GetAMoveOn Network

Leveraging Technology to Enable Mobility and Transform Health

A review of physical-activity tracking technologies and how to assess their effectiveness

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Background: the GetAMoveOn Network+

The GetAMoveOn Network is an interdisciplinary UK community that is addressing the EPSRC Grand Challenge of transforming community health and care through the delivery of tested technologies that promote wellbeing by providing timely, individualised feedback that encourage appropriate activities. We are focusing on movement as a locus for health: it is our test case as it drives so many other benefits that are of value: economically, socially and culturally.

When we move more, we become smarter; as we become stronger, chronic pain decreases. Greater movement, especially in social contexts, improves collaboration. As we move, not only do we reduce stress: we improve our capacity to handle stressful situations and to see more options for creative new solutions. Movement enhances both strength and stamina, improves bone mineral density and balance, reducing incidence of falling and associated hip injuries (causes of death in the elderly). Movement complements other functions, from assisting with sleep and therefore memory and cognition, to helping with diet and associated hormones - improving insulin sensitivity and balancing cortisol. There are recent studies showing benefits of movement related to dementia. And yet, physical inactivity is the fourth leading cause of death worldwide; sedentarism has been called the "new smoking". Meanwhile costs to UK GDP from sedentarism and associated disease are increasing - from sick days lost to work, to elders losing mobility and having to move into care homes.

We have designed ourselves into our sedentarism: sitting during our commute, at desks while we work, and at home on the sofa. There is a critical need to design ourselves back into the natural effects of health accrued simply by moving more. We need solutions that will help build both the evidence and the experience that movement can enhance and benefit people's lives.

New technologies are transforming our ability to capture lifestyle data on individuals in real time. Consumer technologies such as step counters and wifi scales are the tip of an iceberg - research programmes worldwide are proposing lifestyle data capture from devices ranging from video cameras to electricity meters to wearables. Meanwhile pervasive connectivity allows that data to be transmitted, processed through powerful machine learning tools and provided back to people in a heartbeat. While we understand the potential technologies, we do not yet know how to leverage the technology effectively to support transformative health.

Current approaches in ehealth generally only reach a small part of the population that is already interested in fitness, personal data capture, or both. Their uptake is, furthermore, of dubious effect as two recent medical reviews have shown. To have a national impact on health and wellbeing, to reduce the crippling burden of long term health conditions and to move healthcare from the clinic to the community, we need to reach everyone, across a range of abilities and aspirations. We need to connect the potential of the technology with the potential of people and realise the benefits of a healthy, brilliant, population.

Realising this potential requires research on novel technical solutions, supported by theories from sports and health sciences on blending appropriate movement strategies for particular performance aspirations to behavioural and cognitive sciences on ways to engage people to make effective and meaningful progress. We need to understand what measures are appropriate not just to evaluate progress, but to guide it and adapt to it. To have meaningful impact across these dimensions we need to combine a range of expertise including sensor networks, data analytics, interactive visualisation, human computer interaction, online citizen engagement, behaviour change, sports, exercise. The GetAMoveOn Network is a response to this research challenge.

Abstract

Interest in activity tracking and other personal informatics systems has exploded in the last five years, and has been the focus of academic research across a variety of disciplines. Activity trackers allow users to quantify their physical activity and generally include behaviour change techniques to encourage users to do more. A large body of work focuses on how people adopt these trackers and integrate them into their lives, considering not only changes in the tracked behaviour, but also how the trackers become part of one’s daily routine. In addition, an increasing number of interventions for encouraging and assessing behaviour change have used these technologies. Levels of engagement with such devices or interventions are often used to define their success. However, particularly in the case of self-tracking, this is often not an appropriate measure – users sometimes create long-term changes even after a short period of use, either through insights gained or by maintaining changes without engaging with the device.

This paper presents a critical overview of the current work within personal informatics for encouraging NEAT (non-exercise activity thermogenesis) physical activity – all the activities that we do that are not sleeping, eating, or sports-like exercise. We also focus on the appropriate methods for assessing success, particularly given the long-term changes we would like to see arising from work in this area. The paper presents an overview of: current personal informatics technologies for measuring physical activity; research into engagement and use of these technologies and how this has impacted individuals, groups and society; considerations for using these devices in interventions; and finally, a critique of both the methods for studying personal informatics systems, and the interventions using them, to provide new directions for future work.

Introduction

People are becoming increasingly less active in many countries around the world (WHO, 2010). According to the World Health Organisation (WHO, 2013) inactivity is responsible for approximately 3.2 million deaths each year and is also a risk factor for many chronic diseases. One cause of decreased activity is because people are less active in their day-to-day routines – with more sedentary jobs and leisure activities, and less use of active transport, people do considerably less physical activity outside of planned exercise than they once did.

In 1999 Levine et al. coined the term “NEAT”, or Non-Exercise Activity Thermogenesis, to represent all those activities that one does when not sleeping, eating, or engaging in planned sports-like exercise. These non-exercise activities have also been referred to as *“the other 23 hours of the day”* (dcrainmaker.com, 2011) (when one is not doing planned exercise), and include behaviours such as walking, taking the stairs instead of the lift, cycling instead of driving, etc. In the UK, the NHS recommend 30 minutes of activity five times a week to maintain a healthy state (NHS.uk, 2011). Encouraging a greater level of movement in these day-to-day activities is a sensible area to focus on, as these habits may be easier to sustain compared to planned-exercise. In addition, targeting NEAT activities may be particularly useful amongst sedentary workers, older adults and any person who may feel that they are less able to participate in higher-intensity activities, but for whom walking and other NEAT-type activities may be possible. Teaching children good habits from an early age will allow them to lead the way (cf. Masser & Creed, 1977) and lessen the burden created by inactivity-related health issues in future generations.

