and Statistics

During the validation process, another two researchers acting as rescuers performed 2-minute (per session) chest compression-only CPR on the Resusci Anne QCPR training manikin at different target sessions. Each performed nine different sessions and we collected data for a total of 18 sessions. We developed a smartwatch app capable of detecting chest compression depth according to the algorithm and model building process stated above. The researchers wore a smartwatch with the app pre-installed while performing chest compression on a manikin. We compared the chest compression depth results given by the smartwatch and the reference (Resusci Anne) using the Wilcoxon Signed Rank Test for paired and continuous data sets, and considered differences significant for *P* values less than 0.05.

Finally, we conducted a Bland-Altman analysis to assess the agreement on feedback between our method and the reference method, and reported the 95% limits of agreement (LOA) [27]. We created the resulting graph using the *R* statistical package.

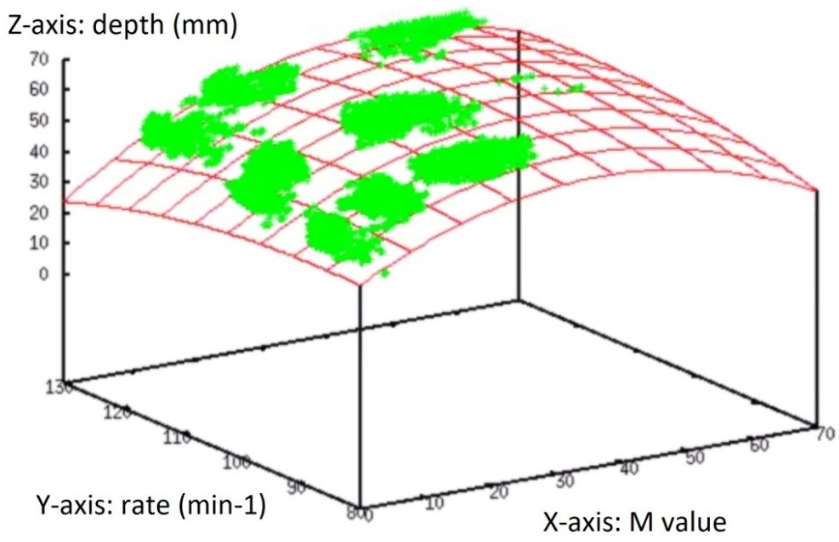

Figure 5.1. 3D surface plotting of a polynomial (as a function of M value and rate) capable of predicting chest compression depth (mm).

5.3.3 Results

The model building process required data collection and labeling to fit the proposed polynomial. We collected a total of 4,584 compressions that covered the target rate from 80 to 140 compressions/min and depth from 40 to 70 mm. The constructed polynomial capable of predicting CCD is illustrated in the following formula and the surface plotting is shown in **Figure 5.1**.

For validation, we performed chest compression-only CPR (each session 2 minutes) at nine different combinations of target rate and depth by another two researchers (different from those who performed CPR for model construction). We collected a total of 18 sessions which included a total of 3,978 compressions. Bland-Altman analysis performed on the whole validating dataset

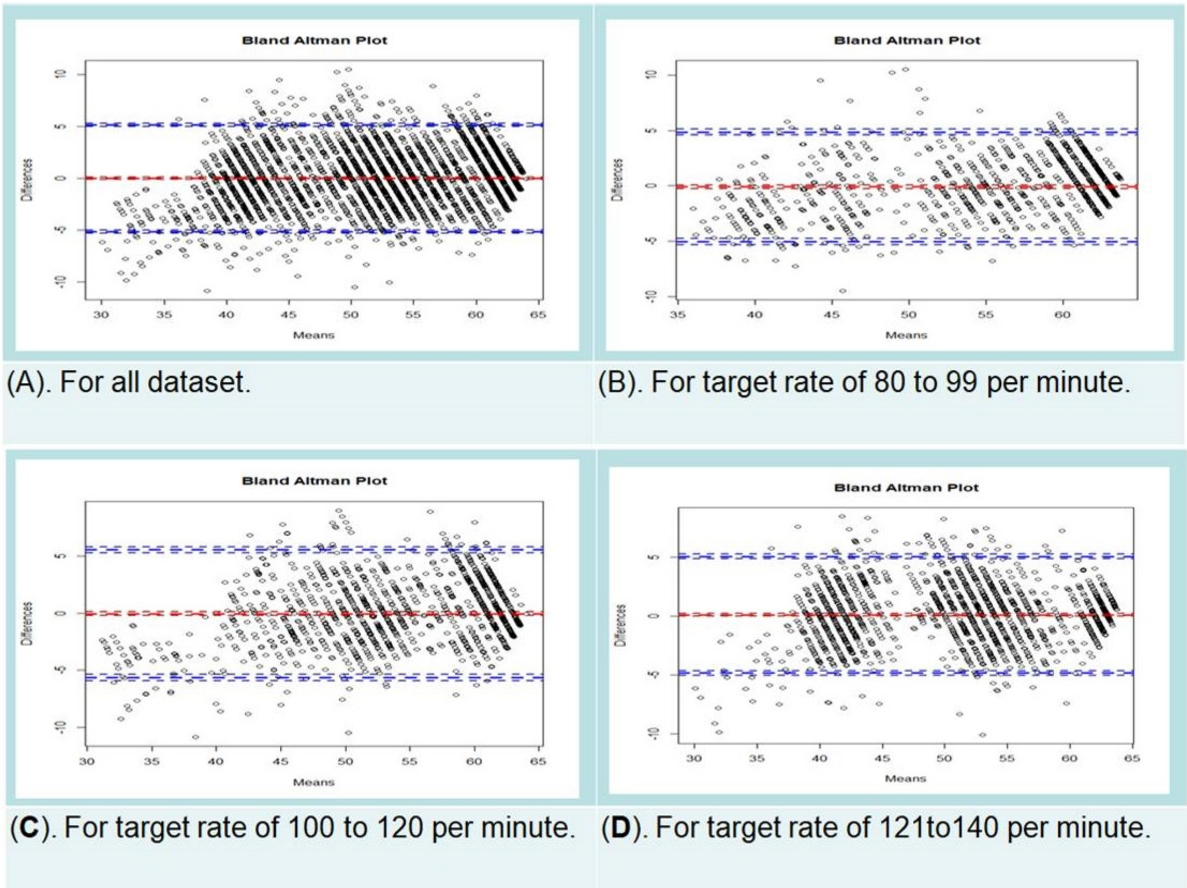

Figure 5.2. Bland-Altman plot of the mean difference plotted from smartwatch app against the reference standard from the Resusci Anne, and 95% limits of agreement as the mean difference (1.96 SD). The upper and lower dotted lines for each of the mean difference and 95% agreement limits represent confidence interval limits (data not shown here). (**A**). For all dataset; (**B**). For target rate of 80 to 99 per minute; (**C**). For target rate of 100 to 120 per minute; (**D**). For target rate of 121 to 140 per minute.

