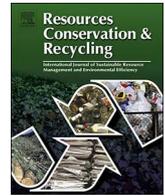




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## Review

## The jury is still out on social media as a tool for reducing food waste a response to Young et al. (2017)



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## ABSTRACT

Young et al. (2017) conclude that “social media...cannot replicate enough of the interaction shown by face to face social influence interventions to change reported behaviour more than the control group (those that did not see the interventions)”.

This statement is premature considering the weight of knowledge that has been accumulated in the behaviour change literature in fields such as psychology and medicine over the past decade. Rather than suggesting that social media cannot be used as an effective behaviour change agent in the realm of food waste we suggest that Young et al. (2017) well illustrates the importance of evidence-synthesis. The lack of behaviour change from a relatively small sample of people in a study with an untargeted intervention provides one small piece of the jigsaw.

Young et al. (2017) pose an important question “Can social media be a tool for reducing consumers’ food waste?” Consumer food waste is thought to account for the largest proportion of all food waste in developed countries (Parfitt et al., 2010). In the 28 European Union countries consumer food waste constitutes between 46.7 and 63.5% of the total estimated food waste of  $87.6 \pm 13.7$  (95% CI) million tonnes (Stenmarck et al., 2016). Efforts to reduce this level of waste have increasingly become important for governments and civil society in the interests of environmental sustainability and cost reduction. Young et al. (2017) in collaboration with a major UK supermarket company aimed to assess the influence of social media (Facebook) interventions on self-reported food waste behaviour in comparison to information interventions (Asda Magazine and e-newsletter) and a control group. This was done in a “field” situation and not a tightly controlled experiment; hence Young et al. (2017) could be an important contribution to our understanding of behaviour change in relation to food waste interventions.

Young et al. (2017) report that there was no difference in the performance of the social media intervention when compared to the information interventions or to the control group. They suggest that all groups (interventions and controls) showed a statistically significant reduction in self-reported frequency and quantity of food waste. Despite reporting the effect size (0.01), Young et al. do not discuss the magnitude of the effect. Statistical significance means very little in the absence of effect size (Sullivan and Feinn, 2012) and a minimal (0.01) effect size means that there was very little change in behaviour.

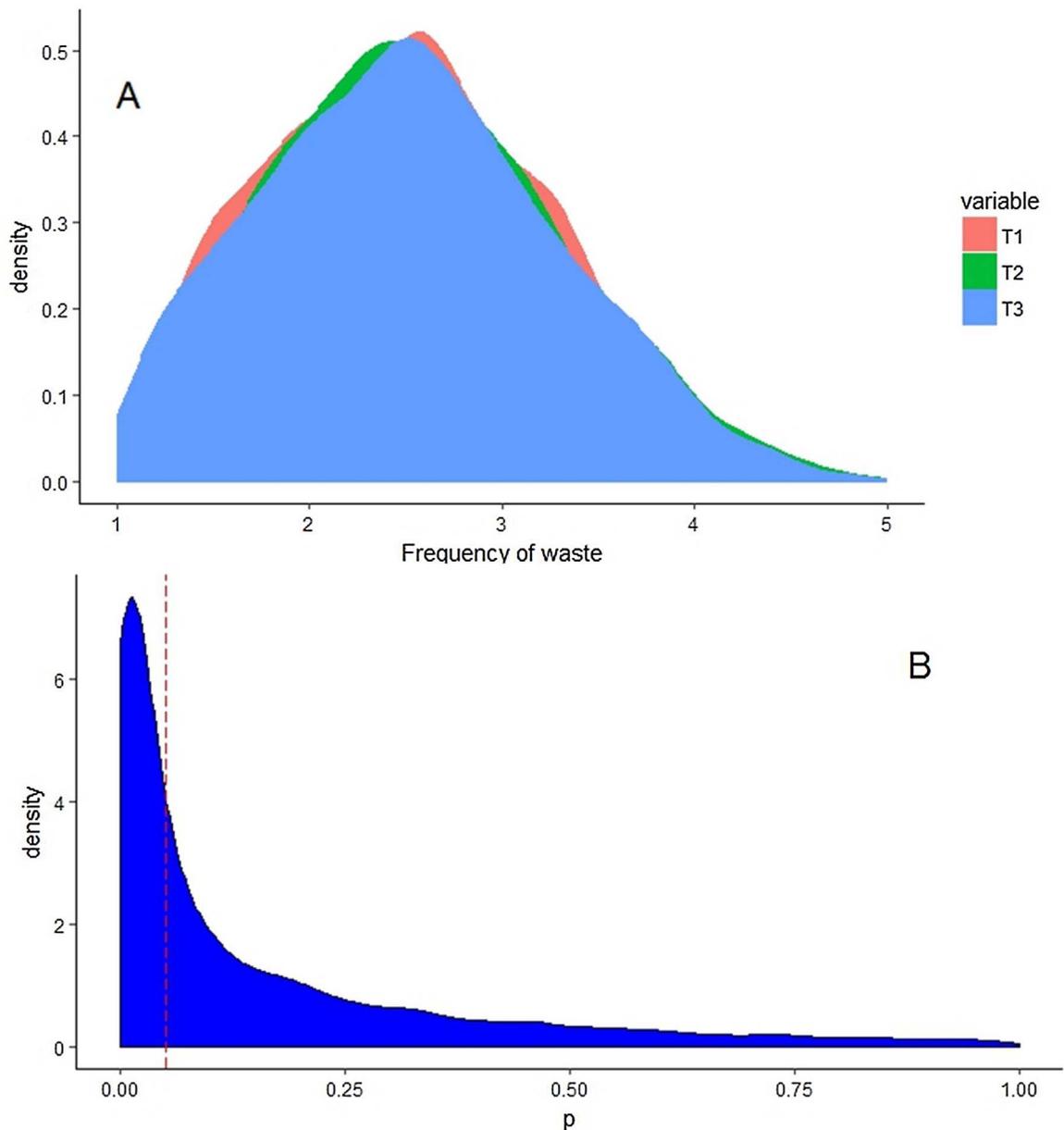
With regard to the category of food wasted a statistically significant decrease in salad waste is reported and Young et al. (2017) suggest this is driving the pattern observed in the frequency and quantity of food wasted over the three time periods. Once again the effect size was minimal (0.01) and the magnitude was not discussed.