The benefits of being more physically active are generally well-understood. This may be, in part, due to the successes of public policy and interventions designed to encourage healthier lifestyles, which have resulted in many people around the world being aware they should be active (Craig and Mindell, 2009). However, despite this knowledge, most of the world's population is still affected by problems related to low levels of physical activity, and we see growing numbers of those affected by associated chronic diseases. Clearly, knowledge alone is not enough for everyone to change their behaviour, and additional interventions or support are needed. A commonly cited average time for creation of a new habit is 66 days (Lally, et al., 2010). However, the time taken to change varies between individuals and changes to physical activity may be particularly difficult because of the effort involved. Indeed, interventions for increasing physical activity typically have high rates of relapse (Buchan et al., 2012). A popular behaviour change model (Michie et al., 2011) suggests that people need capability, motivation and opportunity to change their behaviour, something that those designing interventions should be aware of.

Over the past five years, activity tracking devices and services such as those from Fitbit and Xiaomi have become hugely popular, accounting for 85% of the 23 million wearables shipped in the third quarter of 2016 (idc.com, 2016). Shipments of wearables are expected to grow to more than 245 million per annum by 2019 (up from 84 million in 2015), with a market value of $25 billion (ccsinsight.com, 2015). Many believe these systems will empower and motivate users to manage their health and wellness, and ultimately change behaviour to do more NEAT activity (cf. Rooksby, et al., 2014). They work by passively measuring levels of physical activity taken by the user throughout the day, usually in the form of steps taken, and then utilise behaviour change techniques, such as goal-setting and gamification, to help users change. Interventions based on pedometers, which also count steps, have been shown to be, at least in some cases, successful in increasing levels of physical activity (Bravata et al, 2007). However, despite their recent popularity, the ability for commercial activity trackers to help users change their behaviours is still not well understood. The introduction of technology to the behaviour change process may result in dependencies on the technology (Renfree et al., 2016).

Activity trackers have been the focus of research in many different fields of academia, from sociology (e.g. Lupton, 2016), to health psychology (e.g. Sullivan and Lachman, 2016) and human-computer interaction (HCI) (e.g. Rooksby, et al., 2015). The focus of, and results from, these studies have formed differing and sometimes opposing viewpoints, particularly related to the systems' usefulness for aiding and encouraging behaviour change. This may perhaps be due to the different approaches taken and the outcomes measured between these studies. Nonetheless, we see a need to provide a more comprehensive review of existing literature from these different fields, to create a more complete understanding of how activity trackers are used in the real world and in research.

In this critical review of the literature, we first provide an introduction into the problem area of insufficient physical activity, providing a short overview of some of the existing work in the area and behaviour change techniques that may be leveraged to encourage people to do more. We then introduce personal informatics systems for quantifying movement - activity trackers – and how they work, before moving onto our primary focus in this work, considerations for their real-world use and adoption. Here we focus on motivations, barriers and temporalities of use, drawing from HCI literature in particular, but also including findings from other related fields. We discuss issues related to integrating these systems into our lives, and how this is an important aspect to consider when evaluating them. We also reflect on how real-world use and adoption has been conceptualised in various models of personal informatics, and critique the various methodologies used to study these systems, pointing at strengths and limitations. Finally, extrapolating from our critical review of the research completed in this area, this paper concludes with a series of issues researchers should consider when studying personal informatics and behaviour change technologies.

Physical Inactivity and Activity

Physical inactivity is a "leading risk factor for death", and according to the WHO "globally, 1 in 4 adults is not active enough" (WHO, 2017, no page number given). Here, we overview of the problem of physical inactivity, covering the myriad factors contributing to global physical activity trends, along with the recommended levels of physical activity for different populations.

Inactivity and its causes

According to the World Health Organisation (2013), physical inactivity, which is strongly linked to obesity and is a risk factor for many chronic diseases, is responsible for approximately 6% (3.2 million) of all deaths each year. The Organization for Economic Co-operation and Development (OECD, 2013), who report population statistics for 34 mostly-western countries, found that more than half (52.8%) of the adult population were overweight or obese and obesity levels between 2000 and 2011 increased in *all 34 countries* included in the report. The number of overweight and obese adults is believed to be as high as 68.8% in the US (Flegal, et al., 2012) and 61% in the UK (NHS Information Centre, 2009).

The World Health Organisation (2013) suggest that the global decrease in physical activity is partly caused by inactive work and leisure activities, sedentary occupations, and increased use of non-active transportation. They recommend encouraging moderate intensity activities such as walking and cycling, as these offer significant health benefits and people can *"quite easily"* (WHO, 2017. no page number given) meet recommended activity levels throughout the day.

NEAT activities

Physical activity takes many forms, and positive health benefits are not only the result of vigorous sports activities, or training sessions completed in the gym. In 1999, Levine et al. coined the term “Non-Exercise Activity Thermogenesis”, or NEAT, to refer to all those activities that are not sleeping, eating, or doing sports-like activities, and explained the virtues of these. Since then, studies (e.g. Levine, 2004) have shown the positive health impacts of increasing NEAT through small changes in day-to-day activities such as using the stairs. A recent study showed that even a change as minor as “chair-based fidgeting” (Figure 1) can have significant positive effects on energy expenditure (Koepp, et al., 2016). One way for people to routinely incorporate more NEAT activity into their lives might be through increased use of active transport solutions, such as walking and cycling (Van Kempen, et al., 2010). Research has shown large improvements to both physical and psychological wellbeing after taking up more active transport solutions (Martin, Goryakin and Suhrcke, 2014).

Figure 1. Chair-based fidgeting solutions: FootFidget (www.footfidget.com) and CoreChair (www.corechair.com). Photo from Koepp, et al., 2016.

