

Original Paper

Do daily fluctuations in psychological and app-related variables predict engagement with an alcohol reduction app? A series of N-of-1 studies

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Abstract

Background: Previous studies have identified psychological and smartphone app-related predictors of engagement with alcohol reduction apps at a group level. However, strategies to promote engagement need to be effective at the individual level. Evidence as to whether group-level predictors of engagement are also predictive for individuals is lacking.

Objective: This study aimed to examine whether daily fluctuations in: i) the receipt of a reminder, ii) motivation to reduce alcohol, iii) perceived usefulness of the app, iv) alcohol consumption, and v) perceived lack of time predicted within-person variability in the frequency and amount of engagement with an alcohol reduction app.

Methods: A series of observational *N*-of-1 studies were conducted. The predictor variables were measured twice daily for 28 days via Ecological Momentary Assessments. The outcome variables were measured through automated recordings of participants' app screen views. Nine London-based adults who drank alcohol excessively and were willing to set a reduction goal took part. Each participant's dataset was analysed separately using Generalised Additive Mixed Models to derive incidence rate ratios (IRRs) for the within-person associations of the predictor and outcome variables. Debriefing interviews, analysed using thematic analysis, were used to contextualise the findings.

Results: Predictors of the frequency and amount of engagement differed between individuals, and for the variables 'perceived usefulness of the app' and 'perceived lack of time', the direction of associations also differed between individuals. The most consistent predictors of within-person variability in the frequency of engagement were the receipt of a daily reminder (IRRs = 1.80-3.88, P 's < .05) and perceived usefulness of the app (IRRs = 0.82-1.42, P 's < .05). The most consistent predictors of within-person variability in the amount of engagement were motivation to reduce alcohol (IRRs = 1.67-3.45, P 's < .05) and perceived usefulness of the app (IRRs = 0.52-137.32, P 's < .05).

Conclusions: The utility of the selected psychological and app-related variables in predicting the frequency and amount of engagement with an alcohol reduction app differed at the

individual level. This highlights that key within-person associations may be masked in group-level designs and suggests that different strategies to promote engagement may be required for different individuals.

Keywords: apps; behaviour change; excessive alcohol consumption; engagement; mHealth; n-of-1; time series analysis

Introduction

Excessive alcohol consumption is a public health priority and is implicated in substantial costs to the economy through lost productivity, crime and healthcare costs [1,2]. Digital interventions, including websites, smartphone apps and wearable devices, can increase access to behavioural support, have a low incremental cost once developed and can reduce stigma associated with help-seeking in person [3–5]. Alcohol reduction apps have the added advantage of being available to users as and when needed. Some form of engagement – comprised of both behavioural (e.g. amount, depth and frequency of app use) and experiential (e.g. attention, interest) dimensions [6] – is logically necessary for alcohol reduction apps to be effective [7,8]. Findings from an interdisciplinary, integrative review, in-depth interviews with potential users, theorising within an interdisciplinary research team and the development and evaluation of a novel self-report measure suggest that engagement with digital interventions can be defined as: *“a state-like construct which occurs each time a user interacts with a digital behaviour change intervention, with two behavioural (i.e. amount and depth of use) and three experiential (i.e. attention, interest and enjoyment) dimensions”* [9].

As observed levels of engagement with many digital interventions are considered too limited to support behaviour change [10], efforts have been made to identify factors that predict engagement. Whether or not a user engages with a given digital intervention is likely to depend on: its content (e.g. behaviour change techniques), how that content is delivered (e.g. design features), the context in which the intervention is used (e.g. who the users are, where they are using the intervention), whether or not the intervention succeeds in changing particular ‘mechanisms of action’ that mediate behaviour change (e.g. motivation,

self-regulatory skills) and successful or unsuccessful behaviour change (e.g. the extent of alcohol reduction) [6]. To the authors' knowledge, studies to date have typically focused on the identification of group-level predictors of engagement with digital interventions for alcohol reduction [6]. As strategies to increase engagement need to be effective for individuals [11,12], it is important to examine whether key predictors identified at the group level are also predictive at the individual level.

Published secondary analyses of data from randomised controlled trials (RCTs) of digital interventions for alcohol reduction have identified group-level predictors of engagement. These studies show that demographic (e.g. being female, older and more highly educated) [13–15], psychological (e.g. higher levels of baseline motivation to change) [14,16], drinking (e.g. lower baseline levels of alcohol consumption) [13,14,17] and app-related variables (e.g. the receipt of proactive reminders) [18] predict the total frequency and amount of engagement.

Qualitative studies asking excessive drinkers to reflect on factors they expect to be most important for engagement with apps for alcohol reduction have identified the following: motivation to change, perceived personal relevance of the app (defined as the extent to which the user believes that the app is suited to their individual needs [19]), and perceived usefulness of the app (defined as the extent to which the individual believes that use of the app will help them achieve their goal(s) [20,21]). Although common themes were pulled out from these qualitative studies, agreement between potential users on what factors are expected to be most important for engagement was low [21]. Qualitative research has also been conducted with participants who disengaged prior to completion of an RCT of a web-based alcohol reduction intervention [14]. When retrospectively asked to reflect on why they disengaged from the intervention, users frequently mentioned perceived lack of time (e.g. being too busy, having other priorities), dissatisfaction with the intervention (e.g. poor usability, irrelevant content) and improvement in the condition (e.g. feeling better).

As mentioned, quantitative studies examining predictors of engagement have typically relied on group-level designs, aggregating data across participants. However, individual-level interventions, including alcohol reduction apps, are designed to target within-person

processes that lead to behaviour change. Intervention strategies aimed at increasing engagement (e.g. proactive reminders, rewards, feedback) need to be effective for individuals. It is therefore important to examine whether associations identified at the group level are also identified at the individual level. The *N*-of-1 study design, also known as a single-case design, is ideally suited for the assessment of within-person processes. The *N*-of-1 design can be either observational or experimental and “...receives its name by virtue of its sample size: *N* is equal to one” [22].

Previous qualitative and quantitative research has relied on either prospective or retrospective (as opposed to real-time) self-reports of psychological processes; these are likely to be biased and/or inaccurate [23]. For example, when prospectively predicting what factors are expected to be most important for engagement, potential users tend to highlight app-related aspects, such as the presence of features that enhance motivation to change (e.g. goal setting, self-monitoring and proactive reminders) and perceived usefulness (e.g. tailoring of content, rewards) [19,21]. However, when asked to retrospectively report on factors they think contributed to their disengagement from a digital intervention, different aspects tend to be highlighted, such as perceived lack of time [14]. A data gathering method which overcomes the problems associated with both prospective and retrospective self-reports is Ecological Momentary Assessments (EMAs), which involves the repeated measurement of psychological processes in real-time [24,25]. Methods for the statistical analysis of data from EMA and *N*-of-1 studies include correlational and time series analyses [26,27], with the latter being an under-used approach to date.

The present study used a series of *N*-of-1 studies, harnessing twice-daily EMAs for 28 days, and applied an innovative type of time series analysis to examine whether daily fluctuations in i) the receipt of a reminder, ii) motivation to reduce alcohol, iii) perceived usefulness of the app, iv) alcohol consumption, and v) perceived lack of time predict within-person variability in the frequency (i.e. number of logins) and amount (i.e. time spent per login) of engagement with a theory- and evidence-informed alcohol reduction app, *Drink Less* [28,29]. This study aimed to provide a greater understanding of the temporal direction of the relationships under investigation by assessing predictor variables prior to the measurement of outcome variables.

Methods

Study design

A pre-specified study protocol and analysis plan can be found on the Open Science Framework (osf.io/zn79m). A series of observational *N*-of-1 studies were conducted with twice-daily (i.e. morning and evening) assessments of psychological and app-related predictor variables. The outcome variables were the objectively estimated frequency and amount of engagement with the *Drink Less* app, described in detail in the ‘Measures’ section below. Although the subjective experience (e.g. attention, interest) is also thought to be a key dimension of digital engagement [6,9], only behavioural indicators of engagement (which can be measured automatically via participants’ app screen views) were considered in the present study to minimise participant burden. Although it had been pre-specified in the study protocol that the key outcome of interest was ‘frequency of engagement’, a series of unplanned analyses with the variable ‘amount of engagement’ were also conducted. To help contextualise the quantitative findings, semi-structured debriefing interviews were conducted over the phone after the 28-day study period.

Participants and sampling

The eligibility criteria are outlined in Table 1. Participants were excluded if they were not fluent English speakers. Recruitment was conducted online via the research platform ‘Call for Participants’, social media (i.e. Twitter) and an alcohol reduction charity’s mailing list. The recruitment materials stated that regular drinkers were invited to take part in a study on how people use alcohol reduction apps in their daily lives, which involved responding to twice-daily text messages for 28 days.

Table 1. Participant eligibility criteria.

Eligibility criteria

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- i) Aged 18+ years
 - ii) Own an iPhone capable of running iOS v.8.0 software or higher (i.e. iPhone 4S or later models)
 - iii) Reside in or near London and willing to come to University College London (UCL) for a briefing interview (to ensure adequate study commitment)
 - iv) Report an Alcohol Use Disorders Identification Test (AUDIT) score of ≥ 8 , indicating excessive alcohol consumption [30]
 - v) Interested in using an app to reduce their drinking
 - vii) Willing to set a goal to reduce their drinking
 - vii) Installed the *Drink Less* app and opened it at least once following the briefing interview
 - viii) Willing to engage with the app daily for 28 days, recognising that there may be occasional days where they would not engage with it [31]
 - ix) Willing to respond to twice-daily text messages for 28 days
 - x) Willing to take part in a debriefing interview conducted over the phone
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The number of observations (and not the number of participants) determines the statistical power in *N-of-1* studies [32]. Each participant was asked to respond to twice-daily EMAs for 28 days, resulting in up to 56 data inputs per participant. The measurement frequency of two EMAs per day was informed by prior research conducted within the behavioural science domain [33]. The study duration of 28 days was selected as this is a common duration for digital alcohol reduction interventions [34]. As data were planned to be analysed using Generalised Additive Mixed Models (see the ‘Data analysis’ section below), Monte Carlo simulations [35] estimated the statistical power achieved with a total of 56 data inputs. The power analysis, conducted in R, indicated that the study would have 80% power to detect an incidence rate ratio (IRR) of 1.8 for the association between ‘perceived usefulness of the app’ (predictor variable) and ‘frequency of engagement’ (outcome variable). Given uncertainties regarding the distribution of model parameters, this power analysis should be interpreted with caution. See Table 2 for details about statistical assumptions used to inform the power analysis. To allow for a descriptive (but not inferential) comparison of potential between-person differences in the associations between the predictor variables and app engagement, a total of 8 participants was considered sufficient. As previous *N-of-1* studies report up to 47% study drop-out [33,36,37], we aimed to recruit an additional 50% of the target sample (i.e. 12 participants).

