The impact of communicating personal mental ill-health risk: A randomized controlled non-inferiority trial

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Keywords:	risk communication, mental health, non-inferiority trial, psychological distress, risk algorithm

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The impact of communicating personal mental ill-health risk: A randomized controlled non-inferiority trial

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Abstract (250)

Aim: Risk algorithms predicting personal mental ill-health will form an important component of digital and personalised preventive interventions, yet it is unknown whether informing people of personal risk may cause unintended harm. This trial evaluated the comparative effect of communicating personal mental ill-health risk profiles on psychological distress.

Methods: Australian participants using a mood-monitoring app were randomly allocated to receiving their current personal mental ill-health risk profile (n= 119), their achievable personal risk profile (n=118) or to a control group (n=118) in which no risk information was communicated, in a non-inferiority trial design. The primary outcome was psychological distress at four-weeks as assessed on the Kessler Psychological Distress Scale.

Results: There was high attrition in the trial with 64% of data missing at follow up. Per-protocol (completer) analysis found that the lower bounds of the confidence intervals of the estimated mean change of the current risk (m=0.19, 95% CI: -2.59– 2.98) and achievable risk (m= -0.09, 95% CI: -2.84– 2.66) groups were within the non-inferiority margin of the control group's mean at follow up. Supplementary intention-to-treat analysis using Multivariate Imputation by Chained Equations (MICE) found that 98/100 imputed datasets of the current risk profile group, and all imputed datasets of the achievable risk profile group showed non-inferiority to the control group.

Conclusions: This study provides preliminary support that providing personal mental health risk profiles does not lead to unacceptable worsening of distress compared to no risk feedback, although this needs to be replicated in a fully powered RCT.

Keywords:

Risk communication, mental health, non-inferiority trial, psychological distress, risk algorithm

1. Introduction

Depression and anxiety are leading causes of disability(Whiteford et al., 2013), and preventive interventions are needed to reduce disease burden (Andrews, Sanderson, Slade, & Issakidis, 2000).Identifying at-risk individuals using risk models to deliver targeted lifestyle or drug interventions have long been used in the prevention of cardiovascular disease(Damen et al., 2016) and diabetes (Noble, Mathur, Dent, Meads, & Greenhalgh, 2011). Severalrisk algorithms have been developed and validated to predict mental ill-health (Fernandez et al., 2017; King et al., 2013; King et al., 2011; King, Walker, Levy, & et al., 2008; Wang et al., 2013; Wang, Patten, et al., 2014; Wang, Sareen, et al., 2014), with preliminary support thatinforming patients of their personal risk for depression and their modifiable risk factors with guidance on how to alter behavior, reduces depression incidence(Bellón et al., 2016).

Risk algorithms can be readily incorporated into digital mental health interventions to deliver targeted prevention in an anonymous, cost-effective manner to wide audiences(Deady et al., 2020).Although potentially beneficial, it is unclear whether communicatingthis risk may lead to unintended harms, especially when delivered without human support. Primary care patients generally had a positive attitude towards knowing their personal depression risk, but were concernedsuch information may cause alarm in others(Bellón et al., 2014). Similar concerns have been raised about communicating personal risk of physical diseases, although any adverse effects found are only short-term (less than 1 month)(Collins, Lopez, & Marteau, 2011; Shaw, Abrams, & Marteau, 1999). Onesystematic review reported that informing individuals about their risk of a range of treatable and untreatable physical diseases led to increased short-term distress among those with heightened risk, but no impact on those with low risk (Shaw et al., 1999). Similarlya meta-analysis found that screeningpositive for physical diseases led to a marginal short term increase in depression but no increase in anxiety (Collins et al., 2011). However, no study has experimentally examined the effect of communicating personal risk of mental ill-health on psychological distress.

Understanding one's risk of mental ill-health is considered essential to engaging in prevention. The Health Belief Modelidentifies perceived susceptibility as a key component of preventive health behaviour change (Janz & Becker, 1984), arguing that people are more motivated to engage in prevention behaviours if they believe they are at higher risk of a negative health outcome. In addition, patientsreport that apart from knowing their personal

