Personalizing Reminders to Personality for Melanoma Self-checking

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ABSTRACT

This paper investigates whether different types of persuasive reminder should be sent to patients with different personalities. We describe a study where we presented participants with a personality measure, then describe a scenario with a fictional patient, who has not performed a skin check for recurrent melanoma. We asked patients to imagine they are in that situation and rate validated reminders based on Cialdini's 6 principles of persuasion for their suitability. Participants then chose their favourite reminder, and an alternative reminder to send if that one failed. We found that persuasive reminders that use 'Authority' and 'Liking' are the most popular overall. We also found that personality had an effect when deciding on the type of persuasive reminder to use. In particular, we have found that those with high emotional stability are more responsive to any kind of persuasion, those with low agreeableness rated all types of reminder higher than those with high, and that conscientiousness matters when selecting an alternative reminder.

Keywords

Reminders, Personality, Persuasion, eHealth

1. INTRODUCTION

There is a growing area of research surrounding digital behaviour interventions (also known as persuasive technology) that attempt to change people's attitudes or behaviour. Personalization can play an important role in optimising the effectiveness of these interventions. For example, a meta-analysis by Noar et al. [37] suggests that tailored messages are more effective in causing health behaviour change, and another meta-analysis by Wantland et al. [45] found that tailored messages increased system use. This paper focuses on adapting reminders that prompt people to self-monitor. Whilst this paper is particularly concerned with prompting skin self-examinations, we believe that the applicability of the research is more general, as reminding people to self-monitor is an important technique used in many digital behaviour interventions. For instance, in the domain of healthy eating and physical activity interventions, Michie et al.'s meta-analysis of 122 studies [33] led to them recommend the inclusion of five behaviour change techniques, of which prompting self-monitoring behaviour was one. Despite the case having been made for personalizing digital behaviour interventions [29, 3], research in this area is still quite limited and this paper adds to the research on adapting behaviour change techniques to personality.

Our research aims to encourage people who have been treated for subcutaneous melanoma (skin cancer) to perform Total Skin Self-Examinations (TSSEs). Melanoma is one of the most common cancers in 15-34 year olds and kills over 2,000 people a year in the UK [1]. Early detection of recurrences is a critical goal of follow-up programmes for people who have been previously treated for melanoma [36], as the risk of malignant melanoma is between 8-15 times greater [2] and there is up to a 63% reduction in mortality [11, 25] when patients detect their own recurrences. Hence, experts have argued that patients need to be advised to perform TSSEs at frequent intervals [5]. However, even if patients are taught to self-check often, it is likely that their self-checking will decrease over time without an intervention to sustain their behaviour [21, 24].

Extensive evidence suggests that digital interventions can help promote health behaviour change (e.g. [16, 46, 40])and that apps (i.e. mobile or tablet applications) can be used to support a sustained health self-management strategy [47]. With this in mind, the *ASICA* (Achieving Self-directed Integrated Cancer Aftercare) skin self-examinations app was developed in 2013, as part of an intervention aiming to remove barriers between patients treated for melanoma and dermatology specialists by enabling remote screening and diagnosis of skin changes. One goal was to ensure that patients complete skin self-examinations at least once per month. In a six month pilot study, 20 patients were provided with a tablet with the skin checker app. The same reminder was sent by the team monthly to all patients. Reminders were generally effective, but not for all patients. Accordingly, we decided to investigate how reminders could be personalised. It is likely that personality plays a role in a patient's response to a reminder (along with other relevant factors such as their affective state, daily schedules, etc.), and as personality is relatively stable in adults, it seems a relevant characteristic to consider for the personalization of reminders.

For this research, the Five-Factor model of Personality [18] is used, as it is one of the most popular and reliably validated constructs in use by psychologists. This model describes five personality dimensions: Agreeableness (I), Extraversion (II), Conscientiousness (III), Emotional Stability (IV) and Openness to Experience (V).

This paper builds on previous research [14], which examined the selection of reminders based on Cialdini's 6 principles of persuasion [10]. In the previous study, participants rated 12 reminders for their suitability for a patient with either low or high conscientiousness (as expressed through a story about the patient). There were three main issues arising from that study. The first issue is that the participants' own personality may have impacted their decisions about the suitability of the reminders for the described patients, and that they may have had difficulty to understand what may work best for a patient with a radically different personality to their own. In this paper, we will measure participants' personality and let them rate reminders for a patient with the same (or very similar) personality to their own.

