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Leveraging Technology to Enable Mobility and Transform Health

When wearable devices fail: Towards an improved understanding of what makes a successful wearable intervention

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Abstract

Many champion wearables as devices that will revolutionise 21st century medicine. However, this technology has often failed to provide new insights for healthcare professionals and patients. Regarding behaviour change specifically, current research paints a mixed picture when demonstrating their effectiveness. While some patients claim that these devices are beneficial, recent clinical trials targeting weight loss observed that patients provided with a wearable tracker lost significantly less weight than patients provided with lifestyle support alone. Additional research also highlights failures in the design and implementation of similar devices. Nevertheless, these outcomes remain a key cornerstone in the literature because they emphasise the importance of understanding errors in order to capture the ideal functioning of any new device and/or intervention. Therefore, our white paper has two complementary aims that will hopefully help generate discussion and realise the potential of future technologies.

First, we identify patterns and document the key reasons why wearables and other mobile technologies often fail to change behaviour. The design of any digital device or intervention that aims to improve health and well-being combines elements of engineering, computer science and social science. Therefore, our paper critically considers aspects of (a) device design, (b) theoretical contributions and (c) the individual experience. A clear understanding of these issues can be derived not only from the latest research, but also by looking backwards at early attempts to self-tracking within health and social care (e.g. telehealth). This, in turn, provides new insights concerning how the next wave of wearable technology can be better designed and implemented – increasing the chances of success within specific target environments (e.g., schools, workplaces) and populations (e.g., adolescents, elderly adults).

Second, our recommendations provide guidance on how future research designs and outcome measures may need to be adapted in the future. For example, the vast majority of current investigations fail to adopt measures that are sensitive enough when it comes to capturing progress and accurately quantifying key outcomes. While research continues to rely on outcome measures used in traditional behavioural interventions (e.g., lifestyle modification), these are often not appropriate when feedback relating to physical activity is available 24/7. The absence of recording human-computer interactions is particularly evident when most wearable

technology can easily collect this information (e.g., opening an application) alongside health related (e.g., physical activity) behaviours.

Introduction

Promises & Barriers

Around the developed world, the majority of adults and children do not meet recommended daily activity guidelines, leading to an estimated 3.2 million deaths each year (Lim et al., 2013). As well as reducing life expectancy, a lack of movement negatively impacts across individuals and society as a whole and sedentary behaviour alone has now become an independent risk factor for chronic disease that is separate from physical inactivity (Mercer et al., 2016). For example, children who watch more than two hours of television a day have lower levels of physical fitness, self-esteem, pro social behaviour and academic achievement (Harvey, et al., 2013). Sedentary behaviour is also associated with metabolic syndrome and cardiovascular disease in adults independent of physical activity (Healy et al., 2008). Movement alone, on the other hand, remains one of the most beneficial activities for health, well-being and cognition across the lifespan (Northey et al., 2017).

Tackling this problem will almost certainly require a multi-faceted and interdisciplinary approach particularly when it comes to making the most of low-cost, wearable technologies. While the idea of wireless digital technology that can track health is not in itself new, it is only in recent years that devices have become broadly available to researchers and interested members of the public (Piwek, et al., 2016). These and a plethora of other devices allow anyone to capture data about individuals and society in real time, and instantly provide actionable feedback. Measurements can include physical movement, heart rate, sleep quality, fertility and a variety of other physiological parameters (Figure 1). These wearable technologies remain relatively inexpensive, suitable for long-term monitoring, but also come with important caveats.

