Wearable Technology Applications in Healthcare: A Literature Review: OJNI

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ABSTRACT (ENGLISH)

Wearable technologies can be innovative solutions for healthcare problems. In this study, we conducted a literature review of wearable technology applications in healthcare. Some wearable technology applications are designed for prevention of diseases and maintenance of health, such as weight control and physical activity monitoring. Wearable devices are also used for patient management and disease management. The wearable applications can directly impact clinical decision making. Some believe that wearable technologies could improve the quality of patient care while reducing the cost of care, such as patient rehabilitation outside of hospitals. The big data generated by wearable devices is both a challenge and opportunity for researchers who can apply more artificial intelligence (AI) techniques on these data in the future. Most wearable technologies are still in their prototype stages. Issues such as user acceptance, security, ethics and big data concerns in wearable technology still need to be addressed to enhance the usability and functions of these devices for practical use.

FULL TEXT

Introduction

Wearable technologies enable the continuous monitoring of human physical activities and behaviors, as well as physiological and biochemical parameters during daily life. The most commonly measured data include vital signs such as heart rate, blood pressure, and body temperature, as well as blood oxygen saturation, posture, and physical activities through the use of electrocardiogram (ECG), ballistocardiogram (BCG) and other devices. Potentially, wearable photo or video devices could provide additional clinical information. Wearable devices can be attached to shoes, eyeglasses, earrings, clothing, gloves and watches. Wearable devices also may evolve to be skin-attachable devices. Sensors can be embedded into the environment, such as chairs, car seats and mattresses. A smartphone is typically used to collect information and transmit it to a remote server for storage and analysis. There are two major types of wearable devices that are used for studying gait patterns. Some devices have been developed for healthcare professionals to monitor walking patterns, including the accelerometer, multi-angle video recorders, and gyroscopes. Other devices have been developed for health consumers, including on-wrist activity trackers (such as Fitbit) and mobile phone apps and add-ons. Wearable devices and data analysis algorithms are often used together to perform gait assessment tasks in different scenarios.

Wearable technologies can be innovative solutions for healthcare problems. In this study, we conducted a literature review of wearable technology applications in healthcare. Some wearable technology applications are designed for the prevention of diseases and maintenance of health, such as weight control and physical activity monitoring. Wearable devices are also used for patient management and disease management. The wearable applications can directly impact clinical decision-making. Some believe that wearable technologies could improve the quality of patient care while reducing the cost of care, such as patient rehabilitation outside of hospitals. The big data generated by wearable devices is both a challenge and opportunity for researchers who can apply more AI techniques on that data in the future.

A search in the PUBMED databases was performed in September 2018. All papers containing the terms "wearable technologies" or "wearable devices" in the title or abstract were identified. In addition, the search was limited to articles whose publication dates were within 10 years (from 2008 to 2018). The abstracts of these studies (n=1126) were then inspected to ascertain whether they contained information about the "wearable technology applications in healthcare." The authors then reviewed those studies for information regarding wearable device applications and identified 67 relevant papers.

Results

To summarize the results of the literature review, the wearable technology applications are grouped into three categories based on their roles. For example, wearable devices designed for **weight control and physical activity monitoring are listed in the section of prevention of diseases and maintenance of health. In addition, there are sections of patient management and disease management.**

Prevention of Diseases and Maintenance of Health

Fall Identification and Prevention

In many countries, providing care to an aging population has become a significant challenge. For example, the number of Americans 65 and older will grow from about 49 million in 2018 to approximately 100 million in 2060 (Vespa, Armstrong, &Medina, 2018). The World Health Organization expects that the global elderly population 60 or older will rise to 2 billion by 2050 (World Health Organization (WHO), 2015). The aging population has increased risks for chronic conditions, falls, disabilities and other adverse health outcomes (Ambrose, Paul, &Hausdorff, 2013). Providing preventive interventions to the aged population to improve health outcomes has become an important research and development topic. Wearable devices could be used to address some of the challenges related to detecting and managing adverse health conditions in aging populations. Wearable devices have great potential to be used in fall prevention among older adults. Falls occur in 30% to 60% of older adults each year, and 10% to 20% result in injury, hospitalization or death (Rubenstein, 2006). For the elderly people in the USA, falls lead to four to 12 days of hospital stay per fall (Bouldin et al., 2013). Recent studies have focused on developing wearable devices and associated algorithms to collect and analyze gait (manner of walking) data for fall prevention (Awais et al., 2016).