showed that the mean of differences between our method and the reference standard was 0.003 and the bias between the two methods was not significant (95% CI: -0.079 to 0.085) (**Figure 5.2.A**). Bland-Altman analyses were also performed according to different target rates including rate 80 to 99, rate 100 to 120, and rate 121 to 140. The means of differences were -0.092, -0.037, and 0.094, respectively. The results showed no significant bias between the two measuring methods at each of the three different target rates (95% CI: -0.244 to 0.060, -0.193 to 0.119, and

-0.028 to 0.217) (**Figures 5.2., B** to **D)**. The Wilcoxon Signed Rank Test for paired and continuous data sets showed no significant differences between the two measuring methods in either the whole datasets (P=0.701) or different targets of chest compression rates (P= 0.124, 0.402, and 0.117 for rate 80 to 99, 100 to 120, and 121 to 140, respectively).

5.3.4 Discussion

High quality CPR is a key prognostic factor affecting survival after cardiac arrest. Accurate monitoring and real-time feedback can improve CPR quality. The purpose of this study was to develop and validate a novel depth estimation algorithm based on a smartwatch with a built-in accelerometer for feedback instructions during CPR. The results of this study indicate that our novel algorithm is a reliable method to estimate CCD, ensuring efficient calculation of depth from a smartwatch app with the ability to provide real time feedback during chest compression-only CPR.

The application of the smartwatch as an assistive device to improve CPR quality is an appealing idea and can be implemented during bystander-initiated CPR in a prehospital environment or during professional rescues in clinical care settings. As opposed to smart phones or bulky accelerometer devices, smartwatches are unobtrusive and clinicians can wear them on their wrists while performing CPR without interrupting the clinical workflow. Accurate and real-time CCD measurement is necessary for an accelerometer-based smartwatch to be effectively implemented as a feedback device to improve CPR quality. Most of the current studies or products measure depth during each compression using double integration of the acceleration signal collected from the accelerometer-equipped devices [21, 22].

However, there are problems associated with using double integration method to estimate compression depth. First, to measure distance (CCD) as a function of time of an object (chest wall), the initial value of the velocity or position is required for integration but is unknown using this method [28]. The second problem is integration drift. Due to baseline offsets that include instrumental instability, background noise, or calibration errors, drift effect can be unavoidable and will cause enormous errors when double integration of the acceleration signal is collected by the accelerometer to measure distance. Both of the problems can lead to serious integration errors if not corrected, and researchers around the world are endeavoring to solve these problems with different approaches [28, 29]. Nevertheless, current commercialized products available on the market still rely on accelerometers and double integration to estimate depth, and their potential solution to the drift problems are often protected by patent right [30, 31]. To incorporate increasingly sophisticated computational algorithms, these devices have increased in size and complexity, making them difficult for bystanders to use in the prehospital environment.

Our algorithm was developed by using the built-in accelerometer in a smartwatch. We hypothesized that CCD is correlated to the magnitude of maximal acceleration at a specific time point during each chest compression, and the value is also correlated to that of its proximal point. We generated a statistic value *M*, which is the summation of acceleration squared (to eliminate the negative value of collected acceleration) divided by the number of time points during a specific time interval (to eliminate the boundary effect). The concept of the *M* statistic is similar to the "moving average" commonly used with time series data to smooth out short-term fluctuations [32]. The reason for using acceleration squared is to eliminate the negative value of collected acceleration. We tested using acceleration to a greater power (i.e., the power of four), but the results were not better than using acceleration squared. We chose T as 3 seconds to eliminate the boundary effect, smooth out short-term fluctuations, and highlight long-term trends during each cycle of chest compressions. We also created a simple polynomial (as a function of *M* and compression rate) capable of predicting CCD that can be easily constructed by collecting sufficient data for model fitting. With our experimental design for data collection and labeling, the constructed polynomial formula capable of predicting CCD was the output of Gnuplot with the fit function. Although the proposed method still relies on accelerometer measurement and can be inaccurate due to its nature, we constructed the model by data collection, labeling, and fitting processes. Similar to "supervised machine learning" technique, our model can learn from sample inputs and make prediction on future data with this novel algorithm. The results of our study are promising and can be used to develop a smartwatch app capable of estimating CCD for feedback instructions during chest compression-only CPR. This novel depth estimation algorithm of chest compression can also be expanded to other devices with a built-in accelerometer.

There are limitations in this study. First, we cannot measure if there is full chest recoil after each compression. Leaning is common during CPR and should be minimized due to its negative effect on patients' hemodynamic status [33, 34]. Such deficiency in detection of leaning during chest compressions has been a major drawback in most of the accelerometer-based assistive devices for chest compression-only CPR [28]. Secondly, chest compression experiments were performed on a manikin placed on hard ground by bystanders who were kneeling. The estimated CCD may be inaccurate when chest compressions are performed on patients placed on a soft bed or chair that may absorb some force [35-37].The results may also be different with different CPR positions (e.g., standing). Future studies should be conducted by using different kinds of backboards and/or different CPR positions. Thirdly, we derived the acceleration values by using the scalar projection of the collected acceleration (a) onto gravity (g), which is the magnitude of the vector projection of a onto g, under the assumption that the direction of chest compression is the same as the direction of gravity (which is not always true). Although the smartwatch we used has a built-in gyroscope that can measure the angle in each compression, it cannot measure the direction of the angle after rotation due to the accumulation of error with the integration method. Fourthly, we recruited only two participants to collect the data for model construction and another two participants for validation. We did not include a broader range of participants with different body types, which can have an impact on data collection and validation. Finally, this study aimed at providing adequate feedback for high-quality CPR and we focused in the specified range of rate (80cpm to 140cpm) and depth (4cm to 7cm) for validation purposes. Although we did not collect and validate data outside of this range, future smartwatch app development will provide guidance when the estimations fall beyond the pre-set range of high quality CPR.

One of the major issues related to CPR quality is monitoring and feedback. “You can’t manage what you don’t measure” is frequently quoted in academia [38], and should be true in CPR training and practices. Our study indicates that an app capable of estimating CCD accurately in a real time manner can be developed using the acceleration values collected from the built-in accelerometer in a smartwatch. This work can advance our knowledge of how to make use of the sensor data from a smartwatch and will lead us to the goal of more practical use of wearable devices in the healthcare arena, especially in critical and emergency care settings. With the development of future sensor technologies, it is possible to develop an optimization algorithm that can utilize both accelerometer and gyroscope data for more accurate measurements of depth estimation and leaning detection during CPR.