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3 risk, it was important to be provided with information on how to reduce their risk (Bellón et al.,
4 2014). Our online survey found that people were interested in knowing their personal mental
5 ill-health risk level, modifiable risk factors, and by how much their risk could be reduced (Choi
6 et al., in preparation). However, we do not know if communicating such personal risk
7 reduction has any effect on psychological distress, accuracy of risk perception, and influence
8 on behavior.
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13 This study aimed to examine the impact of communicating personal mental ill-health
14 risk online on prolonged psychological distress. A non-inferiority trial was developed to test
15 the hypothesis that communicating personal risk would not lead to unacceptable
16 deterioration in distress compared to not receiving risk information. The secondary objective
17 was to examine the effects of personal risk profile formats on accuracy of perceived risk and
18 behavior by comparing the effect of two personal risk profile formats (personal risk with and
19 without lowest possible risk).
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26 **2. Method:**

27 **2.1. Design:**

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29 Mindtrack is a mood-monitoring app with a mental ill-health risk assessment
30 component. Embedded in the app was information and consent enabling access to a
31 randomized controlled non-inferiority trial comparing communicating 1) current mental ill-
32 health risk profile, 2) the current risk profile + “achievable” risk profile with modifiable risks,
33 and 3) no risk information (control). The study was approved by the Human Research Ethics
34 Committee (HREC) of the University of Sydney (project number: 2017/728) and registered
35 as ACTRN12617001390370.
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43 **2.2. Participants and recruitment:**

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45 Participants were recruited online using Facebook advertisements and shared social
46 media posts from partners (e.g. Black Dog Institute, beyondblue) from December 2017 to
47 March 2018. An industry organisation also promoted the app to employees via email
48 communications. The promotional material directed interested people to download the
49 free Mindtrack app from Apple or Google Play app stores. People were eligible to participate
50 if they were aged between 18 years and 70 years, were fluent in English, were resident in
51 Australia, had a smartphone and a valid mobile number.
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58 **2.3. Procedures and randomisation:**

Participants provided consent in the Mindtrack app and proceeded to baseline measures including psychological distress and the risk assessment consisting of items from a validated, gender specific risk algorithm to predict mental ill-health among working Australian adults (Fernandez et al., 2017) (Table 1). Participants were then randomised within the app using an automatic random allocation sequence to receive one of two active interventions or the control in a 1:1:1 ratio, as described below. Participants and researchers were not blinded to group assignment.

All participants were encouraged to use Mindtrack to track their mood and complete weekly measures on distress. Participants received a sms and/or phone reminder to complete the endpoint measures at four weeks follow up using an online survey. The app automatically recorded the number of times it was opened and number of moods logged.

2.4. Interventions:

2.4.1. Current mental ill-health risk profile:

Participants received their personal risk estimate of developing mental ill-health within the next 12 months (based on the risk algorithm) immediately after completing the baseline assessment. A screen with an icon array displayed their personal numerical risk, along with a text description "XX out of 100 people with your risk factors are likely to become distressed within the next year" (see Figure 1a).

2.4.2. Achievable mental ill-health risk profile:

In addition to receiving their personal risk estimate as above (Figure 1a), this group were shown their "achievable risk" on the next screen (Figure 1b), in which the icon array displayed the lowest possible risk estimate for that individual, based on the targets being met for all the modifiable risk factors (Table 1). The difference in the risk estimate was shown in a lighter green colour to indicate the reduced risk, with the accompanying text "Many risk factors are changeable. You could lower your risk to XX out of 100 by improving your mental fitness". The screen also displayed their top five modifiable risk factors, each accompanied with a simple message indicating ways they could reduce their risk, e.g. exercising less than three times a week was accompanied by: "Regular exercise is more than just physically good for you, it also reduces stress and your risk of depression and anxiety. Whether it's a walk, a ride or climbing the stairs, how could you add a bit of exercise to your week?".

2.4.3. Controls:

The control group were given the standard Mindtrack app and received risk feedback after the follow up.

2.5. Measures

2.5.1. Primary outcome: Psychological distress

The Kessler Psychological Distress Scale (K10) is a validated measure of nonspecific psychological distress (Furukawa, Kessler, Slade, & Andrews, 2003) with demonstrated sensitivity to change in an Australian sample (Perini, Slade, & Andrews, 2006). Instructions of the K10 were changed to refer to the past week as it was administered weekly in this study. The internal consistency of the K10 was $\alpha=.92$.

2.5.2. Secondary outcome: Perceived risk accuracy

At follow up, participants were asked about their perceived risk of developing a mental health problem within the next year ranging from 0 (certain not to happen) and 100 (certain will happen). To examine accuracy of perceived risk, the participant's perceived risk was subtracted from their actual risk estimate. We recoded the difference into a categorical variable, with $<-10\%$ indicating underestimation, $> 10\%$ indicating overestimation, and accurate if $-10\% \leq D \leq 10\%$, in accordance with previous studies (Rimer et al., 2002). Participants were asked "Have you sought help for a mental health problem from any of the sources in the past month (apart from engaging in this app)?" at follow up.

