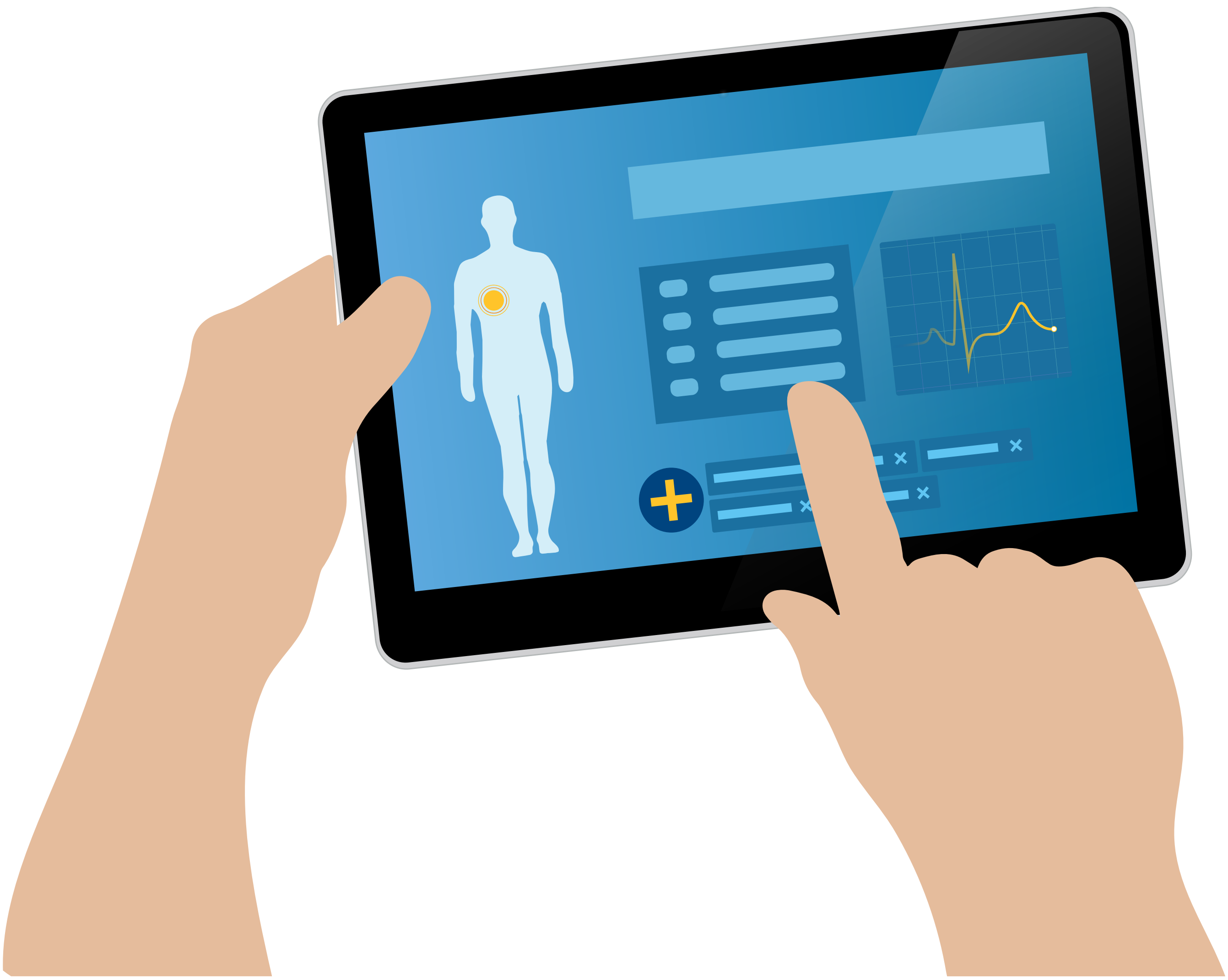
Mobile & Sensor Technology, Big Data and Artificial Intelligence For Healthy Aging



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Mobile & Sensor Technology, Big Data and Artificial Intelligence for Healthy Aging

We live in a world where more people own a mobile device than they own a toothbrush. Mobile devices such as smartphones and wearable devices (wearables) are packed with sensors as simple as a compass to state-of-the-art biometric scanners such as fingerprint and iris scanners. The ubiquitous nature of mobile devices and rapid advancements in sensor technology have shifted its primary use from communication to information gathering and sharing. Various sensors on mobile devices can collect data about nearby objects, location, orientation and direction, altitude, and many more. These powerful and abundant tools are changing how researchers observe and conduct research, how clinicians deliver healthcare, and how we come to understand our health and well-being. In this white paper, we provide you with the latest buzz amongst researchers and clinicians on mobile devices for health (mHealth), big data, and artificial intelligence. We will give examples of what is currently possible and focus on what the future holds for the health of older adults and aging.