5.3.5 Conclusion

Specialized feedback devices designed as assistive devices for CPR have been widely used in CPR training and clinical practices. With the advent of the smartwatch, there is an opportunity to use unobtrusive, wearable devices to assist in CPR without affecting clinical workflow. Our study indicates that this novel algorithm developed for estimating CCD based on a smartwatch with a built-in accelerometer is promising. Further studies will be conducted to evaluate its application for CPR training and clinical practice.

5.4 Concluding Remarks

In this chapter, a novel CCD estimation algorithm for the use of a smartwatch CPR feedback system to assist rescuers in performing high-quality CPR was developed. The validation study shows that it is a reliable method capable of detecting CCD accurately in a real-time manner. In the next chapter, a randomized controlled simulation study that utilizes the smartwatch app as an intervention for improving quality of CPR by healthcare professionals will be described.

5.5 References

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CHAPTER 6. PAPER 3: USING A SMARTWATCH WITH REAL-TIME FEEDBACK IMPROVES THE DELIVERY OF HIGH-QUALITY CARDIOPULMONARY RESUSCITATION FOR HEALTHCARE PROFESSIONALS

6.1 Prologue

In the previous chapter, the system architecture of a smartwatch CPR feedback system was described. For successfully implementing an accelerometer-based smartwatch as an assistive device for feedback instruction during CPR, two novel chest compression rate (CCR) and chest compression depth (CCD) estimation algorithms were developed and the validation (evaluation) studies revealed that it is feasible to use a smartwatch with the developed app as a real-time feedback device during CPR. To answer research question3: "Do rescuers with a CPR watch outperform those without?" A randomized control study was conducted using a smartwatch with the developed app as a feedback device to assist in the delivery of high-quality CPR for healthcare providers.

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6.2 Paper 3 Abstract

Aim: Cardiopulmonary resuscitation (CPR) quality affects survival after cardiac arrest. We aimed to investigate if a smartwatch with real-time feedback can improve CPR quality by healthcare professionals.

Methods: An app providing real-time audiovisual feedback was developed for a smartwatch. Emergency Department (ED) professionals were recruited and randomly allocated to either the intervention group wearing a smartwatch with the preinstalled app, or to a control group. All participants were asked to perform a two-min CPR on a manikin at a 30:2 compression-ventilation ratio. Primary outcomes were the mean CCR and CCD measured on the manikin. A secondary outcome was the percentage of chest compressions meeting both the guideline-recommended rate (100-120 min-1) and depth (50-60 mm) of high-quality CPR during a 2-min period. Differences between groups were evaluated with t-test, Chi-Square test, or Mann-Whitney U test depending on the distribution.

Results: Eighty participants were recruited. 40 people were assigned to the intervention and 40 to the control group. The compression rates (mean±SD, min-1) were significantly faster (but above the guideline recommendation, P<0.001) in the control (129.1±14.9) than in the intervention group (112.0±3.5). The compression depths (mean±SD, mm) were significantly deeper (P<0.001) in the intervention (50.9±6.6) than in the control group (39.0±8.7). The percentage (%) of high-quality CPR was significantly higher (P<0.001) in the intervention (median 39.4, IQR 27.1-50.1) than in the control group (median 0.0, IQR 0.0-0.0).

Conclusion: Without real-time feedback, chest compressions tend to be too fast and too shallow. CPR quality can be improved with the assistance of a smartwatch providing real-time feedback.

6.3 Paper 1 Full Text

6.3.1 Introduction

Despite the advancement of medical research and clinical practices, survival rate from cardiac arrest remains poor worldwide [1-3]. Previous studies have shown that prompt delivery of high-quality Cardiopulmonary Resuscitation (CPR) affects survival from cardiac arrest, whether CPR is initiated by a layperson in the prehospital environment, an emergency physician in the Emergency Department (ED), or a clinician in the inpatient ward [4-6]. In 2005, the American Heart Association (AHA) Guidelines for CPR and Emergency Cardiovascular Care (ECC) were revised and high-quality CPR was first introduced [7]. In the most updated 2015 AHA and European Resuscitation Council (ERC) guidelines, the emphasis on high-quality CPR remains the same. To fulfil the standard of high-quality CPR, rescuers should aim to perform compressions at a rate of 100 - 120/min and a depth of 5 cm (2 in.) to 6 cm (2.4 in.), allow full chest recoil after each compression, minimize pauses in compressions, and avoid excessive ventilation [8].

To improve CPR quality, researchers have sought to develop prompt devices, or methods for providing feedback during CPR training or in clinical practice. In a recent review that included 42 studies with interventions to improve CPR quality, feedback or prompt devices were used as the main intervention in 7 studies and CPR experiments were all performed on manikins [9].To date, there are only a few randomised trials that investigated the effect of feedback or prompt devices using real patients. In a cluster-randomised trial, Hostler et al. showed that real-time audio visual feedback provided by the monitor-defibrillator during CPR altered performance to more closely conform to guidelines in prehospital settings [10]. Another randomised study conducted by Bohn et al. reviewed the influence of different feedback configurations on survival and compression quality for patients with out-of-hospital cardiac arrest (OHCA), and found that the addition of voice prompts had only limited effect on CPR quality [11]. Although the studies to date are limited; the 2015 guidelines still recommend that it may be reasonable to use audiovisual feedback devices during CPR for real-time optimization of

CPR performance, and feedback on compression technique can be considered as part of a broader system of care [12-13].

To help rescuers in performing high-quality CPR and improve adherence to guidelines, various medical device companies have developed and marketed potential solutions to advance emergency care [14-16]. These devices, which incorporate sophisticated computational algorithms, are expensive, impractically large, and too complex to be used by bystanders in the pre-hospital environment. Although these devices can be used for training or clinical practice, they are used primarily by professionals. Currently wearable devices are used for a variety of medical applications [17]. A wearable device can be broadly defined as a mobile electronic device that can be unobtrusively embedded in the user's outfit as part of the clothing or an accessory [18]. With the functionality of biosensors capable of wireless communication, these devices are considered to have the potential to transform the healthcare system and improve quality of care [19].

One of the wearable technologies gaining widespread popularity in the healthcare sector is the smartwatch. With its miniaturized design and intelligent computing technology, a smartwatch can be worn continuously without interrupting the user’s daily activity. Although smartwatches have been used as a platform for a variety of healthcare applications, their applications in emergency settings have just begun [20-21]. To facilitate the delivery of high quality CPR, two different research groups have developed smartwatch apps with visual feedback to improve CPR quality on manikins [22-23]. The results varied in terms of CPR quality and the applications focused mainly on laypersons or medical students. Furthermore, these studies provided only on-screen reminders without audio feedback. Until recently, there have been no randomised control studies with professional healthcare providers that examined the impact of smartwatches on CPR quality. Our study sought to test a smartwatch app with real-time audiovisual feedback on the delivery of high-quality CPR by healthcare providers for patients with cardiac arrest in a simulated emergency setting. We hypothesized that a smartwatch-based chest compression feedback app would improve the quality of CPR on a sensorized manikin.