In research settings, the performance of fall detection using wearable devices has already achieved considerable good results. For example, one study developed a solution to recognize walking and activities (González et al., 2015). The study used a genetic algorithm and two triaxle accelerometer bracelets to detect walking patterns that could lead to disruptive events, such as falling and seizure onset. Pannurat, Thiemjarus, &Nantajeewarawat (2017) presented a method to detect a fall at different phases using a wireless accelerometer and classification algorithms. Their evaluation results showed an 86% and 91% accuracy for fall pre-impact and post-impact detection. Hsieh, Liu, Huang, Chu, &Chan (2017) developed a novel hierarchical fall detection system using accelerometer devices on the waist. The results showed that the system achieved a high accuracy at 99% in identifying fall events. Similarly, Gibson, Amira, Ramzan, Casaseca-de-la-Higuera, &Pervez (2017) presented a fall detection system using a database of fall and daily activities. Their method used the Shimmer biomedical device on the chest to collect data. The detection signals were extracted using compress sensing and principal component analysis techniques. The obtained binary tree classifiers achieved 99% precision in identifying fall events. These studies were performed in research laboratory settings. A recent study (Awais et al., 2016) compared and evaluated the performance of wearable sensors in classifying physical activities for older adults in real-life and in-lab scenarios. This study found that systems developed in a controlled lab setting might not be able to perform well in real-life conditions. Therefore, new systems should be tested in real-life conditions.

Physical Activity and Interaction Monitoring

Prolonged sedentary behavior is associated with many adverse health outcomes. To investigate whether reminders could change student posture and positively influence their wellbeing, Frank, Jacobs, &McLoone (2017) designed wearable device-based system to monitor student activities. Vibration reminders were sent through the wearable devices after 20 minutes of sitting. The results show that the strategy was effective in changing student behavior, although the health effects of this change were inconclusive.

Choo, Dettman, Dowell, &Cowan (2017) evaluated the effectiveness of using wearable devices and smartphones for tracking language patterns. The study conducted a Language Environment Analysis (LENA) using a language-tracking wearable device to collect mother-child communication data. The collected data were used to provide feedback to mothers about the communication pattern. The after-study evaluation showed that mothers had a positive response to the device and felt that the communication data collected by the wearable device provided useful information to improve mother-child communication.

Mental Status Monitoring

Developing wearable devices and algorithms to monitor mental conditions is a relatively new domain. Some wearable devices are equipped with sensors that can detect human physiology status, such as heartbeat, blood pressure, body temperature, or other complex vital signs (e.g. electrocardiograms). Using these signals, new systems can be developed to monitor mental conditions. Stress detection is the most common application of such systems.

To detect stress patterns of children, Choi, Jeon, Wang, &Kim (2017) proposed a framework using wearable devices and machine learning-based techniques. The wearable devices collected both audio and heart rate signals for stress detection. The framework has a potential to be used to remotely monitor child safety through stress patterns. The study results showed that by combining audio and heart rate signals, the system had a better performance in fighting noise signals when compared with audio-only methods. Support Vector Machine (SVM) is one machine learning method. The accuracy of the best algorithm (SVM+Wrapper) is 93.47%. A study by Setz and colleagues (2010) showed that even simple electrodermal activity (EDA) sensors have the capacity to identify stress level. An EDA sensor can measure skin conductance, which usually is correlated with the stress level of a person. They described how a Swiss team developed an EDA-based system called Emotion Board. The system can collect and measure skin conductance signals. The collected signals were processed using linear discriminant analysis (LDA) and an SVM-based classifier was used to detect stress. The evaluation on 33 subjects showed that the maximum accuracy was 82.8%.

Sports Medicine

Wearable devices can help athletes or coaches to systematically manage athletic training and matches. For example, Skazalski, Whiteley, Hansen, &Bahr (2018) used commercially available wearable devices as a valid and reliable method to monitor the jump load of elite volleyball players and to measure jump-specific training and competition load in the players" jumps. The results of this study also indicate that the devices showed excellent jump height detection capacities. The wearable devices can monitor functional movements, workloads, heart rate, etc., so they may be more widely used in sport medicine to maximize performance and minimize injury.