Table 2. Statistical assumptions used to inform the simulation-based power analysis

Considerations	Statistical assumptions and source of information (where available)
Model type	Generalised Additive Mixed Model (GAMM)
Number of observations	Twice-daily EMAs for a period of 28 days (i.e. a total of 56 data inputs per participant)
Seasonality	No seasonality reflected by the day of the week the data were collected
Distribution and point estimate (outcome variable)	The outcome variable (i.e. ‘frequency of engagement’, operationalised as the number of app logins per measurement period) was assumed to follow a Poisson distribution with a mean of 11.7 logins per measurement period [29]. As the outcome variable represents count data, it was expected to follow a Poisson distribution. The mean of 11.7 logins was drawn from a group-level, factorial screening experiment of the <i>Drink Less</i> app [29], as this was judged to represent the best available data
Distribution and point estimate (predictor variable)	The predictor variable (i.e. ‘perceived usefulness of the app’), selected as a basis for the power analysis as data on the relationship of the other predictors and the frequency of engagement were lacking in the extant literature, was assumed to follow an Auto-Regressive (AR) Integrated Moving Average process with first-order autocorrelation, as it was expected that measurements would be similar to those taken 12 hours previously. We drew on results from the between-person, factorial screening experiment of the <i>Drink Less</i> app, which assessed the variable ‘helpfulness of the app’ at 28-day follow-up. This variable was deemed to be conceptually similar to the target variable. It was therefore assumed that the mean level of the predictor variable would be 3.18 ($SD = 0.93$) [29]

Intervention

The *Drink Less* app is a stand-alone intervention designed to promote alcohol reduction in adults who drink excessively. The app is centred around a goal setting module which allows users to select one or multiple weekly goals of their choice (e.g. maximum number of units, alcohol-free days, spending on alcohol, or number of alcohol-attributed calories). The app includes five additional intervention modules: i) Normative Feedback (i.e. a visual gauge of how users’ drinking compares with that of others in the same gender and age group), ii) Cognitive Bias Re-Training (i.e. a game which aims to help users retrain automatic approach/attentional biases towards alcohol-related cues), iii) Self-Monitoring and Feedback (i.e. an interactive calendar which allows users to record and visualise drinks

consumed/alcohol-free days), iv) Action Planning (i.e. a feature which explains the benefits of setting if-then rules and allows users to create, review and edit these), and v) Identity Change (i.e. a feature which allows users to view pairs of positive and negative outcome expectancies, record video messages to watch at a later date, and identify and select values of importance to their identity). Details about how intervention content was selected [38,39], user feedback on a first version of the app [40], the development process [28] and a first evaluation of the app's components in a randomised, factorial screening experiment [29] have been described in detail elsewhere. The *Drink Less* app allows users to set a daily reminder to open the app, which can be switched on or off and set to a suitable timing.

Measures

The following data were collected at baseline to determine study eligibility and to describe the sample: i) age; ii) gender; iii) type of work (i.e. manual, non-manual, other); iv) whether participants owned an iPhone capable of running iOS 8.0 software or higher (i.e. iPhone 4S or later models); v) whether participants were residing in or near London and were willing to come to UCL for a briefing interview; vi) alcohol consumption, measured using the Alcohol Use Disorders Identification Test (AUDIT) [30], a 10-item measure of alcohol consumption, drinking behaviour and alcohol-related problems that provides a score ranging from 0 to 40, with scores of ≥ 8 , indicating excessive alcohol consumption; vii) whether participants were interested in using an app to reduce their drinking; viii) whether participants were willing to set a goal to reduce their drinking; ix) whether participants were willing to engage with the study app daily for 28 days; x) whether participants had previously used an alcohol reduction app and if so, which one; xi) whether participants were willing to respond to the twice-daily text messages for 28 days; and xii) whether participants were willing to take part in a post-study interview, conducted over the phone.

Ecological Momentary Assessments (predictor variables)

The following data were collected twice per day (i.e. morning and evening):

1. 'Motivation to reduce alcohol', measured by asking: "How motivated are you currently to reduce your drinking?". The response options ranged from 1-7, with 1 indicating 'not at all' and 7 indicating 'extremely'.
2. 'Perceived usefulness of the app', measured by asking: "How useful do you currently think the *Drink Less* app is for you?" The response options ranged from 1-7, with 1 indicating 'not at all' and 7 indicating 'extremely'. The decision to focus on 'perceived usefulness of the app' in the present study was informed by a meta-analysis of 59 studies indicating that the variable 'perceived usefulness' is consistently associated with behavioural intentions to use technology ($r = 0.59$) [41]; less is known about the relationship between the variable 'perceived relevance' and key outcome variables. This variable captured participants' beliefs about the app's usefulness, and was considered in the absence of any objective effectiveness data from a confirmatory RCT.
3. 'Alcohol consumption', measured by asking: "How many drinks containing alcohol have you had in the past 12 hours?" Participants were instructed to input integers only (i.e. whole drinks).
4. 'Perceived lack of time', measured by asking participants: "To what extent do you currently have time for the *Drink Less* app?" The response options ranged from 1-7, with 1 indicating 'I don't have any time for the app' and 7 indicating 'I have lots of time for the app'.

Additional predictor variables (tailored to participants' preferences)

5. Whether or not a proactive reminder was received during each 12-hour measurement period. This variable was coded 1 if a reminder was received and 0 if it was not received. A maximum of 1 reminder could be received every 24 hours, and the frequency and timing of the reminders did not change during the course of the study.

Outcome variables

App screen views were automatically recorded, stored in an online database and extracted using the free python library *pandas* to derive the outcome variables 'frequency of engagement' and 'amount of engagement'. The variable 'frequency of engagement' was operationalised as the number of logins during each 12-hour measurement period, with a login defined as a new screen view following at least 30 minutes of inactivity [42]. The variable 'amount of engagement' was derived by calculating the time spent (in seconds) per 12-hour measurement period. For descriptive purposes, the variable 'depth of engagement' was also derived, which was operationalised as the number of app components accessed per 12-hour measurement period, indexed as a proportion of the number of available app components. However, as 'depth of engagement' was strongly correlated with 'amount of engagement' for all participants, no inferential analyses were conducted using this variable.

Procedure

Participants who expressed an interest in taking part were asked to read the participant information sheet, provide informed consent and fill out the online screening questionnaire, hosted via Qualtrics [43]. Eligible participants were invited to a briefing interview at UCL where they were asked to re-read the information sheet and were consented. Participants were asked to download the *Drink Less* app, briefly explore it, and set at least one weekly alcohol reduction goal of their choice. They were also asked if they wanted to switch the daily reminder on or off and if applicable, select a suitable timing for these. After having explored the app, participants were asked to complete a brief survey on their phone, which fetched their unique user ID, generated by the *Drink Less* app. This information enabled the researchers to match participants to their app screen views and hence, derive the outcome variables. Participants were asked a few questions about their expected app use and what they were hoping to achieve using the app (not reported). Participants were subsequently asked to familiarise themselves with the daily EMA questions and response options, and practised inputting their responses to the four questions into a single text message. They were also asked to select a suitable timing for the EMAs. In the morning, participants were asked to select a time between 6am and 10am; and in the evening, between 6pm and 10pm,

ensuring that the selected time points did not fall earlier/later than their usual morning and evening bedtimes, respectively. No particular instructions about app engagement were provided other than that participants were expected to engage with the app at least once daily for 28 days, recognising that there may be occasional days when they would not engage with it. Participants were told that they had to respond to at least 70% of the text messages and take part in the debriefing interview to receive any payment. They were also asked to notify the study team if they decided to change the timing of the daily reminder so that this could be accounted for in the statistical analyses. The briefing interviews lasted between 29 and 63 minutes.

Participants were then asked to respond to the twice-daily text messages for 28 days, sent manually from an iPhone 6S by the first author. The first text message was sent the morning after the briefing interview. When a response was received, participants were sent the following standard response: "Thank you for your responses!". Participants also received weekly updates via text message about their survey response rates to encourage adherence to the study materials (e.g. "Hi X! Thank you for completing the first week of the study. You have responded to X/14 text messages. Keep up the good work!"). If the text messages were not received in the expected format, participants received a standard reply with instructions for how to input the responses (i.e. "Hi X! It appears that your responses are not in the expected format. Please enter your responses as follows: a=X; b=X; c=X; d=X").

After 28 days, participants were invited to take part in a debriefing interview conducted over the phone, during which they were asked about their experiences of engaging with the *Drink Less* app. The interviews lasted between 25 and 47 minutes.

Participants were paid £0.50 per data input (i.e. a maximum of £28), in addition to £32 upon study completion, resulting in a possible total of £60. This was paid to participants in the form of a shopping voucher.

Data analysis

Guided by published research in the behavioural science domain [33,36,37], in time series with >5% missing data, multiple imputation was carried out using an expectation-maximisation with bootstrapping algorithm via the R package *Amelia II*. Data were imputed separately for each dataset (i.e. each participant). A polynomial time trend (e.g. linear, quadratic) was included if this was found to improve the precision of the imputed data points. This was decided upon by examining the 95% confidence intervals (CIs) of the means of the imputed data points. Five imputed datasets were created per dataset with missing values, which were combined prior to further statistical analyses using Rubin's rules [33,36,37].