Targeting an increase in these low-impact NEAT activities may be particularly interesting to the GAMO community, as they might be integrated into their lives of otherwise sedentary individuals through small changes made throughout the day. These activities might be particularly appropriate for older adults, who may otherwise feel incapable of, or fear, sports-like exercise (Cohen-Mansfield et al., 2003), or office workers who have long sedentary hours (Renfree and Cox, 2016).

Physical activity recommendations

One popular recommendation to increase low intensity exercise and help meet recommended levels of physical activity is to simply take more steps. The most well-known recommendation for healthy adults is to reach a level of 10,000 steps a day, a figure that originated from a 1960's Japanese marketing campaign encouraging sales of pedometers (Hatano, 1993). Despite the perhaps dubious source, this goal is known by many people and is widely implemented as the default activity goal for most activity trackers. Research suggests this level is appropriate to improve health (Tudor-Locke et al., 2011a), but it may not be appropriate for all: some children and adolescents should perhaps aim for more steps (Tudor-Locke et al., 2011b); a goal of 5,000-7,000 steps may be better for older adults (Tudor-Locke et al., 2011c); and, a fixed number of daily steps may not be the right approach for those with chronic pain, as overdoing activity on bad days has negative consequences on their ability to remain active (Singh, et al., 2014).

Given the strong focus that many systems have on steps, one might think that taking steps alone is sufficient to meet physical activity recommendations. However, this is not the case: physical activity level recommendations around the world recommend that people do strength training as well as aerobic activity to retain strength and muscle mass. Indeed, exercise that simulates everyday functional activities beyond walking, (e.g., standing from a chair, stretching to reach a shelf) are recommended to maintain physical capabilities. This is particularly important in older age to retain independence, and strength training helps to preserve bone density and reduce the risk of osteoporosis and chronic conditions such as heart disease, arthritis and type-2 diabetes (Seguin and Nelson, 2003). Guidelines in the US recommend that healthy adults take 150 minutes of aerobic activity and 2 days of muscle strengthening activities per week (CDC, 2008). Similarly, the National Health Service (NHS) in the UK recommends healthy adults take either: 150 minutes of moderate aerobic activity and 2 days of strength training; 75 minutes of vigorous physical activity and 2 days of strength training; or, a mix of vigorous and moderate aerobic activity and 2 days of strength training, each week (NHS.uk, 2011). Those working with other populations should be aware of recommendations, such as those produced by the World Health Organisation for 5-17 year olds (WHO, 2011a) and those over 65 (WHO, 2011b). These guidelines all include some sort of resistance or weight training – an activity that currently has low levels of adherence and is not targeted if we only encourage users to take 10,000 steps each day.

Despite the problems outlined with using steps as an only measure of activity, there are some potential benefits: steps are generally not considered sensitive information to share with others, as instead calories burnt or weight might be; steps are easy to understand, and compare between others; and finally, 10,000 steps is an easy to remember and conceptualize goal (cf. Sullivan and Lachman, 2016). Nonetheless, those designing interventions to encourage greater levels of physical activity should remain aware of these recommendations and ensure that their interventions target not only cardiovascular activity, but also resistance-training activities which may be more difficult for current ubiquitous technologies to track reliably.

While many people are aware they should be more active, and want to exercise more, they find it difficult to change. There is a recognised gap between an individual's awareness of recommended activity levels, their desire and intention to do more activity, and their success in doing so (Craig and Mindell, 2009). Additionally, there is also a gap between what people think they do and what they actually do (Vandelanotte C et al. (2011). Ubiquitous computing solutions, such as mobile applications and wearable devices to quantify physical activity, have been presented as a potential resource for those looking to increase their levels of physical activity. As of May 2017 Fitbit's home page (www.fitbit.com) states *"Fitbit motivates you to reach your health and fitness goals"*, and similarly the Withings Activite site (www.withings.com/uk/en/products/activite-steel, accessed May 2017) says *"Activity tracking helps you move more, feel better, and sleep better"*. However, there is still relatively little research looking at the role these systems can play in this process, and more importantly, how they are used in authentic contexts and over longer time periods.

Self-tracking and Personal Informatics

The "Quantified Self" and "personal informatics" are relatively recent expressions, having been coined in 2007 and 2010 respectively. The two terms are often used interchangeably. Personal informatics, meaning to *"help people collect and reflect on personal information"* (Li et al, 2010, p.557) was coined by Li et al. in 2010, while Quantified Self was first used and popularised by two *Wired* editors in 2007 with the advent of the Quantified Self Labs (www.quantifiedself.com). Work in this area has grown significantly since, both commercially and in academia, to the point that in 2017, Kersten-van Dijk et al. referred to personal informatics as *"a new scientific field"* (p.2). Despite the recent interest, personal informatics arguably has much older roots in "lifelogging" – an activity that humans have undertaken for hundreds of years, but which modern technology has now made more accessible.

People throughout history have logged aspects of their lives. Benjamin Franklin famously logged "13 virtues" (including temperance, silence, order, etc.) about himself each day (Franklin, 1791) and in 1945, Bush imagined "the Memex", for total capture of all the files and materials one encounters in life (Bush, 1945; Sellen, 2010). More recently, starting in 2005 (and finishing in 2015) Nicholas Felton manually tracked many aspects of his life, and created annual infographics (www.feltron.com). Additionally, athletes have been tracking aspects of their lives related to their performance for far longer than general consumers.

Active vs. passive tracking

Logging personal information changed significantly with the advent of technologies that allow *passive*, rather than *active* logging – i.e. systems that record data without manual engagement from the user. One of the first technologies for automatically recording human activity was the pedometer, a device first envisaged by Leonardo da Vinci more than half a millennium ago (Da Vinci, published: 1938). Differently to modern activity trackers, pedometers traditionally utilised a small micromechanical switch to count steps, rather than an accelerometer, and as such are more sensitive to positioning on the body and limited in their ability to track different metrics. Despite their simpler technology pedometers have been shown to be successful in encouraging behaviour change when used as part of an intervention to increase levels of physical activity (Bravata et al, 2007).

