出國報告（出國類別：進修）

醫學資訊學在急診醫學的應用

服務機關：國立臺灣大學醫學院附設醫院急診醫學部

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摘要

本次前往美國華盛頓大學「生物醫學與健康資訊研究所」進修醫學資訊學。以智慧型手錶應用在急診的復甦醫學。研究題目為:使用智慧型手錶對於心臟停止病患提供高品質的心肺復甦術。

針對智慧型手錶在臨床醫學的應用的文獻回顧論文，已刊登於應用臨床資訊期刊。此外，已完成以智慧型手錶的加速計收集施救者對急救安妮壓胸時的心肺復甦術的數據，建立演算法(Algorithm)的模型，提供施救者即時回饋。該演算法的描述與驗證(Validation)的論文已經完成，即將投稿中。研究成果摘要並成功於 2017 年 11 月在 AHA ReSS 2017 報告。

職雖職雖然返國敘職，投入臨床服務的工作，但研究工作並未間斷。未來將利用本土的研究資源，結合醫院的電子病歷系統，並將所學應用在國人的健康照顧與預防。

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本文

壹．目的:

　隨著現代資訊科技的發展，穿戴式裝置在健康產業的發展已扮演重要角色。由於其微型體積的優勢，穿戴式裝置可以無阻礙地配戴在人們身上而不影響日常生活，且由於其具備有各種感應器與無線通訊的能力，可以不間斷地提供使用者的感測數據，以非侵襲性的方式傳遞資訊，因此被視為有可能改變健康產業的照顧模式。當病患因為急症而召喚救護車，來到急診室由急診醫師診視，收治到醫院接受院內照顧，一直到康復出院，整個健康照顧的流程都有可能因為穿戴式裝置的介入而改變。

　近來穿戴式裝置最熱門的話題，實屬智慧型手錶（Smart Watch)。因為資訊科技的發展以致於可將其高度複雜的運算能力鑲嵌於其微型的體積中，因此就如同手錶一樣可以每天配戴在人們的手腕上而不影響其日常生活。同時由於其具備各種感測器，可以無間斷收集配戴者的生理數據。如果配戴在施救者手腕上，可以記錄其心肺復甦術施行的數據，經由運算後藉由其介面、聲音、或震動提供回饋，以達成高品質心肺復甦術(High Quality CPR)的目標。

　本研究的目的，在於建立一個以智慧型手錶為標的之應用程式(App)，配戴在施救者的手腕，可以預測心肺復甦術時壓胸的深度與速度，以提供即時的回饋，達成高品質的施救品質以改善心跳停止病人預後。其分項目的下:

Specific Aim 1: To develop an application (app) for a smart watch as an assistive device during CPR for healthcare providers through user-centered design and usability testing.

Specific Aim 2: To conduct a feasibility study by using a smart watch with the developed app to detect the rate and depth of chest compression with real-time feedback instructions during CPR.

Specific Aim 3: To compare the quality of CPR performed by healthcare providers while using the smart watch with preinstalled app with traditional resuscitation using a sensorized manikin to simulate the victim of Out-of-Hospital Cardiac Arrest.

貳. 過程:

一. 背景介紹:

除了早期辨識與及時的呼救外,影響心跳停止病患預後的最主要因素,就是高品質的心肺復甦術 (Cardiopulmonary Resuscitation, CPR) [1]。自從 1966 年美國心臟科醫學會發表第一個心肺復甦術指引以及 Dr. Leonard Cobb 在西雅圖開始大規模訓練大眾心肺復甦術[2],國際上每隔五年就會對 CPR 做修訂。在 2005 年, the American Heart Association (AHA) Guidelines for CPR and Emergency Cardiovascular Care (ECC) 被修訂並且強調高品質的心肺復甦術[3]。另外在 2010 年又強調對於那些不熟悉或不願意施行人工呼吸者,可以施行只有壓胸的心肺復甦術(Chest compression only CPR) [4]. 目前最新的 2015 年指引,高品質的 CPR 再度被強調,施救者應在壓胸時給予適當的深度與速度以提升施救品質並提升病患的預後[5]。

為了改善急救品質並提供即時的回饋,全世界的急救醫學研究者發展各種方法來提供臨床或一般民眾施救時的回饋方法。臺大醫院急診醫學部(本部)江文莒醫師研究 audio-prompts 可以提供定速的音響來指引施救者壓胸時的速度 [6]。臺大醫院教學部的楊志偉醫師利用手機預錄的急救指引,發現可以改善 dispatcher assisted 施救者壓胸的深度與速度[7]。Semeraro 等人利用 iPhone 所發展的應用程式 iCPR 來改善施救品質,發現不管是深度與速度的品質都有顯著提升 [8]。Zoll 這間公司也發展了一套適用於智慧型手機的應用程式,來提供施救者的指引[9]。不過這些應用不是太過繁複無法隨時使用,或是利用手機本身會影響施救者的操作,而降低其實用性。利用智慧型手錶的可攜性以及不影響臨床流程的特性,設計可供臨床工作者或是一般民眾使用的應用程式,於 CPR 訓練或真實場景的急救,為可行性與實用性的評估,為本研究的主要目的與應用。