6.3.2 Methods

●**Study design**

We conducted a randomised controlled simulation study during a study period from April 1st 2018 to June 30th 2018 at the ED of National Taiwan University Hospital (NTUH), a 2400-bed university-affiliated tertiary teaching hospital with daily service of about 8000 outpatients and 300 emergency visits. A smartwatch app capable of estimating CCD and CCR was developed for use in a smartwatch (ASUS ZenWatch 2 model WI501Q, Taipei, Taiwan), one of the major commercially available smartwatches of Android Wear with a built-in accelerometer and speaker. In this app, we introduced a novel algorithm for real-time CCD estimation based on the sensor data collected from the 3-axis accelerometer in the smartwatch. The validation study has been reported elsewhere [24]. User-Centred Design (UCD) was utilized during the design phase and a brief usability test was performed before the implementation of this app [25-26]. This part of the study has been completed and will be submitted in a future paper. ED professionals, who are Advanced Cardiovascular Life Support (ACLS)-certified doctors and nurses, were recruited and randomly allocated to either the intervention group wearing a smartwatch with the preinstalled app, or to a control group without the smartwatch. All participants were asked to perform a two-minute CPR on a Resusci Anne QCPR training manikin using the 30:2 compression-ventilation ratio. The quality of CPR performed on a sensorized manikin (simulated an adult cardiac arrest victim) by healthcare providers was compared between groups. The study protocol was reviewed by the Research Ethics Committee of NTUH and was considered IRB exempt in accordance with the governmental laws and regulations (NTUH-REC No.: 201803090W). This study was also reviewed and determined IRB exempt by the University of Washington Human Subjects Division (IRB ID: STUDY00001681).

Figure 6.1. The smartwatch screen displays a different color of circular background in response to both the estimated chest compression depth (CCD) and rate (CCR). Circular turquoise light indicates the current chest compression is meeting both the guideline-recommended rate (100-120 min^{-1}) and depth (50-60 mm) of high-quality CPR, and red indicates it is not.

The display feedback module of this app shows the estimated values of CCR and CCD in real-time on the smartwatch screen at a 5-Hz refresh rate. It displays a turquoise background of circular light if both the CCR and CCD match the standard of high-quality CPR or a red background if they do not (**Figure 6.1**). The audio feedback module is comprised of two parts. The first part uses verbal commands to help rescuers better adhere to the guideline-recommended rate (100-120 min-1) and depth (50-60 mm) of high-quality CPR. When activated, rescuers hear "Push faster", "Push slower", "Push harder", or "Push softer" in response to the estimated values of CCR and CCD determined by the algorithm implemented on the smartwatch, with the CCR being on the first input for decision in the audio feedback flowchart (**Figure 6.2**). Since too much verbal feedback may disturb the rescuers, we set the feedback interval to be 3 s in this study according to our UCD and usability testing, but it can be adjusted to 5 s or 10 s according to users' preference. For encouragement, rescuers hear "Good job, keep going" if their chest compressions are judged to be fulfilling the standard of high-quality CPR. The second part of the audio feedback is the use of metronome-like sound to guide the tempo during chest compressions. The rate can be set between the frequencies of 100-120 beats per minute, and was set as 110 for this study based on our pre-implementation UCD and usability test.

