The ground truth is out there: Challenges with using pervasive technologies for behavior change

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ABSTRACT
The recent flood of wearable technology and mobile apps, focused on quantifying and providing feedback on consumers' lifestyles, has the potential to impact immensely on health and wellbeing. Despite this, limited evidence is available as to how effective these technologies are in promoting sustained behavior change and how these technologies can be integrated into health care. As researchers seek to evaluate and substantiate that these technologies are efficacious and effective, many challenges are emerging which will impact on the future success of such technologies. This paper provides an overview of the research challenges in applying wearable and mobile technology for monitoring and implementing behavior change interventions with a specific focus on sustained engagement. The paper provides an insight as to how researchers in pervasive health are currently aiming to address these issues through a number of case studies. In particular, the paper discusses methods to improve data collection techniques to support context aware applications, behavior change models, and novel feedback and interaction methods to encourage sustained engagement.

CCS Concepts
Applied computing→ Life and medical sciences →Health care information systems.

Keywords
Wearable computing; Mobile computing; Behavior Change; Ground truth.

1. INTRODUCTION
The use of pervasive computing for tracking health has many benefits over traditional interventions delivered in a primary care setting, which can be time intensive on the part of the physician. For example, studies have shown that patients retain little of the educational material doctors provide at clinic visits [1]. As an alternative, it has been suggested that, primary caregivers can recommend health apps to deliver education and behaviour change techniques [1]. The utility of apps to deliver effective behaviour change has been demonstrated across a number of behaviour domains improve eating habits and increasing physical activity [2, 3]. Effective behaviour change can be facilitated through the delivery of multiple behaviour change techniques, such as goal-setting, rapid intention formation, performance measurement, self-monitoring, individually tailored feedback, goal reviewing and progression. Apps which facilitate these functions have been associated with greater effectiveness [4]. Behaviour change interventions have been applied to many areas including, medication adherence, dietary habits, smoking cessation and increasing levels of physical activity.

Technology interventions can also be personalised and targeted at the individual, providing users with education and tools to better manage their health and wellbeing; for example, by providing them with attainable goals to gradually increase physical activity. Wireless digital devices can enable the digitisation of individual's behaviours, often without the need for interaction. Wearable wrist-worn devices can be used to calculate an individual's energy expenditure and step count [5], their current activity [6], sleep quality [7] and heart rate [8], all of which can then be transmitted to the smartphone for review. Smartphones, via the use of on-board accelerometers and GPS, can also track physical activity levels [9] and sleep efforts [10], whilst various apps encourage self-reporting of food consumption [11], enabling immediate calculation of calorie consumption. These technologies provide opportunities for the collection, interpretation and feedback of a user's lifestyle behaviours in a non-obtrusive and objective manner. Furthermore, as these technologies become increasingly common place, opportunities are emerging to gain valuable new insights into health and behaviour at a population level through big data analytics. This move from individual focused exploratory measurement to large scale exploratory studies provides a unique opportunity to gain insight and understand how each aspect of our lives impacts on one another. New research is now required to create innovative methods to prove that these technologies will be effective and feasible when they scale from small pilot studies to usage in large socially and culturally diverse populations.

2. Challenges with Pervasive Technology
Clearly, there is a wide range of potential use-cases for mobile technology for behaviour change, nonetheless, the adoption of technology for the purpose of public health education or behavioural change interventions are extremely limited [12, 13]. This may be due to a number of reasons. Firstly, the surge in availability of apps and devices in an unregulated market raises concerns as to the appropriateness of their content for different groups of end users [14]. Recent reports have highlighted that many available apps are limited by quality, inaccurate information/absence of evidence-based content and lack of user and clinician engagement in their development [15, 10]. Conversely, many of the apps created for academic purposes, which are evidence based, are not designed and built to the contemporary UI/UX standards that users now expect from commercial grade apps. This therefore, limits the apps reach within an increasingly competitive market. Another issue is that of long-term sustained engagement. Whilst popularity of health apps

is increasing and use has been associated with improved health outcomes, studies are finding that achieving sustained engagement with the technology over time is more challenging [11]. It is therefore important to understand what motivates an individual to adopt health technology and what methods can be utilised to drive sustained engagement; through modern design and interaction personalisation, incentivisation, social integration or gamification [16]. Exciting and motivating and rewarding users so that they transition smoothly through the Stages of the Transtheoretical model (TTM) of behaviour change, can't be left to a device and nor can it be expected that data itself will motivate employees. This is where gamification is such a critical element. There is a need for cross platform apps, validated and underpinned by scientific evidence, which use modern design principles to facilitate long term sustained behaviour change to promote healthier living [17].

A report by Endeavour Partners [18] found that over half of consumers who owned a modern activity tracker, such as Fitbit, no longer used it and that a third stopped using it after just 6 months. An updated study [19] found that whilst there has been some improvement in longer term abandonment rates (> 12 months), shorter term abandonment rates have not improved significantly.