二. 學習及訓練過程:

針對本研究,職於美國西雅圖華盛頓大學「生物醫學與健康資訊研究所」的訓練與學習,除針對所擬定的主題,已完成系統性的文獻回顧論文,並獲刊登在美國醫學資訊協會(American Medical Informatics Association, AMIA)所屬的期刊: Applied Clinical Informatics 外 (**Appl Clin Inform. 2016;7:850-69,如**附錄一),其餘依研究題目的三個主要目的,主要分成以下三個研究主題:

(1) <u>設計屬於急救用智慧型手錶的專屬使用者介面</u>:

根據不同使用者為目的,使用者介面工程學(User interface

engineering)著重在使用者介面的設計，以滿足不同需求並極大化使用者的經驗。所以第一步就是要設計一種使用者界面 user-centered design (UCD)來滿足高品質 CPR 的需求。本研究遵循 usability.gov [10] 的指引(Figure 1)，反覆探詢使用者意見(主要是專業的醫療工作者)，依照以下流程設計出符合使用者需求的介面，提供下一階段應用程式的開發。

- Specify the context of use: Identify the people who will use the product, what they will use it for, and under what conditions they will use it.
- Specify requirements: Identify any business requirements or user goals that must be met for the product to be successful.
- Create design solutions: This part of the process may be done in stages, building from a rough concept to a complete design.
- Evaluate designs: Evaluation - ideally through usability testing with actual users - is as integral as quality testing is to good software development.

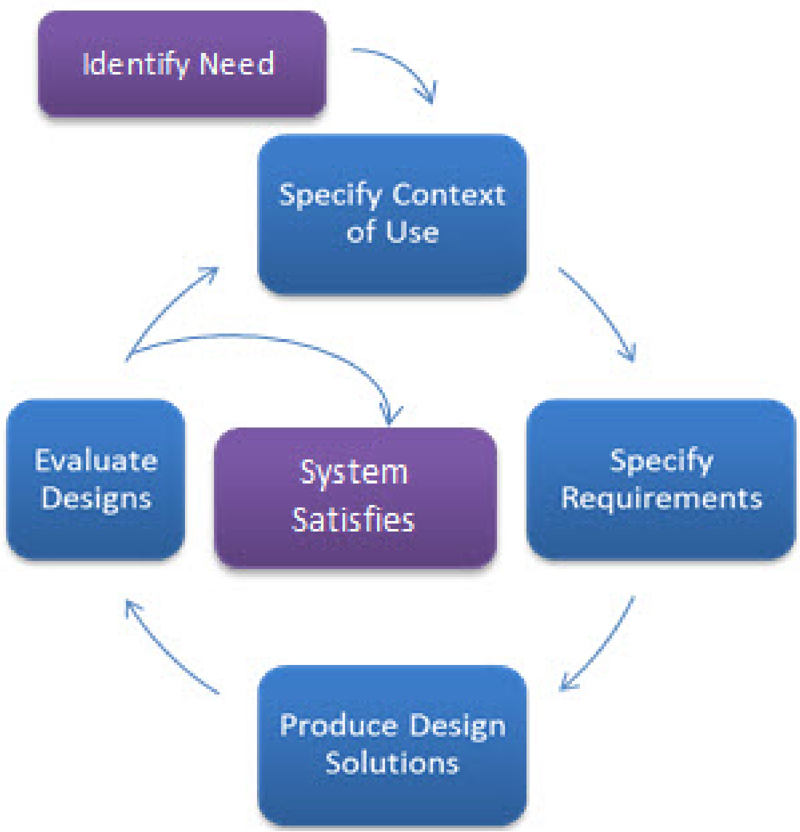

Figure 1. 使用者介面(UCD)的開發流程[10].