Active tracking systems rely upon the user *actively* self-tracking behaviours, doing things such as manually logging the food they have eaten, or keeping a record of dreams. Instead, passive tracking offsets this effort to a piece of technology, such as an activity tracker or a continuous blood glucose monitor, and the records are automatically created, stored and users are notified of their progress (Choe et al., 2017). Examples exist between these two extremes, for example: traditional pedometers allow users to *passively* track the number of steps they take in a day, but they might then need to *actively* check the device at the end of each day and manually transcribe the automatically tracked steps, and take charge of keeping a record of this data elsewhere (e.g. paper diary).

There is considerable effort within ubiquitous computing towards allowing a wider variety of metrics to be tracked passively. This includes commercial efforts such as a beaker that measures its contents and calories (www.myvessyl.com), to research exploring automatic tracking of food consumption with wearables (Thomaz et al., 2015). One of the motivations for this work is to remove the effort of tracking from the user - as we will discuss later, one reason users abandon tracking is because of the sometimes-considerable efforts needed. For example, using the MyFitnessPal app (www.myfitnesspal.com) to keep an accurate record of all the food that one eats requires the user to carefully log not only the types of foods, but also their weights and ingredients. This is, of course, time consuming and may even cause some users to change their eating habits – eating a more limited diet so to save time when inputting their meals into the app (Cordeiro et al., 2015). While there is still no evidence whether these changes are positive or negative, designers of interventions should consider what effect the process of tracking the targeted behaviour may have, as Duncan et al. (2016) have started investigating.

There is ongoing debate on which form of tracking – active, passive or semi-automated – is the most suited for particular activities and goals. Actively tracking behaviours can be beneficial, as the process of manually tracking ensures that the tracked behaviours remain salient and this may be leveraged to benefit the user. Further to this, one potential risk of passive tracking is that the measured behaviour is forgotten (cf. Choe, et al., 2017). For example, if one was to wear an activity tracker and then never engage with the tracked data they might never engage with the behaviour change techniques embodied in the system and therefore not benefit from these. To this end, Cox et al. (2016) suggest designing frictions within interactions to help users switch from mindless interaction to more mindful ones, especially when encouraging behaviour change. Their concept of *design frictions* would bypass the limitation of passive, automated tracking, whilst not putting too much strain on the user, but still encouraging a positive change.

Tracking physical activity

The idea of measuring the number of steps one takes each day is not new, but the application of modern technology to this area is much more so. Notable work in this area, precursory to the current commercial-systems, includes the HCI work published by Consolvo et al. (2006, 2008a, 2008b) on *“Houston”* and “*The Ubifit Garden”* – both systems utilising a step-tracker connected to a mobile phone application, a display showing the number of steps counted. These systems, and other similar works in HCI (e.g. Lin et al., 2006) not only logged the number of steps the users were taking, but were also designed to encourage people change their behaviour and be more active.

Activity tracking has exploded since the first HCI publications starting in 2006 and the advent of the Quantified Self in 2007-08, with particular growth over the last five years. Ayobi et al. (2016) conducted a review of the academic work within HCI, and identified three streams of existing research: psychologically, phenomenologically, and humanistically informed. The psychologically grounded research is mostly related to behaviour change and psychological approaches. The phenomenological grounded stream *“seeks to understand how wearable self-tracking technologies are used and experienced in practice”* (p. 2776) and finally, the humanistically informed stream takes a broader perspective, drawing upon *“concepts and perspectives that are grounded in research fields such as digital humanities, media studies, and sociology”* (p. 2777). Several review papers of the behaviour change literature already exist (e.g. Michie et al., 2011a; Michie et al., 2011b) and Sullivan and Lachman’s paper (2016), provides a strong overview of the behaviour change techniques explored in the literature, related to physical activity and tracking. Therefore, in this paper we include work from all three areas, but mostly draw from the phenomenological and humanistic streams, as these are less understood and reviewed in the current literature.

Figure 2. ActiGraph wGT3X-BT

In contrast to today, when the initial research in activity tracking was conducted 10 years ago, there were far fewer options available for tracking steps. Most work relied on use of large and expensive research systems such as the Actigraph (Figure 2, ActiGraph wGT3X-BT, taken from: http://testing.actigraphcorp.com/products-showcase/activity-monitors/actigraph-wgt3x-bt/), or less expensive and more consumer-focused pedometers (either based on a micromechanical switch or a 3-axis accelerometer). A huge number of commercially-available solutions for measuring the number of steps one takes each day now exist, not only including the more-obvious systems designed specifically for measuring steps ("activity trackers"), but also other wearable devices (such as smartwatches), smartphone applications and even handheld games consoles such as the Nintendo DS. These systems gather their data by interpreting data recorded by built-in accelerometers. There are many other lifestyle tracking apps and devices, allowing users to record the food they eat, their sleep, weight and blood pressure, and mood. Within this review we focus on devices for tracking ambulatory (i.e. step based) physical activity, but where appropriate we also refer to other tracking solutions.

Smartphone applications vs. wearables to track physical activity

Of note, along with the large number of wearable for tracking activity, there are also many free and paid-for smartphone applications available for tracking steps. More recent smartphones, such as the Apple iPhone 5S and above, include a specially designed "co-processor" to track steps without a large overhead on the battery. Using the iPhone as an example, these devices keep a constant record of the previous 7-days steps, so that a user can immediately see their activity data from the previous week when they first download a step tracking app. A benefit of using smartphone apps is the greatly reduced barrier to adoption, as they may be used without an additional purchase, at least for those who already own a smartphone. Recent commercial research has suggested that 68% of Americans own a smartphone (Smith, 2015), although this number may be lower amongst older adults and those with lower socioeconomic status.