Mobile Health

Mobile health (mHealth) is a term that describes the use of mobile devices to support medical and health practice[1]. mHealth is a very broad concept. mHealth systems can be as simple as an app on smartphones for educational purposes or it can also be a complex system where doctors can monitor vital signs and symptoms in real time to update prescription medications. We habitually link mHealth to smartphones, tablets, and laptops, but it is not limited to these devices.

Wearables devices (wearables) are devices that are designed to be worn and equipped with multiple sensors[2]. They are made small and discrete, and used for health and fitness. Many of us are familiar with wearables such as activity trackers and smart watches but there are also smart clothes, smart shoes, smart glasses and so on. The term 'wearables' is most frequently used to refer to consumer-level devices such as FitBit or Apple Watch, but they are sometimes used to refer to medical devices. We will be referring to consumer-level wearables in this white paper.

Smartphones and wearables are closely integrated with each other. Most wearables are developed to work together with smartphones to show graphs of, for example, physical activity level over a week. Wearable data can be viewed through 'apps' in most cases.

Sometimes the apps ask for additional information. For example, they ask to record on the phone how we felt when we woke up. They may also ask to record blood pressure in the morning, blood sugar level before and after a meal, or symptoms of chronic conditions. Such health data are collected by patients. Therefore, they are called patient generated health data[3]. They need us to measure and record the data on a smartphone, which are often shared with doctors and clinicians.

The combination of multiple data sources - one measured automatically by sensors on wearables and another reported by you, patient generated health data - can tell clinicians a more complete picture of your health than either one alone can.

mHealth and wearables open new possibilities for researchers. They are minimally obtrusive and can be worn for a long period of time. They can collect data continuously, repeatedly over time, and frequently. Researchers can use wearables to measure participants and their behaviours outside laboratory settings. Researchers can observe patterns of human behaviours in the real world with the level of detail that was never possible. This is different from how human research studies are commonly conducted. Conventionally, researchers relied on participants' memory and honesty to understand behaviour patterns such as their physical activity level. Researchers could only assess participants periodically.

mHealth and wearables offer a new way of measuring human behaviours and individual health and wellbeing with unprecedented levels of detail. As such, we need a new way of making sense of vast amounts of data and information to understand what they mean to healthy aging.

Sensor
A device that measures a physical property and produces a corresponding output.

Mobile Health (mHealth)
Medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants (PDAs), wearables and other wireless devices.

Wearable devices
Sensor-enabled technologies designed to be worn for specific purposes, most commonly health and fitness.

Patient generated health data
Health-related data generated by patients or carers to help address health issues.

Personal Sensing

Making sense of vast amounts of data from smartphones and services, sensors on wearables, and other sources to evaluate human behaviour is called personal sensing[2]. It is also known as reality mining, personal informatics or digital phenotyping.

Personal sensing is, in a way, a method to make sense of a large amount of data from mHealth and wearables. Personal sensing is unique in that it can use both health and non-health-related data to provide insights into human behaviour. These health and non-health data include a variety of sensor data, patient generated health data, and other data from different sources (Table 1)[3].