根據上面的流程，我們成功開發出以下的使用者介面，依據不同使用者，可以選擇英文或是中文介面與發音(Figure 2)。

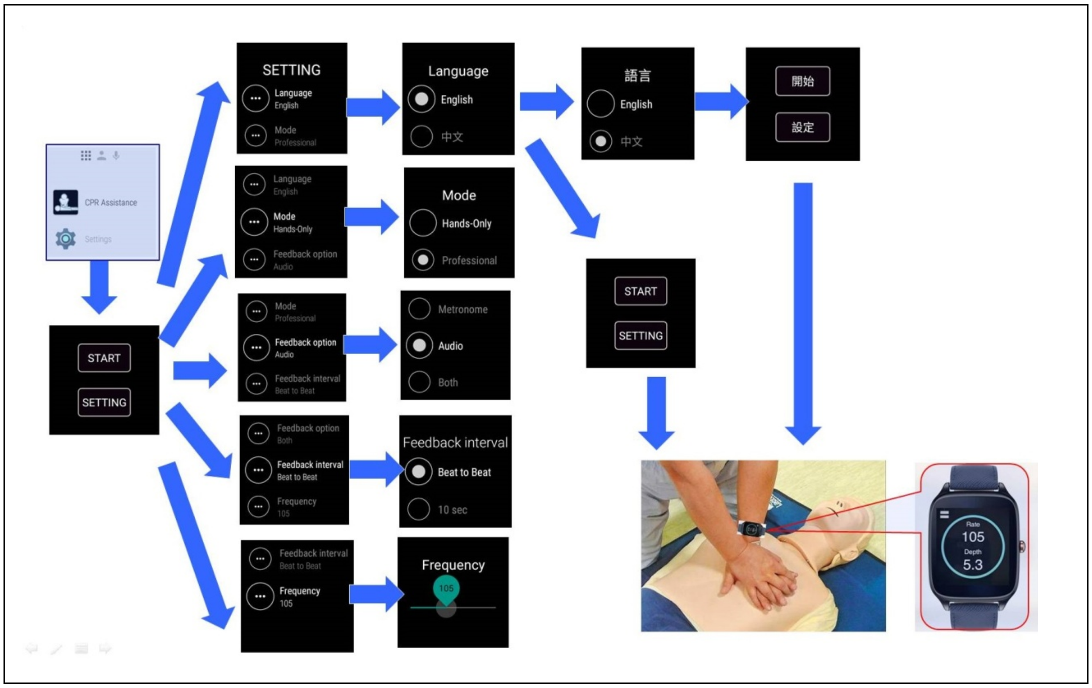

Figure 2. 使用者介面(UCD)的開發結果。

(2) <u>演算法的開發與模型建立後的驗證</u>:

使用智慧型手錶的加速計(Accelerometer)來收集施救者壓胸的數據，以提供即時的回饋。其中最重要的決定因素，在於有效且精確的壓胸深度之及時計算。目前文獻上或是既成的商品(用於智慧型手機)在計算壓胸深度時，所採用的方法，多仰賴於對收集的的加速度做二次積分 (Double Integration)，但是此法的演算複雜，且會將背景的雜訊累加進去，因此並不是個實用的方法。 本研究所開發的方法，在於根據每次壓胸時的最大加速度值，輔以模型建立時所收集到的資料，以類似機械學習(Machine Learning)的方法建立模型。其演算法的細節，因為刻正投稿尚未正式發表，且正申請中華民國專利，因此未在此報告中揭露。另外已收集資料來驗證(Validate)其可行性，成效良好，其先期研究成果(Preliminary Study)的摘要 (A Novel Chest Compression Depth Estimation Algorithm Based on a Smartwatch for High-Quality Cardiopulmonary Resuscitation)投稿美國心臟科醫學會(American Heart Association)復甦會議 (ReSS 2017)獲得接受並成功於 Nov.11-13, 2017 在加州安那翰 (Anaheim, CA)報告。論文摘要如下，並已刊登在 Circulation: Volume 136, Issue Suppl 1。另全文論文已經完成，正準備投稿中。

AHA ReSS 2017, November 11–13, Anaheim, California

A Novel Chest Compression Depth Estimation Algorithm Based on a Smartwatch for High-Quality Cardiopulmonary Resuscitation

Abstract

Introduction: High-quality cardiopulmonary resuscitation (CPR) is a key factor to 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 with built-in accelerometer for feedback instruction during CPR.

Methods: For data collection and model building, an Android Wear was worn by a researcher performing compression-only CPR on Resusci Anne manikin with QCPR sets (as reference standard). Acceleration data was collected by the 3-axis accelerometer of the smartwatch and processed to eliminate gravitational influence. The corresponding values of chest compression depth (CCD) were labeled according to the reference. We developed an algorithm based on the assumption that 1) maximal acceleration measured by the smartwatch accelerometer and the CCD are positively correlated and 2) the magnitude of acceleration at a specific time point and interval is correlated with its neighboring point. We defined a statistic value *M* as a function of time and the magnitude of maximal acceleration. Data were collected and processed and the relationship of *M* value, chest compression rate (CCR) and CCD were determined. A smartwatch app capable of detecting CCD was developed accordingly. During the validation process, a 2nd researcher wearing a smartwatch with pre-installed app performed compression-only CPR on the manikin at target sessions. The CCD results given by the smart watch and the reference were compared using the Wilcoxon Signed Rank Test (WSRT). Bland-Altman (BA) analysis was used to assess the agreement between two methods.

