Mobile Sensors and Wearable Technology

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The Internet of Medical Things and the integration of wearables and sensors to support optimization of health through self-management and remote monitoring have dramatically accelerated over the past decade. With this gaining momentum, wearable devices to measure individuals' physiology such as heart rate and activity levels have become highly popular, increasingly pervasive, and creating a cultural shift to help people to collect, quantify, and observe their own data relating to their behaviours in day-to-day life. This "quantified self" can increase self-awareness regarding behaviour and improve overall health and well-being (Swan 2009). With the potential to change health behaviour through these platforms, the general public has the ability to be more engaged and participatory in their own health. For healthcare providers, these devices are improving patient care through continuous objective reporting, remote monitoring, and precision medicine.

30.1 Commercial Mobile Sensors and Wearable Technologies

Commercial mobile sensors have been the driving force behind the popularity of data tracking for the general public. They allure is the ability to provide an array of program features such as reward systems, opportunities for social interaction, and measured behavioural outcomes, which can increase motivation to engage in healthier behaviours. With these novel features, along with perceptions of affordability, practicality,

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and ease of use, overall change in attitudes and adoption of these devices have improved considerably (Gaoet al. 2010; Kim and Shin 2015; Soliño-Fernandez et al. 2019). One of the most compelling features is the use of various self-regulation strategies to help individuals improve exercise, sleep, sedentary time, mental health, and diet. Users can understand and recognize the necessary steps to change their own behaviour through the use of these devices, which can create opportunities for integrated approaches to support health and patient care.

Google's notable acquisition of Fitbit in 2019 signifies not only the value and expansion of wearables in a global market, but also the acceleration of innovation in this particular domain (Fitbit Inc. 2019). Consumers keen on adopting a healthy and fitness-based lifestyle can purchase wearable technology from a plethora of manufacturers including Fitbit, Garmin, Apple, Samsung, Motorola, or Swarovski. These devices are able to consolidate the various functions found in accelerometers, pedometers, GPS, and heart rate monitors into one device. They can then provide useful measures and personalized feedback on variables such as step counts, physical activity intensity, maximal oxygen uptake, heart rate variability, total daily energy expenditure, sedentary time, and sleep quality. Recent advancements in wearable devices have begun to integrate other features such as fall detection, medication adherence, signs of atrial fibrillation, and environmental noise monitoring (i.e. exposure to noise levels that may pose a risk to a person's hearing). These wearable devices can transmit the collected data into mobile apps, allowing users to consolidate and centralize their personal health data into their own smartphones.

Recent literature has suggested that very few commercial devices have been validated (Bunn et al. 2017; Peake et al. 2018). For the limited number of wearable devices that have been evaluated, these particular devices have been found to be fairly reliable and capable of providing reasonably accurate step counts for adults with no mobility limitations (Evenson et al. 2015). Additional evidence has shown that some of these devices can yield physical activity estimates comparable to research-grade accelerometers (Ferguson et al. 2015; Lee et al. 2014). However, commercial devices have been found to underestimate variables like energy expenditure (O'Driscoll et al. 2018) and overestimate variables like total sleep time and sleep efficiency (Haghayegh et al. 2019).

At the crux of the commercial devices are the interface and software features that incorporate multiple self-regulation strategies to help individuals adopt and maintain health behaviour. Similar to previous content analyses performed on smartphone apps (Abroms et al. 2011; Azar et al. 2013; Breland et al. 2013; Cowan et al. 2013; West et al. 2012), researchers have investigated the use of behaviour change techniques in 13 commercially available sensors (Lewis et al. 2015). The study's results showed that self-monitoring and feedback on behaviour, setting goals, and outlining potential discrepancies between measured performance and goal were strategies commonly used in these devices. Though, strategies like problem solving, action planning, prompting or cues to action were less prevalent. According to intention-based behaviour theories, these particular strategies are important considerations for translating intention into behaviour and forming habitual behaviour (Rhodes and Yao 2015). Wearable devices have incorporated more of these health behaviour strategies in recent years, particularly in the area of physical activity and sedentary behaviours. In fact, recent evidence has shown that wearable devices can promote short-term changes to physical activity and sedentary behaviour in both healthy and clinical populations (Brickwood et al. 2019; Kirk et al. 2019; Lewis et al. 2015; Stephenson et al. 2017). However, the efficacy of these devices in improving other health behaviours such as sleep remains unclear.