Descriptive statistics were calculated for each participant. Time series analyses were conducted using the R package *mgcv*: Generalised Additive Mixed Models (GAMMs) were fitted to estimate incidence rate ratios (IRRs) for the associations between the predictor and outcome variables. The IRR is a measure of relative difference and can, in this particular context, be interpreted as the relative frequency or amount of engagement for the different levels of the predictor variables. The GAMM is a type of multilevel model which has previously been applied to data from *N*-of-1 studies [44]. GAMMs are particularly well-suited to the modelling of time series data with one level of measurement (i.e. repeated measurements nested within one individual), as they accommodate the inclusion of autocorrelation [44]. The analyses proceeded in a number of stages using a backwards selection procedure:

1. As the outcome variables represented counts, data were first assessed for overdispersion (i.e. when the variance is greater than the mean). If there was evidence for overdispersion, a quasi-Poisson distribution (as opposed to a Poisson distribution) was specified.
2. As repeated measures taken from the same individual are often correlated, data from *N*-of-1 studies typically violate the assumption of independence of observations. Autocorrelation was therefore assessed through the autocorrelation function and the partial autocorrelation function. Evidence of first-order

autocorrelation in the present study would mean that measurements were significantly correlated with those taken 12 hours previously.

3. A full model including all predictor variables was first fitted to determine the most appropriate autocorrelation structure for each participant. Model fit was compared using Akaike's Information Criterion [45]. Although the *a priori* power analysis did not take account of adjustment for seasonality or moving average terms, it was determined *a posteriori* that adjusting for the day of the week through the inclusion of a cyclic cubic smoothing term significantly improved the model fit for all participants and that the inclusion of a moving average term improved the model fit for some participants.
4. For visualisation purposes, univariable models for each predictor variable were fitted for each participant, carrying forward the most appropriate autocorrelation structure and moving average terms from the previous step.
5. Parsimonious multivariable models were subsequently built through the stepwise elimination of redundant terms. The predictor variables were sequentially varied to arrive at a best fitting model for each participant.

Debriefing interviews

Telephone interviews were audio-recorded, transcribed verbatim by the first author and analysed using inductive thematic analysis [46], which involved: i) data familiarisation, ii) initial code generation, iii) searching for themes, iv) reviewing the themes, v) defining and naming the themes, and vi) producing the report. Data were coded by the first author and reviewed by the third author. New inductive codes were labelled as they were identified during the coding process. Codes were subsequently reviewed one by one, and systematically organised into themes.

Ethical approval

Ethical approval was granted by UCL’s Computer Science Departmental Research Ethics Chair (Project ID: UCLIC/1617/004/Staff Blandford HFDH). Personal identifiers were removed, and anonymised data were stored securely on a password protected computer. Participants’ contact details were stored separately in a locked cabinet. The SIM card used to deliver the daily text messages was wiped upon completion of the data collection.

Results

Participants

Of 22 participants who completed the online screening questionnaire, 11 met the inclusion criteria and were invited to take part. One participant was unable to initiate the 28-day study during the planned study period. In total, ten participants took part between June 29th and August 9th 2018. One participant broke their phone 14 days into the study and re-downloaded the app onto a new phone without notifying the researchers. Due to technical issues, the new phone’s app screens failed to sync with the database and hence, the outcome data for the last 14 days of the study were lost. This participant was therefore excluded from the inferential analyses, but descriptive statistics were calculated for all 10 participants. Participants’ characteristics are summarised in Table 3.

Table 3. Participants’ demographic, drinking and app-related characteristics.

ID	Gender	Age	Occupational status	AUDIT ^a	Prior use of an alcohol reduction app	Prior use of the <i>Drink Less</i> app
P1	Female	28	Non-manual	16	No	No
P2	Female	20	Other	10	No	No
P3	Female	25	Non-manual	30	No	No
P4	Female	18	Other	12	No	No
P5	Male	21	Other	22	No	No
P6	Female	31	Non-manual	8	No	No
P7	Female	23	Non-manual	12	Yes	Yes
P8	Female	30	Non-manual	11	No	No
P9	Female	28	Other	23	Yes	No
P10	Female	26	Non-manual	10	No	No

Note. ^a AUDIT = Alcohol Use Disorders Identification Test.

Descriptive statistics

Eight participants (80%) opted to have the daily reminder switched on. Overall, participants displayed high compliance with the daily text messages ($M = 93\%$, $SD = 5.8\%$), with the number of missing responses varying from 0% to 16% (see Table 4). Descriptive statistics for the predictor variables are displayed in Table 5.

Participants' total number of logins ranged from 10 to 69 (see Table 6). The total depth of engagement over the 28-day study period ranged from 14% (i.e. accessing one of the app's seven components) to 86% (i.e. accessing six of the app's seven components), and the total amount of engagement ranged from 4 minutes and 24 seconds to 70 minutes and 14 seconds. See Supplementary File 1 for plots of participants' frequency and amount of engagement over the course of the study.

Table 4. Compliance with the twice-daily EMAs.

ID	Compliance, N (%)	Timing of text messages	Daily reminder switched on/off	Timing of daily reminder
P1	56 (100%)	10AM/PM	ON	10AM
P2	55 (98%)	10AM/PM	ON	1PM
P3	50 (89%)	7.30AM/PM	ON	4PM
P4	49 (87.5%)	10AM/PM	ON	11AM
P5	55 (98%)	9.30AM/PM	OFF	-
P6	47 (84%)	10AM/PM	ON	10AM
P7	48 (86%)	9AM/PM	ON	9AM
P8	51 (91%)	10AM/PM	OFF	-
P9	56 (100%)	10AM/PM	ON	10.30AM
P10	54 (96%)	10AM/PM	ON	9AM

Table 5. Descriptive statistics for the predictor variables.

ID	Motivation to reduce alcohol, M ^a (SD); range	Perceived usefulness of the app, M ^a (SD); range	Alcohol consumption (drinks), M ^a (SD); range	Perceived lack of time, M ^a (SD); range
P1	5.3 (1.1); 3-7	5.4 (0.8); 4-7	2.1 (2.8); 0-10	6.1 (1.2); 3-7
P2	6.3 (1.1); 3-7 ^b	6.3 (1.1); 3-7 ^b	0.1 (0.5); 0-3 ^b	4.6 (2.2); 1-7 ^b
P3	5.2 (0.9); 4-7 ^b	5.3 (1.1); 3-7 ^b	1.2 (1.3); 0-5 ^b	4.5 (1.0); 2-7 ^b
P4	4.1 (1.6); 1-7 ^b	2.4 (1.3); 1-5 ^b	0.1 (0.8); 0-4 ^b	4.9 (1.8); 2-7 ^b
P5	3.6 (1.0); 2-6 ^b	3.6 (1.2); 1-7 ^b	1.2 (1.7); 0-8 ^b	3.9 (0.9); 2-7 ^b
P6	5.6 (0.7); 4-7 ^b	4.4 (0.6); 4-6 ^b	0.3 (0.8); 0-3 ^b	4.4 (0.7); 3-7 ^b
P7	4.1 (1.2); 1-6 ^b	3.2 (0.9); 2-5 ^b	1.1 (2.1); 0-6 ^b	2.8 (1.6); 1-6 ^b
P8	5.9 (0.5); 4-7 ^b	6.1 (0.9); 4-7 ^b	0.4 (0.9); 0-4 ^b	2.2 (1.4); 1-5 ^b
P9	4.3 (1.9); 1-7	1.9 (0.9); 1-5	3.9 (4.3); 0-14	6.0 (1.3); 2-7
P10	5.3 (1.6); 1-7 ^b	4.8 (1.0); 1-6 ^b	1.9 (2.9); 0-9 ^b	5.5 (1.0); 3-7 ^b

Note. ^a Mean levels for the predictor variables over the 56 12-hour measurement periods. ^b For participants with missing data, means and standard deviations (SDs) for the complete datasets (after multiple imputation) were computed using Rubin's rules.

Table 6. Descriptive statistics of participants' frequency, amount and depth of engagement with the *Drink Less* app.

ID	Total number of logins over the 28-day study; M (SD); range	Logins per measurement period; M (SD)	Total amount of engagement over the 28-day study (mm:ss)	Amount of engagement per measurement period (mm:ss); M (SD); range	Total depth of engagement over the 28-day study	Depth of engagement per measurement period, M (SD)
P1	39; 0.7 (0.7); 0 – 3	0.70 (0.74)	23:11	00:26 (00:53); 00:00-04:12	71%	10% (12%)
P2	47; 0.8 (0.8); 0 – 4	0.84 (0.78)	60:43	01:06 (02:33); 00:00-16:32	86%	20% (20%)
P3	35; 0.6 (0.6); 0 – 2	0.63 (0.59)	13:12	00:14 (00:27); 00:00-02:19	57%	10% (11%)
P4	10; 0.2 (0.5); 0 – 2	0.18 (0.47)	04:24	00:05 (00:18); 00:00-01:29	43%	3% (8%)
P5	42; 0.8 (0.7); 0 – 3	0.77 (0.74)	18:20	00:20 (00:29); 00:00-01:11	29%	11% (11%)
P6	31; 0.6 (0.6); 0 – 2	0.55 (0.57)	39:19	00:42 (85.42); 00:00-08:12	57%	9% (11%)
P7	64; 1.1 (0.9); 0 – 3	1.14 (0.90)	19:14	00:21 (00:27); 00:00-02:44	14%	10% (6%)
P8	69; 1.2 (0.9); 0 – 3	1.23 (0.85)	70:14	01:09 (02:01); 00:00-10:47	43%	17% (13%)
P9	34; 0.6 (0.7); 0 – 2	0.61 (0.65)	35:26	00:38 (02:04); 00:00-13:40	43%	9% (11%)
P10	N/A ^a	N/A ^a	N/A ^a	N/A ^a	N/A ^a	N/A ^a

Note. ^a Due to a technical issue, data were lost for P10.

Predicting the frequency and amount of engagement

The results from the univariable GAMMs can be found in Supplementary File 2. For visualisation purposes, plots of the IRRs and 95% CIs are depicted in Figures 1-10. Table 7 reports the results from the multivariable GAMMs. In some cases, results from the univariable and multivariable models differed. Hence, interpretations are based on both univariable and multivariable analyses.

Daily reminder

In univariable analyses, the daily reminder was a significant predictor of the frequency of engagement for three participants (P1, P7 and P9; see Figure 1). In multivariable analyses, the daily reminder was a significant predictor for three participants (IRRs = 1.80-3.88, all p 's < .05). For these participants (P1, P6 and P7), the receipt of a reminder was associated with an 80-288% increase in the number of logins in the next 12 hours (see Table 7).