A second issue is that the reminders used were not stringently validated as expressing the correct Cialdini persuasive principle. In this paper, we will report on the validation of the reminder messages and use these validated messages in the main study.

A third issue is that the previous study only investigated Conscientiousness. In this paper, we will investigate the effect of all Five-Factor Model personality traits.

The paper is organized as follows: Section 2 summarises the related work; Section 3 reports on the validation of a set of 12 reminders (2 for each of Cialdini's 6 principles); and Section 4 reports a study using these reminders where participants rated these reminders for their suitability for a patient with a personality similar to their own. Participants also selected their favourite reminder, an alternative reminder to send if that one failed, and indicated the amount of time they would wait between sending the first and second reminder. Section 5 concludes the paper and discusses future work. From the results of this study, we aim to discover which reminders are most effective for certain personalities, which will allow the ASICA app to intelligently select these in the future. Additionally, as there are many e-health interventions which incorporate self-monitoring for long term conditions, it is hoped that the findings from this work will allow such interventions to adapt to the patient personality and improve adherence to self-monitoring.

2. RELATED WORK

Many behaviour changes techniques exist (for example, [34] identified 137 techniques). The use of prompts (also called triggers) is one of the most used techniques, and this paper focusses on a special kind of prompts namely reminders. Many studies across the healthcare domain have shown the effectiveness of digital reminders (e.g. [39, 15, 48, 22, 4]).

To produce effective reminders, we use Cialdini's 6 principles of persuasion [10] (shown in Table 1), as they have been used in multiple contexts and can be easily implemented as reminders [27]. For example, they have been used in reminders for clinic appointments [44] and interaction with an activity monitor app [27].

It has been argued that personalization of prompts will make them more effective. For example, [17] argued that prompts need to be adapted to the user's motivation and ability. Based on this, he distinguishes three types of prompts: *spark prompts* that motivate people who lack motivation to act, *facilitator prompts* that make behaviour easier for motivated people with low ability, and *signal prompts* that remind motivated people with high ability to act. This paper does not consider this kind of adaptation and the reminders that are studied are closest to spark prompts, even though a basic level of motivation can be assumed given the users have been treated for skin cancer. There is also some evidence that prompts may need to be personalized to user demographics. For example, Masthoff et al. [30] showed that prompts in the charity domain may need to be personalized to gender, age, religion and country affinity and Brown et al. [6] suggested that older people are more sensitive to Cialdini's *consistency* technique. Again, demographic characteristics are not considered in this paper though we recognize that user characteristics such as gender and cultural background may well influence the relative effectiveness of prompts.

Table 1: Cialdini's 6 principles of persuasion [9, 27].

Principle	Description
Liking (LIK)	"People like those who like them." If a request is made by someone we like, we are more likely to say yes.
Reciprocity (REC)	"People repay in kind." People are more likely to do something for someone they feel they owe a favour.
Consensus (CON)	"People follow the lead of similar others." People will do the same as other people who are similar to them.
Commitment and Consistency (COM)	"People align with their clear commitments." People will do something if they have committed to it. Also, they will act consistently with previous behaviour.
Authority (AUT)	"People defer to experts." If a doctor advises you to take a medication, you are likely to comply.
Scarcity (SCA)	"People want more of what they can have less of." People will take the opportunity to do something that they can't leave until later.

Personalisation in reminders is a relatively new field. McGee et al. [32] identified the need for the personalising reminder systems, as current personalisation is often limited to only preferred time. Some research has been done on personalising reminders – e.g. adapting to the user's location and movement when providing medication reminders [28] and tailoring mammography reminders to personal risk and the patient's personal barriers to having a mammogram [31].

It has been argued that persuasive techniques or even the choice of a persuasive technique may need to be adapted to the user's personality. For example, studies by Kaptein (e.g. [26]) have investigated the effectiveness of adapting the strategy used in a persuasive prompt (for example, appeal to authority, appeal to commitment) to the user's susceptibility to Cialdini's six social persuasion principles. Dennis et al. [13] have investigated the adaptation of feedback and emotional support to personality. Orji et al. [38] have investigated the adaptation of the selection of persuasive technique to gamer types.