Results: For target CCR of 100-120/min and CCD of 5-6 cm, 2159 total compressions were analyzed. WSRT showed that there was no significant difference between the 2 methods (P=0.084). By BA analysis the mean of differences was 0.0135 and the bias between 2 methods was not significant (95% CI -0.0003 to 0.0274).

Conclusions: Our preliminary study indicates that the algorithm developed for

estimating CCD based on a smartwatch with built-in accelerometer is promising. Further studies will be conducted to validate a broader range of CCR and CCD, and its application for clinical CPR training.

（3）急救用智慧型手錶的隨機對照試驗：

本試驗預計施行對象為有經驗的臨床工作者，比較有配戴智慧型手錶與吳佩戴者之間，在以急救安妮（Resusci Anne） 為對象的模擬環境，所施行急救品質的比較。Figure 3 是招募受測者的海報，當通過本院 IRB 後，即可在院內與院外醫療社群網站公開招募。其中施救者的招募與排除的標準如下：

Eligibility

Ages Eligible for Study: 18 Years to 65 Years (Adult)
Genders Eligible for Study: Both
Accepts Healthy Volunteers: Yes

Criteria

Inclusion Criteria:

- Currently hold a clinical license (board-certified) to practice at an acute care institute
- Currently involved in caring of adult patients at an acute care institute
- Currently hold a valid certificate of Basic Life Support (BLS) or Advanced Cardiac Life Support (ACLS) issued by recognizable organizations or relevant authorities

Exclusion Criteria:

- Those who hold a expiry BLS or ACLS certificate without update
- Those who mainly involved in caring of pediatric patients
- Medical students

Figure 3. 招募受測者的海報（Flyer）。

（4）<u>華盛頓大學其他研究</u>:

在進修期間，修習了華盛頓大學 Fred Wolf 教授（此為 Wolf 教授所開設的最後課程，因為他在隔年即因血癌過世)所開設的 Meta-analysis 的課程，並完成期末作業“Association Between Socioeconomic Status of Neighborhoods and the Provision of Bystander Cardiopulmonary Resuscitation: A Systematic Review and Meta-Analysis”的論文摘要投稿 AHA ReSS 2016 獲得接受，已成功於 Nov 12-14, 2016 在 New Orleans, Louisiana 報告，論文摘要如下，並已刊登在 Circulation: Volume 134, Issue Suppl 1。另外全文論文已經完成，正準備投稿中。

AHA ReSS 2016, Nov 12-14, 2016, Orleans, Louisiana

Association Between Socioeconomic Status of Neighborhoods and the Provision of Bystander Cardiopulmonary Resuscitation: A Systematic Review and Meta-Analysis

Abstract

Introduction: Early provision of bystander-initiated cardiopulmonary resuscitation (BCPR) is a vital determinant of survival for Out-of-hospital Cardiac Arrest (OHCA) but the BCPR rates remain unsatisfactory. To evaluate whether the presence of certain socioeconomic factors had influenced the odds of BCPR, we conducted a systematic

review and meta-analysis to assess the association between some of the quantifiable socioeconomic factors of neighborhood on rates of BCPR provision.

Methods: We searched PubMed and Embase from 1 January 1966 to June 1 2016. We selected median household income and real estate (property) value as the surrogates of neighborhood socioeconomic status (SES), and investigated their associations in the odds of BCPR provision as the outcome. Studies that were surveys, interviews, or reported outcomes qualitatively were excluded. If SES was expressed as more than two categorical variables or continuous variables in the selected studies, we dichotomized the SES into low or high and reconstruct the binary OR accordingly. Odds ratio (OR) was used as effect estimate and were reconstructed if not provided in the original articles.

Results: Fifteen studies were assessed for eligibility from 731 references. Of them, 6 studies were excluded for lacking the exposure of interest and 4 studies were excluded due to the use of duplicate dataset. Finally, 5 studies were selected for analysis. Of them, 4 studies used median household income and 3 studies used real estate value as the surrogates of the neighborhood SES. Meta-analysis indicated that the likelihood of receiving bystander CPR decreased with lower median household income (OR, 0.71; 95% CI, 0.63-0.80; I^2, 56.9%; 4 studies) and lower real estate value (OR, 0.73; 95% CI, 0.66-0.81; I^2, 0%; 3 studies).