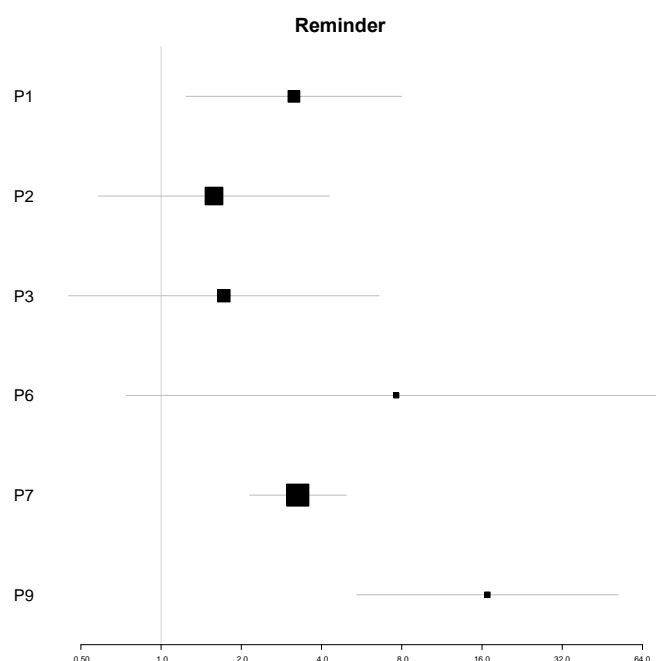


Figure 1. Plots of the IRRs and 95% CIs for the associations of the daily reminder and the frequency of engagement in univariable analyses. The vertical line indicates parity. 95% CIs

that cross the line of parity indicate non-significant IRRs. For P4, the univariable model would not converge. P4 is hence not included in this plot.

In univariable analyses, the daily reminder was a significant predictor of the amount of engagement for three participants (P3, P6 and P7; see Figure 2). In multivariable analyses, the daily reminder was a significant predictor for one participant (IRR = 4.31, 95% CI = 1.73-10.73, $p < .01$). For this participant (P3), the receipt of a reminder was associated with a 331% increase in the amount of engagement in the next 12 hours (see Table 7).

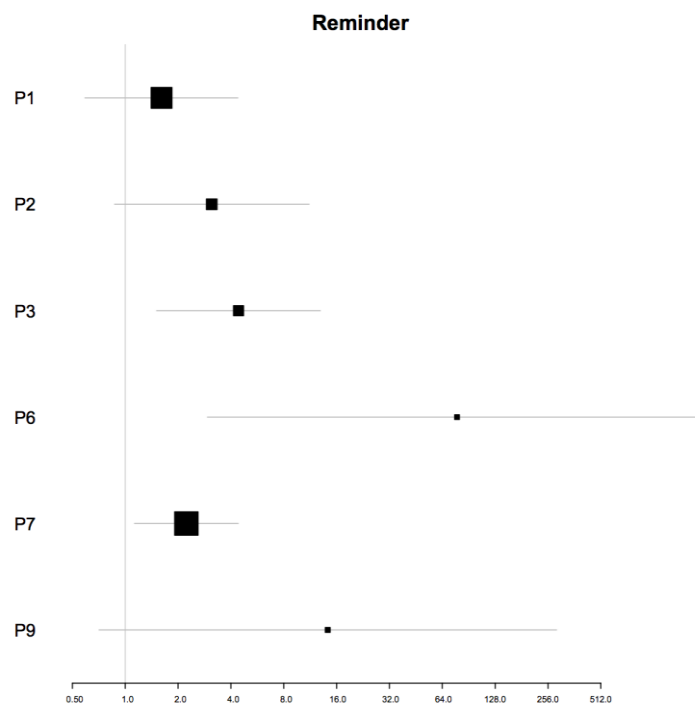


Figure 2. Plots of the IRRs and 95% CIs for the associations of the daily reminder and the amount of engagement in univariable analyses. For P4, the univariable model would not converge. P4 is hence not included in this plot.

Motivation to reduce alcohol

In univariable analyses, motivation to reduce alcohol was a significant predictor of the frequency of engagement for two participants (P4 and P6; see Figure 3). In multivariable analyses, motivation to reduce alcohol was a significant predictor for one participant (IRR = 1.14, 95% CI = 1.02-1.27, $p = .02$). For this participant (P4), a 1-point increase in motivation

to reduce alcohol was associated with a 14% increase in the number of logins in the next 12 hours (see Table 7).

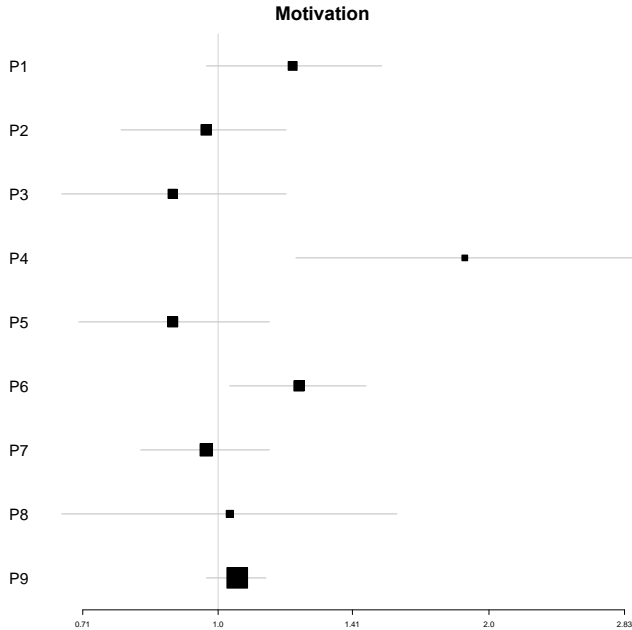


Figure 3. Plots of the IRRs and 95% CIs for the associations of motivation to reduce alcohol and the frequency of engagement in univariable analyses.

In univariable analyses, motivation to reduce alcohol was a significant predictor of the amount of engagement for three participants (P4, P6 and P9; see Figure 4). In multivariable analyses, motivation to reduce alcohol was a significant predictor for three participants (IRRs = 1.67-3.45, all p 's < .05). For these participants (P4, P6 and P7), a 1-point increase in motivation was associated with a 67-245% increase in the amount of engagement in the next 12 hours (see Table 7).

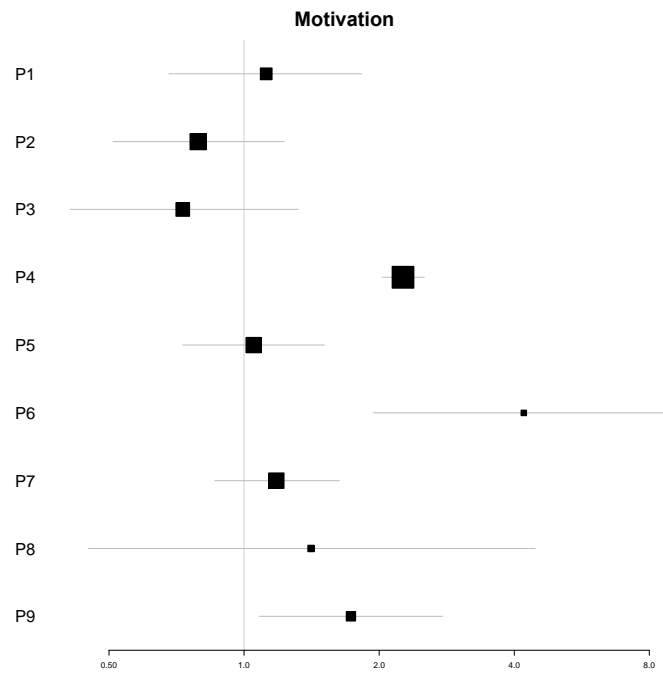


Figure 4. Plots of the IRRs and 95% CIs for the associations of motivation to reduce alcohol and the amount of engagement in univariable analyses.

Perceived usefulness of the app

In univariable analyses, perceived usefulness of the app was a significant predictor of the frequency of engagement for three participants (P4, P6 and P9; see Figure 5). In multivariable analyses, perceived usefulness of the app was a significant predictor for three participants (IRRs = 0.82-1.42, all p 's < .05). For one participant (P1), a 1-point increase in perceived usefulness of the app was associated with an 18% reduction in the number of logins in the next 12 hours, whereas for two participants (P5 and P9), a 1-point increase in perceived usefulness of the app was associated with a 38-42% increase in the number of logins in the next 12 hours (see Table 7).

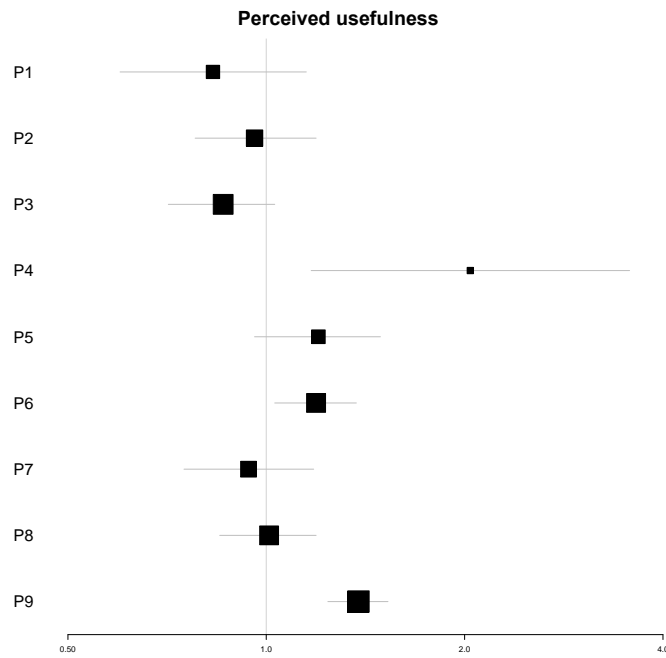


Figure 5. Plots of the IRRs and 95% CIs for the associations of perceived usefulness of the app and the frequency of engagement in univariable analyses.

In univariable analyses, perceived usefulness of the app was a significant predictor of the amount of engagement for three participants (P4, P5 and P9; see Figure 6). In multivariable analyses, perceived usefulness of the app was a significant predictor for four participants (IRRs = 0.52-137.32, all p 's < .05). For one participant (P7), a 1-point increase in perceived usefulness of the app was associated with a 48% reduction in the amount of engagement in the next 12 hours. For three participants (P4, P5 and P9), a 1-point increase in perceived usefulness of the app was associated with a 67-13,632% increase in the amount of engagement in the next 12 hours (see Table 7).