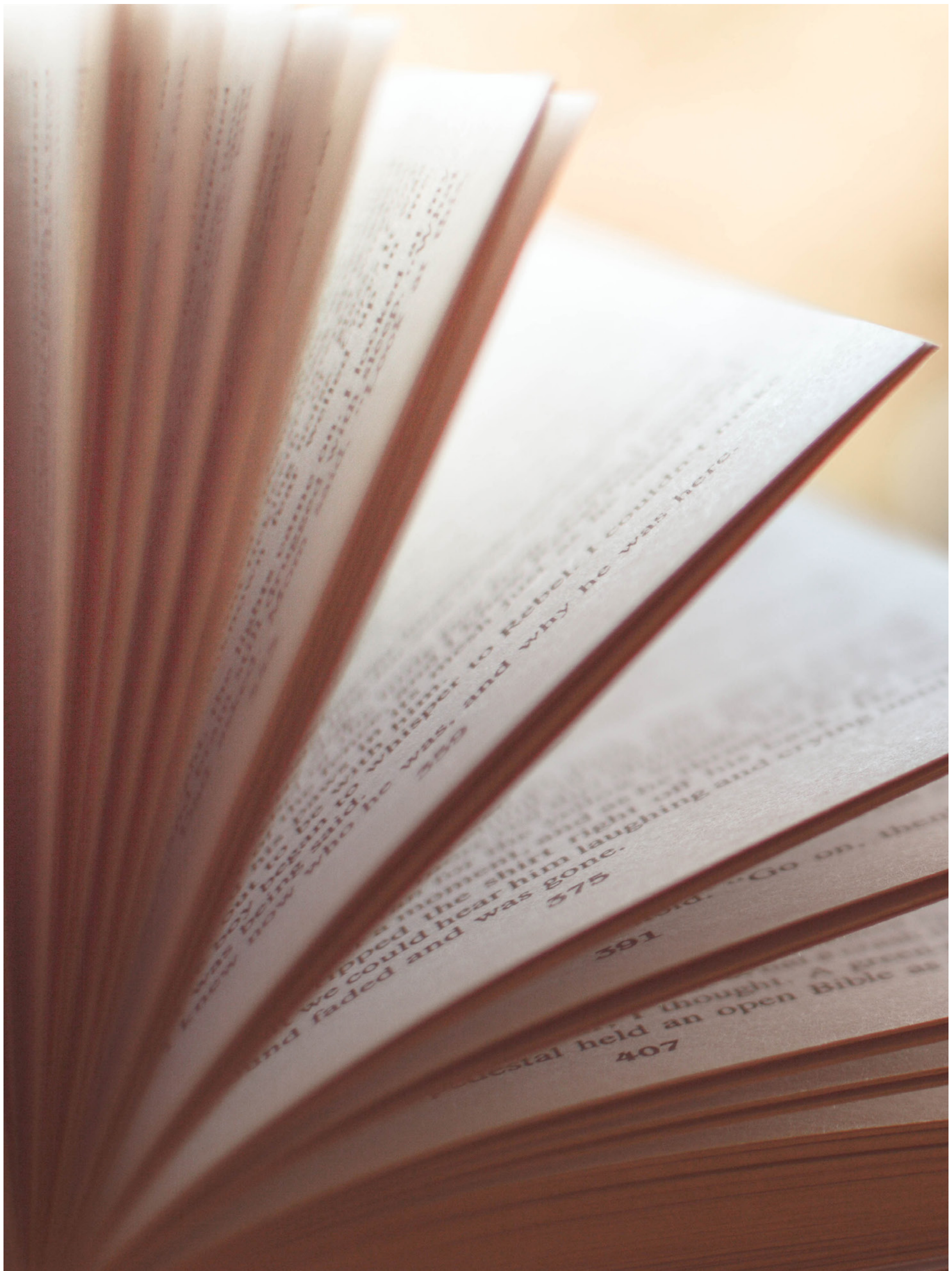
Data sources for personal sensing include sensors, patient generated health data, and other communication and financial data. Sensors are categorized by how they gather data. Some sensors gather data continuously and do not require end users' input. An example is temperature sensor on an activity tracker that continuously measures body temperature. Some sensors operate only when end users actively use the machine. Blood pressure monitor is an example. However, this categorization of sensors between continuous and on-demand data collection is changing as technology advances.

The same can be said to some of patient generated health data. Clinicians often ask patients to keep track of their mood over time to understand the effectiveness of medications on mood swings. Latest research studies are evaluating ways to measure mood using wearable devices.

Researchers can use personal sensing to identify specific characteristics of human behaviours that are linked to health conditions. To learn how personal sensing data can be used by researchers and clinicians, we first need to understand how data from wearables, mHealth, and other sources can be used to understand human behaviour and clinical conditions[2].

Table 1. Sources and types of data potentially useful for research and clinical practice

Data Sources	Data Type
Sensor: continuous	Accelerometry Heart rate Temperature UV exposure Geolocation Noise level
Sensor: on demand	Weight Blood pressure Blood glucose level
Patient generated health data	Diet Mood/stress level Symptoms Medications Behaviours (e.g, tobacco use, alcohol consumption)
Others	Social connectedness (e.g, phone logs, text messages, social media use) Financial data



Data to Knowledge: sensemaking framework

The data to knowledge sensemaking framework is a visual representation of the data, information, and knowledge cycle (Figure 1)[2]. It shows how raw data can be processed to produce information, then eventually knowledge that can be used by researchers and clinicians.

A data to knowledge cycle begins with raw data. Raw data is generated by sensors on mobile phones and wearables. Sensor data are often incomprehensible and meaningless. For example, GPS on the phone gets latitudinal and longitudinal coordinates. They are simply two numbers that are not particularly useful.