The link between personality and the result of reminders in the healthcare domain has also been investigated, e.g [23] found that conscientious people would likely be the most successful at achieving their health objectives, and persuasive categories with a social aspect were likely to be the most successful for conscientious people. Patients low in conscientiousness typically have lower adherence to treatments [7,

Table 2: Reminder messages selected for Study 2 based on the validation results of Study 1

Category	ID	Message	LIK	REC	CON	COM	AUT	SCA	OTH	Kappa
SCA	SCA1	This is your last opportunity for your monthly skin check. Do not miss out - please check your skin now.	0	1	0	7	4	47	1	0.781
	SCA2	You are running out of time to check your skin this month. Please check your skin now.	0	1	0	4	1	21	3	0.421
AUT	AUT1	According to experts, checking your skin regularly is an effective way of identifying recurrent skin cancer. Please check your skin now.	0	0	3	3	54	0	0	0.649
	AUT2	Expert dermatologists emphasize the benefits of regular skin checking. Please check your skin now.	0	0	1	2	56	1	0	0.618
COM	COM1	When you decided to participate, you agreed that checking your skin monthly is a good idea. Please check your skin now.	1	5	1	47	5	0	1	0.849
	COM2	You promised that you would use the Skin Checker iPad to check your skin. Please check your skin now.	1	5	2	49	3	0	0	0.715
CON	CON1	Thousands of people are actively checking their skin each month. Join them - please check your skin now.	1	1	53	4	1	0	0	0.746
	CON2	Other users have found the Skin Checker iPad very helpful. Please check your skin now.	2	1	50	3	2	0	2	0.748
LIK	LIK1	Your family would appreciate it if you performed your monthly skin check so they don't need to worry about you as much. Please check your skin now.	42	8	5	1	0	1	3	0.744
	LIK2	Lots of people care about you and would feel better if you took the time to check your skin. Please check your skin now.	44	6	4	3	2	0	1	0.68
REC	REC1	The Skin Checker iPad was provided to you to help you check your skin. Please return the favour by doing something for us - check your skin now.	0	24	1	3	0	2	0	0.584
	REC2	We spent a lot of time developing this app to help you. Please check your skin for us now.	0	24	2	1	3	0	0	0.584

8]. Therefore, it is likely that patients who are low in conscientiousness would require different types of reminders, and perhaps more frequently, than those patients who are normally highly conscientious.

3. STUDY 1: REMINDER VALIDATION

This section describes our approach to categorize and validate reminder messages. Initially we produced a wide range of reminders attempting to provide wide coverage of Cialdini's principles. We validated the categorisation of these messages in categories linked to Cialdini's principles shown in Table 1. We adopted the approach used in [13], who investigated the categorization of emotional support statements.

3.1 Study Design

3.1.1 Participants

Participants were recruited from Amazon's Mechanical Turk service [35], a crowd-sourcing tool. For this validation experiment, participants had to be based in the US and have an acceptance rate of 90% (meaning that 90% of the work they do is accepted by other requesters as good quality) and were paid \$0.50. We used a Cloze Test [43] for English fluency due to the language based nature of the study. Workers who failed the test were excluded. The validation was run in two studies. 30 participants completed the first study (21 male; 16 aged 18-25, 10 aged 26-40, 12 aged 41-65) and 30 participants the second study (18 male; 7 aged 18-25, 18 aged 26-40, 5 aged 41-65).

3.1.2 Procedure

Participants were introduced to the categories and their definitions (as described in Table 1). Next, they were shown a message and asked to place it into one of the categories (still seeing the definitions). Participants could rate the reminder as 'other' if they did not think the reminder fitted any of the categories. This was repeated for each message. 24 messages were used in Study 1A and 24 in Study 1B. Participants were advised that there were no right or wrong answers and that it was their opinion that counted. The order of messages was randomized.

3.1.3 Validation Measure

We use Free-Marginal Kappa [41] as a metric for establishing how well categorized our reminder messages were. The kappa value describes agreement amongst raters, with 1 indicating unanimous agreement, 0.7 excellent and 0.4 moderate agreement. To be reliably categorized, the kappa score for the message had to be ≥ 0.4.

