TraitMap: harnessing continuous personalised feedback via smartphone sensors to disrupt and change addictive behaviours

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Background: Mental and substance use disorders (M/SUDs) are the leading cause of non-fatal illness worldwide, incurring substantial social and economic costs. The limited impact of interventions to treat people with M/SUD has prompted a clinical shift toward more personality-informed approaches. Within psychiatry, evidence shows key personality traits can be used as endophenotypes for M/SUDs. In mobile health (mHealth) research, applications (apps) that detect risk behaviours and send users personalised feedback are likely to counter many of the harms associated with substance use. **Aims:** To develop and test 'TraitMap', a novel mHealth system that combines self-report measures, continuous biomedical monitoring, and personalised feedback to support complex self-care in people with M/SUDs. Fully realised, TraitMap will detect drug cravings and personalise intervention to disrupt substance-related risk behaviours. **Methods:** A 3-stage project involving 1) collection and analysis of multi-stakeholder feedback via online surveys, 2) design and evaluation of a prototype mobile app tailored to people with M/SUDs, 3) a pilot trial to assess the impact of TraitMap on drug cravings and associated harms that will underpin the future design of a larger randomised controlled trial. **Contribution:** Unlike previous studies, this project will be developed using ResearchKit, an app development platform specifically tailored to medical research needs. Findings from world-leading medical research units at Stanford, Johns Hopkins, and Oxford show ResearchKit counters many of the methodological limitations and data loss that typically characterise Internet trials. By contrast, the highly automated data collection features of ResearchKit will enable the study to streamline informed consent, prompt continued user participation, and collect infinitely richer data sets.

Keywords: addiction, behaviour change, feedback, intervention, mobile health, personalisation

Introduction

Mental and substance use disorders (M/SUDs) inflict the highest costs to society of all diseases, affecting production levels, legal systems, law enforcement, and continued damage to users (Whiteford, Ferrari, Degenhardt, Feigin, & Vos, 2015). Key populations (KPs), most vulnerable to HIV exposure such as men who have sex with men (MSM), people who use drugs (PWUD), sex workers, and transgender individuals

are disproportionately burdened due to stigma-induced psychosocial stress (WHO, 2014). While behavioural interventions support abstinence during early recovery, 80-95% of people relapse within 12 months (Brandon et al., 2007). Relapse is especially problematic in KPs because it exacerbates mental disorders, risk behaviours, and the spreading of HIV to other groups (Gupta, Kumar, & Garg, 2013). The reason many behavioural interventions fail in natural contexts is because patients have difficulty enacting them outside of controlled clinical settings in which they were first introduced (Boyer, Smelson, Fletcher, Ziedonis, & Picard, 2010). As a result, patients with M/SUDs neither have the ability to detect biological and affective changes that trigger drug cravings or modify their behaviours to decrease health risk (Boyer et al., 2010).

Current limitations in the diagnosis and treatment of M/SUDs has prompted a clinical shift toward personality-informed approaches (Trull & Widiger, 2013). Within psychiatry, growing consensus argues that dimensional trait models can more effectively diagnose M/SUDs (Krueger & Markon, 2014; Suzuki, Samuel, Pahlen, & Krueger, 2015). This consensus draws on clear evidence that key personality traits can act as endophenotypes for M/SUDs (Belcher, Volkow, Moeller, & Ferré, 2014). Specifically, high negative emotionality/neuroticism (NEM/N) increases, whereas high positive emotionality/extraversion (PEM/E) and constraint (CON) decreases vulnerability (Belcher et al., 2014). Researchers in mobile health (mHealth) also argue that mobile sensing technology can disrupt and change habitual behaviours via self-monitoring and feedback (Hermsen, Frost, Renes, & Kerkhof, 2016). While the long-term impact of such disruptions remain unclear, mobile applications (apps) offer clinicians unprecedented potential to increase user engagement whilst continuously self-monitoring disease outcomes (Jardine, Fisher, & Carrick, 2015). The fact that mobile apps can detect many of the affective changes that trigger drug craving and risk behaviours suggest their particular efficacy in treating M/SUDs (Boyer et al., 2010; Donker et al., 2013; Litvin, Abrantes, & Brown, 2013).