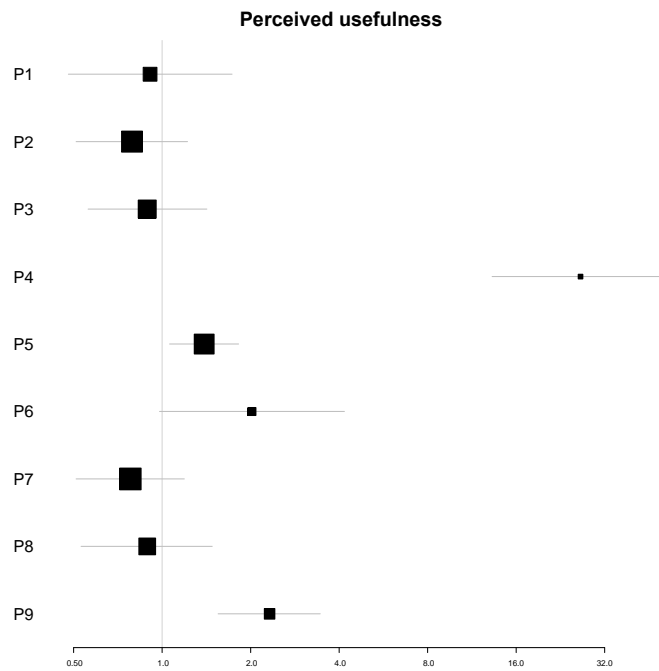


Figure 6. Plots of the IRRs and 95% CIs for the associations of perceived usefulness of the app and the amount of engagement in univariable analyses.

Alcohol consumption

In univariable analyses, the number of drinks containing alcohol consumed in the past 12 hours was a significant predictor of the frequency of engagement for one participant (P2; see Figure 7). In multivariable analyses, the number of drinks containing alcohol consumed in the past 12 hours was a significant predictor for one participant (IRR = 1.50, 95% CI = 1.16-1.93, $p < .01$). For this participant (P2), each alcoholic drink consumed in the past 12 hours was associated with a 50% increase in the number of logins in the next 12 hours (see Table 7).

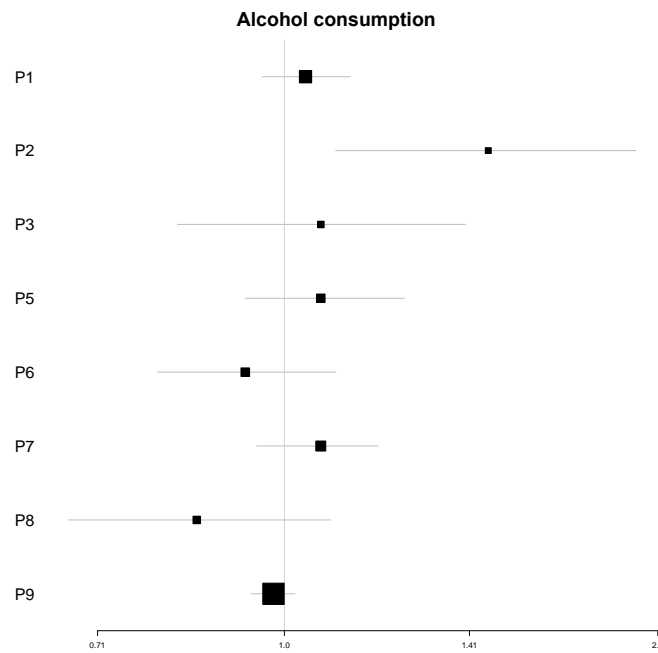


Figure 7. Plots of the IRRs and 95% CIs for the associations of alcohol consumption and the frequency of engagement in univariable analyses. For P4, the univariable model would not converge. P4 is hence not included in this plot.

In univariable analyses, the number of drinks containing alcohol consumed in the past 12 hours was a significant predictor of the amount of engagement for two participants (P2 and P3; see Figure 8). In multivariable analyses, the number of drinks containing alcohol consumed in the past 12 hours was a significant predictor for two participants (IRRs = 1.38-2.38, p 's < .01). For these participants (P2 and P3), each alcoholic drink consumed in the past 12 hours was associated with a 38-138% increase in the amount of engagement in the next 12 hours (see Table 7).

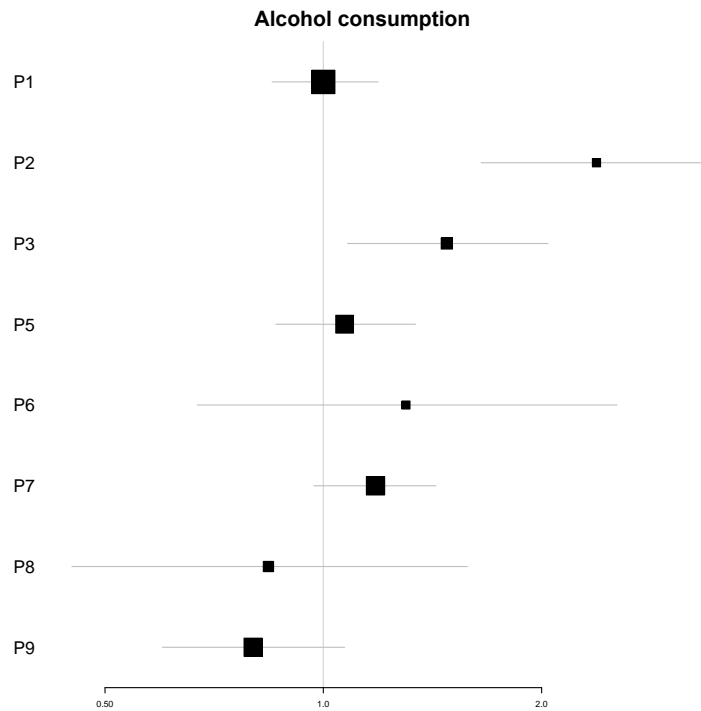


Figure 8. Plots of the IRRs and 95% CIs for the associations of alcohol consumption and the amount of engagement in univariable analyses. For P4, the univariable model would not converge. P4 is hence not included in this plot.

Perceived lack of time

In univariable analyses, perceived lack of time was not a significant predictor of the frequency of engagement for any of the participants (see Figure 10). In multivariable analyses, perceived lack of time was a significant predictor for two participants (IRRs = 0.77-1.13, p 's < .05). For one participant (P6), a 1-point increase in perceived lack of time (meaning that they had more time for the app) was associated with a 23% reduction in the number of logins in the next 12 hours. For the other participant (P2), a 1-point increase in perceived lack of time was associated with a 13% increase in the number of logins in the next 12 hours (see Table 7).

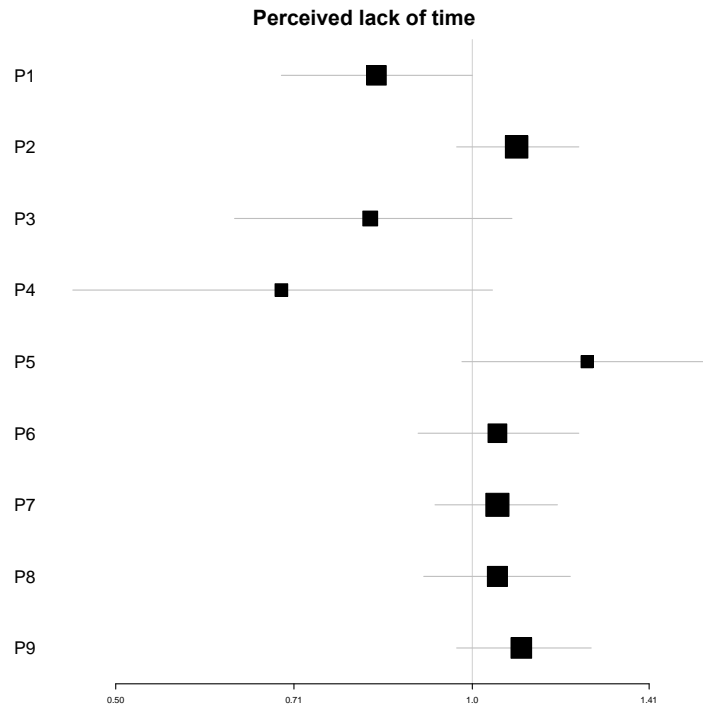


Figure 9. Plots of the IRRs and 95% CIs for the associations of perceived lack of time and the frequency of engagement in univariable analyses.

In univariable analyses, perceived lack of time was a significant predictor of the amount of engagement for four participants (P1, P4, P6 and P9; see Figure 10). In multivariable analyses, perceived lack of time was a significant predictor for two participants (IRRs = 0.20-4.77, p 's < .05). For one participant (P4), a 1-point increase in perceived lack of time (meaning that they had more time for the app) was associated with an 80% reduction in the amount of engagement in the next 12 hours. For the other participant (P9), a 1-point increase in perceived lack of time was associated with a 377% increase in the amount of engagement in the next 12 hours (see Table 7).

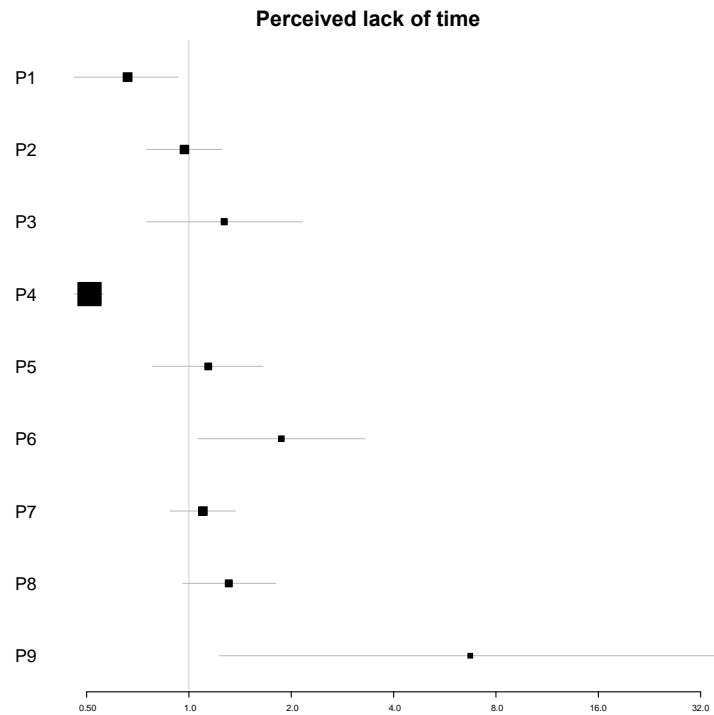


Figure 10. Plots of the IRRs and 95% CIs for the associations of perceived lack of time and the amount of engagement in univariable analyses.