3.2 Results

In Study 1A, 16 out of 24 messages obtained a kappa ≥ 0.4, 11 of which obtained a kappa ≥ 0.7. However, no messages at all were validated with kappa ≥ 0.4 for the *Reciprocity* category, and only one for *Scarcity* (and none with kappa ≥ 0.7). A second run of the study was therefore performed (Study 1B) with 8 new messages (4 designed for Reciprocity and 4 for Scarcity) as well as the 16 messages which had validated in the first study (to ensure there were enough different messages to make it a proper categorization task). For messages used in both studies, an overall kappa was calculated based on both studies. The valida-

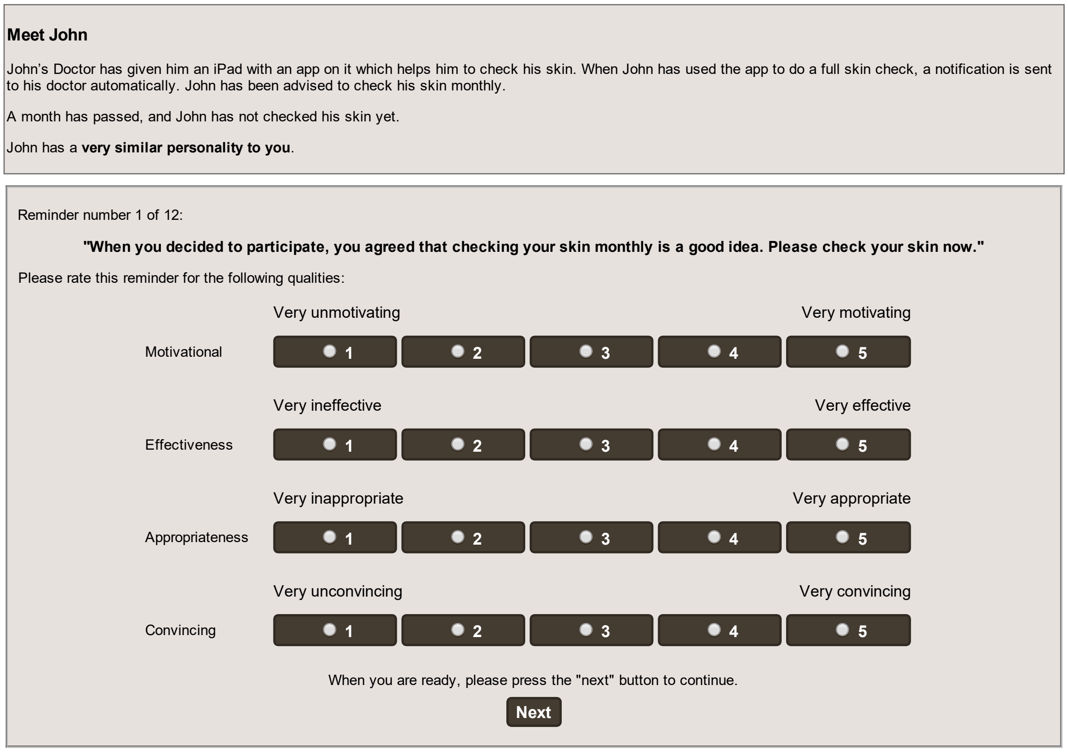


Figure 1: Screenshot of the rating part of the study

tion results of the two messages with the highest kappa per category are shown in Table 2, for each message showing how many participants selected each category as well as the kappa value. In Study 1B, results for Reciprocity were better, though still not excellent, and results for Scarcity were poor for most messages. However, two messages now do have kappa ≥ 0.4.

4. STUDY 2: REMINDER SELECTION

4.1 Study Design

This study investigates which types of reminder are best for those with different personalities. There were three parts to the study. The first section gathered basic demographic information from participants and contained a short personality test. The second part asked participants to rate the reminders for their suitability for "John", a fictional patient, who was described as having a similar personality to the participant. The final part asked participants to pick the best reminder to send, how long they would wait before sending a second reminder if the first one failed, and then asked to pick a second reminder to send.

4.1.1 Participants

The study was administered as a questionnaire on Mechanical Turk [35]. We included a Cloze Test [43] for English fluency to ensure that workers possessed enough literacy skills to understand the language based nature of the task. Participants had to have an acceptance rate of 90%, be based in the US and pass the fluency test in order to be eligible for the study. There were 51 participants (18 female, 33 male; 6 aged 18-25, 35 aged 26-40, 10 aged 41-65).