Conclusions: By using surrogates of median household income and real estate value, this review provides evidence of a consistent association between lower SES and lower rate of BCPR. The underlying reasons linking to such association demand further investigation. Future CPR training and public education should be targeted in such high risk residential areas.

（5）臺大醫院其他研究：

除了在華大的主要研究外，並與本部蔡居霖醫師合作，在方震中主任的指導下，利用臺大急診資訊系統的電子病歷大數據的資料，預測病患發生院內急救事件(Development and Validation of a Triage Tool in Predicting Cardiac Arrest in the Emergency Department)的論文摘要，也同時投稿 AHA ReSS 2017 獲得接受，其論文摘要如下，並已刊登在 Circulation: Volume 136, Issue Suppl 1，其全文論文正撰寫中。此篇論文並獲選為最佳研究論文獎(如附錄二)。

AHA ReSS 2017, November 11–13, Anaheim, California

Development and Validation of a Triage Tool in Predicting Cardiac Arrest in the Emergency Department

ABSTRACT

Introduction: In-hospital Cardiac Arrest (IHCA) has increasingly been recognized as a separate entity from out-of-hospital Cardiac Arrest with regard to epidemiology, clinical prediction, and outcomes. The incidence of adult IHCA was about 1 per 1,000 bed-days in the US and 15 to 20% of these patients survived to hospital discharge. Despite the morbidity and mortality, clinical tools for predicting IHCA are scarce, particularly in the Emergency Department (ED).

Hypothesis: Using Electronic Medical Record (EMR) data, we sought to include patients presenting to our ED to 1) describe the incidence of ED IHCA and 2) develop and validate a triage tool for predicting ED IHCA.

Methods: This retrospective cohort study used EMR data from a tertiary teaching hospital with approximately 100,000 ED visits per year. We extracted data from 741,795 ED visits over a 7-year period (Jan 1, 2009 to Dec 31, 2015). For repeat visits, we randomly selected one visit per patient. Only adult patients were included in this analysis. Patient demographics and triage information including triage levels, vital signs (temperature, pulse rate, systolic and diastolic blood pressure, respiratory rate, and oxygen saturation) and mental status (coded as Glasgow Coma Scale) were extracted as potential predictors. The primary outcome, ED IHCA, was identified via a resuscitation code. The predictive tool was developed in 60% of the data and validated in the remaining 40%.

Results: A total of 330,355 adult ED patients were included during the 7-year study period. Of them, 916 (0.3%) developed ED IHCA. The triage predictive tool, including age, sex, triage levels, and triage vital signs with cutoffs similar to those in published early warning scores, showed excellent discrimination (area under the receiver operating characteristic [AUROC] curve, 0.90) and calibration (P=0.30 for Hosmer-Lemeshow [HL] test). When applied to the validation cohort, it maintained good discriminatory ability (AUROC, 0.87) and calibration (P=0.17 for HL test).

Conclusions: IHCA within the ED is not uncommon. We developed and validated a novel tool in predicting imminent IHCA events in the ED. Implementation of this tool may help identify high-risk patients and reduce potentially preventable deaths.

參. 心得:

職得以帶職帶薪前往世界最頂尖的西雅圖華盛頓大學接受醫學資訊學的研究訓練，要感謝教育部因公出國補助與臺大醫院的鼎力支持，同時還要感謝臺大醫院急診醫學部方震中主任及其他師長同仁的體諒，讓我無後顧之憂可以出國專心研究，此外，還要感謝臺大資工所暨臺大醫院秘書室賴飛羆教授在研究方法的幫助。最後更要感謝恩師 Dr. Anne M. Turner 的指導，安排我接受最紮實的訓練課程與研究。

在美國其間與西雅圖華盛頓大學的急診醫學部有廣泛交流，並曾安排本部同仁前往參訪華盛頓大學醫學中心(UWMC)與港景醫學中心(Harborview Medical Center)的急診資訊系統參觀。此外，並連兩年前往美國心臟學會之復甦醫學會報告研究成果，了解目前的研究趨勢並與各國研究者廣泛交流。職所進修的華盛頓大學生物醫學與健康資訊所，連兩年被 CWUR World University Rankings 評比為醫學資訊學的全世界第三名，並被 Healthcare Management Degree Guide 評比為第一名。其所屬的大學與醫學中心，以及其醫學資訊學的訓練，有以下值得我們學習與參考的地方:

(1) 華盛頓大學生物醫學與健康資訊所強調的是生物醫學以及健康資訊，而非只是電腦的應用或者訊息的傳遞。其研究目的在於回答生物醫學數據(Biomedical Data)、知識表示(Knowledge Representation)、知識與訊息擷取(knowledge and information retrieval)、以及訊息與科技運用(Information and Technology use)的核心問題。因此其教職網羅了各領域的專家，但是以臨床醫師兼修資訊的專家為領導，不管是在醫院或學院端。此外，目前美國醫學資訊學會已經將 Clinical Informatics Fellowship Programs 當作一門次專科訓練，臨床醫師在接受完此次專科的訓練，日後到各醫院可以成為該院資訊的主要規劃與執行者。畢竟只有實際的使用者，才知道資訊的真正需求並設計符合臨床工作的資訊環境，此種規劃值得臺灣的醫學資訊的發展當作借鏡。

(2) 美國各州律法不一，加上各大資訊廠商有其不同的系統，所以電子病歷整合不易，但是他們卻有全國統一的榮民醫院電子病歷系統(VA system)，目前仍然是全世界電子病歷的標竿。臺大醫院目前各個分院電子病歷已經整合，如果病患本來就是臺大醫院的病人當無問題。但是臺灣因為健保的自由度太高，病患可以在全臺各大小醫院遊走，但是我們卻缺乏一個整合全臺的電子病歷交換系統。雖然現在開始推行雲端藥歷，但是尚有病歷整合問題未解。為了病患就醫的安全，此課題值得主管機關重視。

肆. 建議事項:

醫學中心以臨床服務、教學、與研究為要務，其中臨床服務為最重要的使命，如何建構一個友善且安全的就醫環境，乃當務之急。目前臺灣全民健保的涵蓋率已是全世界有目共睹，病患就醫的友善環境也被醫事管理單位所重視，但是安全的就醫環境，尤其是全臺統一事權的電子病歷交換系統，仍然在發展階段。如果妥善規劃，不但可以提供完善的病患服務，並可以供教學與各種研究的基礎。值此醫學資訊蓬勃發展之際，電子病歷的整合應考慮以下幾點，:

(1) 本院投入相當的人力物力，把資訊系統由封閉式的 Main Frame 架構轉型為 Web services，此乃一艱劇的工程並為世界所矚目，唯現有系統仍有不穩定、速度過慢、使用者介面不友善等缺失、不為研究需求服務等缺失。亟待更多人的投入，尤其應選送更多人材至其它先進國家學習，以投入系統的改進與維護。

(2) 醫學資訊不只是為服務病患,此寶貴的資源甚至可以用來研究與教學。在大數據(Big Data)時代，美國各領域極力推動去識別的 Open data 提供大眾下載與應用，醫療也不例外。臺灣雖有健保資料庫，但是對研究者仍有可近性的障礙，值得各界深思。臺大醫院目前已經在建置醫學研究所需電子病歷資料庫提供研究者申請。也許在法規允許下，且在不影響病患隱私的前提下，開放數據供各界使用。結合各領域優秀人才，投入醫學大數據的研究，並促進醫學的進步與民眾的健康。

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Appendix 1

Healthcare Applications of Smart Watches

A Systematic Review

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Keywords
Other clinical informatics applications, Interfaces and usability, Healthcare, Wearable device, Smart watch

Summary

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.

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1. Introduction

1.1 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 only 1% to 2% 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 resides 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.

1.2 Significance

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.

1.3 Objectives

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.

2. Material and Methods

2.1 Literature Search

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 on 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.

2.2 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 remaining 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.

2.3 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.

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 1. The complete description of the included studies is shown in ►Table 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 the 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 2. Number of publications and types of study design in terms of the target population is shown in ►Figure 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 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].

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 ▶Figure 2 (B), the number of publications in terms of the study design and target population reflect the heterogeneity of using smart watches 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. This 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 of 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, 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 application of fall detection algorithms in such devices are possible in the future. Nevertheless, use of 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 the 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 the 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 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 contain 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 purposes. 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 the 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 a 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 watch technologies into clinical settings.

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.

6. Conclusion

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.

Authorship

T.C.L. designed the systematic review and conducted initial database search; C.C.F. screened titles and abstracts of identified records; M.H.M.M. reviewed the selection; T.C.L. and C.M.F. reviewed the full text articles and contributed to data extraction. All authors participated in the drafting of the manuscript and review of the content. A.M.T. supervised the whole process of the systematic review. All authors approved the final version of the review.

Clinical Relevance Statement

With appropriate design and rigorous research, smart watches have the potential to improve many aspects of healthcare delivery.

Conflict of Interest

The authors declare that they have no conflicts of interest in the research.

Human Subjects Protections

Human and/or animal subjects were not included in the project.