2.6 Statistical methods

Power calculations were based on a non-inferiority parallel arm trial design. The non-inferiority margin of the mean difference of the primary outcome measure K10 was set at 4.6 points; the difference between the mean Australian score for people without ($M=14.5$, $SD=9.4$) and with a mental disorder ($M=19.1$) in the 2007 National Survey of Mental Health and Wellbeing (Slade, Grove, & Burgess, 2011). Test criterion for non-inferiority was that the lower bounds of the 95% confidence intervals (CI) of the mean K10 change score for the risk profile groups should fall within 4.6 points of the control group's mean at four weeks follow up. Considering this predefined non-inferiority margin, 68 participants per group were required to determine non-inferiority with a power of 80% using a one-sided Student's t-test for independent samples at 2.5% type I error. A total of 340 participants need to be recruited for estimated 40% attrition.

In non-inferiority trials, intent-to-treat (ITT) analyses have been criticized as anticonservative because they typically decrease the differences between groups and favour

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the null hypothesis, increasing the likelihood of concluding non-inferiority(Sanchez & Chen, 2006). Conversely, per-protocol (PP) analyses do not consider the impact of dropouts, and downplay the influence of continuing participants being more likely to be those who respond. CONSORT guidelines state there is greater confidence if both ITT and PP analyses support non-inferiority (Piaggio et al., 2006). Hence, in this study, per-protocol analysis was performed with complete cases, supplemented by ITT analysis, in which 100 imputed datasets were synthesised with multiple imputation (Azur, Stuart, Frangakis, & Leaf, 2011) using MICE (Multivariate Imputation by Chained Equations) (van Buuren & Groothuis-Oudshoorn, 2011) where missing values for the change in total distress scores from baseline to follow up were imputed with predictive mean matching (Roderick, 1988). Plausibility of the imputed values were inspected visually and the mean endpoint distress scores and its associated 95% CI were calculated for each group for each imputed dataset.

Statistical analyses were conducted using IBM SPSS Statistics version 24. ANOVA, t-tests, and chi-square analyses were used to estimate between-group differences in demographics and baseline measures, and for attrition. Mean distress change scores from baseline to follow up were calculated for each group. Thesewereanalysed usingANCOVA controlling for baseline K10 score and age, comparing the current risk profile group to controls, and the achievable risk profile group to controls, and computed to find the lower bounds of the 95% confidence interval to establish non-inferiority. ANOVA and chi-square tests were used to compare groups over time and for the secondary outcomes.

3. Results:

684 participants enrolled in the study but 329did not meet inclusion criteria (see Figure 2). 355 participants were randomised to one of three feedback interventions: the current mental ill-health risk profile (n=119), achievable mental ill-health risk profile(n=118), or control (n=118).

Majority of participants were women (68%) with a mean age of 31.9 years (SD=12.6). About 80% self-reported a period of mental ill-health in the past two years and 79% had a high risk of mental ill-health in the next 12 months, compared to 12% in a nationally representative sample (Fernandez et al., 2017). There was no significant between group differences on any demographic or clinical baseline characteristics or risk scores (Table 2).

3.1. Attrition

The 4 week follow up K10 score was missing in 80/118 of the control group (67.8%), 75/119 of the current risk group (63.0%) and 71/118 of the achievable risk group (60.2%). There was no differential in attrition between arms of the trial ($\chi^2 = 1.52$, $p = .469$). Overall those who remained in the trial were significantly older than those who dropped out ($t_{1,353} = -2.67$, $p = .008$). There was no other significant association of baseline demographic or clinical measures with attrition (Supplementary Table 1). The mean endpoint distress scores and the density plot for per-protocol, last-observation carried forward (LOCF), and as predicted by MICE are similar (Figure 3).

3.2. Change in distress over time

The per-protocol (completer) mean K10 score at baseline was 26.30 (SD=8.61), and mean score at 4-week follow up was 24.43 (SD= 8.29). Figure 4 presents the change of K10 scores over the four weeks across the groups. Participants showed a significant reduction in distress scores from baseline to Week 1 ($F_{1,198} = 27.35$, $p < .0005$), with no significant difference between groups ($p > .05$), and from baseline to four weeks follow up ($F_{1,126} = 18.522$, $p < .0005$), again with no group differences ($p > .05$).

