Routledge
Taylor & Francis Group

The Journal of Positive Psychology

Dedicated to furthering research and promoting good practice

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rpos20

Predicting individual response to a web-based positive psychology intervention: a machine learning approach

Amanda C. Collins, George D. Price, Rosalind J. Woodworth & Nicholas C. Jacobson

THE JOURNAL OF POSITIVE PSYCHOLOGY
https://doi.org/10.1080/17439760.2023.2254743

Predicting individual response to a web-based positive psychology intervention: a machine learning approach

Amanda C. Collins [a,b,c], George D. Price [a,d], Rosalind J. Woodworth [e] and Nicholas C. Jacobson [a,d,f,g]

[a]Center for Technology and Behavioral Health, Geisel School of Medicine, Dartmouth College, Lebanon, NH, USA; [b]Department of Psychiatry, Dartmouth-Hitchcock Medical Center, Lebanon, NH, USA; [c]Department of Psychology, Mississippi State University, Starkville, MS, USA; [d]Quantitative Biomedical Sciences Program, Dartmouth College, Lebanon, NH, USA; [e]IWK Health Centre, Halifax, Canada; [f]Department of Psychiatry, Geisel School of Medicine, Dartmouth College, Lebanon, NH, USA; [g]Department of Biomedical Data Science, Geisel School of Medicine, Dartmouth College, Lebanon, NH, USA

ABSTRACT

Positive psychology interventions (PPIs) are effective at increasing happiness and decreasing depressive symptoms. PPIs are often administered as self-guided web-based interventions, but not all persons benefit from web-based interventions. Therefore, it is important to identify whether someone is likely to benefit from web-based PPIs, in order to triage persons who may not benefit from other interventions. In the current study, we used machine learning to predict individual response to a web-based PPI, in order to investigate baseline prognostic indicators of likelihood of response ($N = 120$). Our models demonstrated moderate correlations (happiness: $r_{Test} = 0.30 \pm 0.09$; depressive symptoms: $r_{Test} = 0.39 \pm 0.06$), indicating that baseline features can predict changes in happiness and depressive symptoms at a 6-month follow-up. Thus, machine learning can be used to predict outcome changes from a web-based PPI and has important clinical implications for matching individuals to PPIs based on their individual characteristics.

ARTICLE HISTORY
Received 22 September 2022
Accepted 13 July 2023

KEYWORDS
Positive psychology; depression; machine learning; digital intervention

Happiness is often emphasized as a goal to strive toward given that it is typically associated with increased positive emotions, life satisfaction, and a meaningful life (Diener et al., 2009; Myers & Diener, 2018; Seligman et al., 2005). In addition, happier individuals often have more social support, are more successful, and have fewer physical and psychological symptoms (Cohn et al., 2009; Lyubomirsky et al., 2005; Myers & Diener, 2018). Indeed, previous research has suggested that a happiness-success link exists. Specifically, a reciprocal relationship exists between happiness and success such that individuals who experience happiness and positive affect are more likely to achieve goals and be successful or accomplished, thus resulting in them feeling happier (Boehm & Lyubomirsky, 2008; Lyubomirsky et al., 2005; Walsh et al., 2018). Thus, finding ways to capitalize on and improve happiness can provide several benefits for individuals' personal life (e.g. work), subjective well-being, and psychological symptoms (e.g. depression).

Positive psychology interventions (PPIs) have gained popularity over the past two decades due to their emphasis on increasing happiness and reducing depressive symptoms (Bolier et al., 2013). Indeed, findings from two meta-analyses suggest that PPIs are overall effective for these two outcomes, demonstrating small to medium effect sizes (Bolier et al., 2013; Carr et al., 2021). Given that traditional interventions for depression, including cognitive behavioral therapy, target enhanced negative biases, PPIs can serve as a standalone or add-on intervention to target depressed individuals' reduced positive biases and increase happiness. Seligman et al. (2005) created a series of five web-based exercises aimed to increase overall happiness with common themes of (1) gratitude, (2) identifying positivity in one's daily life, (3) reflecting on one's 'best self', (4) identifying one's signature strengths, and (5) using one's signature strengths in new ways. Overall, individuals demonstrated improvements in happiness and reductions in depressive symptoms after one week, with two of the PPI exercises resulting in improvements for 6-months. Thus, their findings provided initial evidence that engaging in a PPI for one week can lead to improvements in well-being. Potentially as important, however, is that participants completed these exercises independently via an online website (i.e. they completed a web-based intervention). Moreover, these findings are in line with meta-analytic findings indicating that short-term (i.e. 1 week) self-guided PPIs are effective in improving well-being and depressive symptoms (Bolier et al., 2013).

CONTACT Amanda C. Collins Amanda.C.Collins@dartmouth.edu Center for Technology and Behavioral Health, Dartmouth College, 46 Centerra Parkway Suite 300, Office # 338S, Lebanon, NH 03766, USA
Supplemental data for this article can be accessed online at https://doi.org/10.1080/17439760.2023.2254743

Web-based interventions

Although PPIs can be delivered in a traditional in-person format, PPIs have gained popularity as a web-based intervention (e.g. self-guided), given their increased accessibility and the decreased cost to deliver them (Bolier et al., 2013; Davies et al., 2020). Indeed, there are several advantages to web-based interventions over traditional in-person interventions. First, web-based interventions can be delivered to larger populations and include fewer resources, including clinicians, to operate (Wilhelm et al., 2019). Second, they are often free or of low cost. Third, they can be completed on an individual's own time from their home instead of during the traditional working day at a clinic, resulting in potential solutions for low access areas (Davies et al., 2020; Teachman, 2014; Woodworth et al., 2017). Fourth, regarding PPIs specifically, web-based interventions demonstrate efficacy for improving well-being and depressive symptoms; however, not all participants may benefit from a web-delivery format.

Web-based interventions aimed at targeting well-being and depressive symptoms demonstrate effectiveness (compared to control conditions) with small to medium effect sizes (Carr et al., 2021; Cowpertwait & Clarke, 2013); however, approximately 21–33% of individuals do not complete the intervention (i.e. drop out) (Cowpertwait & Clarke, 2013; Wantland et al., 2004). In addition, meta-analytic findings suggest that longer and more intensive in-person PPIs demonstrate larger effects than shorter, web-based interventions (Bolier et al., 2013; Carr et al., 2021; Sin & Lyubomirsky, 2009). Thus, it is important to determine when it is appropriate to deliver a PPI online, particularly when considering accessibility, and for whom do specific web-based interventions, including PPIs, work best for in order to assess for individuals who may be less likely to respond to a web-based PPI and triage them to other interventions.