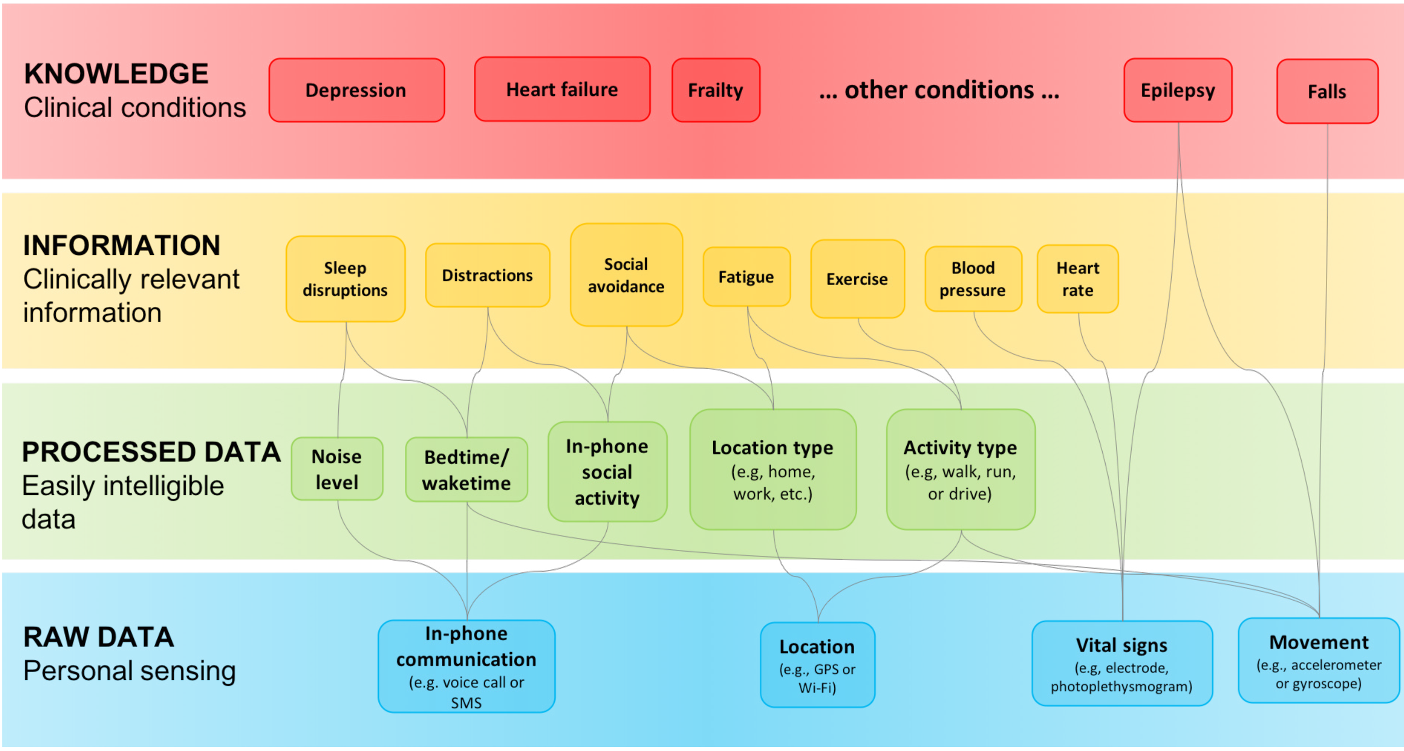


Figure 1. Data to knowledge sensemaking framework with examples of personal sensing. Blue boxes are raw data that are generated from sensors and other sources. They are combined and/or analyzed to be clinically useful information (Green and Yellow boxes). They indicate symptoms, characteristics, and/or signs for different clinical conditions (Red boxes).

Raw Data

Raw data are processed to become understandable information. This initial processing is often done by applying mathematical algorithms or by combining with other data. For example, GPS coordinates can be put on a map which can tell us information about the location.

Processed Data

Processed data are often not clinically meaningful. They require further processing to become clinically relevant information. For example, processed GPS can tell us whether the person was at home, work, gym, restaurant, and so on. Accelerometer sensor data measure physical activity level. Combining two information more accurately distinguish between gym exercise and other physical activities outside gym.

Information

Clinically relevant information can help clinicians identify and evaluate clinical conditions. For example, sleep duration, disturbances, social avoidance, depressed mood, and stress level may be able to tell the severity of depression. Such information can help clinicians design treatment plans that are customized and personalized.

Knowledge

Sense-making framework help us visualize the journey of raw data that gets processed to become clinically meaningful information, which can be used by clinicians to evaluate and understand clinical conditions.

Next, we will describe how data are "processed" to become meaningful information.

Artificial Intelligence Machine Learning and Big data

Artificial intelligence (AI), machine learning, and big data are buzz words that many companies use to get attention. We will briefly describe each, current uses in our lives and in healthcare, and the future they hold.

We have seen examples of AI in movies: C3PO and R2D2 in Star Wars. They are examples of 'General AI'. General AI possesses human-like characteristics such as senses, cognition, and intelligence. We are yet to achieve this level of AI[4].

However, we have developed very good 'Narrow AI'. Narrow AI is an intelligence for a focused topic. One example is hand writing recognition for mails by postal offices. How does a computer read hand writing when everyone has different writing patterns and penmanship? What happens when they are poorly written and illegible? Where does this intelligence come from?