Figure 3. Activity trackers in different form factors. (from left to right) Fitbit Zip clip (www.fitbit.com/zip), Jawbone UP3 wristband (www.jawbone.com/fitness-tracker/up3), Withings Steel HR watch (www.withings.com/products/steel-hr)

Wearable devices that track physical activity come in a large range of different forms: from dedicated activity tracking devices, such as Fitbit and Jawbone devices, to wearables that offer also other functionality, such as smartwatches (Cecchinato et al. 2015; 2017). Different to the activity trackers we focus on in this paper "sports" watches, which include GPS-tracking and occasionally activity-tracking functionality, also exist. Dedicated activity trackers are available in different form factors, including clip-based devices, wristbands and watches (Figure 3), each with different concerns as to how they are integrated into one's everyday life. For example, smartwatches that also track physical activity can present issues with engagement, if the user is bombarded with other non-related notifications (Cecchinato et al., 2017). Traditionally these devices have only used accelerometers to record activity, but more recently they have offered additional tracking metrics through embedded sensors such as heart-rate monitors.

Measures of activity

The majority of commercial apps and devices quantify users' activity by recording the number of steps taken. One limitation of using measuring steps is that they do not account for non-step based activities such as cycling, or any of the strength training activities recommended. Measures such as Nike's fuel (www.secure-nikeplus.nike.com/plus/what_is_fuel/), Mio's PAI (www.mioglobal.com/pai.aspx), energy expenditure (EE) or METs (metabolic equivalents) attempt to offer holistic measures of effort, but current devices may not be accurate enough when tracking these other activities. Research has found that most users consider step tracking to be the most important function of activity trackers (Alley et al., 2016).

Using commercial activity trackers in research

As discussed in the literature (Harrison et al., 2014, Sullivan and Lachman, 2016), commercially-available activity tracking systems are increasingly being used as part of interventions in academic studies, replacing or augmenting costlier and less user-friendly "research" alternatives such as the Actigraph (e.g. Harrison et al. 2013, Cadmus-Bertram et al., 2015). Using these consumer-focused systems offers various benefits over developing one's own hardware or software systems for tracking, by reducing costs and resulting in systems which may more easily be adopted and used in the real world.

Many of the commercially available activity tracking systems offer Application Program Interfaces (APIs) or Software Development Kits (SDKs) to allow other developers to access some of the data stored in their platforms. These tools allow researchers to collect aggregated data which can be used for assessment as well as in interventions (Harrison et al., 2014). However, the algorithms used in commercial systems are a "black box": they are not documented, and researchers are not able to access the raw sensor data. Additionally, because these devices are subject to software and firmware updates that are out of the control of researchers, the accuracy and methods of tracking may change over time, making comparisons even within a single study difficult, or impossible.

It is important for researchers to consider the accuracy of these devices, particularly if they are hoping to use recorded data to make comparisons. Numerous studies have analysed accuracy of devices and apps: a systematic review of 22 studies conducted by Evenson et al. (2015) showed reasonably high validity when tracking steps. However, other evidence suggests that some devices are less accurate among certain populations including the elderly and slow walkers (Feito et al., 2012; Lauritzen et al., 2013). It is also important to consider the importance of accuracy for end-users, who may be distrustful of a device which they perceive to be inaccurate.

Real World Use and Adoption of Activity Trackers

Researchers considering use of commercial trackers should understand how people use and integrate them into their lives. People sometimes adopt trackers in unexpected ways, not only for the purposes of self-improvement as one might expect, but also for other reasons such as for documentation or purely because of an interest in the technology (Rooksby et al., 2014).

There have been frequent press citations of commercial research that suggest high levels of "abandonment" of these technologies, along with short term use (e.g. Arthur, 2014). Indeed, it does seem that health related devices and applications are often used for only a short term: some reports have suggested that approximately one third of devices are abandoned within 6-12 months of purchase (Endeavour Partners, 2014), and others have found that 74% of health-related smartphone apps are used fewer than ten times (Consumer Health Information Corporation, 2011). However, these statistics do not help us understand the reasons why people stop tracking - there is often an assumption that short-term usage represents failure and long-term use is necessary for sustained behaviour change, but this belief is generally not verified with users of the system (cf. Arthur, 2014). More recently, research has focused on phenomenological and humanistic factors (cf. Ayobi, 2016) and begun to provide us with a better understanding the reasons why people track, and the factors that might prevent them tracking over a longer term. This review focuses on the phenomenological and humanistic considerations which may be more relevant for those considering creating an intervention for one of the GAMO target groups.

Taking up tracking

People's reasons for taking up tracking stem from a variety of different motivations. Although behaviour-change and self-improvement are the most relevant motivations to the GAMO community, not all use is driven by these desires. One obvious distinction comes by considering intrinsic and extrinsic motivations, which may be useful when considering behaviour change and engagement with the technology. Those who are driven by intrinsic motivations are perhaps more likely to have self-improvement goals in mind, and hope to reach them using the tracker. Extrinsic motivations may be useful to leverage, and social factors, such as competitions, have certainly been seen to influence behaviour (Rooksby et al., 2014; Fleck and Harrison, 2015).

Lupton (2014) identified five "modes" of self-tracking (private, pushed, communal, imposed and exploited), where only one (private) describes an intrinsically-motivated user taking up tracking of their own volition. The other modes all include some sort of outside encouragement: with *pushed* tracking this imagines an external actor encouraging the user to track, this could either be a friend or an authority figure; *communal* tracking relates to tracking where motivation comes from participation in a group; *imposed* self-tracking is where a user is forced to track for another's benefit, such as when monitoring a workforce; and, *exploited* tracking relates to where individuals' data are *"repurposed for the (often commercial) benefit of others"* (p.10). Imposed and exploited tracking are likely outside the interests of the GAMO network, but private, pushed and communal modes of self-tracking may all be utilised in behaviour change systems and interventions.