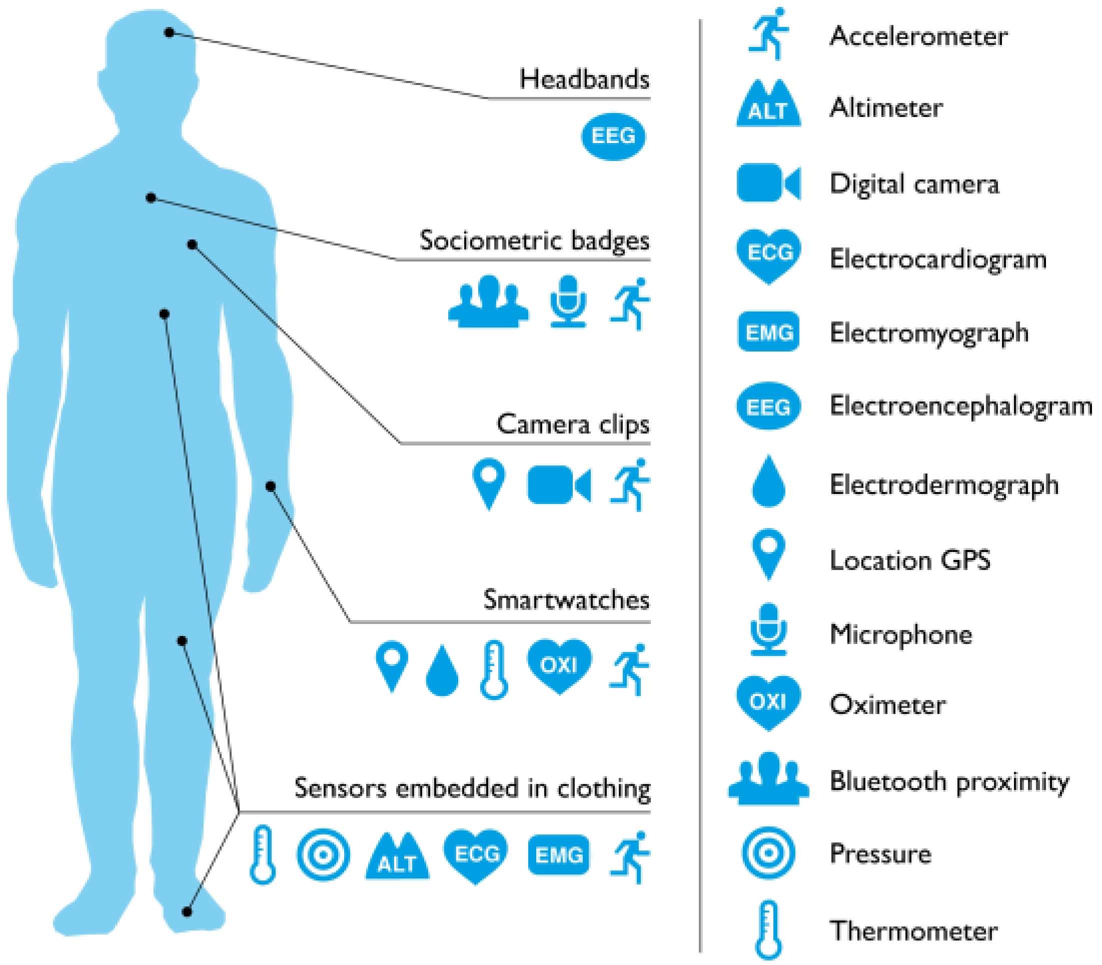

Figure 1: Examples of wearable devices and related measurements (Source: Piwek et al., 2016).

Modern wearables have tremendous potential to characterise health-related behaviours (Franks & Poveda, 2017). By providing people, governments and healthcare services with personalised data, these devices could assist with self-diagnosis and behaviour change interventions (Piwek et al., 2016). This proposition is particularly pertinent when even small changes in behaviour could have far reaching consequences for society as a whole. For example, one analysis published in the *Lancet* revealed that if physical inactivity was decreased by only 10% more than 533,000 deaths could be averted every year (Lee et al., 2012). Wearable activity trackers specifically, could help encourage people to move more and sit less.

A typical wearable intervention will provide participants with a wearable device in isolation or as a supplement to an existing behavioural intervention and some research has supported the notion that simply providing children and adults with tools that help quantify their own activity levels can help change their behaviour (e.g. Lyons, 2017; Staiano et al., 2017). At least one randomised controlled trial has also demonstrated that pedometers (with medical consultations) increased physical activity among older people (Harris et al., 2015).

However, similar interventions involving pedometers and smartphone apps within clinical populations show no evidence of continued behavioural change beyond the duration of the original intervention (Bravata et al., 2007). Results from small trials have also not held up to additional scrutiny. For example, large randomised controlled trials conducted over several years have, in some instances, demonstrated a negative effect when participants were provided with a wearable intervention that aimed to help participants lose weight (e.g. Jakicic et al., 2016). This mirrors similar issues that appeared during the development of home telemonitoring interventions in the previous decade (Kitsiou et al., 2013). For example, several trials reported no benefit when when patients self-monitored blood glucose (Farmer et al., 2007) and many results demonstrate that these interventions led to increased levels of depression (O'Kane et al., 2008).

Nevertheless, these outcomes remain a key cornerstone in the literature because they emphasise the importance of understanding failures or unexpected results in order to capture the ideal functioning of any device and/or intervention. It is therefore crucial to understand both why these devices are not always effective, which will in turn help predict what new novel interventions might show benefits (Kumar et al., 2005).

Overview

Mixed results concerning their effectiveness has put wearable interventions at a crossroads (Bloss et al., 2016; Jakicic et al., 2016). While their potential is clear, wearable technology and the theory which underpins related behavioural interventions has a considerable distance to cover if it is to become a standard behavioural intervention that can help people become more active, healthier and happier.

Therefore, our white paper aims to highlight a number of core reasons why wearable trackers and their deployment within behaviour change interventions have yet to reach their potential when it comes to modifying behaviour in a variety of contexts. Specifically, this paper concerns interventions that involve devices worn on the body rather than those which are smartphone based. However, some overlap is present between these two literatures. This is difficult to avoid completely because smartphones are frequently required to process the incoming data from the majority of wearable devices, but it is conceivable that in the future all processing functionality will be self contained (Piwek et al., 2016)

Here we consider the key reasons why wearables and other mobile technologies often fail to change behaviour. Our discussion also considers how study designs and outcome measures may need to be adapted in the future. Each section is followed by a set of practical recommendations for research and future interventions that incorporate wearable devices; Figure 3 at the end of this paper provides a complete list of those recommendations for easy reference.

Wearables' Design

Comfort and Usability

The design of many wearable trackers can often have an early negative impact on any participant or consumer to the point where a potential treatment effect may be thwarted from the outset (Sullivan & Lachman, 2016). Aspects such as quality of life, acceptability, and cost benefits were infrequently or incompletely reported in telemonitoring trials (Clark et al., 2007), and existing reviews of remote monitoring are often criticised for their poor methodology (Kitsiou et al., 2013). This trend appears to have continued in many research designs that focus on wearable interventions with a few notable exceptions. For example, while Jakicic and colleagues (2016) observed, over a 2-year period, that wearable fitness trackers resulted in reduced levels of weight loss when added to a standard weight loss intervention, their results also shed some light on how device design may have contributed to these failings.

Unlike most consumer devices, the wearable used as part of Jakicic et al's did not provide any real-time feedback by default. This makes it rather different to the majority of wearable devices available today. Participants were asked to wear an additional digital display, but they were free to choose whether they wanted to wear it. The authors acknowledge that it was not possible to measure directly how participants adopted and used the technology, but only 10% of patients reported wearing this display on a daily basis. A third of patients also felt that the armband was not pleasant to wear and often made them feel uncomfortable around other people. Poor design that leads to low levels of comfort and social acceptability could reduce the impact of any similar intervention by limiting potential exercise opportunities (Patel et al., 2015). This alone may explain the negative effects associated with tracking behaviour in this instance, but beyond specific wearable aesthetics, the act of monitoring other health conditions has often resulted in many patients reporting the experience as intrusive and unpleasant (O'Kane et al., 2008).

