synergy article

mHealth: past success, future challenges, and the role of the EHPS.

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Mobile technologies have great potential to extend the reach and effectiveness of health behaviour change interventions, and while a number of important developments have been realised, mHealth research remains in its infancy. As the EHPS is already quite active in mHealth research, it is well-placed to lead from the front on future innovations in the area. At the 2015 EHPS SYNERGY Expert Meeting, our group examined the past, present and future of mHealth. This piece provides an overview of our discussions and offers guidance to EHPS members, including a summary of early successes within mHealth, promising avenues for ongoing research, and research challenges to address that could revolutionize the science and practice of behaviour change.

Early successes in mHealth

Successful SMS-based behaviour change interventions

SMS-based interventions have near universal reach, as all mobile phones can receive text messages, and there is considerable evidence for their effectiveness. Additionally, SMS message delivery is inexpensive, brief, automatic and can reach users in real time anywhere there is a mobile signal. Message content can be tailored to socio-demographics, behaviour, cognition, emotion, and user responses. For example, an SMS message could ask, "Are you in a situation that makes it hard to maintain your healthy lifestyle? Text back 'yes' or 'no'." A response of 'yes' would then trigger an SMS containing helpful situation-specific strategies. SMS messaging also allows users to actively seek support, by for example texting "crave" to the system, which could trigger a series of automated support messages and coping strategies.

Reviews of SMS-based interventions indicate that they may be more effective for simple behaviours (e.g. remembering appointments), than for complex ones (e.g. eating healthily or using sunscreen) (Orr & King, 2015). The frequency of SMS messages plays a role too, with multiple messages per day producing larger effect sizes than daily, weekly or one-off doses (Orr & King, 2015). Other factors do not seem to be associated with effectiveness of SMS interventions, such as target behaviour, user age, one-way versus two-way SMS (i.e. from interventionists to users and vice versa), and message tailoring. As there is growing evidence of the cost-effectiveness of SMS-based interventions, and as many lessons learned from SMS-based interventions are readily applicable to interventions delivered via mobile apps, this should remain an active area of research.

mHealth apps: What works and the user experience

Mobile apps are now part of our everyday lives: from Google Play alone there are around a billion app downloads every month (Statista, 2016). This is impressive reach, but only a minority of apps retain users' engagement over the longer-term (Becker et al., 2013). A recent review on alcohol reduction apps suggests that self-monitoring, goal setting, action planning, and feedback components are positively associated with changes in behaviour (Crane et al., 2015), echoing the findings of meta-analyses in non-digital intervention contexts indicating the importance of self-regulatory processes. The review also indicated that ease of use and use of tailoring were positively associated with user engagement. However, qualitative research suggests self-regulatory BCTs like self-monitoring can be perceived as too effortful, and some users report concerns over context-sensing and data privacy (Dennison, Morrison, Conway, & Yardley, 2013; Gowin, Cheney, Gwin, & Wann, 2015).

More work is needed to uncover mechanisms of action that support effective engagement with health apps and self-regulatory processes to change health-related behaviours (Middelweerd et al., 2014). It is also vital that users' views and concerns are addressed to optimise design and delivery methods within health apps. Combining qualitative and quantitative methods can provide valuable complementary insights, and guidance is now available on how to rigorously apply qualitative methods in all phases of mHealth intervention development (O'Cathain et al., 2015; Yardley, Morrison, Bradbury, & Muller, 2015).

Novel data and methods to change behaviour

The portability and technical capability of smartphones open new avenues for understanding and changing behaviour, particularly in two key areas: detection and personalisation.

A system of connected sensors, wearables, phones and tablet devices offers an 'always on' method of collecting data. This creates a wealth of new data that can be collected with minimal burden for the individual, including detailed streams of time-stamped data on behaviour, use of intervention components, location, biological outcomes and social contexts (e.g. via social networks or electronically activated recorders (Mehl, Pennebaker, Crow, Dabbs, & Price, 2001)), all of which can be used to tailor intervention content to users.