4.1.2 Materials

We selected 12 reminders, the two most reliably validated reminders for each category from Study 1 (see Section 3).

4.1.3 Variables

The independent variable is the personality of 'John', which matched the personality of the participant.

The dependent variables are: Suitability; the most preferred ('best') reminder to send first; the best reminder to send second; and the length of time between the two reminders. Suitability was based on the average rating of each reminder of four measures: *motivational*, *effectiveness*, *appropriateness* and *convincing*, as shown in Figure 1.

4.1.4 Procedure

The study began by asking participants to complete the English fluency test. If they passed, participants were asked to select their gender and age from a range (both fields were optional). We then administered a short personality test for the Five-Factor Model (FFM) [18], using *Personality Sliders*, a newly developed personality test [42] based on the IPIP-NEO 20 item scales [19]. . For each trait from the FFM, participants were shown two stories (developed by [12]), one depicting a person that was low for that trait and the other depicting someone who was high. Participants used a slider to indicate which person they were most like (see Figure 2), resulting in a value for each trait between 18 and 162. These are validated as accurately measuring the FFM [42].

On the next screen, the participants were shown a short explanation of why skin checking is important, and introduced to "John", a patient who has a similar personality to them. Participants were told that John had not performed

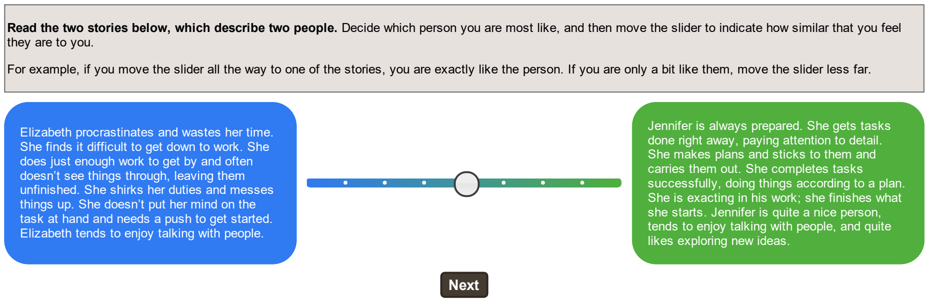


Figure 2: Personality test

Table 3: Correlations between Personality Trait and Mean Rating

	Personality									
	AGR		EXT		CONC		ES		OE	
Reminder	r	p	r	p	r	p	r	p	r	p
SCA1	0.01	0.97	0.09	0.57	-0.13	0.40	0.10	0.50	-0.16	0.30
SCA2	-0.06	0.71	0.10	0.50	-0.14	0.34	0.13	0.38	-0.14	0.37
SCA	-0.02	0.83	0.09	0.37	-0.13	0.20	0.11	0.26	-0.15	0.15
AUT1	-0.19	0.21	0.17	0.27	0.19	0.19	0.18	0.23	0.06	0.70
AUT2	-0.12	0.42	0.04	0.81	0.12	0.44	0.18	0.23	-0.01	0.95
AUT	-0.15	0.15	0.09	0.36	0.15	0.14	0.17	0.09	0.02	0.83
COM1	-0.13	0.40	0.02	0.89	0.06	0.71	0.13	0.40	0.01	0.93
COM2	**-0.33**	**0.03**	-0.26	0.08	-0.04	0.82	0.25	0.10	0.09	0.57
COM	**-0.22**	**0.03**	-0.12	0.24	0.01	0.92	0.18	0.07	0.05	0.64
CON1	0.13	0.39	-0.07	0.65	0.11	0.48	0.15	0.31	0.13	0.38
CON2	0.01	0.94	0.03	0.86	0.19	0.20	0.14	0.36	0.04	0.78
CON	0.07	0.49	-0.02	0.83	0.15	0.15	0.14	0.17	0.09	0.40
REC1	**-0.36**	**0.01**	0.11	0.48	0.18	0.22	0.16	0.27	0.17	0.24
REC2	-0.20	0.18	0.08	0.60	0.17	0.26	0.04	0.80	0.18	0.22
REC	**-0.26**	**0.01**	0.09	0.40	0.16	0.11	0.09	0.38	0.17	0.11
LIK1	-0.06	0.67	-0.02	0.90	-0.02	0.88	0.22	0.13	-0.16	0.77
LIK2	0.14	0.33	0.20	0.20	0.03	0.86	0.13	0.37	-0.17	0.26
LIK	0.04	0.70	0.09	0.39	<0.01	0.99	0.18	0.08	-0.16	0.11
Overall	**-0.09**	**0.03**	0.03	0.42	0.05	0.20	**0.13**	**<0.01**	<0.01	0.93

his skin check yet this month, and that the app needed to send an automated reminder. Next, they rated each of the 12 reminders in turn for their suitability for 'John' using the 4 scales (see Figure 1).