Understanding the design issues that lead to high attrition rates for wearable devices by both patients and consumers remains a concern. Where they are worn and how people engage with them on a daily basis may also be important. The wrist and upper arm have proven problematic despite their popularity and convenience. For example, a study by Finkelstein et al (2016) examining the use of a wrist-worn activity monitor observed that its use decreased significantly over time. However, similar to Jakicic et al (2016) above they did not measure the behaviour of each participant directly in terms of how they were interacting with each device. Where a device is placed on the body may have some influence on wearability; however, other factors that influence the continued use of wearable activity monitors also needs to be better understood

(Piwek et al., 2016). For example, device usage while straightforward to collect, has only been recorded in those with pre-existing health conditions (e.g. hypertension) and not for devices used as part of a behaviour change intervention (Bloss et al., 2016).

Subtle interactions with digital technology remain difficult to capture with self-report measures alone and are often inaccurate when it comes to health-related metrics (Lichtman et al., 1992), but the effect of any fitness tracker may be hindered if patients fail to engage with their device on a regular basis (Andrews et al., 2015). This could be due to a design flaw or something more fundamental. Moving forward, we would encourage future research that adopts a similar approach to Jakicic et al (2016), but which (a) considers the subtle interactions between real-time feedback and the psychological characteristics of those who are most likely to benefit from specific wearable-based interventions (Piwek et al., 2016) and (b) considers the importance of design and usability for a specific device.

Key Recommendations

1. Devices should be designed with comfort and usability in mind to increase social acceptability.

2. Wearables should record and map how a user interacts with their device in order to provide additional insights concerning engagement and drop-out.

Accuracy and Reliability

The majority of trials involving wearable interventions rely on small sample sizes and are of relatively short duration (e.g. Lyons et al., 2017). Part of this may be due to participant adherence as a result of poor design, but also due to several key challenges present at different stages of the data cycle. This is particularly problematic when it comes to issues of accuracy and reliability (van Berkel et al., 2015). Comparisons between different devices continue to show large variations both in terms of step counts and the number of calories burned each day (Chowdhury et al., 2017; Piwek et al., 2016). While devices have been shown to be relatively accurate in controlled laboratory settings (Case et al., 2015), false positives remain an issue for many devices when measuring physical activity (O'Connell et al., 2017). Similar issues have also been observed when measuring heart-rate, with some reports suggesting again that the wrist may not be an ideal position to place such devices. Reported errors have reached as high as 25% (Dooley, Golaszewski & Bartholomew, 2017). Researchers and consumers also have to contend with manufacture updates, which make consumer devices prone to unwanted changes that could hamper research. This is particularly problematic for longitudinal data collection (van Berkel et al., 2015).

Poor levels of accuracy could be viewed as a serious obstacle that needs to be addressed long before a device could be considered suitable as part of a behavioural intervention. Existing off-the-shelf devices can therefore only be considered as a rough guide when it comes to the data and feedback they provide. These issues are likely to be caused by a combination of factors including sensor design and placement, hardware selection, but also pertain to the software within and between devices. For example, while machine learning has emerged as a technique to transform this data into predictions, it is important to understand the limitations of these in a real-world context. Saeb and colleagues (2016a) have recently highlighted multiple issues concerning machine learning when it comes to making clinical predictions about behaviour from a variety of digital sources. These errors are equally as important in a wearable context because as devices become more advanced, the decisions and goals generated may not match the real-world behaviour of the end user.

A lack of accuracy may in itself not be important when it comes to facilitating behaviour change in terms of the feedback provided or when measuring any change, but if individuals are provided with inaccurate information regarding their activity levels on a regular basis, this may then trickle into other unhealthy behavioural patterns as the true reality of their movement is over or underestimated (Goyder et al., 2009; Piwek et al., 2016). In the future, devices, which monitor the context of a specific intervention or an individual's surrounding environment are likely to provide more suitable longitudinal goals and develop personal targets. For example, location tracking would allow for the distinction between a work and home environment. This alone could improve accuracy and reduce false-positives via a simple set of contextual rules. Location data has already been particularly useful in understanding mood and developing early warning systems that enable people to take action (Saeb et al., 2016b). Studies like these are particularly welcome because they focus on a single key issue and a single key feedback system. This makes it easier to identify mechanism of action. However, existing feedback systems within wearable devices can appear over engineered, they are typically based on simple statistics such as average weekly heart rate and level of activity. Such summary statistics appear almost trivial given the complex nature of the data that most wearables collect. It is critical that research around wearable interventions moves from unsophisticated exploratory feedback to intelligent, context-aware, and personalised explanatory feedback which improves when the system "learns" more about the user (Patel et al., 2015; Piwek et al., 2016).

Key Recommendations

3. Ensure devices are validated and locked out to software updates before commencing research.

4. Contextual cues should be given more prominence when it comes to improving accuracy and developing personalised feedback.

Worked Example: Developing New Devices within Primary Care

Adopting a practitioner based approach could help further our understanding of how new wearable technologies might best serve specific domains in health or occupational settings (Grossmeier, 2017)[1]. Primary care remains a key point of contact for patients who are suffering from the effect of a sedentary lifestyle or who have complex needs with varrying degrees of comorbidity (Barnett et al., 2012). This would provide a challenging environment for those who design wearable technology.