Chen, Lin, Lan, &Hsu (2018) developed a method to monitor and detect heat stroke. Heat stroke can harm people when they are doing exercises in hot temperatures. The team proposed a fuzzy logic-based method for inferencing signals collected from multiple wearable devices, environmental temperatures and humidity sensors. The experimental results showed that the system can be used to monitor heat stroke risk and alert users.

Weight Control and Monitoring

Tracking physical activities using wearable devices has become a popular method to help people assess activity intensity and calories expended. There is a growing interest among health consumers to use wearable devices, especially consumer wearable devices, to track weight control activities and outcomes. A study by Dooley, Golaszewski, &Bartholomew (2017) compared and validated three major consumer devices for measuring exercise intensities. The study devices included Fitbit Charge HR, Apple Watch, and Garmin Forerunner 225. The project enrolled 62 participants aged 18-38 and measured their heart rates and energy expenditures using all three devices. A hypothetical ideal "gold standard" test had a sensitivity of 100% and a specificity of 100%. The study showed a high magnitude of errors across all devices when compared to the gold standard. This study indicated that these devices might be useful as a stimulus to increase activity, but they have limitations as a tracking and outcome measurement method.

Although there are studies that show that wearable devices can be used as a stimulus mechanism to increase user activities, there is still a lack of evidence-based studies to validate the use of wearable device for the outcome of weight loss. A recent randomized clinical trial was conducted in Korea to examine the effectiveness of using wearable devices and smartphones to reduce childhood obesity (Yang et al., 2017). The project aimed to enroll a thousand 5th- and 6th-grade students to assess a wearable device-based intervention system called "Happy Me." The outcome measures of the trial were behavioral changes (e.g. physical activity, healthy eating) and anthropometric changes (e.g. body weight, body mass index, waist circumference). The results of the study attempted to provide scientific evidence for the effectiveness of using a wearable device system for weight control.

Public Education

Medical and healthcare education is rapidly changing and is influenced by many factors including the changing healthcare environment, the changing role of health professionals, altered societal expectations, rapidly changing medical science, and the diversity of pedagogical techniques. Technologies such as podcasts and videos with flipped classrooms, mobile devices with apps, video games, simulations (part-time trainers, integrated simulators, virtual reality), and wearable devices (google glass) are some of the techniques available to address the changing educational environment. These technologies should also be used to educate the public about health-related topics.

Patient Management

Wearable technology can also improve patient management efficiency in hospitals. Researchers hope to use wearable technology for the early detection of health imbalances. Wireless communication in wearable techniques enable researchers to design a new breed of point-of-care (POC) diagnostic devices (Ghafar-Zadeh, 2015). For example, garments integrated with wearable solutions, such as commercial portable sensors and devices in the emergency medical services (EMS), emergency room (ER) or intensive care unit (ICU) environments, have facilitated the continuous monitoring of risks that endanger patient lives. The system enables detection of patient health-state parameters (heart rate, breathing rate, body temperature, blood oxygen saturation, position, activity and posture) and environmental variables (external temperature, presence of toxic gases, and heat flux passing through the garments) to process data and remotely transmit useful information to healthcare providers (Curone et al., 2010). Wireless wearable devices have supported mobility in patients. Activity monitoring is used to manage chronic conditions of patients (Chiauzzi, Rodarte, &DasMahapatra, 2015). Wearable device activity tracking abilities provide a mechanism to allow health consumers to enhance their self-management capacities. Many health consumers are already tracking their weight, diet, or health routines in some way. Wearable devices further improve the self-tracking ability by providing sensor data as objective evidence.

Cancer Survivors

Endometrial cancer survivors are the least physically active of all cancer survivor groups and exhibit up to 70% obesity (Basen-Engquist et al., 2009) , but lifestyle interventions can result in improved health outcomes. A study was conducted to evaluate the acceptability and validity of the Fitbit Alta™ physical activity monitor for sociocultural diverse endometrial cancer survivors (Rossi et al., 2018). The study found that the Fitbits were well accepted by 25 participants and the physical activity data indicated an insufficiently active population. Physical inactivity and sedentary behavior are common amongst breast cancer survivors. Another study used wearable activity trackers (WATs) as behavioral interventions to increase physical activity and reduce sedentary behavior within this population (Nguyen et al., 2017). They found that wearable technique programs have the potential to provide effective, intensive, home-based rehabilitation.