What these two converging research domains share above an emphasis on personality-informed intervention is the undying assumption that personality traits can no longer be defined as fixed dimensions (Ferguson, 2010). Rather, traits are highly dynamic qualities that morph considerably in response to spatio-temporal changes (Chapman, Hampson, & Clarkin, 2014). Health-protective personality changes are thus not only achievable but indeed desirable and beneficial (Hampson, Goldberg, Vogt, & Dubanoski, 2006). Findings confirm the timely nature of personality-informed diagnosis (Suzuki et al., 2015; Trull & Widiger, 2013) and intervention to meet continuous support demands in people with M/SUD (Donker et al., 2013; Litvin et al., 2013). The following section examines how such intervention may be achieved.

Review method and strategy

This project undertakes formative research to design and test ‘TraitMap’, a personalised mobile app designed to detect cravings and intervene with self-monitoring and feedback as cravings develop. Thus countering many of the harms associated with drug use. To achieve these aims, a 3-stage app development project is proposed. First, multi-stakeholder feedback is collated via online surveys. Second, a mobile app ‘TraitMap’ is designed to respond to trait vulnerabilities in people with M/SUDs. Finally, a pilot randomised controlled trial examines the feasibility of TraitMap to reduce drug harms in people with M/SUDs.

To design an app that is responsive to people with M/SUDs, the project will need to overcome significant user-centric and technological design challenges. To this end, the study will conduct several online surveys to collect feedback from multi-

stakeholders (e.g., healthcare providers, medical researchers, app developers, end-users). These online surveys will focus on three stages of the app design process: prototyping, evaluation, and pilot study. This iterative process is scheduled to evolve over a 12-month period (July 2016 – July 2017).

1. The Prototyping stage (July – September 2016) will develop the TraitMap prototype based on aggregated findings from an online survey. The survey will be compiled by Principle Investigator (Munro) using Typeform.com and promoted via online support communities. Aggregated multi-stakeholder feedback will inform the initial TraitMap prototype which will be built using open-source development platform ResearchKit (www.researchkit.org). Studies by world-leading medical research units at Stanford, Johns Hopkins, and Oxford show ResearchKit counters many of the methodological limitations and data loss to follow-up that characterize Internet trials (Jardine et al., 2015). Specifically built to support medical research, ResearchKit enables highly automated data collection by utilizing key features such as: (a) streamlined informed consent processes, (b) interactive prompts that 'nudge' users to participate, and (c) mobile sensing technologies such as GPS, touch screen, camera, and accelerometer that collect infinitely richer data sets (Jardine et al., 2015). This project will utilize these features of ResearchKit to gather continuous data sets. First, self-report surveys will apply subjective methods to map changes in personality traits, cravings, drug use, and risk behaviours. Second, mobile sensing technologies will apply objective methods to map changes in passively-collected data. Computer algorithms will identify pattern irregularities in location (from GPS) and movement (from accelerometer) that may trigger craving and relapse events. Third, active tasks will be tailored to disrupt and change users' habitual behaviours under semi-controlled conditions while phone sensors collect continuous data. Active tasks are subjective and objective measures in that they require user input which is passively collected by phone sensors. Active task reminders will be sent to patients daily, requesting they exercise three personality traits outside their comfort zone: (a) a positive-thinking task will instruct patients to tap images on the phone screen that represent positive life outcomes for them (cognitive data collected by touch screen), (b) a stress-busting task will instruct patients to sit in a quiet place for 10 minutes and be mindful, then look directly into the camera (heart rate data collected via camera), and (c) a social-competence task will instruct patients to connect with someone during a 20-minute walk (movement data collected by accelerometer and gyroscope). Each active task group will be tailored to influence the relevant trait changes necessary to support resilience to M/SUDs: (a) positive activity interventions (PAIs) to foster trait improvements in PEM/E (Layous, Chancellor, Lyubomirsky, Wang, & Doraiswamy, 2011), (b) mindfulness-based stress reduction (MBSR) to foster trait improvements in NEM/N (Baer, 2003), and (c) life skills training (LST) to foster trait improvements in CON (Botvin & Griffin, 2014).
2. The Evaluation stage (October – December 2016) will host a focus group comprising of University of Auckland students (n = 5) and mental health providers (n = 5). The initial focus group will begin with a broad overview of TraitMap, its purpose, and general functionality. Text content from the survey and informed consent features will be evaluated to confirm their cultural validity and universality. Questions will evaluate the ease at which users will engage with a coded query for drug use in the form of a weather question. For example,