One approach may involve working directly with practitioners and patient groups directly to design devices from scratch. There is currently a heightened interest in patient-centred research, as exemplified by the Patient-Centred Outcomes Research Institute (PCORI), both in the US and the UK[2]. However, patients are rarely involved in setting research agendas, and there is a frequent mismatch between these two competing priorities. Research-driven participatory design with patients would also address issue of personalisation with wearable technology. Currently, most wearables (and related interventions) are designed on the principle that "one-size-fits-all" - with a limited possibility of customisation and personalisation adjusted to, and by, specific individual. But studies in behaviour economics show that people ascribe more value to things they build and customise themselves – a phenomenon described as "IKEA effect" (Norton et al., 2012). Such participation-driven engagement is very much needed when building long-term wearable-driven interventions.

Early design conversations are likely to challenge some assumptions regarding what an effective wearable health tracker might look like and what it should track. For example, calculating the number of 'steps' an individual takes each day may not be the most useful metric for those who already face some level of physical disability (Kaplan et al., 2017). In addition, there remains considerable debate regarding how many steps equates to a healthy lifestyle (Tigbe et al., 2017). Similarly, health coaches advocate the importance of escaping goals and the experience raining supreme over a numerical approach. This again questions how current tracking devices might

[1] Some research programs are starting to develop devices using approaches that involve end users directly e.g. CLASP (http://myclasp.org/)

[2] http://www.pcori.org/

actually make matters worse where individuals have simply too many barriers to overcome and no change in the design of a device is likely to improve that situation (Rutjes et al., 2017).

Such research is likely to disrupt current thinking in terms of how these devices can be improved and better aligned with the goals of primary health care practitioners and patient needs. Several workshops and discussions could therefore consider how health services might use this technology and subsequent data visualisation to fit around the needs and expectations of patients, while also reducing exclusion and social disparities. Additional workshops might be centred around existing prototype and consumer devices that can track various aspects of a person's health to help facilitate an open and constructive dialogue on how best to approach and accommodate sensors in range of devices that could quickly be up-scaled towards larger production runs in the near future. It may be the case that a single device is indeed the best way forward for specific groups of patients, but these devices could form part of modular platform. Discussions may finally consider how data from various sensors can be used to infer multiple behavioural indicators, which may of particular interest to GPs rather than patients directly.

Adopting the above approach with research-driven participatory design may provide the fastest route for commercialisation of a specific device with additional support from a host institution. Such research may also assist in the development of new regulatory frameworks to enable wearable devices to be integrated into health care systems, which could, in turn, kick-start the development of validation programmes that would sit alongside appropriate training for health care professionals. This knowledge and understanding could then be disseminated to patients as validated devices became standardised, providing appropriate individual and aggregated data for patients, governments and healthcare providers.

Key Recommendations

5. New devices could be designed from the ground-up with input from patients and practitioners at each stage based on the application and expected outcome.

6. Consider the development of a new standard framework to validate devices in the future.

Behavioural Mechanisms Underlying Wearable Interventions

Technologies evolve more rapidly than traditional research models can evaluate them. This rapid pace of technological progress leads to a challenging research environment and is particularly problematic in the social sciences where publication lag-times can often mean that by the time a paper is published, the technology used to build or test a theoretical rationale has become obsolete or replaced (e.g. Jakicic et al., 2016). While wearable technology itself has made great advances, their theoretical contribution towards behaviour modification has been considerably smaller (Ogilvie et al., 2007). This also means that the public perception of wearable trackers is often being driven by unsupported industry claims, which is similar to many other sport or lifestyle products that purport to have large effect on performance (Heneghan et al., 2012). The majority of research papers provide little in the way of explanation as to why a wearable fitness tracker did or did not help patients become more physically active. Even in larger research designs, there is frequently no control group. For example, in Jakicic et al., (2016) participants were provided with significant levels of support across two conditions and the addition of a tracker may have provided little benefit beyond what was already a comprehensive support package.

However, research concerning activity trackers has made some progress and current implementation is not completely uninformed when it comes to applying theoretically informed behaviour change strategies (Sullivan & Lachman, 2016). The most prevalent theoretical factors implemented into existing devices concern concepts of self-monitoring and feedback. Both of these are explored broadly across the existing psychological literature and behaviour change studies (e.g. Kluger & DeNisi, 1996; Bird et al., 2013). However, given the scope of this paper we only consider a handful of key mechanisms that might negate or improve a wearable intervention.

Self-monitoring and Feedback

Self-monitoring can be defined as a fundamental behavioural self-control skill related to monitoring positively valued behaviours that one is encouraged to increase, and negatively valued behaviours that one is encouraged to decrease (Mcfall and Hammen, 1971; Kirschenbaum et al., 1982). Self-monitoring can therefore increase self-efficacy[3] (Du et al., 2011) and reduce perceived barriers to start, or continue, an activity (Wilbur et al., 2003). Research across a variety of health contexts has demonstrated that self-monitoring solutions can facilitate positive behaviour change such as weight loss (Womble et al., 2004), and management of chronic illnesses such as diabetes (Williams et al., 2007), asthma (Shegog et al., 2001) or depression (Christensen et al., 2004). One review on behaviour change techniques used to promote walking and cycling found that self-monitoring and intention formations were the most frequently coded behaviour change techniques for those two activities (Bird et al., 2013). Self-monitoring also reinforces an intrinsic motivation driven by an interest or enjoyment in the task itself rather than relying on external pressures or a desire for reward (Festinger, 1954).