3.3. Non-inferiority mean score change in psychological distress

Per-protocol analysis controlling for age and baseline K10 scores confirmed that the mean K10 score change was not significantly different between groups ($F_{2,124} = .024$, $p = .976$) (Table 3). The estimated difference in mean K10 change score between the current risk profile group and control group was 0.19 (95% CI -2.59– 2.98) ($p = .891$). This equates to an effect size of 0.04, and a total sample of 19,328 would have been required to show that this effect size was 'statistically significant' at alpha 2.5% and 80% power. The estimated difference in mean K10 change score between the achievable risk profile group and controls was even less; -0.09 (95% CI -2.84– 2.66) ($p = .946$), an effect size of 0.01, only detectable with a sample size of 193,480 at 2.5% alpha and 80% power. Even with this relatively small sample, the lower bounds of our obtained confidence intervals for the mean differences in distress were within the predefined non-inferiority margin (4.6 points), suggesting that the current risk and achievable risk groups were non-inferior to controls. Five participants (11%) in the current risk profile group, three (6.4%) in the achievable risk profile group, and four (10.5%) in the control group had higher change scores than the predefined non-inferiority margin.

For the ITT analysis, 98/100 imputed datasets showed non-inferiority of the current risk profile group to the control group as the lower bounds of the 95% CI of the mean change in total K10 score for the current risk group was within the predefined non-inferiority margin.

For the achievable risk group, all imputed datasets were within the predefined non-inferiority margin.

3.4. Perceived risk accuracy

The intervention groups differed significantly on the accuracy of their perceived risk ($\chi^2=12.43$, $p=.014$) (Table 4). Half of the current risk group correctly perceived their risk level, while the achievable risk group were equally likely to be accurate or overestimate or underestimate risk, and the control group tended to underestimate their risk.

3.5. Help-seeking

Most participants (81%) sought help from formal or informal sources during the four weeks of using the app with no significant difference between groups ($p>.05$). About half (47%) reported seeking help from a health professional (mental health professional, GP), 60% reported seeking informal assistance (family, friend, minister), while 26% sought help from helplines or online.

3.6. App engagement

Participants opened the app an average 5.21 times ($SD=6.94$; range 1-55) and logged 7.25 moods ($SD=12.75$; range 0-88) over 4 weeks. There was no significant difference between groups on these engagement metrics (all $ps>.05$)

4. Discussion:

This is the first study empirically evaluating whether communicating personal mental ill-health risk profile has a potentially unintended impact on prolonged psychological distress. Trial attrition was higher than expected at about 64%, and while this is not unusual given online app use and fully automated trial (Geraghty, Torres, Leykin, Perez-Stable, & Munoz, 2013) (Eysenbach, 2005), the study was underpowered and results should be interpreted with caution. The per-protocol analysis supported that providing personal mental ill-health risk profiles did not lead to unacceptable worsening of distress compared to not communicating risk. The supplementary ITT analysis with MICE, while not ideal given the high attrition (Jakobsen, Gluud, Wetterslev, & Winkel, 2017), also showed support for non-inferiority.

In contrast to the small but significant short term increases in distress among individuals informed of their risk for physical diseases (Collins et al., 2011; Shaw et al., 1999),

psychological distress improved within the first week of receiving personal mental ill-health risk feedback. There are several possible explanations. First, this sample displayed above average levels of distress at baseline and were at high risk of developing mental ill-health according to the risk model. Providing this relatively unwell and high-risk group with risk feedback might not cause further distress because of ceiling effects. The high attrition and high representation of high-risk individuals precluded a sensitivity analysis comparing low versus high risk individuals leaving open the question of the impact in low risk groups. Second, risk of physical health problems is often communicated to people free of disease and being informed of high risk of serious disease can lead to distress. As most of our sample have had previous mental ill-health, it is possible they were less perturbed by the risk feedback. Participants may also hold positive beliefs that mental ill-health can be prevented (Jorm, Morgan, & Wright, 2010; Schomerus, Angermeyer, Matschinger, & Riedel-Heller, 2008; Yap, Reavley, & Jorm, 2012), and felt they could reduce their (often high) risk. Third, it is possible that participants in the intervention groups may not have registered their risk seriously because of the nature of risk being presented in an app and there was lack of information about the validity of the risk algorithm.