Applying machine learning to interventions

Fortunately, computational approaches, including machine learning, are commonly used in psychiatric research to answer this question and predict treatment outcomes (Meinlschmidt et al., 2020; Price et al., 2022). The ability to predict treatment outcomes for individuals who are seeking treatment is especially promising to optimize treatment matches. Existing studies have utilized machine learning approaches to predict individual changes in depressive symptoms following a digital intervention from participants' baseline features (Hornstein et al., 2021; Jacobson & Nemesure, 2021; Pearson et al., 2019), demonstrating that it is feasible to predict treatment outcomes in depressed individuals. However, these studies used machine learning to predict treatment outcomes immediately after completion of the intervention and not in the long-term after completion. Given that many individuals experience a relapse in their depressive symptoms within 6-months of completing treatment (Delgadillo et al., 2018; Wojnarowski et al., 2019), it is also important to match individuals to the most appropriate treatment, based on their demographics and current psychiatric presentation, to maximize the effects of treatment and reduce symptom relapse.

Rationale

Given the rise in popularity of PPIs and web-based interventions, the purpose of the current study was to investigate if baseline features would predict individual changes in overall happiness and depressive symptoms for individuals who engaged in a week-long web-based PPI. Furthermore, we investigated whether these baseline features could predict sustained changes over variable periods of time, potentially providing valuable information for who is more or less susceptible to symptom relapse.

To accomplish this aim, we utilized data from a publicly available dataset (Woodworth et al., 2017, 2018) that aimed to replicate findings from Seligman et al. (2005). The original findings from this data indicated that all participants demonstrated improvements in their happiness and depressive symptoms when assessed one week after completing an online intervention (Woodworth et al., 2017). Importantly, a rapid improvement occurred in symptoms after one week of the intervention, with minimal change in symptoms observed in the subsequent follow-ups. However, findings from the multilevel models indicated that differences in the improvement of happiness and depressive symptoms over time could not be distinguished between the three intervention and one placebo groups (each group is described in more detail below). Thus, it may be likely that the PPIs themselves did not lead to the improvements in symptoms given that individuals in the neutral, therapeutic placebo group also demonstrated improvements. Instead, it is more plausible that the 'client factor', or individual participant characteristics, influenced the degree to which an individual experienced improvements in their happiness and depressive symptoms over time, as suggested by Woodworth et al. (2017).

Thus, to better understand who may respond better to PPIs and demonstrate symptom improvements long-term, we utilized machine learning to predict individual changes from baseline features (e.g. individual symptoms and demographics) in happiness and depressive symptoms at the end of a week-long PPI. Specifically, we investigated the changes in happiness and depressive symptoms from pretest to posttest, 1-week follow-up, 1-month follow-up, 3-month follow-up, and 6-month follow-up after completing the web-based PPI. Moreover, given that improvement in symptoms may be due to 'client factors' rather than the specific 'ingredients' of the PPIs themselves, we also examined which individual characteristics at baseline were most influential in predicting improvements in happiness and depressive symptoms over time following completion of the PPI.

Method

Participants

Participants were recruited through the Australian community via newspaper, radio station, television, and internet articles to participate in a 'happiness study'. Two-hundred and ninety-five ($N = 295$) participants enrolled in the study and completed the pre-test (i.e. baseline) measures ($M_{age} = 43.76$, $SD_{age} = 12.43$; 39.66% postgraduate degree, 35.22% Bachelor's degree; 46.10% 'average' income; 85.06% female).

Intervention

Participants were assigned to one of four groups, including three intervention groups (*Gratitude Visit, Signature Strengths*, and *Three Good Things*), and one control group (*Early Memories*). These groups were based on the three strongest interventions and the control group from Seligman et al. (2005). Participants assigned to the *Gratitude Visit* intervention group were instructed to write a one-page letter to one person from their past who had been a positive influence but never been thanked. Then, participants were instructed to deliver the letter to the person and reminisce on previous, positive events together. Participants assigned to the *Signature Strengths* intervention group were instructed to complete a questionnaire that would assess their top five character strengths (Woodworth et al., 2017). Participants then received an email containing these strengths and were instructed to read each description and choose one strength to use in a different way every day over the next week. Participants assigned to the *Three Good Things* intervention group were instructed to write three good things that happened and provide an explanation as to why they happened every day. Participants assigned to the *Early Memories* control group were instructed to write their early memories at the end of each day.

Measures

Authentic happiness inventory

The Authentic Happiness Inventory (AHI) is a 24-item self-report measure that assesses for happiness and life satisfaction (Park et al., 2010; Proyer et al., 2017). Items on the AHI consist of different statements ranging from 1 (negatively worded) to 5 (positively worded). An example item assesses one's mood and ranges from 1 ('I am usually in a bad mood') to 5 ('I am usually in an unbelievably great mood'). Total scores are created by summing individual items, and higher scores indicate greater levels of happiness.

Center for epidemiologic studies depression scale

The Center for Epidemiologic Studies Depression Scale (CES-D) is a 20-item self-report measure that assesses for depressive symptoms (Radloff, 1977). Items on the CES-D are scored on a 4-point Likert scale from 0 ('rarely or none of the time') to 3 ('most or almost all the time'). Four items are positively worded, so we reverse coded these items for the current analyses. Total scores are created by summing individual items, and higher scores indicate greater severity of depressive symptoms.

The CES-D has four subscales (Radloff, 1977; Shafer, 2006): depressed affect (DA), positive affect (PA), somatic complaints (SC), and interpersonal problems (IP). The DA subscale represents general symptoms of depression and negative emotion (e.g. 'I felt depressed). The PA subscale represents a lack of positive affect or anhedonia (e.g. 'I was happy'), and all items in this subscale are reverse scored. The SC subscale represents physical symptoms of depression (e.g. 'My sleep was restless'). The IP subscale represents difficulties interacting with other people or negative beliefs about other people (e.g. 'People were unfriendly').