The majority of consumer devices are designed on the principle that self-monitoring provides people with insights into their everyday behaviour including low levels of physical movement that correlate with poor health, which in turn motivates a change in behaviour (Sullivan & Lachman, 2016). In this manner, self-monitoring is inherently linked with feedback because a user has to review some aspects of the very behaviour that has been monitored. This feedback is typically related to performance (e.g. heart rate, steps taken, calories burned) (Kluger & DeNisi,

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[3] Self-efficacy is “the belief in one's capabilities to organise and execute the courses of action required to produce given attainments” (Bandura, 1997, p3). People with high levels of self-efficacy for physical activity are also more likely to initiate, increase, and maintain this activity, even in the face of obstacles and setbacks. Self-efficacy has previously been identified as one of the most consistent predictors of physical activity in adults of all ages (Bird et al., 2013).

1996). In general, providing people with feedback relating to their performance increases the likelihood of repeating that behaviour (Bandura, 1997). However, in practical terms with wearable interventions, this link has so far received mixed support with an evidence base largely driven by studies on the use of pedometers and clinical telemonitoring technology (e.g. Kitsiou et al., 2013). For example, Baker et al. (2008) observed that a pedometer-based self-monitoring walking program, incorporating a physical activity consultation, was effective in promoting walking and improving positive affect over 12 weeks in community based individuals. Another study by Merom et al. (2007) also showed that pedometers enhanced the effects of a self-help walking programme. Similarly, studies on the effects of telemonitoring on clinical outcomes provide mixed results for different patient groups (e.g. pulmonary and cardiac patients gain more from telemonitoring than those suffering from diabetes and hypertension (Clark et al., 2007).

Current Mechanisms

However, pedometer studies utilise a simpler form of technology and there is very limited evidence to suggest any long-term behaviour change. In theory, modern wearable devices could vastly extend how many behavioural change techniques they incorporate, but to-date this has been slow to materialise. Mercer et al. (2016) used the Coventry, Aberdeen, and London-Refined (CALO-RE) taxonomy to examine if wearable activity trackers incorporate behaviour change techniques. This taxonomy contains 40 techniques derived from behaviour change theories (Michie et al., 2011). While it is beyond the scope of this paper to detail this taxonomy in detail, many of these additional techniques are derived from theories that include elements of instruction, set graded tasks, and prompted self-monitoring. Almost all wearable devices allow an individual to self-monitor their behaviour, obtain feedback, and support users in goal setting (Lyons et al., 2017) however, the average number of behaviour change techniques identified by Mercer and colleagues was only 16.3/40 with 15 techniques absent from all trackers assessed. Identification of these however, may also depend on the user experience. Even techniques related to self-efficacy (such as planning, consequences, and knowledge) were present in less than half of the trackers. To maximise the chances of success, wearable devices and interventions could try to incorporate as many techniques that have been previously identified as being effective. Alternatively, these may be deliberately limited in order to test specific mechanisms of action. In addition, this does not remove the potential to add new items to existing taxonomy's – exploratory research is equally as important as confirmatory in this instance. It remains possible that these devices could contribute to, and challenge existing theory (Abraham & Michie, 2008).

While randomised trials are likely to remain the gold standard when it comes to demonstrating the effectiveness of any intervention, the mechanisms which underlie any specific change in behaviour remain largely hidden. Comparing existing trials to the action of a new drug, the action pathways are always well-established before a trial takes place. Existing trials are therefore unable to inform us about the exact mechanisms which might underlie any subsequent behaviour change (Klasnja & Hekler, 2017).

One causal pathway may involve the use of a device to make self-monitoring easier for the user and increase frequency of self-monitoring over time. An alternative is that active self-monitoring increases salience of behavioural choices more than passive self-monitoring (Mercer et al., 2016). A lack of engagement (e.g. not wearing a device) across many interventions suggest that this might not be the case, but research designs could manipulate what behavioural intervention techniques are made available as part of an intervention to understand which are more effective. This may even require additional basic research to grasp how feedback can best be presented. For example, a series of psychophysical experiments could explore how quickly people can read and remember the same feedback presented in different ways as it relates to physical activity and behavioural goals. A complimentary approach would then aim to better understand exactly what type of feedback is more beneficial. The creative visualisation of wearable feedback could therefore provide a new platform to test the effectiveness of radically different types of presentation that go beyond step counts and heart-rate variability.

Key Recommendations

7. Incorporating more theoretically derived behaviour change techniques could increase the success rate of wearable interventions.

8. More research is required in order to understand wearables' mechanisms of action in relation to behaviour change.

Individual Differences in Wearable Interventions

The Digital Divide

While many people have heard of consumer wearable devices, the predicted buyers are often either young people or those over 60 who already lead a healthy lifestyle (Khalaf, 2014; O'Brien et al., 2015). Current devices, interventions and research only reach a small part of the population that is interested in health or personal data capture (Sullivan & Lachman, 2016). While the line between assessment and intervention has blurred, the digital divide still exists and some debate remains in terms of how these interventions can reach people who are most in need, especially older adults and low-SES populations (Pratt & Frankin, 2016; Sullivan & Lachman, 2016). Considerable progress is required if such interventions are to become commonplace, regardless of ability or personal goals. Even within the context of existing trials, the variation in patients' experience and behaviour is largely ignored. While many will abandon their new device within a couple of months (Ledger & McCaffrey, 2014), others will persevere with these devices and will continue to track specific activities (e.g. runs) (Karapanos et al., 2016).

Measuring Individual Experience

Existing research remains limited concerning how activity trackers are incorporated into everyday life. While this can be considered in a quantitative context from the device itself, qualitative research can also consider the experiential side. Capturing this information can then map directly onto existing conceptual models that have been proposed to describe experience in a way to make it accessible for the design of future technology. For instance, McCarthy and

Wright (2004) decomposed the process of experience into six sub-processes, from anticipation to reflection and recounting. Other approaches focus on the psychological needs fulfilled through a particular experience (e.g., Hassenzahl et al. 2013). Hassenzahl et al. (2010) adapted Sheldon et al.' s (2001) list of psychological needs and showed that the fulfilment of these needs is linked to positive experiences with interactive products.