Patients with Stroke

Stroke, predominantly a condition of advanced age, is a major cause of acquired disability in the global population. Conventional treatment paradigms in intensive therapy are expensive and sometimes not feasible because of social and environmental factors. Researchers used wearable sensors to monitor activity and provide feedback to patients and therapists. In a study by Burridge and colleagues (2017), the researchers developed a wearable device with embedded inertial and mechanomyographic sensors, algorithms to classify functional movement, and a graphical user interface to present meaningful data to patients to support a home exercise program.

Patients with Brain and Spinal Cord Injuries

Patients with brain and spinal cord injuries need exercises to improve motor recovery. Often, these patients are not qualified to monitor or assess their own conditions and they need healthcare provider guidance. Therefore, there is a need to transmit physiological data to clinicians from patients in their home environment. Researchers like Burns and Adeli (2017) are doing just that, by reviewing wearable technology for in-home health monitoring, assessment and rehabilitation of patients with brain and spinal cord injuries.

Chronic Pulmonary Patients

As a chronic illness, chronic obstructive pulmonary disease typically worsens over time, so extensive, long-term pulmonary rehabilitation exercises and patient management are required. A group of researchers designed a remote rehabilitation system for a multimodal sensors-based application for patients who have chronic breathing difficulties (Tey, An, &Chung, 2017). The system included a set of rehabilitation exercises specific for pulmonary patients, and provided exercise tracking progress, patient performance, exercise assignments, and exercise guidance. Patients in the study could receive accurate pulmonary exercises guidance from the sensory data. Further evaluation studies are needed to verify if the proposed remote system can provide a comfortable and cost-effective option in the healthcare rehabilitation system.

Disease Management

Significant progress in the development of wearable device systems for healthcare applications has been made in the past decade. Wearable technology can make disease management more effective as outlined below.

Heart Disorders

Wearable devices have been developed to do cardiovascular monitoring and enable mHealth applications in cardiac patients. Low-power wearable ECG monitoring systems have been developed (Winokur, Delano, &Sodini, 2013). Some wearable devices can monitor heart rate variability (HRV). In a study, a wearable patch-style heart activity monitoring system (HAMS) was developed for recording the ECG signal (Yang et al., 2008). The wearable devices can be used efficiently as health monitoring system during daily routines in many places and situations.

Wearable technology can assess patient heart activity outside of a laboratory or clinical environment. It is possible to perform heart assessments during a wide range of everyday conditions without interfering with a patient's activity tasks. For example, researchers designed a textile-based wearable device for the unobtrusive recording of ECG, respiration and accelerometric data and to assess the 3D sternal seismocardiogram (SCG) in daily life. Researchers also designed a portable and continuous ballistocardiogram (BCG) monitor that is wearable in the ear (Da He, Winokur, &Sodini, 2012). The ear devices can reveal important information about cardiac contractility and its regulation.

The wearable cardioverter defibrillator (WCD) was introduced into clinical practice in 2001, and indications for its use are currently expanding. The WCD represents an alternative approach to prevent sudden arrhythmic death until either Implantable Cardioverter Defibrillator (ICD) implantation is clearly indicated, or the arrhythmic risk is considered significantly lower or even absent (Klein et al., 2010).

Hernandez-Silveira and colleagues (2015) studied the feasibility of using a wireless digital watch as a wearable surveillance system for monitoring the vital signs of patients. The researchers compared the wearable system with traditional clinical monitors. The results showed that the tested wearable device provided reliable heart rate value for about 80% of the patients and the overall agreement between the new device and clinical monitor was satisfactory because the comparison was statistically significant. A similar study by Kroll, Boyd, &Maslove (2016) showed that a wrist-worn personal fitness tracker device can be used to monitor the heart rate of patients even though the collected heart rates were slightly lower than the standard of continuous electrocardiographic (cECG) monitoring.

As well, heat stroke can be potentially damaging for people while exercising in hot environments. To prevent this dangerous situation, a researcher designed a wearable heat-stroke-detection device (WHDD) with early notification ability. If a dangerous situation was detected, the device activated the alert function to remind the user to avoid heat stroke (Chen et al., 2018).