Procedure

The initial study was approved by the Tasmanian Social Sciences Research Ethics Committee and followed ethical guidelines by the Australian Government National Health and Medical Research Council (Woodworth et al., 2017, 2018). Participants interested in the study were instructed to visit the study website to enroll themselves. After giving their informed consent, participants completed pre-test questionnaires, including their contact information, demographics, AHI, and CES-D. Participants were then randomly assigned to one of the four groups described above by researchers, received an email with initial instructions for their assigned intervention prior to beginning the intervention (and after completing pre-test questionnaires), and then received a mid-week email to remind them of their instructions. Both of these emails were individualized for the intervention that the receiving participant was assigned.

After completion of the one-week intervention, all participants received a general email thanking them for their participation and instructing them to complete the follow-up questionnaires, which included the AHI, CES-D, and a question confirming that they completed the intervention. Participants also received this email one week, one month, three months, and six months after completing the intervention. Thus, participants could complete the AHI and CES-D at baseline and five separate follow-up occasions. Participants did not receive compensation for their involvement in the study but were entered into a drawing to receive a book voucher if they completed all follow-up questionnaires.

Data analytic plan

Machine learning modeling approach

A leave-one-out cross-validation (LOOCV) (Webb et al., 2011) approach (70%), with a completely held-out test set (30%) was developed and implemented in Python (v3.9) (Van Rossum & Drake, 2009) using the *scikit-learn* package (for further detail on the implementation and utility of cross-validation within machine learning see Lekkas et al. (2021)). We used an Extreme Gradient Boosted Tree (xgboost) (Ramraj et al., 2016) regressor, a well-documented machine learning algorithm for detecting mental health constructs (Jacobson & Chung, 2020; Jacobson et al., 2019a, 2019b; Sharma & Verbeke, 2020), to detect 1) change in total AHI and 2) change in total CES-D from pretest to posttest (7 days after pretest), 1-week follow-up (14 days after pretest), 1-month follow-up (38 days after pretest), 3-month follow-up (98 days after pretest), and 6-month follow-up (189 days after pretest), respectively, resulting in 10 separate models. We used demographic variables (age, income, education level, and sex), intervention group, elapsed days, individual AHI items, individual CES-D items, and the CES-D subscales as input features for the xgboost model, resulting in the inclusion of 54 input features. The features were subsequently scaled, bounding their values from [0,1], as feature scaling has been shown to increase model performance and efficiency (Shahriyari, 2019). We assessed model performance across three random seeds and reported the average and standard deviation of correlative strength (r) and the Coefficient of Determination (R^2) for each questionnaire outcome and time point of interest. We interpreted and reported correlative strength based on established thresholds for behavioral sciences research ($r \geq 0.3$; moderate association) (Cohen, 2013).

Machine learning model introspection

To address the decreased interpretability of machine learning models as compared to traditional statistical models, a recent methodological approach based upon the Shapley values of game theory has been developed (Arrow et al., 1953). SHAP (SHapley Additive exPlanations) calculates the relative contribution of a feature to the model's outcomes predictions by perturbing the values of the model's input features and assessing their respective influence on the model's predictions. The result is a set of SHAP values that correspond to the relative magnitude and direction by which a given feature influences the model's prediction outcomes (Lundberg & Lee, 2017; for a more detailed tutorial on the implementation of SHAP in predicting individual response to digital interventions, see Lekkas et al. (2021)). We used this approach to determine the top five most influential features for predicting change in happiness and depressive symptoms.

Results

We used a machine learning approach with a completely held-out test set to assess for change in happiness and depressive symptoms at posttest, 1-week follow-up, 1-month follow-up, 3-month follow-up, and 6-month follow-up, respectively. The modeling approach found a moderate correlation for both change in total happiness and depressive symptoms at 6-month follow-up but found weak correlations for both change in total happiness and depressive symptoms at posttest, 1-week follow-up, 1-month follow-up, and 3-month follow-up (i.e. $r < 0.3$; see Table 1). We examined variance of the outcome at the five different timepoints and found that, generally, the variance for change in happiness and depressive symptoms increased as time from baseline increased.[1] Thus, the reduced variability in score distribution at the earlier time points may reflect weaker signal in the outcome metric and subsequently worse performance by the model. Given the weak correlations, we did not examine the most influential features in the posttest, 1-week follow-up, 1-month follow-up, and 3-month follow-up models for the present analyses.

One-hundred and twenty-participants ($N = 120$) completed the 6-month follow-up and were included in our analyses. Overall, participants' happiness scores increased ($M_{baseline} = 70.60$, $SD_{baseline} = 13.53$; $M_{follow\text{-}up} = 75.83$, $SD_{follow\text{-}up} = 14.53$) and their depressive

Table 1. Modeling performance for changes in happiness and depressive symptoms.

Modeling Approach	*Pretest to Posttest Change* $r \pm SD$ (Test Set)	$r \pm SD$ (Validation Set)	*Pretest to 1-Week Follow-Up Change* $r \pm SD$ (Test Set)	$r \pm SD$ (Validation Set)	*Pretest to 1-Month Follow-Up Change* $r \pm SD$ (Test Set)	$r \pm SD$ (Validation Set)	*Pretest to 3-Month Follow-Up Change* $r \pm SD$ (Test Set)	$r \pm SD$ (Validation Set)	*Pretest to 6-Month Follow-Up Change* $r \pm SD$ (Test Set)	$r \pm SD$ (Validation Set)
Happiness (AHI)	0.12 ± 0.12	0.13 ± 0.05	0.21 ± 0.04	0.13 ± 0.03	0.04 ± 0.05	0.07 ± 0.07	0.14 ± 0.10	0.11 ± 0.05	0.30 ± 0.09	0.32 ± 0.04
Depressive Symptoms (CES-D)	0.14 ± 0.06	0.16 ± 0.08	0.13 ± 0.04	0.06 ± 0.07	0.01 ± 0.03	0.05 ± 0.05	0.21 ± 0.03	0.20 ± 0.09	0.39 ± 0.06	0.37 ± 0.03

XGBoost Regressor performance for detecting change in Authentic Happiness Inventory (AHI) and Center for Epidemiologic Studies – Depression Scale (CES-D) total scores from pretest to posttest, 1-month follow-up, and 6-month follow-up. Values are reported for the validation and held-out test set(s) for the three model types as average correlation ± standard deviation.

symptoms ($M_{baseline} = 15.03$, $SD_{baseline} = 11.36$; $M_{follow\text{-}up} = 12.83$, $SD_{follow\text{-}up} = 12.93$) decreased from baseline to the 6-month follow-up. Moreover, our sample's characteristics at both baseline and the 6-month follow-up demonstrated significant heterogeneity, with depressive symptoms varying from non-clinical to mild severity of depressive symptoms (Radloff, 1977; Santor et al., 1995). See Table S1 for a full breakdown of participant characteristics.