The effect size represents the magnitude of the difference between the mean of a test and a control group (Sullivan and Feinn, 2012). It is important to note that a small effect size can be meaningful (Bayliss et al., 2015). So called “t-shirt size” effects have been criticised and it is essential that one relates the effect size to the data presented as an effect size of 0.4 (for example) could be meaningful in one study and not in another (Kline, 2009). Young et al. (2017) do not provide any indication of why they consider such a small effect size behaviourally significant and do not provide the data behind their work (presumably due to commercial confidentiality) to allow researchers to assess this independently.

The data on the frequency of waste is scaled between 1, “Never” and 5 “Most mealtimes” (the intervening values are not defined in Young et al.). The mean values range between 2.36 and 2.63 measured on a 5 point likert scale. We used the R programme (R Core Team, 2016) to simulate data with a similar structure to that of Young et al. (2017) using the means and standard deviations as presented in Table 1 of their Appendix (all R code is available at: [https://osf.io/sqd8g/?view\\_only=27b3f2c5f1684a388ec59c0d100e7a3b](https://osf.io/sqd8g/?view_only=27b3f2c5f1684a388ec59c0d100e7a3b)). We produced 10,000 simulated datasets (Fig. 1a) and tested these with one-way repeated measures ANOVA and then extracted the p values for these tests

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**Fig. 1.** a) The distribution of data for the frequency of waste in Time period 1–3 for the 10,000 simulations of data based on the means and standard deviations reported in Young et al. (2017). b) The distribution of p-values for one-way repeated measures ANOVA on the 10,000 simulated datasets. The red dashed line indicates  $\alpha = 0.05$ . (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(Fig. 1b). The distribution of the datasets (Fig. 1a) shows that the different time periods greatly overlap. Only 46.6% of the 10,000 tests run resulted in a p value less than 0.05 (Fig. 1b).

Young et al. (2017) also report the statistically significant results of *t*-tests comparing time periods for different interventions. For example, again for the frequency of food wasted, those people exposed to the Facebook intervention reported a change in behaviour from Time 1 ( $M = 2.47$ ,  $SD = 0.91$ ) to Time 3 ( $M = 2.41$ ,  $SD = 0.91$ ). Again using simulation (10,000 iterations) we applied *t*-tests to the data. Only 17.07% of the 10,000 tests resulted in a p value less than 0.05 (Fig. 2a). The minimal absolute difference between means to achieve a statistically significant result (i.e.  $p < 0.05$ ) is around 0.1 of a likert scale (Fig. 2b).

Hence, from the data that are presented in Young et al. (2017) and our simulations we would conclude that there was a small statistically significant effect but no behaviourally significant effect of the interventions and of time on food waste behaviour. It is clear from our simulations (Fig. 1b) that the sample size ( $n = 2018$ ) was too small to

adequately identify an effect if one was there. This in combination with the small effect size and the reliance on self-reported measures of food waste (which is acknowledged by Young et al., 2017) increases the risk of bias.

Young et al. (2017) suggest that their paper shows that “social media...cannot replicate enough of the interaction shown by face to face social influence interventions to change reported behaviour more than the control group (those that did not see the interventions)”. This statement is premature considering the weight of knowledge that has been accumulated in the behaviour change literature in fields such as psychology and medicine over the past decade. Meta-analysis has consistently reported small but positive effect sizes of online interventions on behaviour change (Wantland et al., 2004; Barak et al., 2007; Maher et al., 2014; Short et al., 2015). The heterogeneity observed in these meta-analytical studies has been attributed to the type and number of behaviour change techniques employed. Using individually targeted interventions online with repeated reminders is more effective than a single non-targeted approach (Short et al., 2015).

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