Unfortunately, much of this work has only focused on memorable experiences over a short period of time (Karapanos et al., 2016). This is where the application of self-report which combines real-time wearable data can reveal more about both the individual and the intervention. For example, the use of experience sampling alongside an existing intervention would work particularly well in this context (Miller, 2012; Piwek et al., 2015; Piwek & Ellis, 2016). Such data again could be used to design better interventions or devices (Harari et al., 2017).

Individual Differences as Moderators to Success

The interaction between a wearable intervention and a patient is likely to be complex, and further research needs to consider these effects in more detail. What type of person is most likely to benefit from a specific wearable intervention remains a key question for future research. This is very much a problem that can be addressed by by social science because it remains important to understand why people are not currently benefiting from a technology that remains highly adaptable and relatively cheap to produce and administer. For example, a growing body of research has established links between individual differences and health-related mechanisms, behaviours and outcomes. For example, several models have been proposed that aim to explain how personality could affect health via specific health promoting or risky behaviours (Atherton et al., 2014). However, while there is widespread agreement that personality plays a role, there remains no consensus on what traits are most strongly linked to behaviour change. Early indications suggest that conscientiousness can predict many outcomes, with low levels associated with individuals who are more likely to be overweight and less likely to respond to interventions (Bogg & Roberts, 2004). Cause and effect has yet to be established however.

In terms of current research, it is only in recent years that personality has been considered as a possible predictor for other aspects of digital engagement (Shaw et al., 2016; Xu et al., 2016). However, this work could also extend to predicting the adoption and use of wearable interventions. This raises questions regarding not only the intervention itself, but also how individual differences interact with feedback and the theoretical underpinnings of a specific intervention. For example, how might individual differences interact with immediate and delayed rewards in predicting long-term goal pursuit? Experimental work has observed that the presence of immediate rewards is a stronger predictor of persistence in goal-related activities than the presence of delayed rewards (Woolley & Fishbach, 2017). However, how other individual factors feed into this in an applied context remains unknown. Previous research has identified a number of individual differences associated with goal persistence such as self-efficacy (Bandura, 1977), optimistic explanatory style (Seligman & Schulman, 1986), locus of control (Rotter, 1966), levels of pride (Pekrun, Elliot, & Maier, 2009) and grit (Duckworth et al., 2007). Immediate rewards may matter less for those who score higher on grit, as grit involves maintaining effort in pursuit of a goal over a significant amount of time, despite facing multiple setbacks or a perceived lack of progress (Duckworth et al., 2007). One possibility is that the presence of immediate rewards does not predict persistence as strongly for gritty individuals who exhibit continued activity pursuit in the absence of a positive experience.

Future research designs may wish to utilise mediation and moderation models to help better understand why some individuals are more likely to benefit from a wearable intervention and customise interventions appropriately (Hayes, 2016). For example, those who are provided with a wearable tracking device at the start of an intervention could also be assessed across any number of psychological metrics. When it comes to analysing this data, a moderation model would consider how such a variable (e.g. sex) affects the direction and/or strength of the relationship between the intervention and any increases in physical activity (Figure 2). These models are computationally straightforward and can be implemented in a variety of statistical packages.

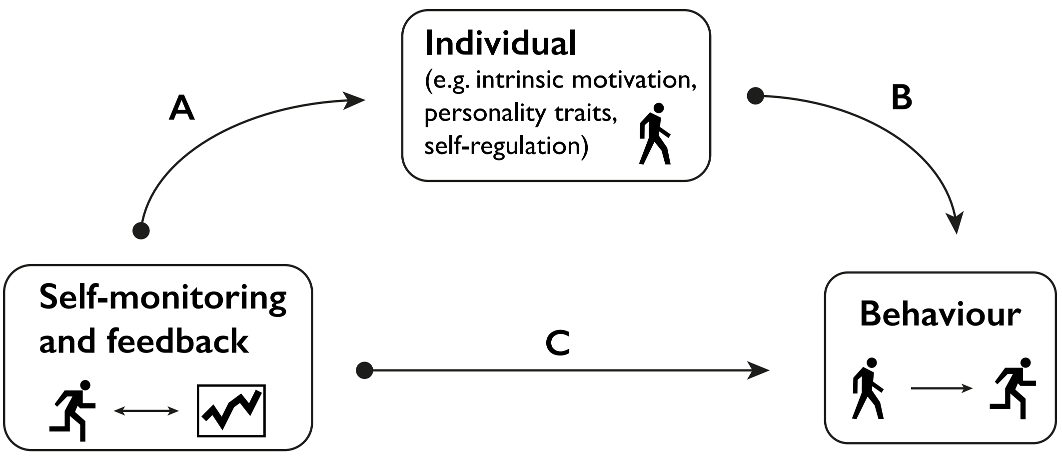


Figure 2: A simple moderation model. The relationship between self-monitoring/feedback and subsequent behaviour is well documented (A-C). However, the moderating effect of the individual remains largely untested in the context of wearable interventions (A-B).

Key Recommendation *9. Understanding the role of individual differences is likely to correlate and predict uptake, success and attrition of future interventions.*

Individual Harm

A potential issue of harm remains largely absent from the existing literature base although it is conceivable that people may become over-reliant on automated systems that provide a false sense of security or fuel a self-driven misdiagnosis (Coyder et al., 2009; Mertz, 2016; Piwek et al., 2016). Excessive self-monitoring could also lead to discomfort and a sense of intrusiveness amongst patients. Several studies have observed that type 2 diabetics who self-monitored their own blood glucose concentration did not benefit from increased glycaemic control but rather found their disease more intrusive (O'Kane et al., 2008). How wearable devices might affect cognitive function also remains unanswered, but recent evidence suggests that we should be cautious when it comes to the additional cognitive demands digital technology might place on those who are already using cognitive energy to focus on changing their behaviour for the better (Ward et al., 2017).