Subsequently, participants were asked to select the reminder that they felt was best for John. The information about the importance of skin checking was repeated to remind the participants. They were then asked how long they would wait before sending a second reminder if the first one failed to provoke John to perform his skin check (1-30 days/ longer). Finally, they were asked to pick the reminder that they would send as the second reminder. Participants could choose to send the same reminder again if they wished.

4.1.5 Hypotheses

Given the exploratory nature of this study, the hypotheses are open-ended. The personality of 'John' will always match that of the participant.

H1: People will rate different reminder types differently overall (some may be better than others).

H1a: People will rate the reminder types differently depending on the personality of 'John'

H2: There will be a difference in the best first reminder type, depending on the personality of 'John'.

H3: The second reminder type will differ from the first reminder type.

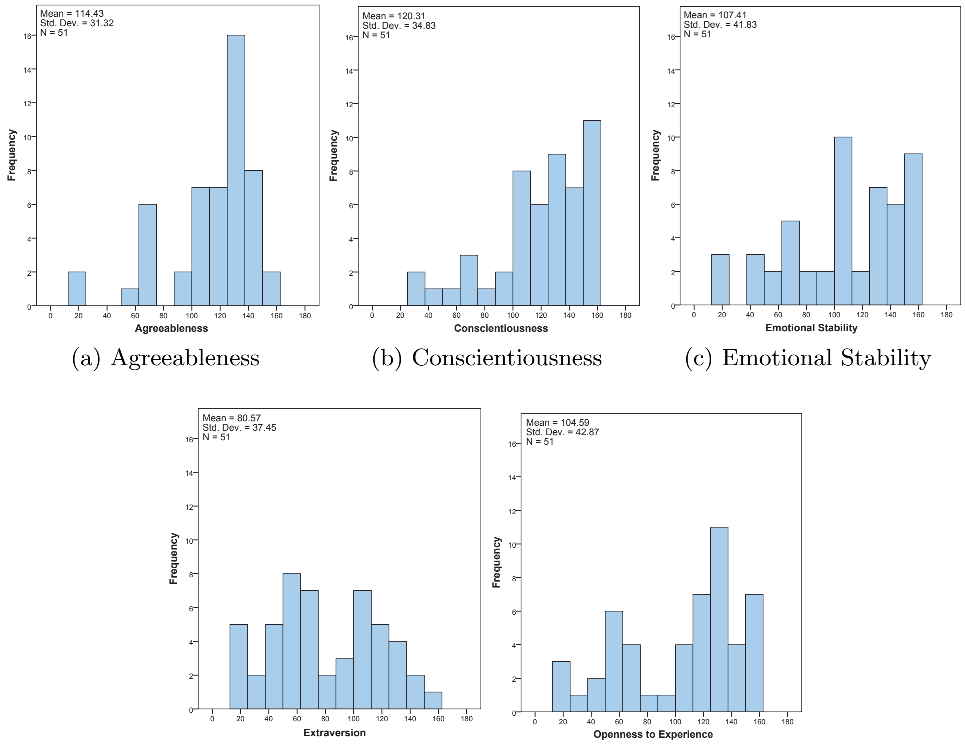
H3a: The second reminder type will differ depending on the personality of 'John'.

H4: The length of time between reminders will vary, depending on the personality of 'John'.

4.2 Results

To investigate the personality diversity of the sample, histograms were drawn for each personality trait. As can be seen from Figure 3, the sample represented a diverse range of personalities.

All data was checked for normality prior to analysis. We also checked that the four measures of *motivational*, *effectiveness*, *appropriateness* and *convincing* reliably measured Suitability. The Cronbach's α of 0.92 indicates an excellent level of internal consistency between the scales.