Rooksby et al. (2014) described five styles of personal tracking identified from their sample of 22 participants, most of whom had taken up tracking as per Lupton's "private" mode, i.e. they were tracking of their own choice. Rooksby's styles include: *directive tracking*, where participants were driven by a goal; *documentary tracking*, where participants wanted a record of their data; *diagnostic tracking*, where participants were looking for links, or relationships, between multiple tracked aspects; *collecting rewards*, where participants were inspired by some sort of gamification or competition; and, *fetishized tracking*, where uses because of their interest in *"gadgets and technology"* (p.1169). Rooksby et al. suggest that directive and documentary tracking were the most common in their sample, which is what one might intuitively expect, but research should consider these different styles when assessing participants' use of tracking technologies in the real world, as they may influence their use and engagement with the technology or intervention.

Even though we have shown that not all tracking is related to self-improvement, this is still undoubtedly one of the larger drivers of people using personal informatics technologies. Furthermore, just because one does not start tracking their behaviour with the intention to change it, this might still be an outcome. One potential way to encourage people who are otherwise not motivated to change might be to leverage behaviour change techniques once they are tracking for another reason.

Barriers to tracking

Media and commercial research (Arthur, 2014; Endeavour Partners, 2014) often cite "abandonment" of wearable devices and characterise this as a failure. Given this apparent use pattern research has considered the reasons people stop using their trackers. As we outline in the following sections, ceasing use of a tracker is not always the same as abandoning tracking, and indeed stopping tracking does not necessarily represent failure. However, users still face challenges when tracking, and research has begun to document the myriad barriers that users must overcome. As expressed by Consolvo et al. almost ten years ago (2009), *"if done poorly, the technology is likely to be abandoned"* (p.414).

For the most part, the research focusing on abandonment considers users of physical - usually wearable - devices, rather than software applications. Whereas tracking with a physical device requires the user to adopt and carry an additional piece of hardware, smartphone apps only require the user to carry their smartphone. However, this does not mean that using a smartphone app is necessarily a better option: using an app might make the tracked behaviour less salient, compared to wearing a device, resulting in lower engagement (cf. Choe et al., 2017). Additionally, carrying a smartphone for tracking steps might sometimes pose issues, particularly for women, when wearing outfits without pockets.

Adopting a new piece of technology, especially one that needs to be carried all the time, can come with many challenges. Through various studies (Harrison et al., 2015; Yang et al., 2015; Clawson et al., 2015; Lazar et al., 2015; Epstein et al., 2016a) researchers have identified a large range of barriers to engagement with tracking system, including: reliability and the tool breaking; battery life and charging the battery; comfort, physical form and aesthetics; quality of data and appropriateness of the tracked data; and, removal of features, such as social support. Some users find the costs associated with tracking too high and stop. This may be particularly true for tracking that has a high manual element, and therefore more of a cost (Epstein et al., 2016a), which should be considered when designing tracking tools.

Though some users stop tracking when faced with barriers, others have created “workarounds” to navigate the barrier and continue tracking (Harrison et al., 2015). These workarounds can be as obvious as purchasing a different tracker to better suit their needs (e.g. form factor, features, etc.), to something more creative such as wearing an “ugly” wrist-based tracker hidden on an ankle.

As Harrison et al. (2015) found in their sample, participants who stopped tracking because of barriers still wished track and claimed they would return if barriers were removed. Thus, we see how activity tracker use over time is not as straightforward as stopping use of and never returning. Indeed, other research has found that users who have stopped will then return to tracking, a phenomenon described as *lapsing* by Epstein et al. (2016b).

Temporality of use

There are several factors that influence when a user tracks and for how long, and those working in the field should be aware of the temporal nature of tracking. Context and situation of use have a large influence on how people interact with their devices (Patel and O'Kane, 2015), which may potentially influence the temporal nature of tracking, and should be carefully considered when designing interfaces and interventions. In addition, social influences may aid people in making sense of, and reflecting on their collected data, as well as provide support and competition. However, this has been identified as an under-studied area in HCI and could be an opportunity for future work (Fleck and Harrison, 2015).

Stopping tracking is often referred to as abandonment, but as work in the field has progressed, we have gained a better understanding of how user adopt these technologies over time, and the more temporal nature of tracking. Whilst a user may stop tracking because of a barrier, this does not necessarily constitute abandonment – users may well return to tracking with the same, or a different tracker. Tracking is a temporal activity, and these "lapses" in tracking are usual, expected, and do not necessarily represent failure.

The literature provides multiple reasons why one might track over a short term. Some users may stop tracking because they have learnt enough, or satisfied their curiosity and then "happily abandon" their tracker (Clawson et al., 2015). This may happen after even a short period of use, as users may find that the data offered is not useful over a longer term (Rooksby et al., 2014; Epstein et al., 2016a). Other research has found that users may stop tracking after a change in "life circumstance", such as when they change their preferred physical activity, or experience a significant life event (such as falling pregnant, or getting divorced) (Epstein et al., 2015; Epstein et al., 2016a). However, other research (Harrison, 2015) has found that users may return to tracking after a change, such as or moving house, or going on holiday, so they can once again get an understanding of how many steps they are taking.

Personal Informatics Models

Models are used to help understand and describe the use of a tool, and within personal informatics two such models have been suggested: Li et al.'s (2010) stage-based model of Personal Informatics Systems and Epstein et al.'s 2015 update of this, the Lived Informatics Model.