30.2 Clinical Mobile Sensors and Wearable Technologies

Mobile and wearable sensor technologies have begun to expand into the healthcare landscape. Unlike commercial devices, which are generally centred on physical activity levels, mobile sensors and wearables in the clinical domain focus on accurate and continuous measurement of physiological variables and biomarkers to support clinical decision making and treatment for various health conditions and diseases (Alemdar and Ersoy 2010; Appelboom et al. 2014; Chan et al. 2012; Chen et al. 2011). These devices can be integrated into adhesive bandages and clothing, and can track and monitor cardiac function (i.e. electrocardiography), heart rate, blood pressure, respiration, oxygen saturation (i.e. pulse oximetry), skin conductance, glucose levels, kinematics, body and ambient temperature, and global positioning. With aggregated measures of these variables, insight into medical status (e.g. vital signs, level of self-care and self-management), chronic disease risk, and physiological anomalies can be observed and captured to help inform clinicians and patients about appropriate treatment. Recently, these diagnostic tools have been applied to preventative health care and the detection of abnormal heart conditions. For instance, atrial fibrillation can be fairly transient and asymptomatic and is not often diagnosed until a serious health incident like a stroke or syncope occurs. Devices such as AliveCor have been used to monitor the electrical activity of the heart via a bipolar electrode in clinical and non-clinical populations, and allow patients to share ultrasound and electrocardiogram data with their healthcare provider (Baquero et al. 2015; Ferdman et al. 2015; Haberman et al. 2015).

Clinical sensors can also extend beyond the patient and be integrated into a broader wireless network, linking the patient to his or her immediate surroundings and to the healthcare provider. An early example of this was the Advance care and alert portable telemedical MONitor (AMON) project, which used a wearable monitoring system to remotely track and relay health information and data between the patient and clinician (Anliker et al. 2004). Aimed at supporting individuals at risk of cardiac and respiratory disease, this wrist-worn device included a number of features such as vital sign (blood pressure, oxygen saturation, pulse, ECG) and physical activity monitoring, online analysis and emergency detection, and a communication interface (e.g. SMS). Despite issues in measurement accuracy, the device demonstrated a feasible approach to improve outpatient care while encouraging patients to self-monitor and live independently.

In the USA, rigorous testing is necessary in order for devices to be approved and classified as a medical device. In recent years, there has been an increasing number of US Food and Drug Administration's (FDA) approved devices and made available to the public, such as the aforementioned AliveCor device (AliveCor Inc. 2020). Furthermore, FDA approved devices that have appeared on the market address a number of different medical conditions. Most recently, the Apple Watch received FDA clearance for the electrocardiogram and irregular rhythm notification functions as Class II medical device (U.S. Food and Drug Administration 2020a). Another illustration of this growing development is the approval and categorization of Adherium's digital inhaler add-on as a medical device (U.S. Food and Drug Administration 2020b). This digital inhaler monitoring device has been found to improve medication adherence among patients with asthma by tracking medication use and providing reminders to patients via an online portal (Chan et al. 2015). As well, there has been a rise in the adoption of wearable glucose monitoring sensors among diabetes patients (e.g. FreeStyle Libre Flash) (Welsh and Thomas 2019). These types of digital monitoring system provide a cost-effective way to continuously receive real-time biofeedback on glucose levels from the interstitial fluid via a sensor patch (Kompala and Neinstein 2019). The sensor can relay data to a smartphone and cloud drive, allow the user to check their readings and trends, and notify the user of hyperglycemia and hypoglycemic episodes—thereby helping people alter their behaviour and manage their diabetes more effectively (e.g. exercise, caloric intake, decisions to prevent hypoglycemic episodes) (Kompala and Neinstein 2019).

In essence, devices such as the AliveCor and Apple Watch illustrate the coalescing of commercial and medical devices and a trend towards affordable and accessible technology becoming available to the public and opportunities for the public to monitor their own health. Furthermore, these medical diagnostic tools have an immense potential to prevent and detect serious health conditions and diseases. As more of these devices continue to develop and become adopted by the general public, so will the integration of these technologies into medical practice.

30.3 Using Mobile Sensors and Wearable Technologies to Change Health Behaviour

An important area that warrants thorough exploration is the coupling of clinical monitoring with behavioural change theory to improve health-related behaviours and health outcomes. A recent qualitative investigation exploring the role of sensor technology to sustain behaviour change found that simply tracking health data alone is insufficient to sustain patient motivation to achieve health goals (Miyamoto et al. 2016). Applying behaviour change theories to the development of these devices may address the dynamic nature of patient motivation.