(a) Agreeableness (b) Conscientiousness (c) Emotional Stability

(d) Extraversion (e) Openness to Experience

Figure 3: Personality Trait Distributions

Table 4: Homogeneous subsets for Reminder Type

Subset	Reminder Type	Mean Rating	S.E.
1	AUT	3.70	0.09
	LIK	3.37	0.10
2	LIK	3.37	0.10
	SCA	3.15	0.10
	CON	3.11	0.11
	COM	2.96	0.10
3	COM	2.96	0.10
	REC	2.54	0.12

Effects of Personality and Reminder Type on Mean Rating. A 6-way ANCOVA of Reminder Type on Mean Rating was performed with covariates of each personality trait score. This was significant ($F(5, 601) = 14.29$, $p < 0.001$) and is shown in Figure 4. Post-hoc tests revealed 3 homogeneous subsets (see Table 4). Authority and Liking were the highest rated categories and Commitment & Consistency and Reciprocity were the lowest rated. This supports *H1*. There were significant effects for the covariants Agreeableness ($F(1, 601) = 4.98$, $p = 0.03$) and Emotional Stability ($F(1, 601) = 12.24$, $p = 0.001$), providing support for *H1a*.

Effects of Personality on Mean Rating. To explore *H1a* further, partial correlations were performed for each personality trait (controlling for other traits) for each Re-

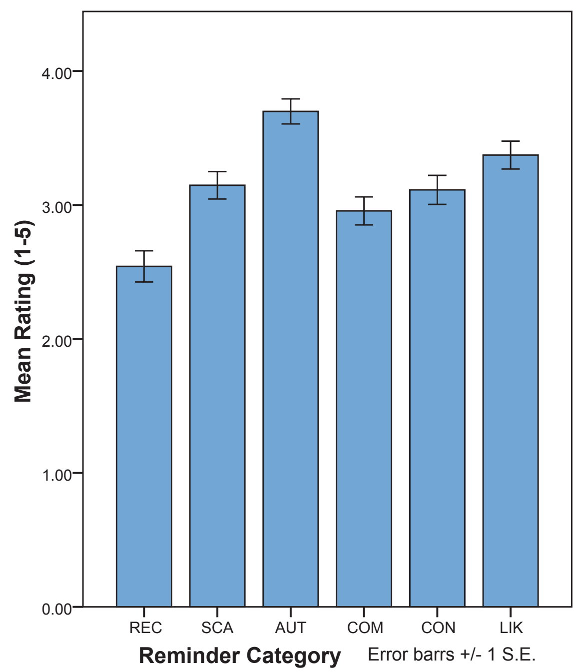


Figure 4: Mean ratings for each category

Table 5: Chi-Squared frequencies for alternative reminder type, for Conscientiousness

	Reminder Type						
CONC	AUT	CON	COM	LIK	REC	SCA	Total
Low	0*	0	4	0	0	5*	9
High	15*	0	10	11	1	5*	42
Total	15	0	14	11	1	10	51

minder, each Reminder Category and Overall. The correlations are shown in Table 3. There were significant correlations for Agreeableness for COM2 and COM, Agreeableness for REC1 and REC and Agreeableness overall. There was also an overall effect for Emotional stability. Participants with low agreeableness rated COM and REC higher than participants with high agreeableness. Participants with high Emotional Stability rated reminders higher that participants with low emotional stability. It should be noted that the correlations we found are quite small and may be of small use to adapt to without further investigation.

Effects of Personality on Best and Alternative Reminder Category. To test *H2*, a Multinominal Logistic Regression was performed of all personality trait scores on the category of the first reminder that was chosen to give to John. This showed no significant effects.

To test *H3a*, a Multinominal Logistic Regression was performed of all personality trait scores on the category of the alternative reminder that was chosen to give to John if the first reminder failed. This showed a significant effect for Conscientiousness ($\chi^2(4) = 14.45$, $p < 0.01$). To investigate the direction of this effect, we divided participants into 2 groups for conscientiousness - a 'low' group with scores less than the midpoint of the scale and a 'high' group. We then ran a χ^2 analysis of Alternative Reminder Category $\times$ Conscientiousness group. This was significant at ($\chi^2(4) = 14.14$, $p < 0.01$). The adjusted residuals show that High Conscientious participants selected AUT reminders, while low conscientious participants selected SCA reminders.