Although others have reported that patients want be provided with risk reduction information (Bellón et al., 2014), we found no added impact of communicating this potential risk reduction. Communicating risk did not lead to higher help-seeking or app engagement among participants. This is similar finding to other studies which found providing online feedback with mental health screening does not facilitate formal help seeking (Batterham, Calear, Sunderland, Carragher, & Brewer, 2016).

Despite efforts to accurately communicate risk using easily understandable natural frequencies and pictograms (Waldron, van der Weijden, Ludt, Gallacher, & Elwyn, 2011), only half of the current risk group were accurate in their risk estimate. Nonetheless this provides encouraging support that communicating personal risk can improve perceived risk accuracy, as a recent study found that high risk people tended to overestimate their risk (Wang et al., 2020). A limitation in asking participants to rate their perceived risk at four-weeks follow up may have been measuring their recall rather than accurate understanding of risk. Further, the mixed results in the achievable risk group may reflect they have confused their “current risk” and “achievable risk” in their responses. Changing behaviour might require challenging this risk-perception gap as in motivational interviewing. Help-seeking too was assessed only at the follow-up, so it is unclear whether this was a proactive “treatment-seeking” sample, which may have biased study findings.

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This study provides preliminary support that communicating personal mental ill-health risk profiles does not have major adverse effects on prolonged distress, even when communicated online without personal contact, suggesting there is potential for it to be safely incorporated in digital prevention interventions for common mental disorders. While both the per-protocol and ITT analysis supported an inference of non-inferiority, the high attrition rate meant that these results need to be interpreted with caution, and findings need to be replicated in a fully powered RCT in order to draw confident conclusions that communicating personal mental ill-health risk does not cause prolonged distress. Although our sample was relatively unwell and high risk compared to the general population, this is the exact target group for selective prevention interventions. Future research is needed to explore the impact of communicating risk on low-risk people, and to explore how to engage and motivate people to manage and reduce their risk once this is communicated. The COVID-19 pandemic has accelerated digital health service development and provision (Wind, Rijkeboer, Andersson, & Riper, 2020). Understanding how best to implement and possible negative effects will be increasingly important.

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Data statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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For Peer Review

a) Current risk

b) Achievable risk

Figure 1. Example personal mental ill-health risk profile

CONSORT 2010 Flow Diagram

Figure 2. Participant flow.

	Per Protocol (N=129)	LOCF (N=226)	MICE (N=22600)
T1_K10_total			
Mean (SD)	24.4 (8.29)	25.9 (8.63)	24.8 (12.6)
Median [Min, Max]	23.0 [10.0, 49.0]	25.0 [10.0, 48.0]	23.0 [10.0, 49.0]

Figure 3. End point K10 scores as observed per-protocol, LOCF, and predicted by MICE.

Figure 4. Change in K10 mean score over time across the groups.

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For Peer Review

Table 1. Items in the mental ill-health risk assessment

Women	Men
Age	Age
Being from an Aboriginal and/or Torres Strait Islander background	Being a carer *
Satisfaction with the hours worked *	Agree with the statement 'I have lot of freedom to decide at work' *
Satisfaction with employment opportunities *	Doing physical activity 3 or more times per week *
History of common mental disorders	Drinking between 1 and 4 drinks per week (ref. none) *
	Drinking more than 4 drinks per week (ref. none) *
Satisfaction with health *	History of common mental disorders
Agree with the statement 'I am pushed around' *	Satisfaction with health *
Agree with the statement 'I don't have anyone that I can confide in' *	Satisfaction with the neighbourhood *
	Neutral satisfaction with partner (ref. satisfied with partner) Dissatisfied with partner (ref. satisfied with partner) Not having a partner (ref. satisfied with partner) *
	Neutral satisfaction with the way tasks are divided at home (ref. satisfied) Dissatisfied with the way tasks are divided at home (ref. satisfied) Not having to divide tasks at home (ref. satisfied) *
	Agree with the statement 'I don't have anyone that I can confide in' *
	Agree with the statement 'I am pushed around' *
	English as a second language

* Denotes risk factors that are potentially modifiable.

Table 2. Demographic and baseline characteristics of participants.