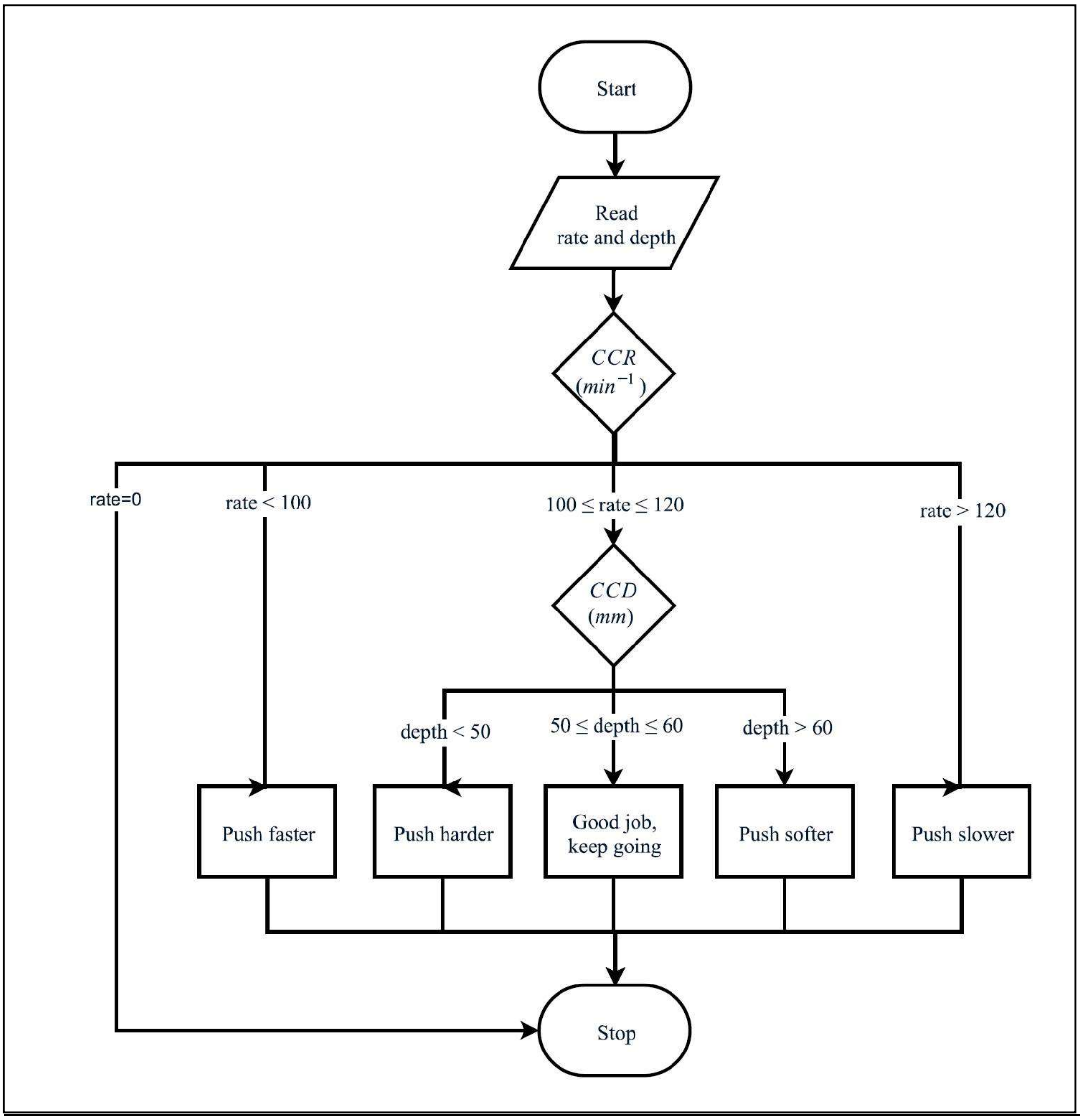

Figure 6.2. The audio feedback flowchart, where chest compression rate (CCR) was designed on the first input for decision in the feedback algorithm, and chest compression depth (CCD) the second.

Although this study focused mainly on healthcare providers who should perform chest compressions and ventilation at a 30:2 ratio, the app can also be utilized by laypersons to perform chest compression-only CPR by adjusting it to "hands-only" mode. In our study, the app was set to "professional" mode. Rescuers (allocated to the intervention group) heard "Please open airway and give two rescue breaths, first breath, second breath" after approximately 30 consecutive compressions during the CPR attempt.

●**Inclusion and exclusion criteria**

Participants were recruited through the use of flyers distributed via hospital intranet and by word of mouth from current researchers. Informed consent was obtained and participants were apprised of the nature of the research and participation. All subjects were told that their CPR performance would be evaluated, and participant identifiers to be collected included only profession, years of working experience in their current position, age, and gender. Participants eligible for enrolment included those healthcare providers who were 20-65 years old, currently held a clinical license to practice nursing or medicine and board-certification at an acute care facility, currently involved in caring for adult patients at an acute care facility, and currently held a valid certificate of ACLS issued by recognizable organizations such as AHA or other relevant authorities. Individuals who were medical students, younger than 20 or older than 65 years old, without an active ACLS certificate, or individuals who were primarily involved with taking care of paediatric patients were excluded from the study.

●**Data collection**

Participants were recruited and eligibility was assessed. All enrolled participants received a two-minute demonstration of the feedback features of the smartwatch by one of our researchers before the experiment. The standard of high-quality CPR for healthcare providers was also reviewed during the demonstration. Afterwards, participants were randomly allocated to either the intervention group or the control group by simple randomization using a coin toss [27]. Without any trial attempt, all participants were asked to perform CPR for two minutes, with chest compression and ventilation at a 30:2 ratio. They performed CPR on a Resusci Anne QCPR training manikin (Laerdal Medical, Stavanger, Norway) placed on the floor in one of our ED observation units (**Figure 6.3**). A standardized Bag-Valve-Mask was ready to be used beside the manikin. Participants received instant reminding by an investigator if they forgot to perform ventilation in response to the audio command alerted by the watch in the intervention group or by the supervision of the investigator in the control group after about 30 consecutive chest compressions, and were labelled as failure to be adherent to the 30:2 compression-ventilation guideline (no matter how many times they were reminded during a 2-min CPR). Beat-to-beat CCR and CCD in each compression were recorded using Laerdal PC SkillReporting software (Laerdal Medical, Stavanger, Norway).

Figure 6.3. Fig. 3. A participant allocated to the intervention group wearing a smartwatch (ASUS ZenWatch 2) with pre-installed app performed chest compression on the manikin.

●**Data analysis**

The collected data were processed using Microsoft Excel 2007 (Microsoft, Redmond, Washington, USA) and analysed using SPSS statistical software for Windows (Release 17.0, SPSS Inc., Chicago, IL, USA) or MedCalc for Windows (version 15.2.2, MedCalc software, Mariakerke, Belgium). The corresponding real-time sensor data generated by the accelerometer on the smartwatch were also collected using SensorsApi (Google, Menlo Park, California), but not utilized in this study.

Primary outcomes were the episode mean values of beat-to-beat CCR and CCD measured on the manikin by each participant during the 2-min period [28]. A secondary outcome was the percentage of beat-to-beat chest compressions meeting both the guideline-recommended rate (100-120 min^{-1}) and depth (50-60 mm) of high-quality CPR by each participant during the 2-min period. The tertiary outcome was the number of participants receiving at least one reminder from the investigator for forgetting to perform ventilation after about 30 consecutive chest compressions during CPR in each group. Differences between groups were evaluated with the t-test, Chi-Square test, or Mann-Whitney U test depending on the distribution.

6.3.3 Results

In this randomised controlled simulation study, 80 ED professionals were recruited. No one was excluded due to ineligibility. Of the enrolled participants, 40 people were assigned to the intervention group and 40 to the control group. A total of 11,737 compressions were collected, 5,775 (49%) of which were performed by the intervention group. Participant demographics are shown in **Table 6.1**. There were no differences between the intervention and control groups in terms of participant profession, years of working experience in their current position, age, and gender.

Table 6.1. Participant Demographics.

	Control (n=40)	**Intervention (n=40)**	**P Value**
Age, Years			
Mean (SD)	29.7 (4.7)	30.2 (4.7)	0.618
Gender (n, %)			
Male	5 (12.5)	7 (17.5)	0.531
Female	35 (87.5)	33 (82.5)	
Profession (n, %)			
Physician	3 (7.5)	2 (5.0)	0.644
Registered Nurse	37 (92.5)	38 (95.0)	
Working Experience, years			
Mean (SD)	5.7 (3.9)	6.2 (4.4)	0.531

The compression rates (episode mean±SD, min^{-1}) were significantly faster (but above the guideline recommendation, $P<0.001$) in the control group (129.1±14.9) than in the intervention group (112.0±3.5). The compression depths (episode mean±SD, mm) were significantly deeper ($P<0.001$) in the intervention group (50.9±6.6) than in the control group (39.0±8.7). Data comparison graphs on the chest compression distributions are shown in **Figure 6.4**. The percentage (%) of high-quality CPR was significantly higher ($P<0.001$) in the intervention group (median 39.4, IQR 27.1-50.1) than in the control group (median 0.0, IQR 0.0-0.0). The percentage distribution of high-quality CPR is shown in **Figure 6.5**. The number of participants who received the investigator reminders for forgetting to perform ventilation after about 30 consecutive chest compressions was significantly higher (P<0.01) in the control group (11 over 40) than in the intervention group (1 over 40).