The authors of this paper have found similar issues around sustained engagement within their own research. The Gray Matters study sought to develop a health promotion intervention to encourage lifestyle changes targeted to lowering the risk of developing Alzheimer's disease [20]. The study piloted a behaviour change intervention, delivered though a mobile app and wearable activity monitor for 6 months with 146 middle aged individuals. Results from the intervention were promising, with usage of the app being associated with increased intrinsic motivation and actual changes in, healthy behaviours, with accompanying reductions in subjective memory complaints. Excellent adherence with the app was observed over the 6-month period, with 122,719 behavioural logs being input. The average user answered 7.3 ± 3.16 questions per day during their participation in the study. Nevertheless, when approaching the end of the intervention period, participants were informed the pilot was coming to an end which was followed by a large drop in engagement between weeks 22-24, as shown by Figure 1.

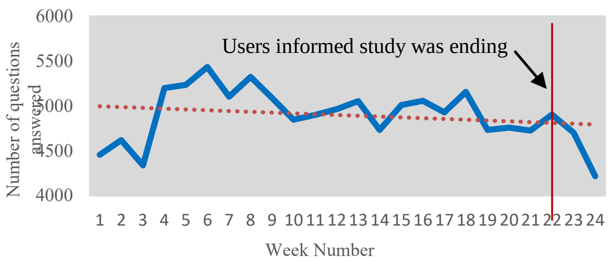

Figure 1. Number of user responses over 24 weeks of the Gray Matters study. Drop in responses noticeable from week 22-24.

Given these issues, researchers need to develop new strategies in order to foster sustained engagement with pervasive health behaviour change interventions to ensure that they are effective. The creation of applications and tools for data collection, aggregation and automated analysis could provide consumers and researchers with the ability to gain better insight in this data. This will provide opportunities to create unique, robust, ubiquitous applications and providing meaningful feedback which is adapted to the user's needs. This feedback will be key to successful sustained adoption of these technologies.

The following Sections provides an overview of research opportunities that will support long term sustained behavior change and subsequently provide opportunities for the creation of more meaningful insights into behaviors and health outcomes.

2.1 Accuracy of data

While new activity monitors offer promise to consumers, researchers and clinicians working to assist people to increase their physical activity, monitor energy consumption and feedback on sleep behaviours, a major limitation to the adoption of these devices in research and clinical settings is the limited scientific evidence regarding their reliability and validity. Ferguson et al. [22] evaluated seven consumer grade activity trackers against two research grade monitors. Participants wore the technology for 48 hours under free living conditions. Results demonstrated that whilst consumer grade activity monitors generally correlate well with research devices, the mean absolute difference between the two can vary substantially depending on what is being measured. Median absolute differences were generally modest (<10%) for sleep and steps, moderate for TDEE (<30%), and large for MVPA (26-298%). Whilst inaccuracies in the measurement may be an important concern for researchers, the impact on the consumer may not be as severe. It may be more important to provide the ability to monitor trends rather than the precise figure, with motivation being the key to engagement. It is therefore important that researchers understand these limitations in terms of accuracy and investigate how these inaccuracies may impact upon a consumer's motivation and trust with such a device. Improving the accuracy of such measurements, including removing the ability to cheat/ falsify the metrics, will be important in ensuring users trust the information they are being given and therefore feel the tool is useful.

2.2 Validated methods to deliver behavior change

To appropriately deliver an education based behavioural intervention program, a suitable method of delivery, using proven behaviour change techniques is required. The term delivery encompasses both the psychological message of the intervention material and also the mode of distribution. One such model is the TTM of behaviour change as presented in Figure 2. The TTM is a stage theory that is often used as a guiding framework for many health-related interventions. This model posits that an individual's willingness to make behavioural changes is driven by their readiness to change [21].

Fig. 2. Transtheoretical model of stages of change (circles) and key functions to encourage movement to next stage (boxes).

By grounding the technology within a behavioural theory it may be possible to better support an individual's behaviour in the long term, ensuring their self-efficacy remains high and assisting at the right time when they relapse.

2.3 Context and prompting engagement

Contextualising the information gleaned from wearable and mobile solutions has the potential to support positive behaviour change. Providing just in time messaging and displaying data at the time of decision has shown to be effective in supporting behaviour change [23]. Context aware solutions, with the ability to infer what the user is doing from obtained sensor data are necessary to facilitate this just in time messaging. As solutions become increasingly intelligent in terms of their application, moving away from simply counting the number of steps to becoming context aware digital assistants, new tools and methodologies will be required for collecting, analyzing and evaluating these solutions. The automatic recognition of context is performed through the application of machine learning techniques to data gleaned from low level sensors (e.g. accelerometer or GPS). The training of these algorithms, from a data driven perspective, relies largely on the gathering, pre-processing, segmentation and annotation of the sensor data into distinct classes. The data must therefore be correctly labelled prior to being used as a training set in a machine learning paradigm.