	Control (n=118)	Current risk (n=119)	Achievable risk (n=118)	Difference
Age (SD)	30.92 (11.87)	31.64 (13.16)	33.14 (12.80)	$F_{2,352}=.950, p=.388$
Gender				$\chi^2=2.359, p=.308$
<i>Female</i>	85 (72%)	81 (68%)	74 (63%)	
<i>Male</i>	33 (28%)	38 (32%)	44 (37%)	
Aboriginal or Torres Strait Islander	6 (5%)	3 (2.5%)	1 (1%)	
English as second language	17 (14%)	16 (13%)	20 (17%)	$\chi^2=.611, p=.737$
Education				$\chi^2=1.949, p=.745$
<i>High school</i>	38 (32%)	36 (30%)	32 (27%)	
<i>Trade or other certificate</i>	30 (25%)	37 (31%)	32 (27%)	
<i>University degree</i>	50 (43%)	46 (39%)	54 (46%)	
Work status				
<i>Not working</i>	26 (22%)	26 (22%)	17 (14%)	$\chi^2=5.776, p=.216$
<i>Part time paid work</i>	43 (36%)	48 (40%)	40 (34%)	
<i>Full time paid work</i>	49 (42%)	45 (38%)	61 (52%)	
In relationship	71 (60%)	67 (56%)	67 (57%)	$\chi^2=.431, p=.806$
Previous poor mental health	94 (80%)	92 (77%)	93 (79%)	$\chi^2=.200, p=.905$
K10 score (SD)	25.95 (8.054)	26.77 (9.19)	26.19 (8.60)	$F_{2,352}=.287, p=.751$
Risk score (SD)				
<i>Male</i>	.48 (.30)	.40 (.26)	.50 (.26)	$F_{2,112}=1.466, p=.235$
<i>Female</i>	.58 (.25)	.58 (.24)	.55 (.26)	$F_{2,237}=.528, p=.590$
Risk category				
<i>Low to average</i>	26 (22%)	26 (22%)	24 (20%)	$\chi^2=.121, p=.941$
<i>High</i>	92 (78%)	93 (78%)	94 (80%)	

Table 3. Mean K10 scores across groups from baseline to follow up (per protocol)

K10	Current risk (n=44)	Achievable risk (n=47)	Control (n=38)
Baseline (SD)	27.07 (8.73)	26.89 (9.17)	27.34 (7.73)
4-week follow up (SD)	24.59 (6.59)	24.19 (9.72)	24.55 (8.37)
Mean change (SD)	-2.48 (7.09)	-2.70 (5.64)	-2.79 (8.25)
Estimated mean change (95% Confidence Intervals)	-2.39 (-4.27 – -.51)	-2.77 (-4.59 – -.96)	-2.81 (-4.83 – -.78)

For Peer Review

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Table 4: Accuracy of perceived risk

	Current risk group	Achievable risk group	Control
	N (%)	N (%)	N (%)
Accurate	22 (50%)	15 (32%)	6 (16%)
Overestimate risk	12 (27%)	15 (32%)	11 (30%)
Underestimate risk	10 (23%)	17 (36%)	20 (54%)

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Supplementary Table 1: Baseline demographic and clinical characteristics of those who dropped out and completed 4 week follow up.

	Dropped out (n=226)	Remained in trial (n=129)	Significance
Age (SD)	30.54 (11.80)	34.26 (13.67)	$t_{1,353} = -2.69, p = .007$
Gender			$\chi^2 = .877, p = .349$
<i>Female</i>	149 (65.6%)	91 (37.9%)	
<i>Male</i>	78 (34.4%)	37 (28.9%)	
Education			$\chi^2 = 3.354, p = .187$
<i>High school</i>	75 (33.2%)	31 (24%)	
<i>Trade or other certificate</i>	61 (27 %)	38 (29.5%)	
<i>University degree</i>	90 (39.8%)	60 (46.5%)	
Work status			
<i>Not working</i>	38 (16.8%)	31 (24%)	$\chi^2 = 2.780, p = .249$
<i>Part time paid work</i>	87 (38.5%)	44 (34.1%)	
<i>Full time paid work</i>	101 (44.7%)	54 (41.9%)	
In relationship	123 (54.4%)	82 (64.6%)	$\chi^2 = 2.450, p = .118$
Previous poor mental health	175 (77.4%)	104 (80.6%)	$\chi^2 = .324, p = .569$
K10 score (SD)	25.86 (8.63)	27.09 (8.55)	$t_{1,353} = -1.29, p = .197$
Risk category			
<i>Low to average</i>	48 (21.2%)	28 (21.7%)	$\chi^2 = .000, p = 1.000$
<i>High</i>	178 (78.8%)	101 (78.3%)	