Machine learning (ML) is the answers to the questions. They can examine a set of data, learn patterns, and make predictions. It is different from traditional programs that operate based on explicit rules and defined parameters. For the example of mailing address, a ML algorithm examined a set of hand written mailing addresses, learned different ways people write letters, and makes an accurate prediction of each letter of a hand-written mailing address. Machines need hundreds of thousands, if not millions, of examples of different hand writings before it can almost always correctly identify mailing addresses. A large dataset that has millions of examples – often called 'big data' - is an essential ingredient for successful AI.

Big data is defined as a vast amount of data that is ever increasing in its size, very complex, and most importantly, adds value to the intended use[5]. Wearable data is one example. Wearables generate enormous amounts of data. The data size is increasing at a very fast rate. Wearable data are getting more complex as more sensors are used. In recent years, the term 'big data' is frequently used to imply machine learning methods that help us turn a large amount of data into meaningful information. These terms are increasingly used interchangeably, blurring the original definitions.

Narrow Artificial Intelligence
Artificial intelligence focused on specific tasks.

Machine learning
Algorithms that have the ability to learn from data without explicitly programmed instructions.

Big data
A large amount of data that is ever increasing in size, very complex, and has value.

Machine Learning and Wearables

In a very similar way a postal office system can learn hand writings from millions of examples and read mailing addresses automatically, wearables recognize when you walk, run, sleep, swim, golf, and so on.

An accelerometer is a sensor embedded in wearables that measures movements in three directions: up and down, backwards and forward, and side by side. Accelerometers record your wrist movements in different directions every second. Imagine the pattern of your wrist movement when you walk. It creates a similar pattern for every cadence. ML is used on a large dataset collected from people's wrist movements while they walk. Machine learning can then learn the pattern, and the next time a similar pattern is made, it will know that you took a step.

Similarly, ML is used to measure sleep duration and quality. Our nerve systems go through different phases while we are sleeping, which creates unique patterns of body movements. Certain patterns are associated with deep sleep stage. ML algorithms learn body movement patterns and is able to determine your sleep quality.

ML coupled with wearables have opened a wide array of new possibilities for clinicians and researchers. A few examples that are currently being researched include detecting fall incidents, detecting seizure episodes, emotional arousal (stress level and mood swings), and nutritional intake.

mHealth is a source of big health and wellness data. Research studies have only begun to scratch the surface of its potential uses with powerful machine learning algorithms. It can drastically change how we access health care at home and in community. It also holds unimaginable promise for the future of health care.

Machine Learning in Health Care

AI is embedded in many aspects of health care and it holds enormous potential for the future. However, it is not immediately clear to most where in health care and how ML and AI are currently used. They are used in a broad range of health care services and research areas including medical imaging, critical care, oncology, and many others. We will provide examples of current uses as well as most cutting-edge research studies that hold great promise.

Current and Future Health Care with Machine Learning

Predicting patient outcomes in the Intensive care unit

One area where machine learning plays a large role is in Intensive Care Units (ICUs). ICU physicians are faced with difficult clinical decisions such as assessing which patients require longer ICU stays or de-escalate to regular hospital beds, which patients can tolerate and benefit from invasive treatments, which patients will develop complications from treatments, and so on. Predicting these outcomes is very important to patients and family members as well to make informed decisions[6,7].

ICU stays are extremely expensive and accurate predictions on medical outcomes can help manage ICU resources efficiently. These medical outcome predictions are made based on thousands of patient records using machine learning. Such information can guide physicians, patients and family, and hospital administrators to make accurate decisions.

Artificial Intelligence Making diagnosis

One research study examined close to 100,000 images of the eyes of diabetic patients who suffer from retinopathy which can lead to blindness[8]. Using machine learning method, the program learned the patterns presented in the eye images. When it was tested on new images, it was able to determine retinopathy at 99% accuracy.

Using neural networks - a type of machine learning method – a system learned over 120,000 images of skin cancer[9]. This system can tell difference between the most common type of skin cancer from the deadliest form of skin cancer. This system can make diagnosis as accurate as 21 trained dermatologists. This study is especially remarkable as the service can be provided to general consumers as a smartphone app.

Finding drugs that are right for you with Maching Learning

Drugs are developed meticulously and go through rigorous testing for its safety and effectiveness. One downside of this is that they are often only tested by a group of patients who are very similar. This brings a question, how will a drug work for a 90 year old when they were only tested for 40 to 65-year-olds?

With machine learning, we can examine previous effects of the drug on patients who have very similar characteristics to you. In this case, machine learning determines the group of individuals who have similar characteristics as you[10].

We have discussed how mHealth and wearables can be used. We explained how machine learning enable innovative use of the big data generated from these technologies. We will discuss what it means and how it can help with healthy aging.

Aging-in-place

Canadian population is aging very quickly. There are more older adults (i.e. 65 and older) than those who are 14 years and younger. This is a sign of a healthy nation. Older adults are living longer than ever before.