Happiness modeling performance & feature influence

Using baseline demographic variables, individual AHI and CES-D items, and CES-D subscales incorporated into an xgboost regressor modeling approach, we were able to moderately detect change in AHI total score from baseline to 6-month follow-up ($r_{Test} = 0.30 \pm 0.09$, $r_{Validation} = 0.32 \pm 0.04$; see Table 1). We assessed feature importance and directionality via SHAP. When considering the top five most influential features for the models predictions, higher scores of *Successful* (AHI), *Enthusiastic* (AHI), and *Accomplished* (AHI) and lower scores of *Sleep* (CES-D), predicted increases in happiness 6 months after completion of the intervention. Although age emerged as a significant feature, there was no clear directionality to interpret how age influences overall happiness over time (see Figure 1).

Depressive symptoms modeling performance & feature influence

Using baseline demographic variables, individual AHI and CES-D items, and CES-D subscales incorporated into an xgboost regressor modeling approach, we were able to moderately detect change in CES-D total score from baseline to 6-month follow-up ($r_{Test} = 0.39 \pm 0.06$, $r_{Validation} = 0.37 \pm 0.03$; see Table 1). We assessed feature importance and directionality via SHAP. When considering the top five most influential features for the model's predictions, lower scores of *Bothered* (CES-D) and *Crying* (CES-D) and higher scores of *Keeping Score* (AHI), *Hopeful* (CES-D), and *Enthusiastic* (AHI) predicted decreases in depressive symptoms 6 months after completion of the intervention (see Figure 1). No baseline demographic features were observed amongst the top five most influential features.

Discussion

In the current study, we utilized machine learning to predict individual changes in happiness and depressive symptoms from baseline characteristics after a one-week web-based PPI. We found a moderate correlation in predicting change in happiness and depressive symptoms between baseline and the 6-month follow-up. However, the present approach found weak correlations for the models assessing change in happiness and depressive symptoms at posttest, 1-week follow-up, 1-month follow-up, and 3-month follow-up.

Taken together, our findings indicate that 'client factors', or individual characteristics, were only able to moderately predict improvements in happiness and depressive symptoms 6 months after completing the PPIs, and not immediately after the PPI. Thus, although it is possible that the specific ingredients of each PPI contributed to the long-term improvements in happiness and depressive symptoms, it may be more likely that the individual characteristics contributed more to the improvements at 6 months, regardless of intervention type, as suggested by Woodworth and colleagues (2017) in their original findings. We discuss the most influential features in further detail below to give better insight into what individual characteristics may be more important in increasing happiness and decreasing depressive symptoms.

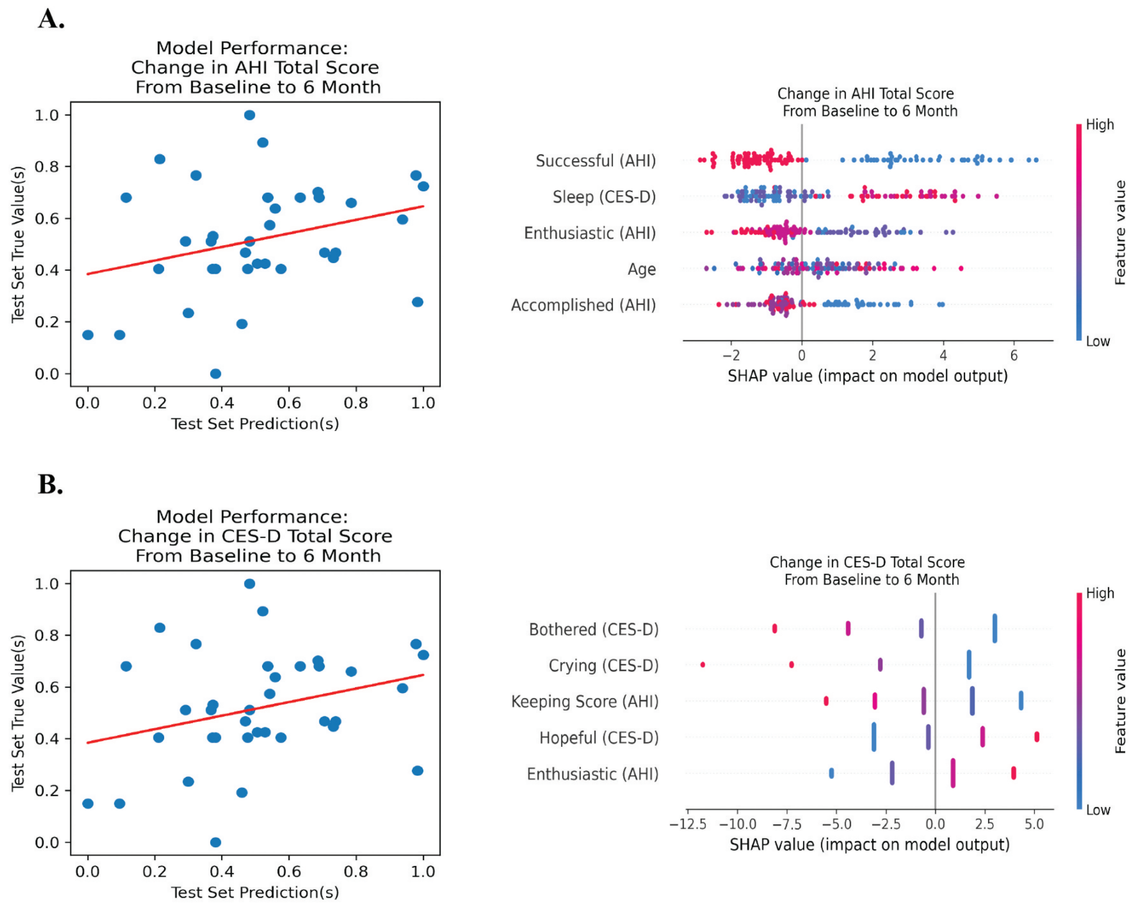

Figure 1. Top feature importance for change in happiness and depressive symptoms from pretest to 6-month follow-up. The machine learning model(s) actual versus predicted values plotted with respective correlative strength and the top five most influential features for the models predictions. The dot color on the SHAP plots correspond to the value of the listed feature, and position of the dot on the x-axis corresponds to the relative impact on the model prediction. For example, a low score on the AHI Successful item strongly, positively influences the model's prediction of lower happiness at the 6-month follow-up. (a) Baseline demographic variables, individual AHI and CES-D items, and CES-D subscales to predict change in AHI total score from baseline to 6-month follow-up. (b) Baseline demographic variables, individual AHI and CES-D items, and CES-D subscales to predict change in CES-D total score from baseline to 6-month follow-up. AHI = Authentic Happiness Inventory; CES-D = Center for Epidemiological Studies Depression Scale.