Table 7. IRRs for the associations between the predictor and outcome variables for each participant in the multivariable GAMMs.

	Frequency of engagement		Amount of engagement	
	IRR (95% CI)	p-value	IRR (95% CI)	p-value
P1				
Reminder	1.80 _{2,1} (1.19-2.74)	.01	-	-
Motivation to reduce alcohol	1.14 _{2,1} (1.02-1.27)	.02	1.12 _{0,0} (0.68-1.83)	.65
Perceived usefulness of the app	0.82 _{2,1} (0.68-0.99)	.04	-	-
Alcohol consumption	-	-	-	-
Perceived lack of time	0.93 _{2,1} (0.86-1.02)	.15	-	-
P2				
Reminder	1.99 _{1,0} (0.67-5.94)	.22	-	-
Motivation to reduce alcohol	-	-	-	-
Perceived usefulness of the app	-	-	-	-
Alcohol consumption	1.50 _{1,0} (1.16-1.93)	< .01	2.38 _{1,0} (1.65-3.43)	< .01
Perceived lack of time	1.13 _{1,0} (1.01-1.25)	.03	-	-
P3				
Reminder	-	-	4.31 _{0,0} (1.73-10.73)	< .01
Motivation to reduce alcohol	0.89 _{1,0} (0.67-1.19)	.45	-	-
Perceived usefulness of the app	-	-	-	-
Alcohol consumption	-	-	1.38 _{0,0} (1.11-1.73)	< .01
Perceived lack of time	-	-	1.19 _{0,0} (0.79-1.77)	.40

P4^a				
Reminder	-	-	-	-
Motivation to reduce alcohol	1.88 _{0,0} (1.22-2.91)	< .01	2.03 _{0,0} (1.72-2.40)	< .001
Perceived usefulness of the app	-	-	137.32 _{0,0} (49.45-381.34)	< .001
Alcohol consumption	-	-	-	-
Perceived lack of time	-	-	0.20 _{0,0} (0.14-0.29)	< .001
P5				
Motivation to reduce alcohol	-	-	-	-
Perceived usefulness of the app	1.42 _{2,2} (1.15-1.75)	< .01	1.93 _{0,0} (1.06-1.82)	.02
Alcohol consumption	-	-	-	-
Perceived lack of time	1.08 _{2,2} (0.81-1.43)	.60	-	-
P6				
Reminder	3.88 _{2,0} (1.37-11.03)	.01	-	-
Motivation to reduce alcohol	1.07 _{2,0} (0.93-1.21)	.35	3.45 _{0,0} (1.34-8.83)	.01
Perceived usefulness of the app	1.12 _{2,0} (0.94-1.34)	.21	-	-
Alcohol consumption	0.92 _{2,0} (0.83-1.02)	.13	-	-
Perceived lack of time	0.77 _{2,0} (0.61-0.97)	.03	1.24 _{0,0} (0.71-2.17)	.45
P7				
Reminder	3.26 _{1,0} (2.15-4.96)	< .001	-	-
Motivation to reduce alcohol	-	-	1.67 _{0,0} (1.16-2.40)	< .01
Perceived usefulness of the app	-	-	0.52 _{0,0} (0.33-0.80)	< .01
Alcohol consumption	-	-	-	-
Perceived lack of time	-	-	-	-
P8				
Motivation to reduce alcohol	-	-	-	-
Perceived usefulness of the app	-	-	-	-
Alcohol consumption	0.85 _{1,0} (0.67-1.09)	.20	0.82 _{0,0} (0.47-1.43)	.50
Perceived lack of time	-	-	1.33 _{0,0} (0.97-1.82)	.08
P9				
Reminder	-	-	-	-
Motivation to reduce alcohol	-	-	1.20 _{1,1} (0.92-1.58)	0.18
Perceived usefulness of the app	1.38 _{1,0} (1.24-1.53)	< .001	1.67 _{1,1} (1.22-2.29)	< .01
Alcohol consumption	-	-	-	-
Perceived lack of time	-	-	4.77 _{1,1} (1.09-20.79)	.04

Note. All models were adjusted for the day of the week using a cyclic cubic smoothing term. The dash symbol (-) indicates that a predictor variable was not included in the best fitting model. Numbers in subscript indicate the lags of autoregressive (AR) and moving average (MA) terms, respectively. A lag value of 0 indicates that an AR or MA term was not included. *P*-values significant at the .05 level are highlighted in bold font. ^a For P4, GAMMs would not converge. Therefore, Generalised Additive Models (GAMs) were fitted.

Debriefing interviews

Establishing a routine

When asked to reflect on their engagement with the *Drink Less* app, the majority of participants (P2, P3, P5, P6, P7, P8) mentioned that they established a routine to engage with the app on a daily basis over the 28-day study. They would, for example, remember to open the app every morning upon waking or when travelling to work, or every evening when returning home after work. Some participants (who had opted to receive the daily push notification) thought this was facilitated by the daily reminder.

"I've sort of made a habit of it now, and [I'm] probably going to continue as well." – P2

"I was using it every day, because I just wanted to put the summary in for the day, even if it was a drink free day. So I would always use it." – P8

Purposeful vs. purposeless engagement

The majority of participants (P1, P3, P6, P7, P8, P9, P10) reported that they quickly learnt which features they 'had to' engage with. They would only open the app for a specific purpose, which typically involved logging drinks or alcohol-free days in the calendar and reviewing their progress on the dashboard, as opposed to opening the app for entertainment.

"I can just go on, quickly, input the stuff, have a check of how I'm doing against the target, and then go off it." – P7

Momentary triggers and barriers to engagement

The majority of participants did not feel inclined to open the app when they were in a social setting, not necessarily because they anticipated feeling embarrassed if friends, family or

colleagues would ask about why they were using an alcohol reduction app, but because they wanted to stay focused on their interactions with other people.

"Not necessarily just because like: "Oh, I don't want them to know that I'm doing it", more just like, I'm busy and I'm having a good time, and I'll do it later" – P7

Some participants (P4, P5, P7, P9) mentioned that they thought they were more likely to open the app when feeling bored. One participant (P2) tended to open the app to combat momentary cravings to drink. Some participants (P2, P7, P9, P10) thought they were less likely to use the app when they were hungover or experiencing low mood.

"I'd sort of open the game to distract myself, and say that I should not be saying yes to everything." – P2

Discussion

Principal findings

This series of *N*-of-1 studies found that the utility of app-related and psychological variables in predicting two facets of behavioural engagement (i.e. the frequency and amount of engagement) with an alcohol reduction app differed within and between individuals. This suggests that different strategies to promote engagement may be required for different individuals, and that such strategies may have differential effects on the various facets of engagement.

In line with findings from group-level studies [47], the receipt of a proactive reminder was significantly associated with the frequency of engagement for a few participants. However, this was not the case for all participants who had opted to have the reminder switched on. This suggests that some participants may be more responsive to prompts than others. However, for some participants, significant associations were only observed in the multivariable (and not in the univariable) analyses. As this may reflect suppression effects, results for participants with inconsistent associations across uni- and multivariable analyses

should be interpreted with caution. For participants receiving the daily reminder in the middle of a 12-hour measurement period (e.g. P3), it was not possible to assess whether the receipt of the reminder occurred prior to or following app engagement, as all predictor variables were entered into one multivariable model.

In contrast to results from group-level studies [14,16], motivation to reduce alcohol was significantly associated with the amount, but not necessarily the frequency, of engagement for some participants. For these individuals, being more highly motivated to reduce alcohol may make them more willing to spend time (and perhaps also effort) on the app, providing that they had decided to open the app in the first place.

Previous group-level studies have identified a negative relationship of baseline alcohol consumption with the frequency of engagement, such that the higher the alcohol consumption, the less frequent the engagement [13,14,17]. In the present study, none of the participants engaged with the app at a lower rate after sessions of heavier alcohol consumption. Instead, alcohol consumption was positively related to the frequency and amount of engagement for some participants. It is plausible that the direction of the relationship between engagement and the target behaviour may vary across individuals: while some participants may be more prone to engage when they are doing well (i.e. having abstained from or consumed less-than-typical amounts of alcohol), the reverse may hold for other participants.

The variable 'perceived lack of time' has typically been explored qualitatively in interviews with participants who have dropped out of RCTs of digital interventions [14]. For some participants in the present study, this variable was significantly associated with the frequency and amount of engagement. However, the direction of the relationships varied across participants, with some participants displaying lower rates of engagement after having indicated that they had a lot of time available for the app. It should, however, be noted that for some participants (i.e. P2, P6), significant associations were only observed in the multivariable analyses. Hence, results for these participants should be interpreted with caution. P4 (who displayed significant negative associations across both uni- and multivariable analyses) may have rated themselves as having a lot of time for the app at the

time of the morning or evening survey, but this might have changed a few hours later, which may have interfered with their app use. More frequent EMAs may therefore help to detect a relationship between ‘perceived lack of time’ and engagement for some participants. Alternatively, participants’ availability/receptivity to engage could be automatically inferred from their calendar or phone activity [48].

In line with findings from group-level studies [41,49], the variable ‘perceived usefulness of the app’ was found to be one of the most consistent predictors of both the frequency and amount of engagement with the *Drink Less* app. The direction of the associations differed across participants; although ‘perceived usefulness of the app’ tended to be positively associated with the frequency and amount of engagement, the reverse was observed for some participants. Again, this might be indicative of the need to capture this variable at a higher resolution (i.e. more frequent EMAs). Alternatively, this variable may have been subject to social desirability. It should also be noted that for some participants (i.e. P1, P7), significant associations were only observed in the multivariable analyses.