Blood Disorders

Wearable trackers have drawn interest from health professionals studying blood disorders. Overall, the U.S. prevalence of hypertension among adults was 29.0% during 2015–2016 (Fryar, Ostchega, Hales, Zhang, &Kruszon-Moran, 2017). Wearable devices can detect hypertension with physiological signals (Ghosh, Torres, Danieli,

&Riccardi, 2015). Some of the most widely used wearable devices are applications for evaluating and monitoring blood pressure, including cuff-less blood pressure sensors, wireless smartphone-enabled upper arm blood pressure monitors, mobile applications, and remote monitoring technologies. They have the potential to improve hypertension control and medication adherence through easier logging of repeated blood pressure measurements, better connectivity with health-care providers, and medication reminder alerts (Goldberg &Levy, 2016).

The study of blood flow is called hemodynamics. Patients with orthostatic hypotension have pathologic hemodynamics related to changes in body posture. Researchers designed a new cephalic laser blood flowmeter that can be worn on the tragus to investigate hemodynamics upon rising from a sitting or squatting posture. This new wearable cerebral *blood flow* (*CBF*) meter is potentially useful for estimating cephalic hemodynamics and objectively diagnosing cerebral ischemic symptoms of patients in a standing posture (Fujikawa et al., 2009). In another study, researchers detected site-specific blood flow variations in people while running, using a wearable laser doppler flowmeter (Iwasaki et al., 2015).

Diabetes Care Management

Patients and healthcare providers need to track many factors that influence blood glucose dynamics (e.g., medication, activity, diet, stress, sleep quality, hormones, and environment) to effectively manage diabetes. Recent consumer technologies are helping the diabetic community to take great strides toward truly personalized, real-time, data-driven management of this chronic disease (Heintzman, 2016). These consumer technologies include smartphone apps, wearable devices and sensors. One well-known example is the wearable artificial endocrine pancreas for diabetes management, which is a closed-loop system formed by a wearable glucose monitor and an implanted insulin pump (Dudde, Vering, Piechotta, &Hintsche, 2006). Closed-loop control (CLC) for the management of type 1 diabetes (T1D) is a novel method for optimizing glucose control. More studies of CLC were conducted recently. For example, overnight CLC improved glycemic control in a multicenter study of adults with type 1 diabetes (Brown et al., 2017). Researchers also explored the possibilities of using Google Glass to simplify the daily life of people with diabetes mellitus (Hetterich, Pobiruchin, Wiesner, &Pfeifer, 2014).

With the increasing cost of healthcare, wearable devices and systems could have potential to facilitate self-care through monitoring and prevention. For instance, a wearable bioelectronic technology was developed to provide non-invasive monitoring of sweat-based glucose level (Lee et al., 2017).

Parkinson"s Disease

To manage Parkinson"s disease, wearable devices offer huge potential to collect rich sources of data that provide insights into the diagnosis and the effects of treatment interventions. Ten-second whole-hand-grasp action is widely used to assess bradykinesia severity, since bradykinesia is one of the primary symptoms of Parkinson's disease. Researchers developed a wearable device to assess the severity of the Parkinsonian bradykinesia (Lin, Dai, Xiong, Xia, &Horng, 2017). Many assessments of dyskinesia severity in Parkinson's disease patients are subjective and do not provide long-term monitoring. In another study an objective dyskinesia score was developed using a motion capture system to collect patient kinematic data (Delrobaei, Baktash, Gilmore, McIsaac, &Jog, 2017). The portable wearable technology can be used remotely to monitor the full-body severity of dyskinesia, necessary for therapeutic optimization, especially in the patients" home environment. The Parkinson@home study (de Lima et al., 2017) showed the feasibility of collecting objective data using multiple wearable sensors during daily life in a large cohort.

Autism

It is important for autistic children to recognize and classify their emotions, such as anger, disgust, fear, happiness, sadness and surprise. Daniels and colleagues (2018) conducted a project that used Google Glass to study the feasibility of a prototype therapeutic tool for children with autism spectrum disorder (ASD) to see if the children would wear such a device. The feasibility study supported the utility of a wearable device for social affective learning in ASD children and demonstrated subtle differences in how ASD affected neurotypical controls children perform on an emotion recognition task.