The importance of theoretical models lies in their ability to produce a nomenclature of psychosocial determinants, understand the mechanisms for why a behaviour might occur, and subsequently, target key constructs to elicit behaviour change (Davis et al. 2014). For instance, theoretical frameworks such as the social cognitive theory indicate goal setting and reflection on own performance are both necessary in order to stimulate and anchor behavioural modification (Bandura 1986). A recent systematic review examining the potential of smartphone technology to measure and influence physical activity behaviour found that the most commonly applied theoretical framework was the social cognitive theory (Bort-Roig et al. 2014). Moreover, the review further highlighted five behaviour change strategies commonly found on these devices that were associated with changes in physical activity behaviour: physical activity profiling, goal setting, real-time feedback, social support networking, and online expert consultation.

Research studies investigating the efficacy of sensors and wearables in the clinical domain have begun to incorporate behaviour change strategies to address patient motivation regarding chronic disease self-management behaviours. Examples of clinical studies that have integrated and explored the use behaviour change strategies in the technology include:

- A feasibility study using wireless blood pressure monitors, glucose monitoring, and weight scales to support diabetes self-management and health outcomes utilized the social cognitive theory to frame the intervention. After three months, patients saw improvements in weight, systolic blood pressure, and haemoglobin A1C levels, decreased level of distress, and felt more empowered in managing their diabetes (Ho et al. 2015).
- A quality improvement evaluation of a web-based tool coupled with electronic home monitoring that supported individuals with heart failure with patient self-management and telemonitoring by health professionals used the Connelly Framework for Self-Care in Chronic Illness (Connelly 1993) to guide the development of the app's behaviour change strategies, which resulted in decrease in heart failure-related hospitalizations and all-cause hospitalizations, and improved clinical, quality of life, and self-care outcomes (Ware et al. 2020).

30.4 Current Limitations and Potential Impact on Health

Undoubtedly, mobile sensors and wearable technology are continuing to develop and improve and the long-term impact of these devices is warranted. One of the major barriers to understanding the long-term impact to health behaviour and health outcomes has been adherence to the wearable sensor itself. Previous research has shown that adherence to commercial devices tends to decline after six months (Kim and Shin 2015). Potential reasons for this may be related to equipment itself (e.g. usability, comfort, and battery life) and a diminishing novelty effect (Alemdar and Ersoy 2010), lack of professional support to help the user to understand the context and meaning of the data collected (Miyamoto et al. 2016), and the lack of key psychosocial constructs that are important for translating intention into behaviour and forming habitual behaviour (Rhodes and Yao 2015). Use of wearables in healthcare faces similar challenges, with two additional challenges: health professionals not co-monitoring the data with patients, and measurement of discrete diseases rather than part of a comprehensive service to support patients holistically (Arsenijevic et al. 2018).

Despite the current limitations, mobile sensors and wearable devices can improve patient delivery and care. In the context of patient care, these sensors can continuously collect personal data in various environmental contexts as part of an all-encompassing health network. In turn, the amassed data can be used in multifactor analyses to identify the user's specific needs and prevent further decline in health (Banaee et al. 2013). As well, clinicians will be able to remotely monitor their patient's current condition in real-time and appraise overall data trends, be notified of any immediate changes to health status (e.g. irregularities, decompensation), and better administer appropriate actions and treatment (e.g. modify medication dosage, curtail adverse events). While in healthy populations, the data collected would allow for the prediction and detection of anomalies in behaviours to encourage and support healthy lifestyle behaviours.

Mobile sensor and wearable technology can also ease the care process and establish the patient's sense of safety and support from their healthcare team. The devices can allow health professionals work as an interdisciplinary team to remotely monitor and concurrently manage their patients and the data collected can expedite continuous care (e.g. from emergency medical care or community-based care and the patient's home), while helping patients feel supported and safe by being closely monitored by their provider. Moreover, this technology can enable healthcare professionals extend services to previously underserved areas.

Ultimately, the adoption of mobile sensors and wearable technologies can considerably increase a healthcare provider's ability to provide adequate and timely care through active provider-patient engagement, which can improve the patient's health and well-being and the overall patient experience. Furthermore, the integration of these technologies into patient care can alleviate healthcare costs, enhance the quality and efficiency of healthcare services, and advance preventive care.

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