For some participants, none of the variables assessed were significantly associated with the frequency (i.e. P3 and P8) or amount of engagement (i.e. P8) in either the uni- or multivariable analyses. This raises the question as to what was driving engagement for these participants. One plausible explanation in relation to frequency, as mentioned in the debriefing interviews, is that these participants established a routine to engage with the app. If this were indeed the case, habit formation could be trialled as a promising strategy to promote engagement for other users [50]. The debriefing interviews were unable to shed light on key factors that may have driven participants’ amount of engagement since it was difficult for participants to introspect about momentary influences on time spent on the app (particularly as the time unit of interest was seconds rather than minutes or hours). It should be noted that although daily engagement with alcohol reduction apps such as *Drink Less* may be brief on average, thus making it difficult for users to introspect about momentary influences on their app use, this may not generalise to apps for other behaviours or activities. For example, apps for physical activity or mindfulness meditation, which have typically been designed to be kept open whilst performing the target behaviour, may

generate larger amounts of engagement. Hence, it may be easier for users to reflect on their daily engagement with such apps [51,52].

Strengths

To the authors' knowledge, this was the first study to examine within-person predictors of the frequency and amount of engagement with an alcohol reduction app. The predictors assessed in this study were selected based on prior evidence from group-level studies and in-depth qualitative studies with potential users of alcohol reduction apps. Compliance with the twice-daily EMAs was high (0-16% missing data), and the automatic recording of the outcome variables in real-time ensured that participant burden and missing outcome data were minimised. This study provides initial evidence that it is feasible and acceptable to gather data in this manner and that a novel time series approach (i.e. Generalised Additive Mixed Models) can be successfully used to model data from *N*-of-1 studies.

Limitations

This study was conceptualised as a series of observational *N*-of-1 studies; however, participants engaged with an active digital intervention and study materials which included behaviour change techniques known to alter cognition and behaviour (e.g. prompts, self-monitoring) [53]. It is therefore possible that both predictor and outcome variables were subject to non-random fluctuations, which were caused by participants' engagement with the intervention and study materials. However, as engagement with digital interventions cannot be studied in isolation without asking participants to engage with a particular intervention and related study materials, it was not possible to overcome this particular limitation.

The study sample was almost exclusively women. As men tend to exhibit more alcohol-related problems than women [54,55], it is unclear whether the same patterns of results would be observed in a more balanced or male-dominated sample. None of the participants dropped out of the study, suggesting that they were highly motivated to take part in the research. It is therefore possible that different patterns of results may be obtained in

samples of less committed participants. The *Drink Less* app is currently available for iOS only. As market research suggests that iPhone users tend to be more affluent than Android users [56], different patterns of engagement might be observed in a sample of Android users. Participants were all aged <32 years; older adults may display different patterns of engagement. It should, however, be noted that the aim of the present study was not to produce results that are generalisable at the group level. In addition, one participant (P7) had used the app prior to the study period, which may have influenced their engagement. However, as participants serve as their own controls in *N-of-1* studies, the finding that P7 engaged more frequently with the app when they had received the daily reminder is meaningful information; it could be used to inform the development of personalised engagement strategies for this unique user.

In order to keep participant burden to a minimum, other facets of engagement during each login session (e.g. attention, interest) were not assessed. This study was therefore unable to highlight potentially interesting relationships between the predictor variables and experiential engagement [6,9]. Moreover, many participants opted to be reminded during the first measurement period (i.e. during the day time). As there is more time for engagement in the day time (as compared with the night time), this may have confounded the observed relationship between the receipt of the daily reminder and the frequency and amount of engagement.

Avenues for future research

Descriptive plots were used to summarise the associations of each predictor variable with the key outcome variables across participants; it was not possible to pool results from the multivariable models in a meta-analysis. As time series analysis is becoming increasingly popular in the context of *N-of-1* studies, suitable meta-analytic techniques are evolving [44], and this should be considered in future research. For studies with a greater number of participants, multi-level models (including the Generalised Additive Mixed Model) can be used to estimate both within- and between-person effects [57].

Future research should test the feasibility of using both time- and event-prompted EMAs, with participants being prompted to respond to a few questions about their experiential engagement immediately after having opened the app. This would require careful piloting given the additional participant burden and unpredictability of response requests: it is possible that this might create a disincentive to open the app as participants may anticipate an additional cost directly linked to doing so. As indicated in the debriefing interviews, it is plausible that participants' physical location (e.g. being in a social setting) is negatively associated with behavioural engagement for some participants. This could be explored further by means of accessing the location sensing data from participants' smartphones.

The feasibility and utility of just-in-time adaptive interventions (JITAs) [58] for promoting engagement with alcohol reduction apps should be explored further. The JITA is a type of intervention that is specifically designed to address the dynamically changing needs of individuals. JITAs use inputs from, for example, EMAs or data collected via wearables or the phone's location sensors to inform what type of support each individual might need in different situations or contexts. They then automatically trigger support when the system infers that the individual is in need of or most receptive to that support. In the context of the results from the present study, a JITA could, for example, be delivered when an individual's level of perceived usefulness of the app or motivation to reduce alcohol is inferred to be below a given threshold for action, with a view to promoting the frequency of engagement.

Future research should consider the use of observational or experimental *N-of-1* study designs as a valuable part of intervention development. Results from the present study are currently being used to inform the optimisation of the *Drink Less* app, involving, for example, the optimisation of the content and timing of the daily reminder, with a view to promoting engagement.

Conclusion

This series of *N-of-1* studies found that the utility of psychological and app-related variables in predicting the frequency and amount of engagement with an alcohol reduction app differed within and between individuals. This highlights that important within-person

associations may be masked in group-level designs and suggests that different strategies to promote engagement may be required for different individuals.

Acknowledgements

The authors would like to thank the participants for their time. OP is funded by Bupa under its partnership with UCL and Cancer Research UK (C1417/A22962). CG, EB and RW receive salary support from Cancer Research UK (C1417/A22962). We gratefully acknowledge all funding. We also acknowledge the members of UCL's Tobacco and Alcohol Research Group for providing feedback on an early draft of the manuscript.

Author contributions

OP, FN, CG, AB, SM, EB and RW designed the study. OP collected the data, conducted the statistical analyses and wrote the first draft of the manuscript. All authors have contributed to the final version of the manuscript and agree with its submission to JMIR.

Conflicts of interest

OP, FN, CG, AB and SM have no conflicts of interest to declare. EB has received unrestricted research funding from Pfizer. RW undertakes research and consultancy and receives fees for speaking from companies that develop and manufacture smoking cessation medications.

Abbreviations

AUDIT – Alcohol Use Disorders Identification Test

AR - Autoregressive

CI – Confidence Interval

EMAs – Ecological Momentary Assessments

GAMMs – Generalised Additive Mixed Models

IRR – Incidence Rate Ratio

JITAs – Just-in-Time Adaptive Interventions

MA – Moving Average

RCTs – Randomised Controlled Trials

References

1. Gowing LR, Ali RL, Allsop S, Marsden J, Turf EE, West R, et al. Global statistics on addictive behaviours: 2014 status report. *Addiction* 2015;110:904–919.
2. Lim SS, Vos T, Flaxman AD, Danaei G, Shibuya K, Adair-Rohani H, et al. A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990-2010: A systematic analysis for the Global Burden of Disease Study 2010. *Lancet* 2012;380(9859):2224–2260. PMID: 23245609
3. Griffiths F, Lindenmeyer A, Powell J, Lowe P, Thorogood M. Why are health care interventions delivered over the internet? A systematic review of the published literature. *J Med Internet Res* 2006;8(2). PMID: 16867965
4. Ritterband LM, Tate DF. The Science of Internet Interventions. *Ann Behav Med* 2009;38:1–3. PMID: 19816750
5. Schueller SM, Muñoz RF, Mohr DC. Realizing the Potential of Behavioral Intervention Technologies. *Curr Dir Psychol Sci* 2013;22(6):478–483.
6. Perski O, Blandford A, West R, Michie S. Conceptualising engagement with digital behaviour change interventions: a systematic review using principles from critical interpretive synthesis. *Transl Behav Med [Internet]* Springer US; 2017 Dec 13 [cited 2016 Dec 19];7:254–267. Available from: <http://link.springer.com/10.1007/s13142-016-0453-1>
7. Donkin L, Christensen H, Naismith SL, Neal B, Hickie IB, Glozier N. A systematic review of the impact of adherence on the effectiveness of e-therapies. *J Med Internet Res [Internet]* 2011 Jan [cited 2015 Oct 5];13(3):e52. Available from: <http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3222162&tool=pmcentrez&rendertype=abstract> PMID: 21821503
8. Yardley L, Spring BJ, Riper H, Morrison LG, Crane DH, Curtis K, et al. Understanding and Promoting Effective Engagement With Digital Behavior Change Interventions. *Am J Prev Med [Internet]* Elsevier; 2016;51(5):833–842. Available from:

<http://linkinghub.elsevier.com/retrieve/pii/S0749379716302434>

9. Perski, O., Blandford, A., Garnett, C., Crane, D., West, R., & Michie, S. (2019). A self-report measure of engagement with digital behavior change interventions (DBCIs): development and psychometric evaluation of the “DBCI Engagement Scale.” *Translational Behavioral Medicine*. doi:10.1093/tbm/ibz039
10. Michie S, Yardley L, West R, Patrick K, Greaves F. Developing and evaluating digital interventions to promote behavior change in health and health care: Recommendations resulting from an international workshop. *J Med Internet Res* 2017;19(6):e232. PMID: 28663162
11. Johnston DW, Johnston M. Useful theories should apply to individuals. *Br J Health Psychol* 2013;18(3):469–473. PMID: 23724956
12. Molenaar PCM. A Manifesto on Psychology as Idiographic Science: Bringing the Person Back Into Scientific Psychology, This Time Forever. *Measurement* 2004;2(4):201–218.
13. Linke S, Murray E, Butler C, Wallace P. Internet-based interactive health intervention for the promotion of sensible drinking: Patterns of use and potential impact on members of the general public. *J Med Internet Res* 2007;9(2):1–12. PMID: 17513281
14. Postel MG, de Haan HA, ter Huurne ED, van der Palen J, Becker ES, de Jong CAJ. Attrition in web-based treatment for problem drinkers. *J Med Internet Res [Internet] Journal of Medical Internet Research*; 2011 Jan 27 [cited 2016 Feb 8];13(4):e117. Available from: <http://www.jmir.org/2011/4/e117/> PMID: 22201703
15. Garnett C, Perski O, Tombor I, West R, Michie S, Brown J. Predictors of engagement, response to follow-up and extent of alcohol reduction in users of a smartphone app, Drink Less. *JMIR mHealth uHealth* 2018;
16. Chiauzzi E, Green TC, Lord S, Thum C, Goldstein M. My student body: A high-risk drinking prevention website for college students. *J Am Coll Heal* 2005;53(6):263–274. PMID: 15900990
17. Radtke T, Ostergaard M, Cooke R, Scholz U. Web-based alcohol intervention: Study of systematic attrition of heavy drinkers. *J Med Internet Res* 2017;19(6):1–12. PMID: 28659251
18. Kelders SM, Kok RN, Ossebaard HC, Van Gemert-Pijnen JEWC. Persuasive system design does matter: a systematic review of adherence to web-based interventions. *J*