Happiness modeling performance & feature influence

Given that our results indicated a moderate correlation for detecting long-term change in happiness from baseline features, we implemented SHAP to assess the top five most influential features in the model's prediction of outcome change. When examining AHI items that influenced outcome change for happiness, *Successful, Enthusiastic*, and *Accomplished* emerged as the top predictors of all AHI items. Specifically, higher scores of *Successful, Enthusiastic*, and *Accomplished* at baseline predicted increases in happiness 6 months after completion of the intervention. This is in line with prior research indicating a happiness-success link (Boehm & Lyubomirsky, 2008; Lyubomirsky et al., 2005; Walsh et al., 2018). Moreover, individuals who are able to use their resources to work toward goals are more likely to benefit from PPIs (Sheldon & Lyubomirsky, 2021). Thus, we find similar results here, which suggest that those who feel more successful, accomplished, and enthusiastic (i.e. motivated) compared to other people are more likely to experience sustained increases in happiness for 6 months after a web-based PPI.

When examining CES-D items that influenced outcome change for happiness, *Sleep* emerged as the top predictor of all CES-D items. Specifically, higher scores of restless sleep at baseline predicted decreases in happiness 6 months after completion of the intervention. Sleep has been found to be an important individual factor in maximizing treatment benefit (Dolsen et al., 2017). Given that sleep impacts learning and memory, individuals who experienced poorer sleep may not have been as engaged in the PPI and thus not experienced its full benefits. Indeed, our results provide support for this: individuals who feel like their sleep is restless at baseline are more likely to experience decreases in happiness 6 months after a web-based PPI.

Depressive symptoms modeling performance & feature influence

Given that our results indicated a moderate correlation for detecting long-term change in depressive symptoms from baseline features, we were able to assess for feature importance for outcome change. When examining CES-D items that influenced outcome change for depressive symptoms, *Bothered, Crying*, and *Hopeful* emerged as the top predictors of all CES-D items. Specifically, lower scores of *Bothered* and *Crying* and higher scores of *Hopeful* predicted decreases in depressive symptoms 6 months after completion of the intervention. The impaired disengagement hypothesis suggests that depressed individuals have difficulties disengaging from negative information (Collins et al., 2021; Koster et al., 2011), so, in line with this hypothesis, our findings suggest that individuals who are able to disengage from negative information at baseline experienced decreases in depressive symptoms later on. Moreover, this may be due to individuals being asked to engage *more* with happiness during the PPI, resulting in them redirecting their attention from negative to positive information. Thus, individuals who feel less bothered by things at baseline are more likely to experience sustained decreases in depressive symptoms for 6 months after a web-based PPI.

Individuals who experience elevated depressive symptoms experience more negative and less positive affect (Bylsma et al., 2008). *Crying* and *Hopeful* represent items from the negative affect and positive affect subscale, respectively (Radloff, 1977), so our findings indicate that individuals who experience lower negative affect (i.e. fewer crying spells) and increased positive affect (i.e. more hopeful about the future) at baseline experienced sustained decreases in depressive symptoms for 6 months after a web-based PPI.

When examining AHI items that influenced outcome change for depressive symptoms, *Keeping Score* and *Enthusiastic* emerged as the top predictors of all AHI items. Specifically, higher scores of *Keeping Score* and *Enthusiastic* predicted lower levels of depressive symptoms 6 months after completion of the intervention. As noted above, individuals who feel more successful, including that they are doing well in life (if they were to keep score), and are and feel that they are more enthusiastic about doing anything are more likely to experience sustained decreases in depressive symptoms for 6 months after a web-based PPI. Interestingly, *Enthusiastic* was the only item that emerged as a top predictor in both models, suggesting that individuals who are more enthusiastic, and thus motivated, in their life may be the most likely to reap the benefits of web-based PPIs and experience increases in happiness *and* decreases in depressive symptoms.

Clinical implications

Our findings indicate baseline features can predict outcome changes following a web-based PPI, providing important clinical implications. Given that individuals overall experienced sustained increases in happiness and decreases in depressive symptoms after 6 months, and, coupled together with the original findings indicating significant changes both immediately (i.e. 1 week) and long-term (i.e. 6 months) in happiness and depressive symptoms (Woodworth et al., 2017), it appears that the web-based PPI is feasible for treating individuals who experience reduced happiness in their life and/or individuals with depressive symptoms. Moreover, 48 participants (40%) endorsed clinically significant depressive symptoms (i.e. equal to or above the CES-D cutoff of 16; Radloff, 1977), providing important clinical implications for depression.

However, it is important to note that we did not investigate other factors that could have resulted in long-term changes in happiness and depressive symptoms, including medication, therapy, engagement in the intervention after the immediate study period (e.g. 1 week) ended. In addition, original findings from Woodworth et al. (2017) indicated that all participants experienced changes in happiness and depressive symptoms, including individuals in the neutral, placebo group. Thus, it is likely that these ‘client factors’ may be more effective than the PPI ingredients. Moreover, it may be that the interventions utilized in the current study are helpful for people to establish habits to help improve their mood, and these habits may become more frequent for individuals with these specific characteristics (e.g. individuals who are more accomplished and motivated), so we present our clinical implications below and focus on who would specifically benefit web-based PPIs, rather than the implications of the specific ingredient of each PPI.

Further investigation of feature importance revealed specific happiness beliefs and depressive symptoms that had a significant impact on outcome changes. First, those who experienced higher levels of happiness at baseline, including feeling enthusiastic, accomplished, and successful, were more likely to experience increased happiness and decreased depressive symptoms. Indeed, these specific characteristics are often associated with increased goal motivation and self-esteem, so they may have been more motivated to complete the intervention and capitalize on their preexisting higher levels of happiness, in line with prior research (Lyubomirsky et al., 2005; Sheldon & Lyubomirsky, 2021). Thus, individuals who may feel depressed but are able to experience happiness in their daily lives and are motivated to increase their happiness levels may be a good fit for week-long, web-based interventions, including PPIs.