Examples are becoming more frequent with Etkin (2016) observing that while counting steps led participants to move more, it decreased people's enjoyment of walking. The argument followed that by invoking the metaphor of "measuring" and highlighting quantitative outcomes, attention is drawn away from the intrinsic joys of an activity towards external rewards (Deci et al., 1999). Physical activity is therefore viewed as work, which may decrease the likelihood of continued engagement. In other words, instead of supporting people by construing exercise as an enjoyable and meaningful activity leading to prolonged engagement, wearable trackers may establish new mechanisms, which guarantee a short-term increase in activity at the risk of negative long-term effects.

Similarly, Tonietto & Malkoc (2016) conducted 13 studies using unambiguous leisure activities that people commonly schedule (e.g., going to the cinema, taking a coffee break). They found that scheduling a leisure activity (vs. a spontaneous action) made it feel less free-flowing and more work-like. Furthermore, scheduling diminishes utility from leisure activities, in terms of both excitement in anticipation of the activities and experienced enjoyment. Importantly, the authors found that maintaining the free-flowing nature of the activity by "roughly scheduling" (without pre-specified times) eliminates this effect, thus indicating that the effect is driven by a detriment from scheduling rather than by a boost from spontaneity. This is similar in terms of how goals are typically calculated and determined by wearable devices (Piwek et al., 2016) however, these findings highlight another important opportunity to improve individuals' experiences and utility by leveraging scheduling behaviour while also providing important implications for changing behaviour.

Other work has considered specific populations who are more likely to be at risk of harm. While some research has shown a positive impact on those with serious mental illness over a 6-month period (Naslund et al., 2016), others have suggested that the potential to cause additional stress still remains. For example, Simpson & Mazzeo (2017) observed an association between the use of calorie counting, fitness trackers and eating disorder symptomology. This supports earlier research where individuals who report using calorie tracers manifest higher levels of eating concern and dietary restraint (Jacobi et al., 2004). Similar issues have been reported with sleep trackers where false positives lead patients seeking treatment for sleep distorters that do not exist. (Baron el al., 2017). Like much of the concerns with the quantified self-literature, the unrealistic quest for perfection in movement or sleep can cause more harm than good, particularly when individuals start to place so much faith in data that they believe is more consistent of their experience than other more validated techniques (van Berkel et al., 2015).

Finally, there is evidence that health behaviours can cascade across social interactions. Aral & Nicolaides (2017) observed across a large sample of over 1 million individuals that exercise is socially contagious. Less active runners influenced more active runners, but this relationship did not reverse. This "contagiousness of exercise" also varied depending on gender and the strength of relationship between friends. These results remain problematic for those who are moving less, but does provide insights on how future research can make better use of social connections to improve future interventions. Work by Aral & Nicolaides (2017) also makes use of pre-existing data-sets to test specific theoretical propositions and individual differences. Such an approach should be the focus of future research as more data becomes available from wearable devices and better methods are developed to secure, extract, and evaluate this complex data (Piwek and Ellis, 2016).

Key Recommendations

10. Given current gaps in theoretical knowledge, the type and timing of feedback is an area worthy of additional investigation.

11. Future research should consider issues of harm and negative social influence which are frequently ignored or overlooked.

12. Research designs should leverage power from pre-existing data sets wherever possible before collecting additional data.

Conclusions

The benefits of physical activity are well established for individuals and society as a whole (Lee et al., 2012). Promise remains for many new real-time, wearable interventions that can help drive behaviour change and get people moving more frequently. While we have considered elements of design, theory and individual differences separately, there is considerable overlap across all three domains. This reflects a positive interdisciplinary movement within the research base however, the science regarding the feasibility and effectiveness of such devices to influence health-related behaviours has plenty of scope in terms of how it moves forward. Progress has remained static in some areas largely because existing adaptations have not been driven by theoretical constructs alongside controlled experimental trials. Behaviour change is complex, and research is urgently needed to understand how individuals, devices and their related technologies can most effectively be designed and implemented to optimise future interventions.

Even at this stage, it remains unclear how existing interventions may help those individuals who are (a) regularly exposed to wearables that provide an ever-increasing stream of behavioural and physiological feedback, (b) generally in good health, and (c) not provided with any medical supervision or consultation. Therefore, it remains essential to investigate and evaluate the relationship between health-related feedback (e.g. number of steps taken per day) and the impact this can have on behavioural goals (e.g. how does the number of daily steps for an individual relate to the average step count for a relevant population group).

Moving forward, we would argue that research programmes should aim to strike a balance between controlled trials and basic research principles with input from those working in applied contexts. It remains difficult to dismantle which single elements of an intervention bring the biggest impact. It may even be too early for large-scale trials when it comes to testing if wearable interventions can help increase physical activity levels, particularly when many critics would argue that much of this applied research is not useful when it comes to changing how decisions are made within public health (Ioannidis, 2016).

While unpredictable, basic research is required to understand how the design and functionality of existing devices can be improved at the outset. Current wearable devices are based around an immutable design (from a hardware perspective) and collect a pre-determined set of data. This may need to adapt to a user's context, social situation, and relate to a specific behavioural intervention that has a pre-defined start, beginning, and end. This basic foundation to support wearable interventions is required to support any future transformation of behaviour on a larger scale. In addition, as we move further towards individualised medicine, a one-size fits all approach is unlikely to be the best way forward, particularly when the social effects of quantifying behaviour are not entirely positive (e.g. Aral & Nicolaides, 2017).