Li's model was based on early adopters of personal informatics tools and breaks down the stages of engagement and transformation that characterise these systems. When this model was published in 2010, there was still relatively little literature on the topic and thus it is heavily influenced by the transtheoretical model of behaviour change (Prochaska et al., 1998) to describes the stages one goes through when tracking. Li's model focuses on expert users, who might experience fewer barriers than naive users (Rapp and Cena, 2014).

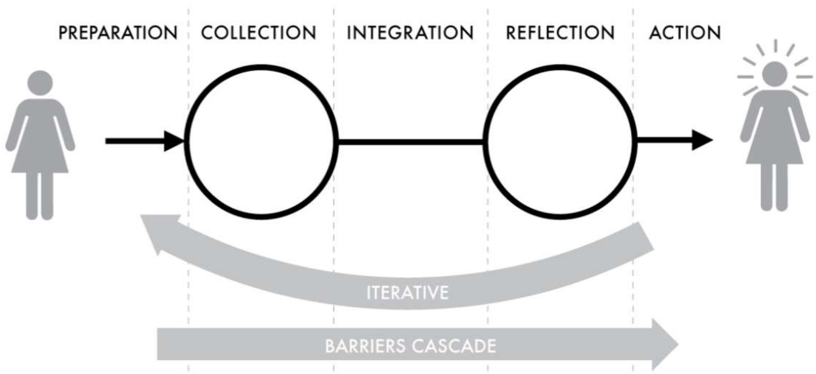

Figure 4. A Stage-based model of Personal Informatics Systems (Li et al., 2010).

As personal informatics has grown – to the point that it is now considered a field of its own (Kersten-Van Dijk et al., 2017) – so has our understanding of users' engagement. Li's model did not incorporate the nuances of everyday life and how these influence tracking behaviours.

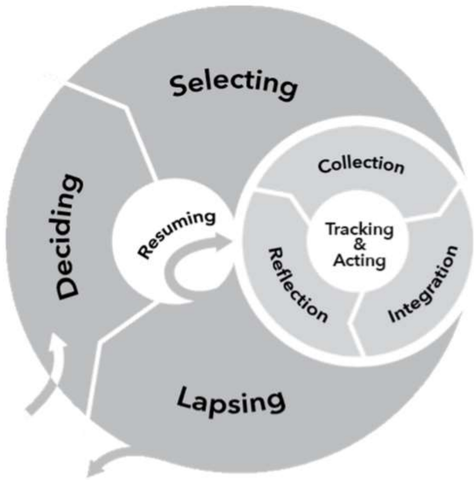

Figure 5. The Lived Informatics Model of Personal Informatics (Epstein et al., 2015).

Rooksby et al.'s (2014) understanding of the situated use of personal informatics systems informed Epstein's (2015) take on the stage-based model, the "lived informatics model". This model provides a more comprehensive understanding of how people track over time, using different systems and tracking different metrics. It also includes *lapsing* and *resuming,* two key temporal concepts outlined in the previous section. After lapsing users may resume tracking, or stop tracking and leave the model. Additionally, the model shows *collection*, *reflection* and *integration* behaviours happening cyclically during tracking, rather than in a linear fashion, showing how these processes do not happen in distinct stages, but during a process of use, reflection and action.

Methods for Studying Activity Tracking Systems

Given the nuances we have presented so far about motivations, barriers, and temporalities of tracking, one can see that the task of studying personal informatics systems in general, but in particular behaviour change systems, is not trivial. The most appropriate methods, of course, depend on the research questions being asked, something which can also be a contentious issue.

Explorative research is invaluable when first investigating adoption and use of new technologies and helps with sensitisation of issues. However, early adopters often use technologies very differently to the late majority (Rogers, 2003). Additionally, the technologies are constantly changing and progressing, adding an additional layer of complexity and the need to update studies. The problems of "novelty effects" and short-term studies of behaviour change technologies are also particularly important to consider (cf. Brynjarsdottir et al., 2012), especially when physical activity behaviours may be so resistant to change, and understanding "life after tracking" is also important. However, longitudinal studies are costly, take time, and results may be published too late to be useful (cf. Coleman, 2016). Here we provide considerations and critically overview the research approaches that have been taken within personal informatics studies.

Studies with researcher-supplied devices

Many of the initial studies of activity trackers, in what Ayobi et al. (2016) identified as in the psychologically informed stream, supplied participants with devices - often prototypes - and studied how these were used in the real world, but over relatively short-term periods. Systems provided by researchers may not necessarily be used in the same way as those purchased by consumers (although this may be appropriate for some interventions): changes to behaviour and use patterns observed in short-term studies could be a result of novelty effects, and participants may act differently when they know they are being observed as part of a study. In addition, these studies tend to rely upon participants engaging with systems, which often do not reflect real-world use.

Various studies (e.g. Collins et al, 2014; Harrison et al., 2014) report participants with low levels of engagement with tracking technologies, resulting in difficulties analysing data gathered from them. In 2016 findings from Jakicic et al. were widely report in popular press, with headlines such as "*There's Even More Evidence That Fitness Trackers Don't Work"* (Oaklander, 2016). However, participants in Jakicic et al.'s (2016) RCT engaged with their tracker for an average of approximately 4 hours per day, a detail picked up and criticised by popular press (Coleman, 2016). Supplying participants with devices might also increase the investigators' workload - almost one third of the 50 participants in Harrison et al.'s (2014) study experienced technical issues with their device and saw the investigators as the *"first line of support"* (p.702) - regularly contacting them to fix technical issues, such as batteries running out.