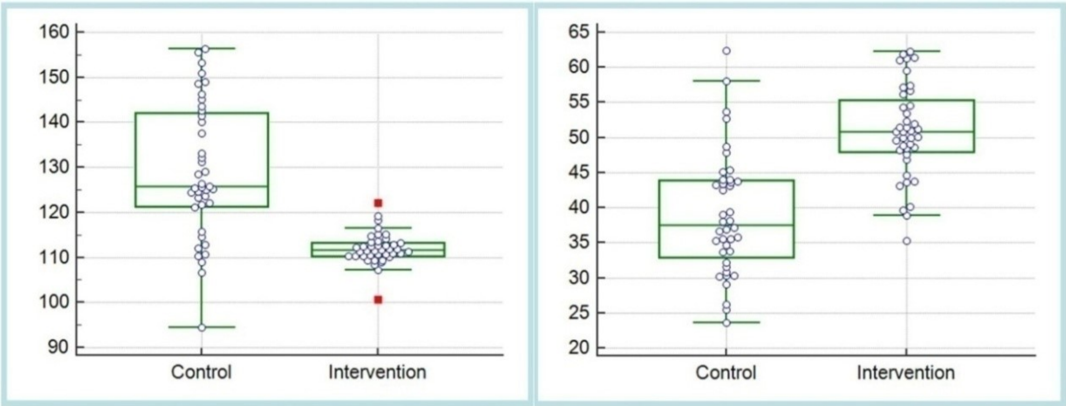

Figure 6.4. Data comparison graphs on chest compression distribution in chest compression rate (min^{-1}, left figure) and chest compression depth (mm, right figure) using box-and-whisker plots. The far out values (or outer fences, defined as a value that is smaller than the lower quartile minus 3 times the interquartile range, or larger than the upper quartile plus 3 times the interquartile range) are marked as red squares.

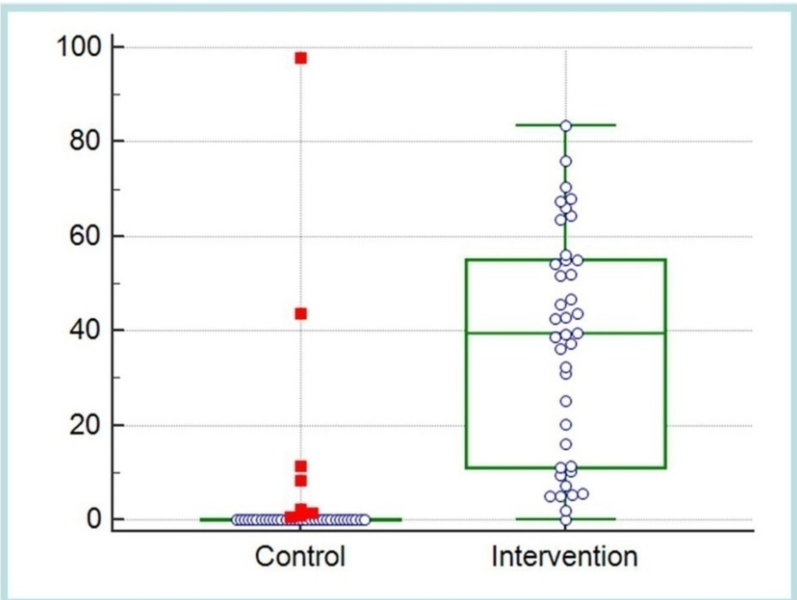

Figure 6.5. The percentage (%) distribution plots (box-and-whisker plots) of high-quality CPR in the control (left) and the intervention group (right). The far out values (or outer fences, defined as a value that is smaller than the lower quartile minus 3 times the interquartile range, or larger than the upper quartile plus 3 times the interquartile range) are marked as red squares.

6.3.4 Discussion

This study evaluated the impact of a smartwatch app capable of detecting CCD and CCR while also providing real-time feedback on CPR quality for cardiac arrest. It compared the quality of CPR performed by healthcare providers on a sensorized manikin (simulated cardiac arrest) with or without the smartwatch app. The results showed that CPR quality could be significantly improved by using a smartwatch with real-time feedback.

As opposed to smartwatch, a smartphone has been an indispensable device for everyone during our daily activities. There have been various smartphone applications that provided feedback on CPR quality, but these applications mainly focused on CPR training [29-30]. Although smartphones might be considered to be wearable, they most often reside in a pocket or purse and could be difficult for use during CPR since rescuers would have to hold a smartphone in one hand while performing chest compression with the other hand. In terms of using a commercially available electronic device to assist during CPR, researchers have utilized the Microsoft Kinect with motion sensing ability to track hand position and provide real-time feedback during CPR [31-32]. Although the results are promising in terms of CPR quality, their applications are limited due to the size and lack of portability of the device. Our study is a great example of using modern information technology as an assistive device in improving the quality of healthcare. Although it is a simulation study performed on a manikin, it has great potential to be utilized in clinical settings.

For clinical practice in Taiwan, healthcare providers working in acute care settings have to pass ACLS training classes offered by recognizable organizations every three years. This ensures that they have sufficient knowledge and experiential skills to practice in clinical settings where cardiac arrests may happen unexpectedly. Based on this simulation study performed on a manikin, we found that participants in the control group tended to deliver chest compressions at a faster rate and more shallow depth than the recommended guideline standards. The percentage of high quality chest compressions remained poor in the control group without feedback. In addition, the adherence to the 30:2 compression-ventilation ratio was significantly better in the intervention group than in the control group. With a smartwatch that provides real-time feedback in the intervention group, compression depth and rate were within the range recommended in the guidelines. The overall performance in the smartwatch group was superior to the control group.

Previous reports suggested that, even for healthcare providers, CPR quality was often suboptimal and associated with poor outcomes [33-35]. With newer technology capable of monitoring CPR quality, it is now possible to receive real-time feedback to improve resuscitation performance. This study demonstrates how a readily available, off-the-shelf consumer electronic device can facilitate the delivery of high-quality CPR. A smartwatch can be easily worn on the wrist without interrupting daily activity, making it a particularly valuable assistive device. Although this study aims to evaluate CPR quality with focus on healthcare providers in the ED, its applications can also be extended to the prehospital setting to be used by layperson for bystander CPR. The smartwatch app in this study provides three different feedback mechanisms: visual feedback on the screen, audio feedback from the speakers, and metronome guidance that was set as 110 min^{-1}. While we found differences between the intervention and control groups, based on the study design we cannot tell whether one feedback mechanism was responsible for these differences. Further study will be needed to compare the effect of the individual feedback mechanisms.