- Med Internet Res [Internet] Journal of Medical Internet Research; 2012 Jan 14 [cited 2015 Oct 28];14(6):e152. Available from: <http://www.jmir.org/2012/6/e152/> PMID: 23151820
19. Perski O, Blandford A, Ubhi HK, West R, Michie S. Smokers' and drinkers' choice of smartphone applications and expectations of engagement: a think aloud and interview study. *BMC Med Inform Decis Mak BMC Medical Informatics and Decision Making*; 2017;17(25):1–14.
 20. Davis FD. Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Q* 1989;13(3):319–340.
 21. Perski O, Baretta D, Blandford A, West R, Michie S. Engagement features judged by excessive drinkers as most important to include in smartphone applications for alcohol reduction: A mixed methods study. *Digit Heal*.
 22. Sedgwick P. What is an “n-of-1” trial? *Br Med J* 2014;348:1–2. PMID: 2014260588
 23. Nisbett RE, Wilson TD. Telling more than we can know: Verbal reports on mental processes. *Psychol Rev* 1977;84(3):231–259. PMID: 17882490
 24. Smyth JM, Stone AA. Ecological Momentary Assessment Research in Behavioral medicine. *J Happiness Stud [Internet]* 2003;4:35–52. Available from: <http://www.springerlink.com/openurl.asp?id=doi:10.1023/A:1023657221954>
 25. Stone AA, Shiffman S. Ecological momentary assessment (EMA) in behavioral medicine. *Ann Behav Med* 1994;16(3):199–202.
 26. McDonald S, Quinn F, Vieira R, O'Brien N, White M, Johnston DW, et al. The state of the art and future opportunities for using longitudinal n-of-1 methods in health behaviour research: a systematic literature overview. *Health Psychol Rev Taylor & Francis*; 2017;11(4):307–323. PMID: 28406349
 27. Vieira R, McDonald S, Araújo-Soares V, Sniehotta FF. Dynamic modelling of n-of-1 data: powerful and flexible data analytics applied to individualised studies. *Health Psychol Rev Taylor & Francis*; 2017;11(3):222–234.
 28. Garnett C, Crane D, West R, Brown J, Michie S. The development of Drink Less: an alcohol reduction smartphone app for excessive drinkers. *Transl Behav Med* 2018;1–12.
 29. Crane D, Garnett C, Michie S, West R, Brown J. A smartphone app to reduce excessive alcohol consumption: Identifying the effectiveness of intervention components in a

- factorial randomised control trial. *Sci Rep* 2018;8(4384):1–11.
30. Inauen J, Shrout PE, Bolger N, Stadler G, Scholz U. Mind the Gap? An Intensive Longitudinal Study of Between-Person and Within-Person Intention-Behavior Relations. *Ann Behav Med [Internet] Annals of Behavioral Medicine*; 2016;50(4):516–522. Available from: <http://dx.doi.org/10.1007/s12160-016-9776-x>
 31. Duan N, Kravitz RL, Schmid CH. Single-patient (n-of-1) trials: A pragmatic clinical decision methodology for patient-centered comparative effectiveness research. *J Clin Epidemiol [Internet] Elsevier Inc*; 2013;66:S21–S28. Available from: <http://dx.doi.org/10.1016/j.jclinepi.2013.04.006> PMID: 23849149
 32. Kwasnicka D, Dombrowski SU, White M, Sniehotta FF. N-of-1 study of weight loss maintenance assessing predictors of physical activity, adherence to weight loss plan and weight change. *Psychol Heal [Internet] Routledge*; 2017;32(6):686–708. Available from: <http://dx.doi.org/10.1080/08870446.2017.1293057> PMID: 28323457
 33. Kaner E, Beyer F, Garnett C, Crane D, Brown J, Muirhead C, et al. Personalised digital interventions for reducing hazardous and harmful alcohol consumption in community-dwelling populations. *Cochrane Database Syst Rev [Internet]* 2017;CD011479(9). Available from: <http://doi.wiley.com/10.1002/14651858.CD011479>
 34. Gilks W, Richardson S, Spiegelhalter D. Markov chain Monte Carlo in practice. CRC press; 1995.
 35. Quinn F, Johnston M, Johnston DW. Testing an integrated behavioural and biomedical model of disability in N-of-1 studies with chronic pain. *Psychol Heal* 2013;28(12):1391–1406. PMID: 23863041
 36. Hobbs N, Dixon D, Johnston M, Howie K. Can the theory of planned behaviour predict the physical activity behaviour of individuals? *Psychol Health [Internet]* 2013;28(3):234–249. Available from: <http://www.tandfonline.com/doi/abs/10.1080/08870446.2012.716838> PMID: 22943555
 37. Garnett C, Crane D, West R, Brown J, Michie S. Identification of Behavior Change Techniques and Engagement Strategies to Design a Smartphone App to Reduce Alcohol Consumption Using a Formal Consensus Method. *JMIR mHealth uHealth [Internet]* 2015;3(2):e73. Available from: <http://www.ncbi.nlm.nih.gov/pubmed/26123578> PMID: 26123578

38. Crane D, Garnett C, Brown J, West R, Michie S. Behavior change techniques in popular alcohol reduction apps: content analysis. *J Med Internet Res* [Internet] 2015;17(5):e118. Available from: <http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=4468601&tool=pmcentrez&rendertype=abstract> PMID: 25977135
39. Crane D, Garnett C, Brown J, West R, Michie S. Factors influencing usability of a smartphone app to reduce excessive alcohol consumption: Think aloud and interview studies. *Front Public Heal* 2017;5:1–19.
40. Babor TF, Higgins-Biddle JC, Saunders JB, Monteiro MG. *The Alcohol Use Disorders Identification Test: Guidelines for Use in Primary Care*. 2nd ed. Geneva: World Health Organisation; 2001.
41. King WR, He J. A meta-analysis of the technology acceptance model. *Inf Manag* 2006;43(6):740–755. PMID: 25246403
42. Google Analytics. How a web session is defined in Analytics [Internet]. 2017 [cited 2018 Feb 6]. Available from: <https://support.google.com/analytics/answer/2731565>
43. Qualtrics. Qualtrics Survey Software [Internet]. Provo, Utah; 2016. Available from: <http://www.qualtrics.com/>
44. Shadish WR, Zuur AF, Sullivan KJ. Using generalized additive (mixed) models to analyze single case designs. *J Sch Psychol* [Internet] Society for the Study of School Psychology; 2014;52(2):149–178. Available from: <http://dx.doi.org/10.1016/j.jsp.2013.11.004> PMID: 24606973
45. Akaike H. A New Look at the Statistical Model Identification. *IEEE Trans Automat Contr* 1974;19(6):716–723. PMID: 1100705
46. Braun V, Clarke V. Using thematic analysis in psychology. *Qual Res Psychol* 2006;3(May 2015):77–101. PMID: 223135521
47. Vervloet M, Linn AJ, van Weert JCM, de Bakker DH, Bouvy ML, van Dijk L. The effectiveness of interventions using electronic reminders to improve adherence to chronic medication: A systematic review of the literature. *J Am Med Informatics Assoc* 2012;19:696–704.
48. Hekler EB, Rivera DE, Martin CA, Phatak SS, Freigoun MT, Korinek E, et al. Tutorial for Using Control Systems Engineering to Optimize Adaptive Mobile Health Interventions. *J Med Internet Res* 2018;20(6):e214.

49. Schepers J, Wetzels M. A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects. *Inf Manag* 2007;44(1):90–103. PMID: 25246403
50. Beeken RJ, Leurent B, Vickerstaff V, Wilson R, Croker H, Morris S, et al. A brief intervention for weight control based on habit-formation theory delivered through primary care: results from a randomised controlled trial. *Int J Obes [Internet]* Nature Publishing Group; 2017;41:246–254. Available from: <http://dx.doi.org/10.1038/ijo.2016.206>
51. Laurie J, Blandford A. Making time for mindfulness. *Int J Med Inform [Internet]* Elsevier Ireland Ltd; 2016;96:38–50. Available from: <http://dx.doi.org/10.1016/j.ijmedinf.2016.02.010> PMID: 26965526
52. Baretta D, Perski O, Steca P. Exploring Users' Experiences of the Uptake and Adoption of Physical Activity Apps: Longitudinal Qualitative Study. *J Med Internet Res* 2019;7(2):e11636.
53. Wilding S, Conner M, Sandberg T, Prestwich A, Wood C, Miles E, et al. The question-behaviour effect: A theoretical and methodological review and meta-analysis. *Eur Rev Soc Psychol [Internet]* Routledge; 2016;27(1):196–230. Available from: <http://dx.doi.org/10.1080/10463283.2016.1245940>
54. Wilsnack RW, Vogeltanz ND, Wilsnack SC, Harris TR. Gender differences in alcohol consumption and adverse drinking consequences: cross-cultural patterns. *Addiction* 2000;95(2):251–265.
55. Nolen-Hoeksema S, Hilt L. Possible contributors to the gender differences in alcohol use and problems. *J Gen Psychol* 2006;133(4):357–374. PMID: 17128956
56. Berg M. iPhone Users Earn More [Internet]. *Stat - Stat Portal*. 2014 [cited 2019 Jan 28]. Available from: <https://www.statista.com/chart/2638/top-line-platform-stats-for-app-usage-in-the-us/>
57. Kwasnicka D, Inauen J, Nieuwenboom W, Nurmi J, Schneider A, Short CE, et al. Challenges and solutions for N-of-1 design studies in health psychology. *Health Psychol Rev [Internet]* Taylor & Francis; 2019;1–36. Available from: <https://doi.org/10.1080/17437199.2018.1564627>
58. Spruijt-Metz D, Nilsen W. Dynamic Models of Behavior for Just-in-Time Adaptive Interventions. *IEEE Pervasive Comput* 2014;3:13–17.