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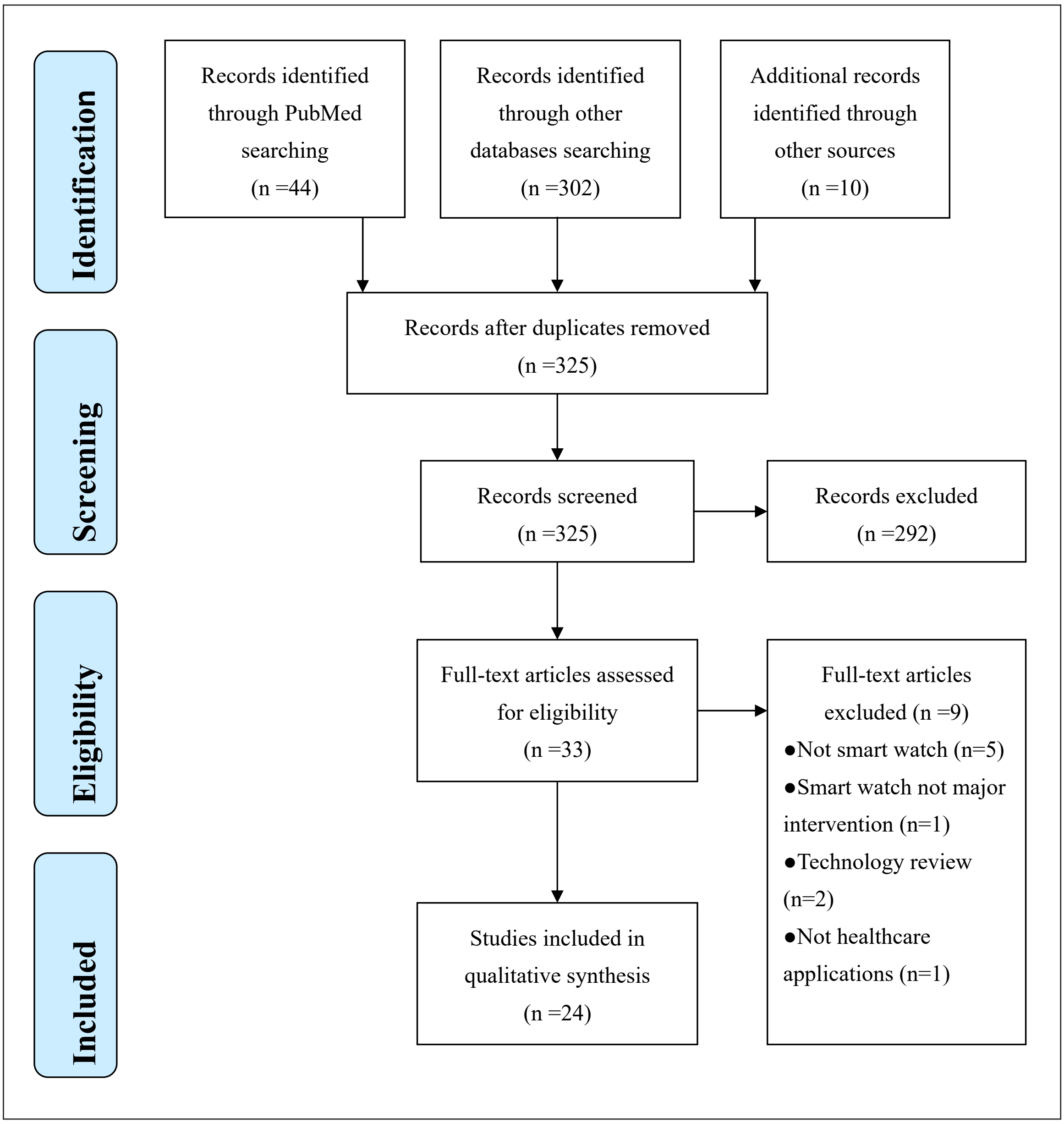

Fig. 1 The study selection process.