Healthy nations have unique health care system challenges. As more and more people live to old age, they are more likely to live with chronic conditions. In fact, about 63% of older adults have two or more chronic conditions while 14% have 6 or more[11].

Successful management of chronic conditions such as diabetes, hypertension, and arthritis requires frequent interactions with doctors. However, healthcare system is designed to deal with episodic and acute health problems such as accidental injuries and infections. They are not optimized to deal with chronic and mental health conditions that require long and frequent care. As a result, health care system is overloaded, inefficient, costly, and slow.

One way to resolve unique challenges is by encouraging older adults to stay at home and in community independently and autonomously[12]. This is called aging-in-place.

Aging-in-place has many benefits. It helps older adults to maintain physical and mental health. Aging-in-place is also linked to increased sense of identity, independence, autonomy, and security. They contribute to increased quality of life. Aging-in-place encourages people to stay healthier and happier. It is also far more cost effective to provide services that support aging-in-place than hospital beds, long-term care homes, and other institutions[13].

Aging-in-place and Technology

Innovative use of technologies, understanding of behavioural science, and transformative policy development can support older adults to age-in-place successfully. In particular, health technologies such as mHealth and wearables play an essential role because aging-in-place occurs at home and in community.

One popular use of mHealth for aging-in-place is by supporting chronic condition management. mHealth, wearables, and personal sensing allow monitoring of symptoms, communicating with clinicians, and delivering care at home and in community.

We often think that technology for healthcare is complex and sophisticated. This is not necessarily true; there are many effective but simple and affordable solutions. Smartphone apps that educate older adults about medicines and drug interactions are an example of such simple solutions. It can reduce potentially dangerous situations where wrong drugs are used in mix that can lead to lethal health outcomes.

Another application of mHealth for aging-in-place is fall prevention and detection. With wearables becoming more and more powerful, they can detect falls and alert clinicians when necessary.

Personal sensing is a new topic even among researchers and its possibilities for aging-in-place have only begun to be explored. Personal sensing is advantageous because it can collect data continuously which opens doors for more effective screening of health conditions. Frailty screening is an example use of personal sensing. Frailty describes a state of an individual's health where they are more likely to develop illnesses[14].

Frailty is conventionally measured by a series of physical assessments and asking questions about past behaviours such as exercise and food intake. Personal sensing with wearables has potential to replace and provide more accurate frailty level. This can tell doctors how much an individual can tolerate different medical care and treatments. In the end, it can support older adults to stay independent and successful at aging-in-place.

Technology - innovative or not - can never succeed without users. Successful adoption and continued use of new technology by older adults is the basis for many technology-driven health programs. The likelihood of adopting a new technology is measured by technology acceptance. In the next section, we will present our study that examined wearable acceptance by older adults.

mHealth acceptance by older adults

Technology acceptance has been researched previously when new technology was introduced such as computers, ATM machines, the Internet, and social media. Researchers identified a handful of key factors that greatly influence the decision to adopt and use new technology (Figure 2)[15]. It is found that how useful and how easy it is to operate a technology determine acceptance and future use.

How do we know if a technology is useful and easy to use? They are explained by personal characteristics such as age, previous experience with the same or similar technology, cost, and availlable support from family and friends.

Measuring technology acceptance was useful for companies that first introduced computers for their employees; and banks that rolled out ATM machines. However, wearables are different from them. Wearables are worn on the wrist, becoming a part of individual's identity; like how teenagers wear trendy clothes to identify themselves. This is why we examined the technology acceptance model for wearables. We wanted to know if we can measure technology acceptance and if that can tell us the adoption and use of wearables by older adults in local community.

Our study confirmed that technology acceptance model can be used to measure older adults' decision to accept wearables [16]. Usefulness and ease-of-use were major factors for accepting wearables. We also found the acceptance was closely linked to the cost of wearables and previous encounter with similar technologies.

Wearables collect health and well-being information, which many consider private and sensitive. Logically, those who had high concerns about privacy were less likely to use a wearable device.

Understanding older adult's acceptance of wearables can help researchers and healthcare systems in many ways. Such knowledge is vital to designing future health programs that look to use wearables. They can also inform policy makers about what programs can work and prepare for expected challenges. Researchers who plan to use wearables to study aging-in-place can also benefit from the expected acceptance level of wearables by older adults. Findings from this study directly and indirectly contribute to successful aging-in-place.

Aging-in-place
The ability to live in one's own home and community safely, independently, and comfortably, regardless of age, income, or ability level.

Technology acceptance model
A theoretical explanation of what determines adoption and use of new technology.

Frailty
A state of decreased overall health that puts an individual vulnerable to negative health outcomes.