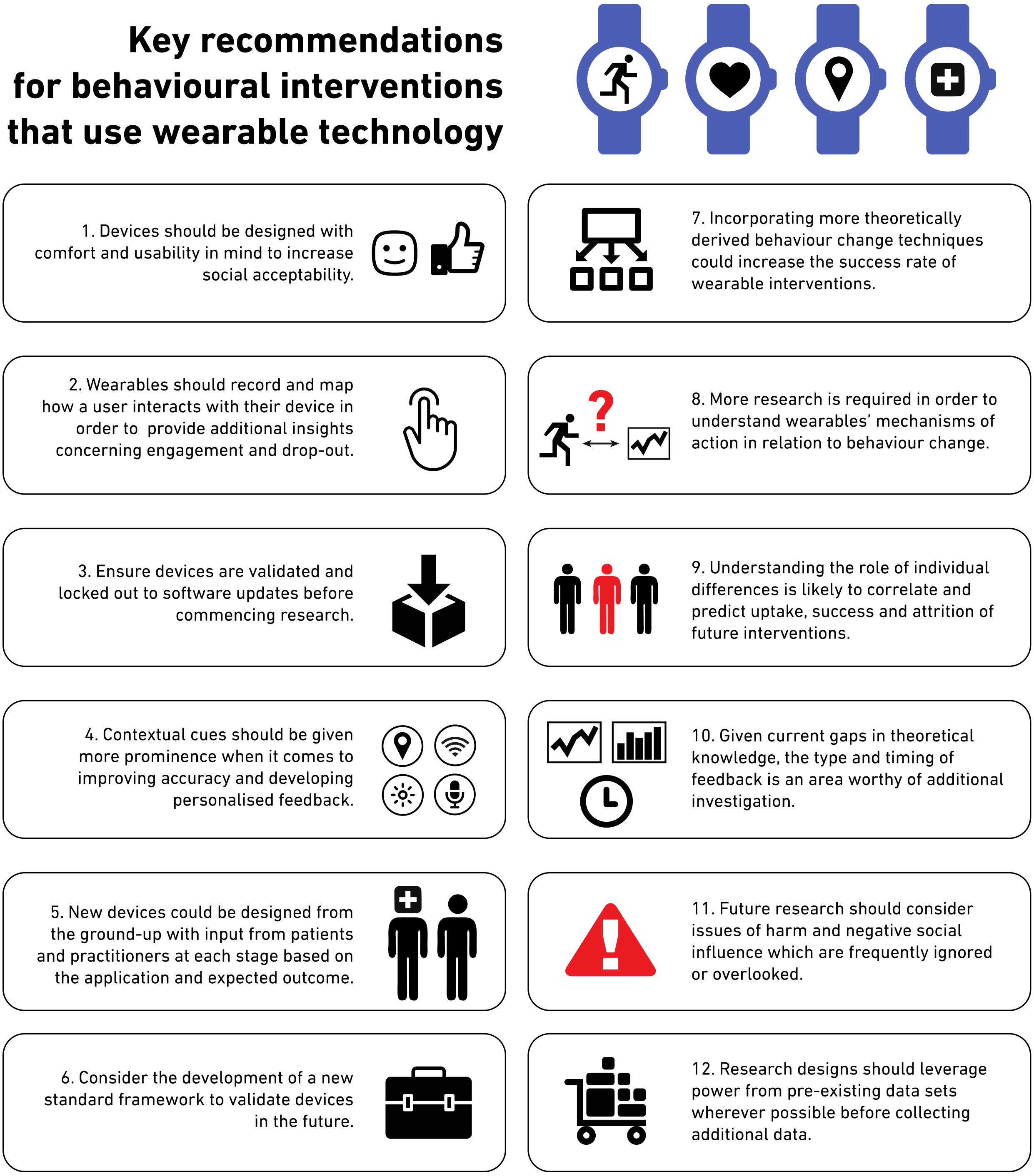
Finally, it would be naive to assume that wearable devices will be the single aspect of technology that will help people move more. Wearable trackers are likely to become part of a larger set of intervention systems within a digital context and understanding their limitations is crucial in order to understand their future application (Muse et al., 2017; Webb & Wadden, 2017). Interventions may need to include other linked devices that further monitor behaviour directly or act passively to support and motivate individuals and groups (Steinberg et al., 2013). Nevertheless, we remain optimistic that wearable interventions alone, combined with the right research agenda, can transform health for individuals and society.

Summary of impact

Given the widespread individual and societal problems associated with low levels of physical activity, it is more important than ever for research investigating positive behaviour change interventions procures a relevant information gain. This means that, first, we need to be aware of what we already know so that new information can be placed in context. While there is much promise in wearable technology when it comes to changing behaviour and getting people to move more, there is an inherent risk that the research landscape becomes dominated by well publicised successes and failures without understanding why these results are occurring. This is particularly difficult when it comes to wearable interventions because of their cross-disciplinary nature, but failures or limitations of any intervention are particularly important because they can help reveal the ideal functioning of any new device and/or intervention

Here we consider the reasons why wearable interventions are unlikely to have reached their full potential. We provide a list of recommendations to both provoke discussion and suggest how interventions could become more successful in the near future. Our recommendations are based purely on research that is currently available. We can be fairly certain that several existing research programmes worldwide are already addressing some of the key issues outlined as part of this white paper. In sum, this paper advances thinking by challenging both current wearable intervention strategies and the way in which they are assessed and administered. We hope our guidelines will generate discussion, improve research designs and provide some guidance on how wearable interventions can be improved in the future to maximise success.

Figure 3: A summary infographic of key recommendations for behavioural interventions that use wearable technology.



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