To investigate *H3*, a χ^2 analysis was run on Best Category $\times$ Alternative Category. This was significant ($\chi^2(20)$=40.01, p=0.005). Most participants selected AUT (n=19) or LIK (n=16) for the first reminder and shifted to AUT (n=15), LIK (n=11), SCA (n=10) and COM (n=14) for the second reminder. REC and CON were selected least.

Effects of Personality on Time between reminders. A correlation analysis showed no significant relation between personality trait and the time participants wanted to wait before sending the second reminder (1-30 days or 'longer'), providing no support for *H4* Most participants selected 1 or 2 days (mean 2.29±1.69; see Figure 5).

5. DISCUSSION AND CONCLUSIONS

We have found that personality should be taken into account when deciding on the type of persuasion that should be employed when sending reminders. In particular, we have found that those with high emotional stability are more responsive to any kind of persuasion. Those with low agreeableness rated all types of reminder higher than those with

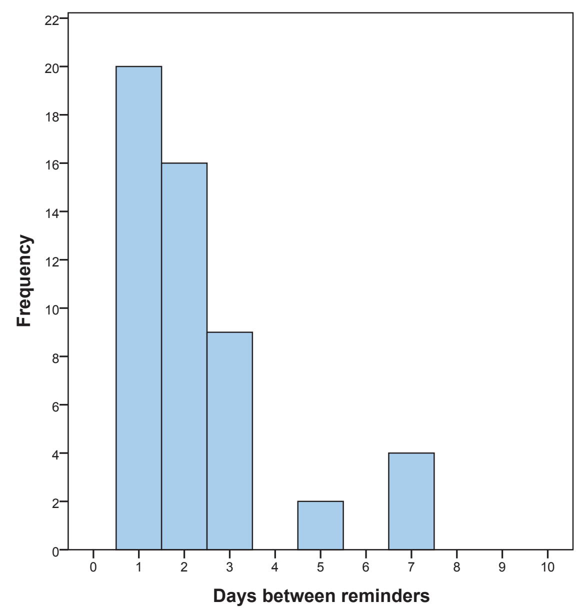


Figure 5: Days to wait between reminders

high, especially commitment/consistency and reciprocity. This is an interesting finding which requires further investigation.

We have also found that if a reminder fails to persuade, many participants picked a reminder of a different category to the first (Authority and Liking are the most popular for the first reminder, and there is a trend to using more Scarcity and Commitment for the second). There is a trend for conscientiousness– those with high conscientiousness prefer alternative reminders which use Authority, whereas those with low conscientiousness prefer Scarcity. This seems appropriate as those with low conscientiousness are more likely to procrastinate and have lower adherence to health treatments [7], so a reminder with a temporal emphasis may persuade them to act earlier. Overall, it seems that participants started with a more generic reminder for the first, then personalised the alternative one subsequently. There was no effect of personality for the time between the two reminders, with most participants waiting 1-3 days.

We have now made an important first step in the tailoring of persuasive reminders to personality. As we now have some indication of how the reminders should be selected, the next step is to consult with medical experts to establish whether they think that the adaptations are appropriate and safe. We will also consult with a patient group to identify any possible issues. These can then be incorporated into an algorithm to allow an intelligent system to utilize these adaptations. We could also make this algorithm more sophisticated by taking the patient's previous record on performing skin checks into account. For example, a neurotic patient who has always completed their skin check on time in the past may require a different reminder to a neurotic patient who is habitually late when performing their skin checks. After this process, the adaptations can be incorporated into the app, so that the effects on real patients can be tested.

In this study, we did not investigate the effect of age and gender on support type - this should be considered in future work. We also do not propose a means of determining the patient's personality so we know what to adapt to. While methods to detect personality automatically remain unreliable, we propose that a quick and easy personality test such as the Tipi test [20] or *Personality Sliders* [42] could be integrated into the set-up of the App.

Further investigations could also be performed into the generalizability of the algorithm for tailoring persuasive reminders in other domains such as physical activity, healthy-eating or other long term health conditions which require a large amount of self monitoring from patients. This would only require minor adjustments to the reminder content for the domain in question. With the rise of many health-monitoring systems and apps, this could be a valuable contribution to sustaining long-term health behaviour change.

6. ACKNOWLEDGEMENTS

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