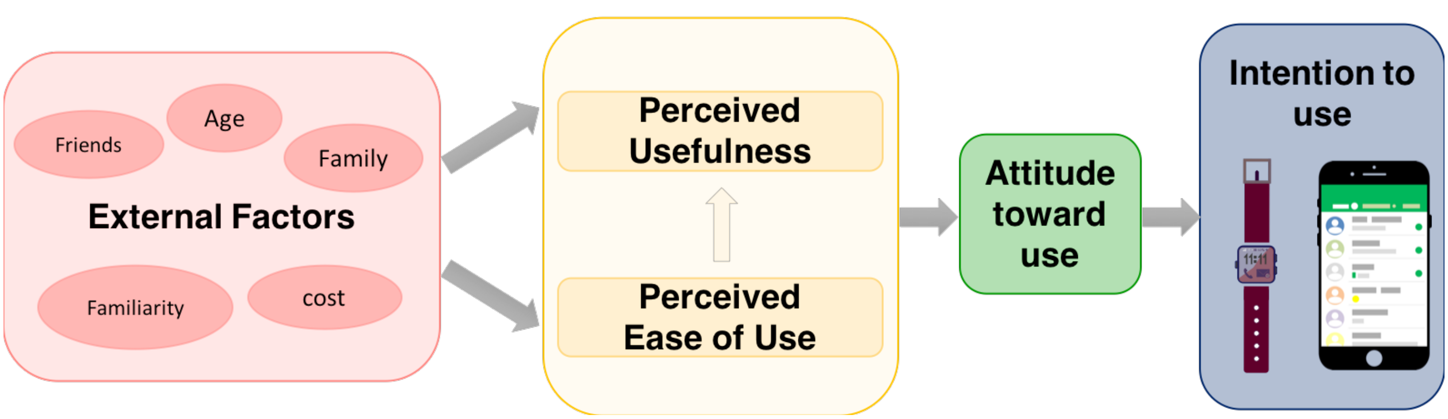


Figure 2. Technology acceptance model describes what factors determine the adoption of a new technology.

mHealth for Aging-in-Place

mHealth has been used for diverse purposes and in different settings. We provide examples of current uses for supporting health and well-being of older adults as well as its current research efforts for future uses.

"There is an App for that"

There is a variety of smartphone apps available in the market. There exist apps developed by universities and research institutes based on scientific evidence to support healthy aging. They have shown to help with smoking cessation, weight management, and stress reduction[17, 18].

Another area where mHealth apps can support aging-in-place is education. For example, mHealth apps can educate older adults about potential dangers of drug to drug interactions.

Adverse drug events – when wrong medications (i.e. incorrect dosage, incorrect combinations of drugs, etc.) result in harmful health outcomes - are problems for older adults with multiple chronic conditions. They tend to take multiple medications. They are almost twice more likely to be hospitalized as a result of adverse drug events[19]. Unfortunately, it costs healthcare system billions of dollars every year and negatively affects one's ability to successfully age-in-place.

We wanted to find out if mHealth apps can be used to check for drug interactions[20]. We found all apps that claim to check for drug interactions and examined their quality of information including how accurately they detect drug interactions and the information they provide.

App for aging-in-health

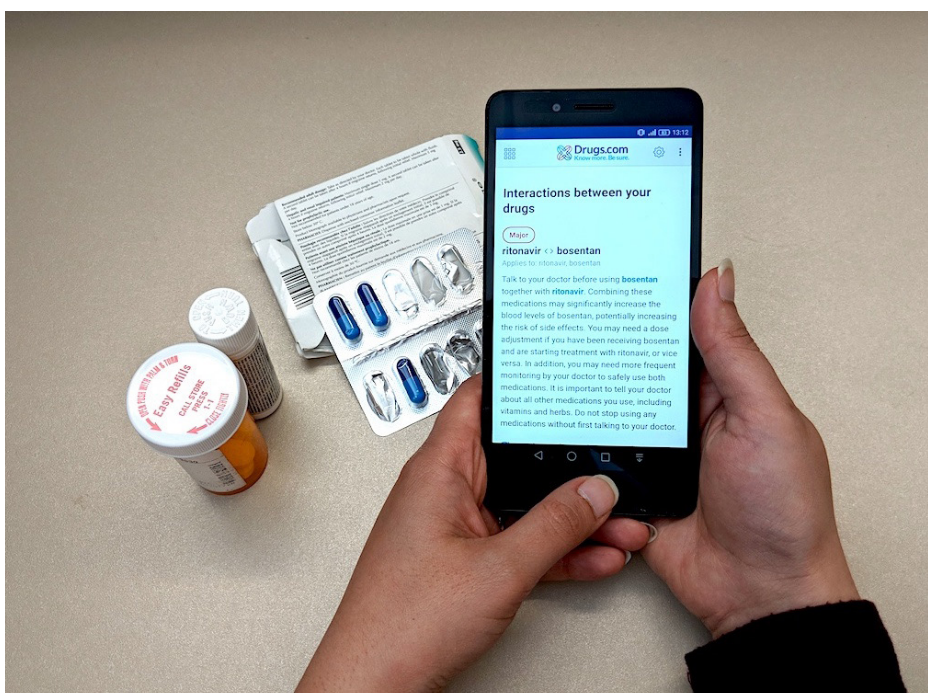
We wanted to find out if mHealth apps can be used to check for drug interactions. We found all apps that claim to check for drug interactions and examined their quality of information including how accurately they detect drug interactions and the information they provide.