There are limitations in this study. First, this study was conducted in our ED observation unit instead of a real resuscitation unit. Background noise may influence the effect of audio feedback and thus the CPR quality when in real-world clinical practice. Second, allowing full chest recoil after each compression is recommended by the guidelines but was not measured in this study. Leaning can hinder chest recoil and should be avoided due to its effect on preventing the return of blood flow to the circulation [8]. Such deficiency in detection of leaning has been a major drawback of any attempt to derive complete feedback from the accelerometer-based devices [36]. Third, participants performed chest compression on a manikin that was placed on hard ground. The estimated CCD may be inaccurate when CPR is applied on a patient lying on a bed or on a soft surface [37]. Fourth, this study was designed for healthcare providers who should perform compression to ventilation at 30:2 ratio. We also evaluated participants' adherence to the guideline, but we did not evaluate hand position on the chest or measure the ventilation quality. Fifth, we sought to compare CCD and CCR on the same basis during the two-minute CPR attempt (participants without delivering ventilation tend to perform more chest compressions than those with ventilation), so participants received instant reminding of ventilation since CPR quality decreased significantly faster when performing continuous chest compression compared to 30:2 ratio [38]. Sixth, in this study most of the recruited participants were nurses, young, and female. The lack of diversity in professions and working experience may have affected the overall performance in this study. Lastly, data on participant demographics were recorded and compared, but we did not collect participants' weight, body mass index, or physical fitness, which may have influenced CPR quality [39-40].

6.3.5 Conclusions

Without real-time feedback, chest compressions even when performed by trained medical professionals tend to be too fast and too shallow. CPR quality, in terms of rate and depth of compressions, was improved with the assistance and feedback through a smartwatch providing real-time instructions in a simulated environment.

6.4 Concluding Remarks

This chapter describes a randomized simulation study that utilized the smartwatch app we developed to facilitate the delivery of high quality CPR in a controlled environment. As anticipated, chest compressions performed by healthcare professionals showed significant improvement in CCR and CCD through the real-time feedback mechanism of the smartwatch. For future application in clinical settings, healthcare providers can have an additional tool to measure the quality of CPR with feedback instructions for patients presented as OHCA in the ED or in-hospital Cardiac Arrest (IHCA) in the ward. In addition to use by healthcare providers, in the future this platform has the potential of being extended to the prehospital setting by EMTs or laypersons. If successfully implemented in real world scenarios, the improved outcome will inform the public about the importance of bystander CPR. In the next chapter, the major findings and conclusions from each chapter, the overall limitations of the dissertation, the contributions of this work, and the opportunities for future work will be described.

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CHAPTER 7. CONCLUSIONS

The goal of this dissertation is to develop a novel application using a smartwatch worn on the rescuer's wrist to facilitate the delivery of high-quality CPR during emergency settings. To achieve the overarching research goal, three aims were formulated. Aim 1 is to develop an application (app) for a smartwatch as an assistive device during CPR for healthcare providers through UCD and usability testing (see **Chapter 4**). Aim 2 is to conduct a feasibility study by using a smartwatch with the developed app to detect the rate and depth of chest compressions with real-time feedback instructions during CPR (see **Chapters 4** and **5**). Aim 3 is to compare the quality of CPR performed by healthcare providers while using the smartwatch with the preinstalled app with traditional resuscitation using a sensorized manikin to simulate the victim of cardiac arrest (see **Chapter 6**).

Chapter 7 summarizes the major findings and conclusions from each chapter with respect to the research questions addressed (**Section 7.1**). The contributions of this dissertation to biomedical informatics are discussed in **Section 7.2**. The limitations and weaknesses of these research findings are discussed in **Section 7.3**. Finally, a discussion of the directions for further research opportunities (**Section 7.4**) and concluding remarks (**Section 7.5**) are addressed.

7.1 Major Findings and Conclusions from Each Chapter

In **Chapter 2**, a literature corpus relating to current CPR standards, quality measurement, and quality feedback research works was collected as research resources for my ongoing dissertation work. **Chapter 3** (paper 1) is a systematic review of healthcare applications of smartwatches. By using PRISMA as the systematic review methodology, 24 articles were selected for detailed review amongst 356 articles screened. A systematic review of research related to smartwatches was conducted to gather the most updated applications in the healthcare domain. The main finding of this study revealed that while there is an enormous opportunity for healthcare applications using smartwatches, most of the identified studies focused on applications involving health monitoring for the elderly (6; 25%).

Chapter 4 addresses the first research question: “What user interface is best suited for the CPR watch to meet the needs of rescuers?” The software development process that utilized the UCD process for the user interface of a smartwatch app to be used as a feedback device during CPR, along with the related usability testing on this app are discussed. To provide feedback on the quality of chest compressions during CPR, accurate measurement of the CCR and CCD in real-time is the most important step for the smartwatch-based device as an assistive device in clinical settings. By using the moving average and machine learning method, in this chapter a new method of estimating CCR from data collected by the built-in accelerometer of the smartwatch is introduced.

Chapter 5 (paper 2) is related to the second research question: “Is it feasible to use a CPR watch as an assistive device to improve CPR quality?” This paper describes a depth estimation algorithm of chest compression based on the smartwatch we used to provide feedback for improving CPR quality. To successfully implement an accelerometer-based device for providing effective feedback instructions during CPR, we believe that it is important to develop robust algorithms for real-time and accurate measurement of CCD during chest compressions. Instead of using double integration of the acceleration that was used by most of the previous accelerometer-based devices reported in the literature, which is characterized by computational complexity and error accumulation, we developed a relatively simple and effective method to accurately estimate CCD. This paper also describes a validation experiment conducted to examine the accuracy of depth estimation for our algorithm. The result of this study is promising and the algorithm has served as the basis of the real-time analysis module of our wearable application (**Section** 4.2.1).

Finally, **Chapter 6** (paper 3) addresses the third research question: "Do rescuers with a CPR watch outperform those without?" This paper describes a randomized control study by applying the smartwatch app we developed to facilitate CPR quality on a manikin simulating a cardiac arrest victim presented to the ED. By using a smartwatch with a preinstalled app capable of detecting CCD and CCR while also providing real-time audiovisual feedback, the quality of CPR performed on a sensorized manikin (simulating the victim of OHCA) by healthcare professionals was compared. A total of 80 participants were recruited and randomly allocated to either the intervention group wearing a smartwatch with feedback or the control group without feedback. The results showed that chest compressions tend to be too fast and too shallow without real-time feedback, and the proportion of CPR quality meeting both the guideline-recommended rate and depth can be significantly improved with the assistance of a smartwatch. This paper affirms the hypothesis of this dissertation that a smartwatch based chest compression feedback app could improve the quality of CPR in a simulated environment.

7.2 Contributions

This dissertation has expanded our knowledge in several key areas.