This need for accurate ground truth transcends applications from activity recognition to electronic momentary assessment, experience sampling and context aware reminding. The issue is how best to engage with the user in order to gain valuable ground truth information without over burdening the user. Traditional methods of annotating data, such as through video annotation or a human observer are labour intensive, time consuming and some approaches, in particular video annotation, can have implications with data privacy. Furthermore, the need to install or wear video cameras for recoding daily activities reduces the scalability of the approach. As an alternative, users are often asked to annotate their own data through a mobile interface. In many cases this requires the user to actively start and stop the recording of training data. A prompted approach to ground truth annotation based on activity recognition (AR) and change point detection has been proposed previously [24]. Based on the output from an AR module the prompt labelling module polls for class transitions from any of the activities (e.g. walking, running, etc.) to the standing still activity. Once a transition has been detected the app prompts the user, through the provision of a notification message on the mobile phone, to provide a label for the last activity that was carried out. The raw data from the accelerometer is then stored to the mobile device before being transmitted to the cloud for processing and storage. This is illustrated in Figure 3.

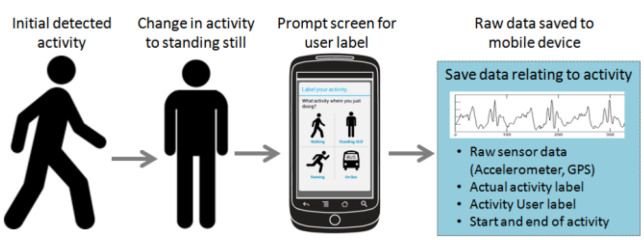

Figure 3. Shows an example of the user interaction with the prompt labeling screen.

Tools such as this are an important asset when trying to create solutions that will function accurately and generate meaningful insights when the interventions are scaled to population level.

2.4 Novel feedback and interaction methods

Personalisation is considered as another feature to support long-term engagement with wearable and mobile devices. Allowing of personalization of goals and feedback based on demographic information such as age and gender is not a new concept. The connected nature of wearable and mobile devices is, however, opening new avenues for personalisation based on ability (how many steps are you capable of walking in a day), preferences (what activities you enjoy) and history (what have you achieved in the past). This allows for highly actionable and achievable goals. Furthermore, it provides an opportunity to provide personalised feedback and allow the user to tailor what information they view and in what format. The gamification experience can also be personalized to further improve engagement with the user gaining virtual badges and incentives based on their performance/ usage. Figure 4 shows an example of personalized goals (a) personalised step count goals from Fitbit and (b) gamification in the form of unlockable badges from Withings.

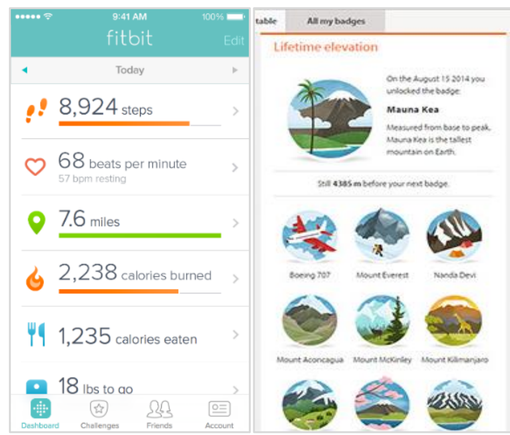

Figure 4. Examples of (a) personalization of goals from Fitbit and (b) unlockable badges from Withings.

Over the last five to ten years, machine learning tools and libraries, such as, Waikato Environment for Knowledge Analysis (WEKA) and openCV, have made implementing complex machine learning solutions more accessible to developers. Cloud based APIs are further adding to this, allowing developers to implement complex functionality such as artificial intelligence, computer vision, text analysis and speech recognition with less effort. These new tools create opportunities for novel feedback and interaction methods which are more intuitive and easy to use. Additionally, this will facilitate new levels of personalization, going beyond just personalized goals, allowing the system to personalize feedback and engagement based on a user's emotional state, attitudes and ability. Apps utilizing machine learning for the purposes of personalization are reaching the market. Your.md is a symptom checker app that uses machine learning and artificial intelligence to tailor its recommendations. The user interacts with the app through a chat based interface. Your.md then asks questions based on what the user inputs. Whilst this interaction is still in many ways basic, it illustrates how artificial intelligence may be used to provide a more intuitive and personalized service.

3. Conclusion

This paper has presented some of the challenges associated with utilizing pervasive computing technology for behavior change. In particular ways in which technology can be used to improve long term sustained engagement have been identified as a grand challenge for engineering and computing. This paper has in particular focused on improving the accuracy of sensing, utilizing context aware prompting, evidencing behavior change interventions on recognized behavior change theories and using intelligent personalization as methods with which to automate this engagement. Other important aspects integral to successful use of these technologies include automating recruiting, data cleaning, data analysis, remote monitoring and technology support. Researchers in pervasive health need to engage with medical, public health, and behavioral researchers to share and use data generated from these large cohort studies to provide unequivocal evidence of mobile and pervasive health technologies in accelerating health research and providing better health outcomes.

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