As mobile phones and wearables also offer capacity for processing these data streams, and channels through which feedback, prompts and other BCTs can be delivered, highly tailored personalised interventions that 'know' and react to users' contexts, cognitions, behaviour and outcomes are within reach. Just-In-Time Adaptive Interventions (JITAIs) are one example: these use algorithms to collate data and deliver support and intervention components when and where they are needed most. While most JITAIs currently rely on decision rules and algorithms created a priori, machine learning techniques offer an alternative approach to personalising and optimising behavioural support. For example, collaborative filtering techniques can predict how an individual will rate the usefulness of a support message by using the ratings of other users with a similar history. The same could be undertaken to identify patterns of behavioural responses to elements of an intervention (e.g. spells of physical activity). This machine learning approach will likely produce JITAI algorithms and interventions that are far more personalized, adaptable and timely than what our present theoretical understandings ever could, and will contribute to the creating the next generation of behavioural theories.

In addition to improving the effectiveness of interventions, new streams of data can help us to investigate theoretical motivational and behavioural processes within-persons in real time. Many behavioural theories were conceptualized at the within-person level, but previous research has largely used between-person methods to test theory. As between-person and within-person processes may differ (Hamaker, 2012), data from intensive longitudinal studies will allow us to investigate both simultaneously. These new data can help us to refine theories to include both between-person differences and within-person change processes, and help us to understand how psychological phenomena evolve over time. Finally, new technologies like GPS via smartphones enable us to integrate the role of the environment into psychological processes and theories as well.

Tools for creating and testing mHealth interventions

While developing and evaluating mHealth applications historically required considerable monetary investments and multidisciplinary collaborations between behavioural scientists, statisticians and computer scientists, new software tools have begun to streamline these processes. Open-source software tools including LifeGuide (www.lifeguideonline.org), Life Guide Toolbox (forthcoming via www.lifeguindeonline.org), Mobile Coach (https://www.mobilecoach.eu), and MyExperience (http://myexperience.sourceforge.net/) enable behavioural scientists with no programming experience to create e/mHealth interventions and mobile experience sampling applications. Control over intervention development reduces reliance on external programming expertise and therefore reduces cost, increasing accessibility to researchers with limited resources. Such platforms also allow for adapting and improving interventions iteratively based on user feedback and experience.

Some platforms also enable efficient adaptation and reuse of entire interventions (or their components) in diverse research and implementation contexts. Such modular systems and authoring tools can be integrated within virtual research environments (e.g. LifeGuide and Purple (Schueller, Begale, Penedo & Mohr, 2014)), and support collaboration and sharing of intervention components between disparate teams, thus avoiding the need to start from scratch for each new intervention. While these advances do not negate the need for collaboration with computer scientists and industry partners, they increase the number of individual researchers who can develop and test their own low-cost mHealth interventions.

Challenges in mHealth research

While advances in mobile technology hold promise of a new era for behavioural theory and intervention development, and use of more objective indicators of behaviour and health, these new opportunities also pose significant challenges.

Making sense of 'big data'

The vast amounts of data gathered by digital sensors and longitudinal ecological momentary assessments in mHealth interventions (i.e. 'big data') are often noisy and may contain missing data points. Producing robust analyses therefore requires well-informed cleaning or transformation, as well as a priori documented strategies to handle missing data. For example, erroneous signals must be removed from GPS data, and accelerometer data needs screening for spurious information. Modelling dynamic within-person processes over time requires complex statistical techniques, e.g. multilevel modelling and time series analyses (e.g. ARIMA), and so collaboration with statisticians remains important. While challenging, using big data within simulation methods (e.g. agent-based simulation) presents new opportunities for predicting the dynamics of behaviour change over time. In agent-based modelling, an agent (e.g., a model of human behaviour selection and performance) is created, ideally based on psychological theory. Then, the simulation predicts the behaviour of the agent at a particular moment in time, in a specific context (e.g. in the presence of reminders, high social norms). For example, Tobias (2009), created and validated a theory-based agent-based model to test how reminders affect habit development over time. Such methods, however, require programming skills and emphasize the importance of collaborations with computer scientists.