Depression

Wearable technology can also assist with the screening, diagnosis and monitoring of psychiatric disorders, such as depression. The analysis of cognitive and autonomic responses to emotionally relevant stimuli could provide a viable solution for the automatic recognition of different mood states, both in normal and pathological conditions. Researchers explored a system based on wearable textile technology and instantaneous nonlinear heart rate variability assessment to characterize the autonomic status of bipolar patients (Valenza et al., 2015). In another study, a wearable depression monitoring system was proposed with an application-specific system-on-chip (SoC) solution. The system accelerated the filtering and feature extraction of heart-rate variability (HRV) from an electrocardiogram (ECG) (Roh, Hong, &Yoo, 2014) to improve the accuracy of successfully recognizing depression.

Discussion

Most wearable technologies are still in their prototype stages. Issues such as user acceptance, security, ethics, and big data concerns in wearable technology still need to be addressed to enhance the usability and functions of these devices for practical use.

User Acceptance

User preferences need to be considered to design devices that will gain acceptance both in a clinical and home setting. Sensor systems become redundant if patients or clinicians do not want to work with them. A body-worn sensor system should be compact, embedded and simple to operate and maintain. It also should not affect daily behavior, nor seek to directly replace a healthcare professional. It became apparent that despite the importance of user preferences, there is a lack of high-quality studies in this area. Researchers should be encouraged to focus on the implications of user preferences when designing wearable sensor systems. These issues become increasingly important if they seek to obtain measurements over longer time periods, for example, in monitoring chronic diseases, or during activity levels where the data collection is essential but not necessarily lifesaving (Bergmann &McGregor, 2011).

One concern about older adult use of wearable device applications is their acceptance and interest in using consumer-wearable devices for personal health purposes. A recent review by Kekade and colleagues (2018) of 31 studies shows that more than 60% of elderly people were interested in the future use of a wearable device for improving physical and mental health. However, not many elderly people were currently using wearable devices because generally there is a lack of awareness among the older generations. The study showed that wearable devices should be tested to determine if they meet the needs of elderly people, especially sick and female participant groups (Kekade et al., 2018). The study also indicated that older populations could benefit from using wearable devices; however, more work should be done to increase the awareness of the technology use.

Security

Patient confidentiality and data security are major concerns when using wearable devices since it can be challenging to ensure compliance with HIPAA regulations. The communication security of the collected data in Wireless Body Area Networks (WBAN) is a major concern (Ali &Khan, 2015). Encryption is a key element of comprehensive data-centric security. Encrypted data and the use of encryption as an authentication mechanism within an organization's network is generally trusted, but direct access to keys and certificates allows anyone to gain elevated privileges. Key management is vital to security strength. The dependability of cryptographic schemes for key management has become an important aspect of this security. However, the extremely constrained nature of biosensors has made designing key management schemes a challenging task. For this reason, many lightweight key management schemes have been proposed to overcome these constraints. Because the physiological data are transmitted over the WiFi, there is a need for secure WBAN communications to prevent eavesdropping and the interrupting of personal information. This security can be achieved by using a cryptographic scheme to ensure basic security services like confidentiality, integrity and authenticity. However, most cryptographic schemes require secret keys. Because the security of these cryptographic schemes depends upon the keys, there is a need for secure key agreement and distribution among the nodes in the network. Security must be evaluated based on the stringent HIPAA principles for information privacy and security.

Ethical Issues

Mobile technology is increasingly being used to measure individuals' moods, thoughts and behaviors in real time.

Current examples include the use of smartphones to collect ecological momentary assessments (EMA); wearable technology to passively collect objective measures of participants' movement, physical activity, sleep, and physiological response; and smartphones and wearable devices with global positioning system (GPS) capabilities to collect precise information about where participants spend their time. Although advances in mobile technology offer exciting opportunities for measuring and modeling individuals' experiences in their natural environments, they also introduce new ethical issues. A study by Roy (2017) in Chicago discussed ethical challenges specific to the methodology (e.g., unanticipated access to personal information) and broader concerns related to data conceptualization and interpretation (e.g., the ethics of "monitoring" low-income youth of color). Lessons can be learned from the collection of GPS coordinates and EMAs done in this study to measure mood, companionship and health-risk behavior with a sample of low-income, predominantly racial/ethnic minority youth living in Chicago area. While Roy (2017) encouraged researchers to embrace innovations offered by mobile technology, the discussion highlighted some of the many ethical issues that also need to be considered in the process.