Second, individuals who reported more sleep difficulties at baseline experienced less happiness overtime. Sleep plays a big role in cognitive flexibility, learning, and memory (Stickgold & Walker, 2013) and has been found to be associated with treatment compliance (Dolsen et al., 2017). Thus, individuals who have more sleep difficulties may not benefit from a week-long, web-based interventions, including PPIs. Instead, they may benefit from targeting their sleep difficulties first before engaging in a self-guided online intervention targeting happiness to increase treatment compliance and maximize the potential benefits.

Third, individuals who are easily bothered by things, have crying spells, and do not feel hopeful about the future may not benefit from a short, web-based intervention, including PPIs. In particular, being easily bothered and having crying spells are often associated with increased negative affect. It is likely that these individuals may benefit from a more traditional therapy, including cognitive behavioral therapy, rather than a self-guided online intervention. Thus, it may be beneficial to triage individuals presenting with these symptoms to CBT instead of a web-based PPI to better address their negative biases.

Strengths and limitations

One important strength of the current study is the novel use of a machine learning approach coupled with feature introspection via SHAP to investigate what baseline features predicted outcome changes following a web-based PPI. Our findings provide initial evidence of who would respond well to this type of intervention, potentially maximizing treatment match. Moreover, our findings could help inform clinicians' decisions when choosing the best treatment for someone who experiences reduced happiness and elevated depressive symptoms.

The inclusion of multiple timepoints to model changes in happiness and depressive symptoms is considered a strength of the current study. The ability to accurately predict symptom changes at the 6-month follow-up is particularly important given that individuals typically experience a relapse in depressive symptoms within that time period. Thus, our findings suggest that it may be possible to identify baseline features that increase treatment efficacy for a web-based PPI while decreasing the likelihood for depressive symptom relapse.

Although our findings provide important information as to who may benefit from a web-based PPI, the current sample demonstrated non-clinical levels of depressive symptoms. Thus, no clear conclusions can be drawn as to how moderately or severely depressed individuals would respond to this intervention. Moreover, some individuals with clinical depression actually devalue or avoid positivity and happiness (Jordan et al., 2021; Winer & Salem, 2016), so it is possible that PPIs may not address the underlying devaluation of positivity. Future research should investigate how these individuals respond to web-based PPIs, which emphasize valuing happiness, in order to maximize treatment match for them. In addition, we did not examine other factors (e.g. intervention engagement) that may influence changes in participants' symptoms as this was not collected in the original dataset. Given that the current intervention was only active for one week, it is important to investigate with future research whether participants continued engaging with the intervention after the study ended as this may give further insight into how and why some participants experienced long-term improvements in their symptoms.

Our sample size was also relatively small for machine learning analyses, so we utilized different approaches to handle this potential issue. Specifically, we used LOOCV and completely separated our training data and test data, which is considered sufficient at any sample size to provide unbiased estimates (Vabalas et al., 2019; Varma & Simon, 2006).

Conclusion

Our current findings provide evidence that machine learning can use baseline features to predict changes in happiness and depressive symptoms following a week-long, web-based PPI. Importantly, the baseline features can predict sustained changes long term (i.e. 6 months), which provides relevant clinical information regarding depressive symptom relapse. Individuals who demonstrate positive views about themselves, their past, and their future at baseline are more likely to experience sustained increases in happiness and decreases in depressive symptoms. Whereas individuals who are less hopeful or have sleep difficulties may not respond well to the PPI and may benefit from a different intervention. Future work should investigate other individual factors that may impact how individuals respond to web-based PPIs. with a particular emphasis on how moderately or severely depressed individuals respond, in order to optimize treatment match and increase patient compliance.

Note

1. The variance of change in outcome measures are as follows: 57.98, 58.57, 115.27, 123.36, and 123.81 for AHI, and 64.78, 49.62, 78.14, 95.33, and 103.78 for CES-D, for posttest, 1-week follow-up, 1-month follow-up, 3-month follow-up and 6-month follow-up, respectively.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was partially funded by the National Institute of Mental Health (NIMH) and the National Institute Of General Medical Sciences (NIGMS) under R01 MH123482-01.

ORCID

Amanda C. Collins http://orcid.org/0000-0002-8258-2272
George D. Price http://orcid.org/0000-0002-9164-4973
Rosalind J. Woodworth http://orcid.org/0000-0002-5454-659X
Nicholas C. Jacobson http://orcid.org/0000-0002-8832-4741

Data availability statement

The data that support the findings of this study are openly available in Journal of Open Psychology Data at https://doi.org/10.5334/jopd.35.

Open Scholarship

This article has earned the Center for Open Science badge for Open Data. The data are openly accessible at https://doi.org/10.5334/jopd.35

References

Arrow, K. J., Barankin, E. W., Blackwell, D., Bott, R., Dalkey, N., Dresher, M., Gale, D., Gillies, D. B., Glicksberg, I., Gross, O., Karlin, S., Kuhn, H. W., Mayberry, J. P., Milnor, J. W., Motzkin, T. S., Von Neumann, J., Raiffa, H., Shapley, L. S., Shiffman, M. … Thrall, R. M. (1953). *Contributions to the theory of games (AM-28), volume II*. Princeton University Press; JSTOR. http://www.jstor.org/stable/j.ctt1b9x1zv

Boehm, J. K., & Lyubomirsky, S. (2008). Does happiness promote career success? *Journal of Career Assessment*, *16*(1), 101–116. https://doi.org/10.1177/1069072707308140

Bolier, L., Haverman, M., Westerhof, G. J., Riper, H., Smit, F., & Bohlmeijer, E. (2013). Positive psychology interventions: A meta-analysis of randomized controlled studies. *BMC Public Health*, *13*(1), 119. https://doi.org/10.1186/1471-2458-13-119

Bylsma, L. M., Morris, B. H., & Rottenberg, J. (2008). A meta-analysis of emotional reactivity in major depressive disorder. *Clinical Psychology Review*, *28*(4), 676–691. https://doi.org/10.1016/j.cpr.2007.10.001

Carr, A., Cullen, K., Keeney, C., Canning, C., Mooney, O., Chinseallaigh, E., & O'Dowd, A. (2021). Effectiveness of positive psychology interventions: A systematic review and meta-analysis. *The Journal of Positive Psychology*, *16*(6), 749–769. https://doi.org/10.1080/17439760.2020.1818807