Implementation and competing in a global marketplace

mHealth also faces challenges when it comes to reaching large audiences. At present, app stores are largely dominated by behaviour change apps developed in the private sector, which have minimal evidence of effectiveness. At the same time, behaviour change apps developed within academia may have evidence for their effectiveness, but cannot get easily distinguished among the thousands of downloaded apps. As search algorithms within app stores are based on number of downloads, number and quality of user reviews, app quality and social proof (likes/shares/+1s received via social media) (Butters, 2014), academically developed apps may languish in the lower realm of the search result hierarchy, creating a potentially misleading situation for end-users. To improve the visibility of our effective mHealth apps, we must connect with specialists in search engine optimization, be proactive in obtaining formal reviews from users, and make efforts in promotion and advertising outside of research settings.

Another challenge is the speed with which the private sector moves in relation to academia. In the private sector, ideas rapidly turn into new products and services, and user feedback and usage patterns are constantly fed back into the design and adaptation process. Within academia, however, new ideas require funding to get going, links with design and build teams must be forged and paid for to realize the work, ethical approvals must be obtained, and study results need to be written up and published in order to compete for subsequent funding. When combined, these time-consuming extra steps mean that by the time an academically-developed app has evidence for its effectiveness, its technology and user-facing components might already be outdated. To overcome this challenge, behavioural science teams should partner with experienced software developers and experts in human-computer interaction (HCI) to streamline these processes, though this inevitably increases costs.

Interdisciplinary working and collaborations with industry

Partnerships between behavioural science, computer science and HCI are key to developing and evaluating useful, usable, and rewarding digital interventions. As behavioural and computer sciences use very different language, models and concepts, successful collaboration requires an openness to learning about each other's concepts and terminology, ways of working and incentives, as well as knowing what each field brings to the table in terms of evidence, theories and methods. This process is challenging, but the prizes are great in terms of fostering innovative 'transdisciplinary' thinking and providing new insights that would not be possible within monodisciplinary silos.

When collaborating with industry on mHealth projects, it is important to clearly communicate how our expertise as behavioural scientists shapes our intended vision for projects and make this accessible and usable by industry partners. Conversely, it is equally important that industry partners grasp the importance of collecting data in forms that can be used to advance behavioural science. Below are a few tips to foster collaborations with industry when applying behavioural science in practical settings (Additional tips in Pronk et al., 2015):

1. Recognize the different incentives/goals of partners, including risks. While academics primarily wish to further knowledge and disseminate this in peer-reviewed journals, companies may be primarily focused on financial profit.
2. Work to unify timelines. Industry is often driven by rapidity (e.g. 'fail fast', 'sprints') whereas academia emphasises systematic and rigorous methodologies which can take months or years to produce evidence.
3. Clarify channels of communication/ collaboration. The skills required for successfully working across sectors are complex and are not a part of the academic curriculum in behavioural science. Define the preferred means of communication to help things move smoothly.
4. Monitor progress regularly, both positives and negatives. Identifying (potential) issues in the collaboration as early as possible can help to ensure all parties get what they want out of the project. Similarly, identify positive aspects as something to celebrate.

What role can the EHPS and its members play?

Developments in mHealth research will further advance health psychology and behavioural science, but several challenges must be overcome to realise the full potential of these technologies. For further reading on the topic, see the other papers in this special issue, as well as a recently published series in the November issue of the American Journal of Preventive Medicine which focused on digital health interventions (Yardley, Choudhury & Patrick, 2016). In our view, the EHPS and EHPS members can take leading roles in several key areas (Table1), and we look forward to driving developments within the field.

Table 1

Potential Roles of the EHPS:

- Offer networking events to help foster connections across disciplines
- Help to improve the ability of health psychologists to work competently within and across (currently) disparate disciplines.
- (Continue to) offer training in mHealth methodologies, advanced statistics, intervention development, and technical mHealth topics

Roles of EHPS Members:

- Improve use of open-science frameworks and resource sharing.
- Further develop existing digital platforms to enable flexible, iterative development of mHealth functions
- Foster strong collaborations with computer science and industry partners
- Be the future of mHealth research! Harness individual-level methods (e.g. n-of-1), mixed-methods approaches, and dynamic models of behaviour based on big data to unravel momentary processes and mechanisms of action

References

Becker, S., Krinnen, A., Meister, S., Diamntidis, C.J., Unger, N., and Mitchell, A. (2013). User Profiles of a Smartphone Application to Support Drug Adherence — Experiences from the iNephro Project. Plos One. DOI: 10.1371/journal.pone.0078547.