Big Data

Wearable devices may collect very large amounts of personal data due to their capacity for continuous data recording at high frequencies coupled with potential large population use. The collected data fits into the big data domain by meeting the four "V" characteristics (volume, variety, veracity, velocity) of big data. Because wearable devices can collect highly personalized data among large populations, the collected information not only could be used to improve personalized intervention, but also used for population pattern discovery. Researchers in nursing science explored new ways of symptom science research in the era of big data (Corwin, Jones, &Dunlop, 2019) . They reviewed the concepts of an interdisciplinary approach and team science, as well as their benefits and challenges.

With significant growth of the internet, mobile devices and cloud computing, the Wearable Internet of Things (Wearable IoT) has become an emergent topic of research and applications (Hiremath, Yang, &Mankodiya, 2014). A network of sensors will generate even more complex and larger data sets. Such data also creates new opportunities, such as the development of IoT sensing-based health monitoring and management (Hassanalieragh et al., 2015), generating new models to define human behavior (Paul, Ahmad, Rathore, &Jabbar, 2016), analyzing connection communities (Sun, Song, Jara, &Bie, 2016), and developing new mobile health applications (Lv, Chirivella, &Gagliardo, 2016).

For example, in blood transfusions, big data have been used for benchmarking, detecting transfusion-related complications, determining patterns of blood use, and defining blood order schedules for surgery. More generally, rapidly available information can monitor compliance with key performance indicators for patient blood management and inventory management leading to better patient care and reduced use of blood (Pendry, 2015).

Integrating multimodal and multiscale big health data from wearable sensors is a great challenge since heterogeneous data need to be processed to generate unified and meaningful conclusions for clinical diagnosis and treatment. Health data accompanied with a large amount of noisy, irrelevant and redundant information also give spurious signals in clinical decision support systems (Zheng et al., 2014).

Future Trends

Interoperability

There is further work required regarding interoperability challenges. For example, the fifth generation of wireless networking technology (5G) enables us to connect many times more hospital devices to the network at once and to gain remote access at home. Australia"s Commonwealth Scientific and Industrial Research Organization (CSIRO) developed a project called the Hospital Without Walls, which aimed to provide continuous monitoring of patients in certain diagnostic categories (Wilson et al., 2000). The key technology used was a miniature, wearable, low-power radio that could transmit vital signs and activity information to a home computer, and data was sent by telephone line and the Internet to appropriate medical professionals. The initial clinical scenario for this work was monitoring elderly patients who had presented to hospitals following repeated falls. Accelerometers built into the radio sets monitored activity and detected and characterized falls. Simultaneous measurement of heart rate also provided information about abnormalities of cardiovascular physiology at the time of a fall. It is believed that with these future developments, unobtrusive and wearable devices could advance health informatics, lead to fundamental changes of how healthcare is provided, and help to reform underfunded and overstretched healthcare systems.

New Devices

Hemoglobin is a red protein responsible for transporting oxygen in the blood. Wearable technologies provide portable, noninvasive point-of-care ways to measure hemoglobin concentration. The wearable devices have the potential to increase the quality of care. Unfortunately, a study showed that widely available noninvasive point-of-care hemoglobin monitoring devices were systematically biased and too unreliable to guide transfusion decisions (Gayat et al., 2011). Wearable devices with better accuracy are needed. For future development, wearable devices should also play a role in disease intervention through integration with actuators that are implanted inside/on the body. New wearable drug delivery systems for blood pressure management are likely to be developed in the future.

AI

The advancement of wearable technology and the possibilities of using AI in healthcare is a concept that has been investigated by many studies. The availability of the smartphone and wearable sensor technology are leading to a rapid accumulation of human subject data, and machine learning is emerging as a technique to map those data into clinical predictions.

For instance, seizure prediction can increase independence and allow preventative treatment for patients with epilepsy. A study by Kiral-Kornek and colleagues (2018) presented a proof-of-concept for a seizure prediction system that would be accurate, fully automated, patient-specific, and tunable to an individual's needs. A deep learning classifier was trained to distinguish between preictal and interictal signals. This study demonstrated that deep learning in combination with neuromorphic hardware can provide the basis for a wearable, real-time, always-on, patient-specific seizure warning system with low power consumption and reliable long-term performance.