Cohen, J. (2013). *Statistical power analysis for the behavioral Sciences* (0 ed.). Routledge. https://doi.org/10.4324/9780203771587

Cohn, M. A., Fredrickson, B. L., Brown, S. L., Mikels, J. A., & Conway, A. M. (2009). Happiness unpacked: Positive emotions increase life satisfaction by building resilience. *Emotion*, *9*(3), 361–368. https://doi.org/10.1037/a0015952

Collins, A. C., Lass, A. N. S., Jordan, D. G., & Winer, E. S. (2021). Examining rumination, devaluation of positivity, and depressive symptoms via community-based network analysis. *Journal of Clinical Psychology*, *77*(10), 2228–2244. https://doi.org/10.1002/jclp.23158

Cowpertwait, L., & Clarke, D. (2013). Effectiveness of web-based psychological interventions for depression: A meta-analysis. *International Journal of Mental Health and Addiction*, *11*(2), 247–268. https://doi.org/10.1007/s11469-012-9416-z

Davies, F., Shepherd, H. L., Beatty, L., Clark, B., Butow, P., & Shaw, J. (2020). Implementing web-based therapy in routine mental health care: Systematic review of health professionals' perspectives. *Journal of Medical Internet Research*, *22*(7), e17362. https://doi.org/10.2196/17362

Delgadillo, J., Rhodes, L., Moreea, O., McMillan, D., Gilbody, S., Leach, C., Lucock, M., Lutz, W., & Ali, S. (2018). Relapse and recurrence of common mental health problems after low intensity cognitive behavioural therapy: The WYLOW longitudinal cohort study. *Psychotherapy and Psychosomatics*, *87*(2), 116–117. https://doi.org/10.1159/000485386

Diener, E., Napa Scollon, C., & Lucas, R. E. (2009). The evolving concept of subjective well-being: The multifaceted nature of happiness. In E. Diener (Ed.), *Assessing well-being* (Vol. 39, pp. 67–100). Springer Netherlands. https://doi.org/10.1007/978-90-481-2354-4_4

Dolsen, M. R., Soehner, A. M., Morin, C. M., Bélanger, L., Walker, M., & Harvey, A. G. (2017). Sleep the night before and after a treatment session: A critical ingredient for treatment adherence? *Journal of Consulting and Clinical Psychology*, *85*(6), 647–652. https://doi.org/10.1037/ccp0000184

Hornstein, S., Forman-Hoffman, V., Nazander, A., Ranta, K., & Hilbert, K. (2021). Predicting therapy outcome in a digital mental health intervention for depression and anxiety: A machine learning approach. *Digital Health*, *7*, 20552076211060659. https://doi.org/10.1177/20552076211060659

Jacobson, N. C., & Chung, Y. J. (2020). Passive sensing of prediction of moment-to-moment depressed mood among undergraduates with clinical levels of depression sample using smartphones. *Sensors*, *20*(12), 3572. https://doi.org/10.3390/s20123572

Jacobson, N. C., & Nemesure, M. D. (2021). Using artificial intelligence to predict change in depression and anxiety symptoms in a digital intervention: Evidence from a transdiagnostic randomized controlled trial. *Psychiatry Research*, *295*, 113618. https://doi.org/10.1016/j.psychres.2020.113618

Jacobson, N. C., Weingarden, H., & Wilhelm, S. (2019a). Digital biomarkers of mood disorders and symptom change. *NPJ Digital Medicine*, *2*(1), 3. https://doi.org/10.1038/s41746-019-0078-0

Jacobson, N. C., Weingarden, H., & Wilhelm, S. (2019b). Using digital phenotyping to accurately detect depression severity. *Journal of Nervous & Mental Disease*, *207*(10), 893–896. https://doi.org/10.1097/NMD.0000000000001042

Jordan, D. G., Collins, A. C., Dunaway, M. G., Kilgore, J., & Winer, E. S. (2021). Negative affect interference and fear of happiness are independently associated with depressive symptoms. *Journal of Clinical Psychology*, *77*(3), 646–660. https://doi.org/10.1002/jclp.23066

Koster, E. H. W., De Lissnyder, E., Derakshan, N., & De Raedt, R. (2011). Understanding depressive rumination from a cognitive science perspective: The impaired disengagement hypothesis. *Clinical Psychology Review*, *31*(1), 138–145. https://doi.org/10.1016/j.cpr.2010.08.005

Lekkas, D., Price, G., McFadden, J., & Jacobson, N. C. (2021). The application of machine learning to online mindfulness intervention data: A primer and empirical example in compliance assessment. *Mindfulness*, *12*(10), 2519–2534. https://doi.org/10.1007/s12671-021-01723-4

Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, *30*, 4765–4774.

Lyubomirsky, S., King, L., & Diener, E. (2005). The benefits of frequent positive affect: Does happiness lead to success? *Psychological Bulletin*, *131*(6), 803–855. https://doi.org/10.1037/0033-2909.131.6.803

Meinlschmidt, G., Tegethoff, M., Belardi, A., Stalujanis, E., Oh, M., Jung, E. K., Kim, H.-C., Yoo, S. S., & Lee, J. H. (2020). Personalized prediction of smartphone-based psychotherapeutic micro-intervention success using machine learning. *Journal of Affective Disorders*, *264*, 430–437. https://doi.org/10.1016/j.jad.2019.11.071

Myers, D. G., & Diener, E. (2018). The scientific pursuit of happiness. *Perspectives on Psychological Science*, *13*(2), 218–225. https://doi.org/10.1177/1745691618765171

Park, N., Park, M., & Peterson, C. (2010). When is the search for meaning related to life satisfaction? *Applied Psychology: Health and Well-Being*, *2*(1), 1–13. https://doi.org/10.1111/j.1758-0854.2009.01024.x

Pearson, R., Pisner, D., Meyer, B., Shumake, J., & Beevers, C. G. (2019). A machine learning ensemble to predict treatment outcomes following an Internet intervention for depression. *Psychological Medicine*, *49*(14), 2330–2341. https://doi.org/10.1017/S003329171800315X

Price, G. D., Heinz, M. V., Nemesure, M. D., McFadden, J., & Jacobson, N. C. (2022). Predicting symptom response and engagement in a digital intervention among individuals with schizophrenia and related psychoses. *Frontiers in Psychiatry*, *13*, 807116. https://doi.org/10.3389/fpsyt.2022.807116

Proyer, R. T., Gander, F., Wellenzohn, S., & Ruch, W. (2017). The authentic happiness inventory revisited: Addressing its psychometric properties, validity, and role in intervention studies. *Journal of Well-Being Assessment*, *1*(1–3), 77–96. https://doi.org/10.1007/s41543-018-0006-0

Radloff, L. S. (1977). The CES-D scale: A self-report depression scale for research in the general population. *Applied Psychological Measurement*, *1*(3), 385–401. https://doi.org/10.1177/014662167700100306

Ramraj, S., Uzir, N., Sunil, R., & Banerjee, S. (2016). Experimenting XGBoost algorithm for prediction and classification of different datasets. *International Journal of Control Theory & Applications*, *9*(40), 651–662.