Butters, K. (2014). How Does Google Play Rank Mobile Apps. Retrieved November 2, 2015, from http://getappcase.com/blog/app-stores/how-does-google-play-rank-mobile-apps

Crane, D., Garnett, C., Brown, J., West, R and Michie, S. (2015). Behaviour Change Techniques in Popular Alcohol Reduction Apps: Content Analysis. Journal of medical internet research, 17(5):e118) doi:10.2196/jmir.4060

Dennison, L., Morrison, L., Conway, G., & Yardley, L. (2015). Opportunities and challenges for smartphone applications in supporting health behaviour change: A qualitative study. Journal of Medical Internet Research, 15(4), e86. doi: 10.2196/jmir.2583

Gowin, M., Cheney, M., Gwin, S., Wann, T. F. (2015). Health and fitness app use in college students: A qualitative study. American Journal of Health Education, 46(4), 223-230. doi: 10.1080/19325037.2015.1044140

Hamaker, E. L. (2012). Why researchers should think “within-person”: A paradigmatic rationale. In M. R. Mehl, & T. S. Conner (Eds.), Handbook of research methods for studying daily life (43-61). New York, NY: Guilford Press.

Mehl, M. R., Pennebaker, J. W., Crow, D. M., Dabbs, J., & Price, J. H. (2001). The Electronically Activated Recorder (EAR): A device for sampling naturalistic daily activities and conversations. Behaviour Research Methods, Instruments, & Computers, 33(4), 517-523. doi: 10.3758/BF03195410

Middelweerd, A., Mollee, S.J., van der Wal, C.N., N., Brug, J., J te Velde, S. (2014). Apps to promote physical activity among adults: a review and content analysis. International Journal of Behavioural Nutrition and Physical Activity, 11:97. doi:10.1186/s12966-014-0097-9

O’Cathain, A., Hoddinott, P., Lewin, S., Thomas, K. J., Young, B., Adamson, J., … Donovan, J. L. (2015). Maximising the impact of qualitative research in feasibility studies for randomised controlled trials: Guidance for researchers. Pilot and Feasibility Studies, 1(32). doi:10.1186/s40814-015-0026-y

Orr, J. A., & King, R. J. (2015). Mobile phone SMS messages can enhance healthy behaviour: a meta-analysis of randomised controlled trials. Health Psychology Review, 1-36. doi: 10.1080/17437199.2015.1022847

Pronk JT, Lee SY, Lievense J, Pierce J, Palsson B, Uhlen M, Nielsen J. How to set up collaborations between academia and industrial biotech companies. Nature biotechnology. 2015 Mar 1;33(3):237-40.

Schueller, S. M., Begale, M., Penedo, F. J. & Mohr, D. C. (2014). Purple: A modular system for developing and deploying behavioural intervention technologies. Journal of Medical Internet Research, 16(7), e181. doi: 10.2196/jmir.3376

Statista, (2015). Accessed 5 October 2016 from https://www.statista.com/statistics/281106/number-of-android-app-downloads-from-google-play/

Tobias, R. (2009). Changing behaviour by memory aids: a social psychological model of prospective memory and habit development tested with dynamic field data. Psychological review, 116(2), 408-438. doi:10.1037/a0015512

Yardley, L., Choudhury, T., & Patrick, K. (Eds.). (2016). Digital Health: Leveraging New Technologies to Develop, Deploy, and Evaluate Behavior Change Interventions [Special section]. American Journal of Preventive Medicine, 5, 814-863.

Yardley, L., Morrison, L., Bradbury, K., Muller, I. (2015). The person-based approach to intervention development: Application to digital health-related behaviour change interventions.

Journal of Medical Internet Research, 17(1), e30. doi: 10.2196/jmir.4055.

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