when asked “what was the weather like yesterday?” users will be prompted to reply “clear” for no drug use, “cloudy” for marijuana, “rainy” for alcohol, “snowy” for crack/cocaine, and “other” for other illicit drugs. This textual analysis will be followed by open-ended questions related to the suitability of the active tasks to reduce drug cravings and risk behaviours. Questions will specifically address whether people with M/SUDs may have issues with (a) continuous phone monitoring, (b) frequency of probes sent to their phone, and (c) adherence to a daily regimen of active tasks. Finally, stringent measures for patient confidentiality such as encryption methods and de-identified collected data will be evaluated. Such concerns are of paramount importance if any smartphone is lost, stolen, or sold during the trial. One month after design iterations are made, the focus group (n = 10) will be asked to download and pre-test TraitMap for 2 weeks. On completion of the pre-test, feedback will be recorded via an online survey which will inform developers of any design flaws that need correction prior to launching the pilot trial.

3. The Pilot stage (January – June 2017) will conduct a pilot randomised controlled trial to assess the viability of TraitMap to reduce drug craving and risk behaviours in people with M/SUDs. The pilot trial will aim to recruit a broad range of people with M/SUDs from online support groups and the App Store. Consumer popularity of Apple products combined with the benefits of being listed in the App Store is likely to assist the project in gaining direct access to a diversity of user groups. A series of screening questions will correlate eligibility criteria with patient responses and thus automate screening and enrollment. Interested participants will be asked to complete a screening survey and admitted to the study only if they are >18 years of age, own an iPhone and are familiar with its use, and actively seek treatment for M/SUDs. A confirmation message will be sent to patients who do not qualify. Respondents that do qualify will complete an informed consent process via a comprehension quiz, generated PDF and email, and request for electronic signature. Participants meeting the inclusion criteria will be randomised to the TraitMap group or non-personalised control arm. Follow-up surveys at 4-, 8- and 12-week intervals will aim to identify key differences and similarities in drug craving and risk behaviours between groups.

Data management and analysis

At the minimum level of data management, the study will need to ensure the security of data and privacy of patients. For this purpose, researchers need to look outside the ResearchKit platform for support. One likely method of securely hosting automatically de-identified data in the cloud is to recruit the Sage Bionetworks Bridge server. While this choice is purely based on previous ResearchKit projects, app developers may choose to adopt another solution. To avoid becoming overburdened by extensive data sets, researchers will need to adopt highly efficient tools for data analysis once the data has been collected. Health Cloud and Watson cognitive computing tools that currently support ResearchKit will allow researchers to store, aggregate and model data, combining it with other data sources to enrich research findings.

Significance

Despite the potential of highly tailored interventions to innervate health improvements in people with M/SUDs, research to date has overlooked personalization and typically

applied personality to predict behaviour (Chapman et al., 2014). By contrast, this study examines to what extent mobile apps designed to detect and change trait vulnerabilities in patients with M/SUDs can reduce drug cravings and associated risk behaviours. Contribution to current research is likely to be significant, as the project:

- will enable streamlined informed consent, prompt continued user participation, and collect infinitely richer data sets (Jardine et al., 2015)
- reflects a timely paradigm shift and recent calls for dimensional trait models to help clinicians diagnose and treat mental illness (Suzuki et al., 2015)
- may help foster a deeper understand of how critical changes in personality can impact recovery outcomes (Belcher et al., 2014)
- may help developers identify the responsive app determinants most likely to elicit key trait and behavioural changes (Litvin et al., 2013)

While the project's size and focus on people with M/SUDs may limit extrapolating findings across populations (i.e., the cohort effect), the influence of the project is projected to have a wider impact. Personalized mHealth apps are clearly not only relevant to groups particularly vulnerable to M/SUDs such as KPs but also to the broader social spectrum wishing to influence positive improvements to their health.

Timeline

This study is scheduled to take place over 12 months, with a proposed starting date of 30th July 2016, and finishing date of 30th June 2017. While the app development team is scheduled to design and test the mHealth app over a 6-month period (July–December 2016), participant feedback will be restricted to the time taken to engage with the online surveys. Each of the three 40-item surveys (prototype, evaluation, and pilot) is anticipated to take approximately 10 minutes to complete. Each user feedback stage of the study will be 'live' for three months: i.e., prototype (July–September 2016); evaluation (October–December 2016); and pilot (January–March 2017).

Facilities available

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