Santor, D. A., Zuroff, D. C., Ramsay, J. O., Cervantes, P., & Palacios, J. (1995). Examining scale discriminability in the BDI and CES-D as a function of depressive severity. *Psychological Assessment*, *7*(2), 131–139. https://doi.org/10.1037/1040-3590.7.2.131

Seligman, M. E. P., Steen, T. A., Park, N., & Peterson, C. (2005). Positive psychology progress: Empirical validation of interventions. *American Psychologist*, *60*(5), 410–421. https://doi.org/10.1037/0003-066X.60.5.410

Shafer, A. B. (2006). Meta-analysis of the factor structures of four depression questionnaires: beck, CES-D, Hamilton, and Zung. *Journal of Clinical Psychology*, *62*(1), 123–146. https://doi.org/10.1002/jclp.20213

Shahriyari, L. (2019). Effect of normalization methods on the performance of supervised learning algorithms applied to HTSeq-FPKM-UQ data sets: 7SK RNA expression as a predictor of survival in patients with colon adenocarcinoma. *Briefings in Bioinformatics*, *20*(3), 985–994. https://doi.org/10.1093/bib/bbx153

Sharma, A., & Verbeke, W. J. M. I. (2020). Improving diagnosis of depression with XGBOOST machine learning model and a large biomarkers Dutch dataset (n = 11,081). *Frontiers in Big Data*, *3*, 15. https://doi.org/10.3389/fdata.2020.00015

Sheldon, K. M., & Lyubomirsky, S. (2021). Revisiting the sustainable happiness model and pie chart: Can happiness be successfully pursued? *The Journal of Positive Psychology*, *16*(2), 145–154. https://doi.org/10.1080/17439760.2019.1689421

Sin, N. L., & Lyubomirsky, S. (2009). Enhancing well-being and alleviating depressive symptoms with positive psychology interventions: A practice-friendly meta-analysis. *Journal of Clinical Psychology*, *65*(5), 467–487. https://doi.org/10.1002/jclp.20593

Stickgold, R., & Walker, M. P. (2013). Sleep-dependent memory triage: Evolving generalization through selective processing. *Nature Neuroscience*, *16*(2), 139–145. https://doi.org/10.1038/nn.3303

Teachman, B. A. (2014). No appointment necessary: Treating mental illness outside the therapist's office. *Perspectives on*

Psychological Science, *9*(1), 85–87. https://doi.org/10.1177/1745691613512659

Vabalas, A., Gowen, E., Poliakoff, E., Casson, A. J., & Hernandez-Lemus, E. (2019). Machine learning algorithm validation with a limited sample size. *PLOS ONE*, *14*(11), e0224365. https://doi.org/10.1371/journal.pone.0224365

Van Rossum, G., & Drake, F. L. (2009). *Python 3 reference manual*. CreateSpace.

Varma, S., & Simon, R. (2006). Bias in error estimation when using cross-validation for model selection. *BMC Bioinformatics*, *7*(1), 1–8. https://doi.org/10.1186/1471-2105-7-91

Walsh, L. C., Boehm, J. K., & Lyubomirsky, S. (2018). Does happiness promote career success? Revisiting the evidence. *Journal of Career Assessment*, *26*(2), 199–219. https://doi.org/10.1177/1069072717751441

Wantland, D. J., Portillo, C. J., Holzemer, W. L., Slaughter, R., & McGhee, E. M. (2004). The effectiveness of web-based vs. non-web-based interventions: A meta-analysis of behavioral change outcomes. *Journal of Medical Internet Research*, *6*(4), e40. https://doi.org/10.2196/jmir.6.4.e40

Webb, G. I., Sammut, C., Perlich, C., Horváth, T., Wrobel, S., Korb, K. B., Noble, W. S., Leslie, C., Lagoudakis, M. G., Quadrianto, N., Buntine, W. L., Quadrianto, N., Buntine, W. L., Getoor, L., Namata, G., Getoor, L., Han, X. J., Ting, J.-A., Vijayakumar, S. … Raedt, L. D. (2011). Leave-one-out cross-validation. In C. Sammut & G. I. Webb (Eds.), *Encyclopedia of machine learning* (pp. 600–601). Springer US.

Wilhelm, S., Weingarden, H., Ladis, I., Braddick, V., Shin, J., & Jacobson, N. C. (2019). Cognitive-behavioral therapy in the digital age: Presidential address. *Behavior Therapy*, *51*(1), 1–14. https://doi.org/10.1016/j.beth.2019.08.001

Winer, E. S., & Salem, T. (2016). Reward devaluation: Dot-probe meta-analytic evidence of avoidance of positive information in depressed persons. *Psychological Bulletin*, *142*(1), 18–78. https://doi.org/10.1037/bul0000022

Wojnarowski, C., Firth, N., Finegan, M., & Delgadillo, J. (2019). Predictors of depression relapse and recurrence after cognitive behavioural therapy: A systematic review and meta-analysis. *Behavioural and Cognitive Psychotherapy*, *47*(5), 514–529. https://doi.org/10.1017/S1352465819000080

Woodworth, R. J., O'Brien-Malone, A., Diamond, M. R., & Schüz, B. (2017). Web-based positive psychology interventions: A reexamination of effectiveness. *Journal of Clinical Psychology*, *73*(3), 218–232. https://doi.org/10.1002/jclp.22328

Woodworth, R. J., O'Brien-Malone, A., Diamond, M. R., & Schüz, B. (2018). Data from, 'web-based positive psychology interventions: A reexamination of effectiveness. *Journal of Open Psychology Data*, *6*, 1. https://doi.org/10.5334/jopd.35