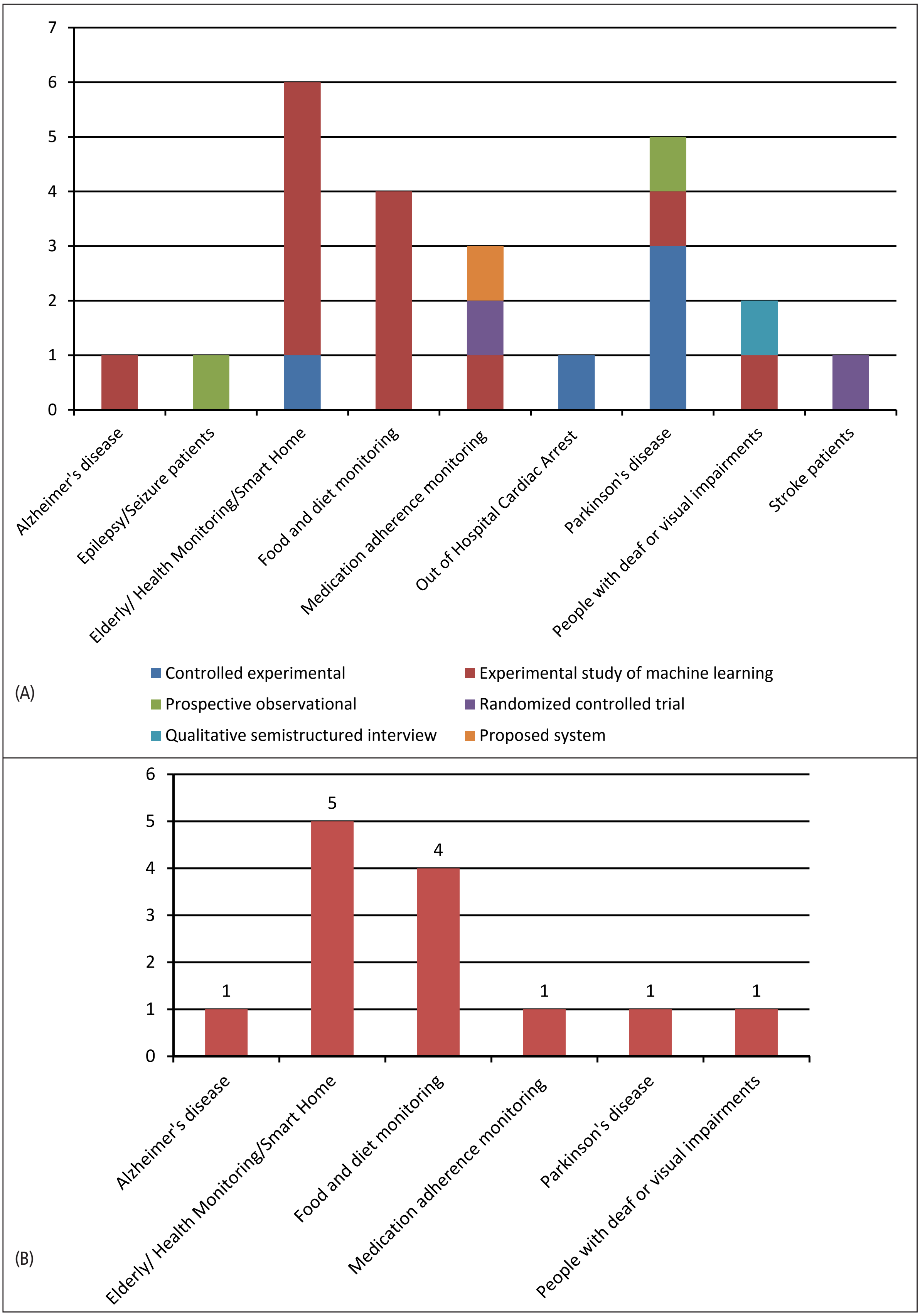

Fig. 2 (A).Number of publications (Y-axis) and types of study design in terms of the target population (X-axis). (B).Number of publications (Y-Axis) with respect to different target population (X-axis) for study design using experimental study of machine learning.

Table 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 needing	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 needing 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	Elderly living in smart home monitoring system	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

Table 1 Continued

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
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 needing 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	Elderly living in smart home monitoring system	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

Table 1 Continued

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
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	Elderly living in smart home monitoring system	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

Table 1 Continued

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
Thomaz 2015 [26]	Conference Proceedings	Experimental study of machine learning	People needing 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 needing 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 non-adherence 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 needing food and diet monitoring	6 volunteers	To explore how far the multiple sensors (accelerometer and gyroscope) on a wrist-worn smart watch 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

Table 1 Continued

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
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 needing 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	People seeking health monitoring system	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

Table 1 Continued

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
Ye 2015 [32]	Conference Proceedings	Experimental study of machine learning	People needing 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/subacute 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 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%)

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Appendix 2

Resuscitation Science Symposium

Young Investigator Award

Presented to

Tsung-Chien Lu

Development and Validation of a Triage Tool in Predicting Cardiac Arrest in the Emergency Department

Resuscitation Science Symposium Young Investigator Networking Event • November 10, 2017 • Anaheim, California

Tom P. Aufderheide, MD, FACEP, FAHA
Co-Chairman, Resuscitation Science Symposium

Ben Abella, MD MPhil, FAHA
Co-Chairman, Resuscitation Science Symposium

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