Explorative Interviews with existing users

Qualitative studies exploring the real-world use and adoption of consumer activity trackers began to appear soon after their commercial availability (e.g. Rooksby et al., 2014), often recruiting participants who purchased trackers themselves. This period marks the start of the phenomenological grounded research stream (cf. Ayobi et al, 2016). Much of this explorative work focuses on the ways in which people engage with activity trackers in the wild, often using qualitative methods such as interviews to gain insights into their practices. Findings may be more akin to "real-life" compared to those using researcher-supplied devices, but conducting single "snapshot" interviews with participants is somewhat limiting as it relies upon self-reporting interactions, potentially some-time after they even happened. This can potentially result in poor recall which may introduce a bias, and the nuanced ways in which people interact with systems over time may be lost. Because of this, researchers are less able to build a picture of how the ways in which people interact with these devices change over time. Additionally, as much of this research is conducted with early adopters, who may be expert users, these results may not be generalizable to the population.

A criticism (Kersten-Van Dijk et al., 2017) of the explorative work in personal informatics relates to the lack of presentation of prevalence of styles and responses to use, which may potentially be useful when designing interventions. However, many may argue that this is not the role of early, explorative work, which should instead focus on creating a *rich picture* of how people interact with these systems. There should, perhaps, be more follow-up qualitative research conducted between the initial explorative work and creation of interventions, to provide a better understanding of the frequency in which people use their trackers in different ways, and the factors that cause this. This would involve building upon existing explorative research to help better define their findings and implications, before the creation of specific design recommendations, or costly interventions based only on explorative results.

Longitudinal and repeated measures studies

Instead of the "snapshot" (i.e. single moment in time) approach, longitudinal studies look at usage over time. These repeated-measures studies may be conducted through multiple interviews, surveys, or automatically collected data. Longitudinal studies can help researchers better understand behavioural effects over time, and can provide insights for a better understanding of the temporal aspects of engagement with the systems.

Traditionally longer, controlled, studies such as Randomised Control Trials (RCTs) have be considered the best way to evaluate the efficacy of behaviour change interventions. These studies may provide a greater understanding of the efficacy of a behaviour change intervention as they move beyond novelty effects and utilize control groups. Several trials have been completed using activity tracking systems (e.g. Cadmus-Bertram et al., 2015, Poirier et al., 2016, Lewis et al., 2015) but, RCTs are expensive and time consuming, and might not be best suited to the fast-paced nature of work in personal informatics. This is especially true considering the long publication timings, meaning that published findings may be "out of date" by the time they come out.

New approaches and the future

Klasnja, et al. (2011) discuss the difficulties with evaluating technologies for health behaviour change, arguing that large scale studies with control groups are necessary for demonstrating behaviour change in mature technologies but are not practical for novel systems. They also reiterate the importance of understanding why a behaviour change technology works and that randomised control trials' may not be the most valuable method because of this limitation. A more recent paper (Hekler et al., 2016) recommends applying the principles of agile programming to research, and suggests that findings should be published and discussed in the community as the research progresses.

Considering the relatively young age of this field, and the fact that we do not yet have a complete understanding of how people use and integrate activity trackers into their lives, we argue that it is important to take a rich, qualitative, approach. Use of mixed methods is important, and including qualitative aspects allows researchers to not only understand that a tool *is* successful, but *why* it is successful. Longitudinal work is important, and although RCTs might not be best approach for research in personal informatics, it is very important that we have a good understanding of how people use activity trackers over time, and in particular for behaviour change if any changes made are lasting, or as a result of a novelty effect. Overall, it is crucial to take a humanistic and more holistic approach, considering all the various factors involved, including use and adoption.

Summary of impact and conclusions

In this paper, we have provided a review of the literature, starting with the growing problem of people being inactive, and a potential solution in the form of tracking physical activity. We then consider how these are used in the real world, and how they might be useful for people creating interventions to encourage increased physical activity. Finally, we provide an overview of how these systems are evaluated, and present some suggestions for researchers in this area. Throughout the paper, we have highlighted limitations and strengths, and stressed on the importance of carefully considering the target group, their motivations, their everyday practices and what barriers they might encounter. We hope our paper will be a useful resource for manufacturers of personal informatics devices and designers of future interventions to more carefully, and with a holistic approach, consider how their devices and interventions are adopted by participants in the real world, and the effects this has on their use.

To summarise the arguments of our review, we articulate four primary take-home messages that researchers and practitioners should consider when designing interventions:

1. Be aware of recommendations for physical activity levels in the different populations you are designing interventions for, and consider how your intervention supports users goals, along with satisfying these recommendations. Systems that encourage cardiovascular work, but with no strength training may be at worst unhelpful, and could potentially even be detrimental to the overall health of potential users if they cause users to stop doing other activities.

2. If you're considering use of an activity tracking device or application of some sort in your intervention, consider the benefits and limitations of each approach, either: having to create, maintain and provide support for, your own system; or, having to integrate your intervention with an existing commercial product, and then having to deal with a potential lack of control over this system.

3. Be aware of how your specific user group may adopt and use activity tracking applications and devices in the real world: the different reasons for, and ways in which, people use them, adapt them, and adapt their lives to make use of them.

4. Think carefully about how you will evaluate your intervention. RCTs are often seen as the gold standard for trialling efficacy of behaviour change interventions, but they provide little insight into why an intervention did, or did not, work, and they are time consuming and costly to run. Using

qualitative methods such as interviews are essential for understanding how people used the intervention, what worked and what did not. Short-term studies and “snapshot” approaches do not provide insight into how the intervention works over time, so evaluations should be longitudinal and use repeated measures.

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Paul Marshall is a senior lecturer in interaction design. His research interests centre on the design and evaluation of technologies that extend and augment individual human capabilities in the wild. This has included work on physical interaction and tangible interfaces; on technologies for face-to-face collaboration; on the design of technologies to fit specific physical contexts; and on extended cognition and perception. A recent focus has been on how communities and individuals use data for better understanding or wellbeing.

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