Another study aimed to automatically score Parkinsonian tremors by proposing machine-learning algorithms to predict the Unified Parkinson's Disease Rating Scale (UPDRS) (Jeon et al., 2017). In this study, the tremor signals of 85 patients with Parkinson's disease (PD) were measured using a wrist-watch-type wearable device consisting of an accelerometer and a gyroscope. Nineteen features were extracted from each signal, and the pairwise correlation strategy was used to reduce the number of feature dimensions. With the selected features, a decision tree (DT), support vector machine (SVM), discriminant analysis (DA), random forest (RF), and k-nearest-neighbor (kNN) algorithm were explored for automatic scoring of the Parkinsonian tremor severity. The performance of the employed classifiers was analyzed using accuracy, recall and precision and was compared to findings in similar studies.

As machine-learning algorithms are increasingly used to support clinical decision-making, reliably quantifying their prediction accuracy is vital. Inaccurate results can mislead both clinicians and data scientists. Cross-validation (CV) is the standard approach where the accuracy of such algorithms is evaluated on a part of the data the algorithm has not seen during training. A study compared two popular CV methods: record-wise and subject-wise approaches (Saeb, Lonini, Jayaraman, Mohr, &Kording, 2017). Using both a publicly available dataset and a simulation, researchers found that record-wise CV often massively overestimates the prediction accuracy of the algorithms.

In summary, various designs of wearable technology applications in healthcare are discussed in this literature review. Further evaluation studies for those applications are needed to confirm the benefits of wearable technologies for the future.

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Dr. Wu’s research focuses on identifying unmet medical needs and implementing technological solutions to meet them. For example, he has developed a national mammogram image archive, and a web-based training method for dentists to interpret dental images. Dr. Wu was the first researcher who proposed to use HIPAA messages for public health data collection and sharing in 2005. He designed a new user interface, a fisheye viewer, to view gene expression data for bioinformatics researchers. His writing has appeared in the *Journal of Medical Informatics*, the *Journal of Medical Systems*, *BMC Bioinformatics* and *Academic Radiology*. Dr. Wu is a past recipient of the Best Article Award for his work in the *Journal of Digital Imaging*.

Having 15 years of teaching experiences in health informatics, Dr. Wu published a textbook about electronic health records, *“Information Technology in Healthcare.”* This book describes key concepts in the discipline of health informatics, particularly electronic medical records, which are now widely used in healthcare. In addition, he is a certified Oracle Database Administrator (DBA) and has taught database courses for more than 10 years.

Jake Luo completed his PhD degree in machine learning computer science at the Queen’s University, Belfast, U.K. He is an Associate Professor in the Department of Health Informatics and Administration at the University of Wisconsin-Milwaukee. His research interest lies in data-driven predictive analysis using machine learning-based algorithms and technologies, such as data mining, natural language processing, and knowledge representation and modeling. He is interested in investigating how these computing technologies can be used to improve healthcare by providing intelligent decision support for clinicians, medical researchers, patients and policymakers. Dr. Luo’s active research programs involve developing innovative heath data science technologies for knowledge discovery, adapting machine learning algorithms to enhance clinical data processing, implementing collaborative team science initiatives to improve health services and research, and creating intelligent clinical informatics tools to support evidence-based decision making.

Dr. Luo has developed tools and methods that have been shared with researchers at multiple institutions, including Vanderbilt, Mayo Clinic, UC-San Francisco, and Pfizer, etc. He co-authored a paper that won a Distinguished Paper Award at the AMIA Clinical Research Informatics Summit. One of his papers, “Dynamic Categorization of Clinical Research Eligibility Criteria,” was also one of the top 25 hottest papers in the *Journal of Biomedical Informatics*. To improve biomedical research collaboration, he leads several projects that aim to integrate services and expert resources located at disparate institutional silos. His team designed and implemented scalable infrastructures for system functionality enhancement, data management, and computational analysis. These systems provided secure and policy-compliant access to enhance translational and comparative effectiveness research. For example, the Request Management System provides a single-entry point for more than 1,500 clinical investigators to consult domain experts and establish collaboration across multiple institutions. He led crucial research programming and development efforts for the informatics infrastructures used in major centers. His lab analyzed clinical trial data collected from over 250,000 studies for new knowledge discovery, such as predicting severe adverse events using advanced computational models. His currently funded projects include developing data-driven methods to analyze and predict drug adverse events and systematically integrating medical image-text to bridge the gaps between textual and imaging information representations.

DETAILS

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