We found that apps were either very high or low in quality. Quality was evaluated by looking at how engaging and functional the app is, its aesthetics, and the quality of information. About 50% of apps were high quality and 30% were low quality. High quality apps detected two drugs that are known to interact and described its potential harmful health outcomes accurately.

However, low quality apps did not detect two interacting drug pairs and sometimes provided inaccurate information. These apps are very dangerous to consumers as they can lead to dire health consequences.

These findings highlight the danger of health information available to consumers. It raises questions about the need for regulation of mobile apps that meant to be used for health and well-being.

As a consumer, there are limited resources available to guide us with finding safe and informative apps. One example is the Health App Library by National Health Service of the U.K.



mHealth for chronic disease management

Smartphones are increasingly used by older adults in recent years. Researchers have been studying mHealth systems to take advantage of its great adoption level by the general public. To understand the characteristics and current status of mHealth systems, we searched for research studies that used such systems for chronic condition management for older adults.

mHealth systems have been researched more and more over frequently in recent years. In 2010, only 1 study have utilized mHealth system for managing chronic conditions while there more than 10 studies by 2015. These studies most frequently used mHealth systems for managing diabetes, heart failure, hypertension, and COPD management[21].

mHealth systems were used to collect biometric measures such as blood glucose, body weight, blood pressure, step count, and heart rate. In addition, they are used to record symptoms, medication use, diet, exercise level and other relevant information – often called patient generated health data.

Most mHealth systems focused on supporting self-monitoring of chronic conditions and gave automatic feedback and education. Only a few studies explored other ways to support chronic condition management such as sharing symptoms with family members and friends or updating treatment plan.

mHealth systems are used differently from study to study. A simple mHealth system encouraged older adults to record their medication uses on the phone[22]. Recording medication uses on smartphone encouraged to stay on track with their medication regimen. Another study asked COPD patients to record symptoms daily. These symptoms were reviewed by specialists and nurses every day and called patients to make changes to medications when necessary[23]. A more sophisticated mHealth system was used for diabetes management[24]. This system gave a warning to clinicians when blood glucose level was abnormal. Otherwise, the system gave an encouraging and educational message.

mHealth systems have evolved and changed drastically since its introduction. Evidence for its effectiveness for managing chronic conditions at home and in community is clear and plentiful. Future mHealth systems can further improve and expand by incorporating new emerging technologies such as personal sensing.

mHealth for fall prevention and detection

A new emerging area of mHealth research focuses on using wearable data collected from multiple sensors continuously. Fall detection and prevention is one example of where wearables and sensor technology can be best put to use.

Falls frequently lead to loss of independence, decline in quality of life, and overall well-being. There are many causes for falls. They include poorly lit home environment, loss of strength and balance from aging, and medications with side effects.

Many clinical assessments exist to find the causes and risk factors for falls. They are often time consuming and not effective in preventing falls.

The high prevalence of falls among older adults have motivated researchers to find a better solution. Wearables have been getting a lot of attention as they can continuously monitor body movements for days and months in real life environments[25]. We carried out a research study to see if wearables can be used to identify those who are at high risk for falls.

We used wearable data collected from older adults who live at home and in community. From the wearable data, we were able to identify high risk fallers as accurately as conventional assessments. We could identify those who are likely to fall with higher accuracy when used both the wearable data and home care admission assessments.

This study is an example of how personal sensing can be used to support successful aging-in-place. With information about who are likely to fall in the near future, health programs can be delivered to the right people at the right time. It also shows how technology can save time for doctors and nurses.

Conclusion

We have summarized the current state of mobile and sensor technology, big data and artificial intelligence for healthy aging. As we have summarized, the field of mHealth is undergoing a revolutionary change. Mobile and sensor technology has greatly advanced recently, and it has introduced wearables as a new tool to collect a large amount of health data. Machine learning enables the interpretation of big data generated from wearables and other sensors, allowing us to understand human behaviours in a whole different way. We have also examined the current research studies that attempt to bridge these new technologies into healthy aging.

The potential for technology is immense but unrealized. Collaborative efforts in all aspects by everyone involved – researchers, policy-makers, clinicians, patients, caregivers, and general public – are required to reach a future where we fully leverage these technologies for healthy aging.

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