Based on the first paper (**Chapter 3**), the systematic review, it has found that there was a lack of detailed description of UCD or usability testing before implementation in most of the healthcare applications using smartwatches. This study utilized the UCD process for the development of the user interface for a smartwatch app to be used as a feedback device during CPR for professional healthcare providers. A brief usability test to evaluate the product by testing it on users was conducted. This work could be used to enhance the knowledge of future software development and user interface design processes in wearable devices for healthcare providers.

This dissertation introduced novel methods for estimating CCR and CCD by using the sensor data exclusively collected from the built-in accelerometer of a smartwatch. Several technologies have been reported to estimate CCD as feedback devices by using the accelerometer data, and most of them derived chest displacement from acceleration by applying a double integration method. As mentioned in paper 2 (**Chapter 5**), there are problems associated with using a double integration method to estimate compression depth, including the difficulty of determining the initial velocity and integration drift, which will cause enormous errors without adequate correction. This paper explores a new alternative to estimate CCD by using a simple hypothesis that CCD is correlated to the magnitude of maximal acceleration at a specific time point during each chest compression, and the value is also correlated to that of its proximal point. By generating a statistic value M, which is the summation of acceleration squared (to eliminate the negative value of collected acceleration) divided by the number of time points during a specific time interval (to eliminate the boundary effect), and a simple polynomial (as a function of M and compression rate), a model capable of predicting CCD can be easily constructed by collecting sufficient data for model training and adoption in a smartwatch. To validate the algorithm we developed, we compared the CCD results given by the smartwatch app and the reference using the Wilcoxon Signed Rank Test, and used Bland-Altman analysis to assess the agreement between the two methods. The results of the validation indicate that our novel algorithm is a reliable method to estimate CCD, ensuring efficient calculation of depth from a smartwatch app with the ability to provide real-time feedback during chest compression-only CPR. This novel depth estimation algorithm of chest compression can also be expanded to other devices with a built-in accelerometer.

There is strong evidence that CPR quality is related to the chance of successful resuscitation and survival for patients with cardiac arrest. In an effort to improve CPR quality, resuscitation guidelines recommend monitoring CPR quality and using metronomes and real-time feedback systems to guide rescuers during resuscitation attempts. In paper 3 (**Chapter 6**), we described a randomized control study by using a smartwatch app we developed with real-time audiovisual feedback as the intervention to facilitate the delivery of high-quality CPR on a manikin simulated as a cardiac arrest patient. This study shows that the compression rates were significantly faster than the guideline recommendation in the control group than they were in the intervention group. The compression depths were significantly deeper (and better) in the intervention group than in the control group. The percentage of high-quality CPR was significantly higher in the intervention group than in the control group. It is astonishing to find that chest compressions by healthcare providers tend to be too fast and too shallow without real-time feedback. The major contribution we found in this study is that CPR quality can be improved with the assistance of a smartwatch providing real-time feedback in a simulated environment, which exhibits great opportunity to be implemented in future real-world practices in both prehospital environments for laypersons and emergency clinical settings for healthcare providers.

7.3 Limitations

As with all studies, this dissertation has some limitations. The limitations of the method adopted have been discussed in each chapter. This section describes the overall limitations of this dissertation work.

First, since this is a simulation study and participants performed CPR on a manikin, its application on real patients suffering from cardiac arrest demands further evaluation. A future clinical trial will be conducted to evaluate the clinical application of this app in real emergency settings after it is IRB approved. Second, the CPR experiment was conducted in a controlled environment (one of our ED observation units) without many competing sounds (background noise) that may influence the effect of audio feedback when in a real resuscitation unit. With an appropriate setting, the audio effect can be synchronized to external speakers via Bluetooth protocol if the app is to be used in a resuscitation unit. Third, the Hawthorne effect is inevitable since the participants in the intervention group need to wear a smartwatch while performing a sequence of CPR [1]. However, the effect is minimal since the control group was also observed in this study.

7.4 Opportunities for Future Work

The findings from this study present the opportunity for future work. This section highlights three main areas for future work.

The smartwatch app in this study aims at providing real-time feedback for professional healthcare providers who perform CPR on victims in the ED. In the future, this app could be tested in other settings. For example, it could be tested for use by EMTs in the field or during ambulance transport. It could also be tested with the "hands-only" (chest compression-only) mode to guide laypersons performing bystander-initiated CPR on victims with cardiac arrest in out-of-hospital settings.

Studies have shown that CPR performance can be improved with CPR coaching for cardiac arrest [2-4]. In addition to a wearable application that can be used as a standalone app, the system we developed (**Section 4.2**) also exhibits a mobile application that can display CPR quality synced with the smartwatch using Bluetooth protocol in a real-time manner. In future studies, we can investigate the CPR coaching effect with the help of the smartphone application that provides real-time feedback from the CPR leader.

In the randomized simulation study, we provide three different feedback mechanisms: visual feedback on the screen, audio feedback from the speakers, and a metronome to guide the rescuers to perform CPR. We also showed that CPR quality, in terms of rate and depth of compressions, was improved with the assistance and feedback through a smartwatch providing real-time instructions. Further studies could compare the effects of each of the individual feedback mechanisms in improving CPR performance.

7.5 Concluding Remarks

Sudden cardiac death from cardiac arrest is a leading cause of mortality and responsible for an estimated 15–20% of all deaths [5]. Despite major advances in treatment and prevention of cardiac arrest, survival rates remain poor [6-7]. This dissertation aims to address this gap and seeks to enhance survival outcomes following resuscitation through the application of smartwatch technology. A smartwatch app was developed that utilized sensor data collected from the built-in accelerometer to provide real-time CCR and CCD while performing chest compressions on a manikin. This system was applied in a controlled and simulated CPR performance study comparing the differences in chest compression performance with and without audiovisual feedback by the smartwatch. The statistical results indicated that audiovisual feedback provided an effective method with respect to increasing the percentage of high-quality CPR. Results from the study support a number of conclusions and future research opportunities. Most notably, this dissertation provides a great example of using modern informatic approaches to solve real-world clinical problem.

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white paper will be accepted.

VITA

Tsung-Chien (Jonathan) Lu is an Emergency Physician working in National Taiwan University Hospital (NTUH), which is a 2400-bed university-affiliated tertiary teaching hospital serving approximately 2000 inpatients, 7000 outpatients, and 300 emergency visits daily. As an Attending Physician at academic medical center, he is responsible for caring those patients who suffered from acute illness or trauma presented to the Emergency Department. He also oversees the practice of residents and interns rotating at my department during routine shift duties. In additional to clinical practice, he is also an Adjunct Lecturer teaching Emergency Medicine in National Taiwan University (NTU) College of Medicine. His research interest lies in the vast field of Emergency Medicine and Biomedical Informatics.