Description: Supplemental methods and results for 'A meta-analysis of social marketing campaigns to improve global conservation outcomes'

Supplementary Methods

Data collection and coding

In addition to the eight variables included in our full model of behavior change, campaigns also incorporated techniques to remove tangible external barriers to behavior change, but we did not formally analyze campaigns' effects on this variable. Instead, barrier removal activities were considered to be a constant process across all campaigns, and we accounted for any influence of this variable by incorporating campaign heterogeneity through random effect for campaign in our modeling methods.

In order to assign data to variables included in our full behavior change model, we employed intensive selection and validation processes, typical of meta-analyses (e.g., Bamberg & Möser, 2007), to ensure the consistency of constructs measured across independent studies and the validity of pooling these results. The final set of eight variables (Table S1) included in our full behavior change model achieved a balance between maximizing the number of unique, potentially informative variables and maximizing the number of campaigns that had valid data for each variable. We confirmed all results and sample sizes reported in Rare's database for items included in the analysis during this validation process.

We followed further selection procedures when considering campaigns that had multiple questionnaire questions (items) for a single variable so that our final dataset included no more than one measure per variable per campaign. Several studies have found varying relationships between predictors and behaviors that are attributed to mismatches in construct specificity (i.e., measuring general pro-environmental attitudes and specific behaviors), but focusing on attitudes

specific to a targeted behavior has generally improved model predictions (Ajzen & Fishbein, 1980; Ajzen, 1991; McKenzie-Mohr *et* al., 1995; St John *et* al., 2010). Consistent with this research, we reviewed all cases where multiple items measured a single variable and selected the one item to be analyzed that most specifically related to the targeted behavior change. For example, in a campaign that measured normative attitudes using the two statements, "We should protect marine resources" and "All fishers should follow regulations of the marine sanctuary," we included data from the latter item in the analysis. In cases where two items were of similar specificity, we took average measurements to be analyzed.

Path analysis

Meta-analyses employing path models (i.e. meta-analytic structural equation modeling: MASEM) typically collect correlations between variables from primary studies, pool correlations into a combined matrix, and test path models on this matrix (e.g., Bamberg & Möser, 2007). We had to adapt these methods due to limitations of the primary data currently available. Data collected from Rare contained metrics suitable for meta-regression analyses, including counts of people responding affirmatively to questionnaire items and total sample sizes; however, correlations between variables were never calculated and reported for any individual campaign. Retroactively obtaining correlations from primary data files was not possible due to time and logistical constraints (e.g., older campaign data is not centrally stored, questionnaires are in several languages). Therefore, we created a table of effect sizes calculated during meta-regression procedures for each variable measured in each campaign under random-effects assumptions, which used inverse variance weighting.

Goodness of fit for all models in our path analysis was evaluated on several criteria. We used the Yuan-Bentler residual χ^2 that provides more reliable test statistics given smaller sample sizes and mild nonnormality of data (Bentler & Yuan, 1999), where nonsignificant results indicate the model is consistent with the observed data. Bentler's comparative fit index (CFI) and root-mean-square error of approximation (RMSEA) were also used to examine model fit (Bentler, 2000). Although several recommendations exist for setting index cutoff values, it is generally accepted that values of CFI < 0.90 and RMSEA > 0.10 indicate poor model fit, whereas larger CFI (0.95 – 1.0) and smaller RMSEA (0.0 – 0.06) are optimal criteria for acceptable models, especially for large sample sizes (Cheung & Chan, 2005). Lastly, we compared the fit of models relative to each other while accounting for parsimony using Akaike's Information Criteria (AIC), where lower values indicate better fit relative to other candidate models (Akaike, 1974).

Supplementary Results

Path analysis

Table S1 shows information for pooled correlations among variables measured in this study. The upper triangular matrix presents the number of campaigns (out of 84 included in the meta-analysis) that measured each variable pair, which ranged from 12 (barrier removal attitude and behavior intention) to 71 (interpersonal communication and behavior change). Although most campaigns did not measure all eight variables, we were able to extract an adequate number of effects from campaigns necessary to calculate all bivariate correlations. The lower triangular matrix presents estimated confidence intervals for pooled correlations resulting from campaign effect sizes calculated under the random-effects assumption. The 95% confidence intervals

around mean correlation coefficients were positive and did not include 0 for most variable pairs (indicating significance at the $p < 0.05$ level). Variables that did not correlate significantly were systems knowledge with normative attitudes, solutions knowledge with normative attitudes, and barrier removal attitudes with solutions knowledge, normative attitudes, interpersonal communication, and behavior intention.

From goodness of fit measures for path models, the Knowledge-only model, IC1 (the model where IC was removed completely), and IC2 showed moderately significant departure from the data with values for CFI and RMSEA outside acceptable ranges. IC3 showed adequate fit based on most criteria but had an RMSEA greater than the maximum cutoff (0.10) proposed by Hu & Bentler (1999). There was considerable overlap of relationships specified in IC3 and IC4, with the difference being interpersonal communication directly influenced knowledge types in IC3 but was allowed to covary with knowledge types in IC4. Since IC4 was best-supported among alternative models by RMSEA and AIC values, we applied these relationships between interpersonal communication, knowledge, and attitudes to the full model set. By adding behavior intention as a moderator between attitudes and behavior change, the full model showed acceptable fit to the data. Despite meeting fit criteria, this model contained nonsignificant and negligible standardized path coefficients ($p < 0.05$) for the influence of barrier removal attitudes on behavior intention and the influence of solutions knowledge on all three attitude variables. We removed these paths to test our final, full model to further improve model fit. Although solutions knowledge and barrier removal attitudes did not directly influence any variable in the full model, we kept these variables in the model because removing one or both resulted in poorer model fit (highest CFI = 0.918; lowest RMSEA = 0.118).

Supplementary References

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Table S1

95% confidence intervals (lower triangular matrix) of pooled correlations and number of campaigns (upper triangular matrix) that measured each pair of variables. Intervals in bold indicate significant correlations ($p < 0.05$).

Variable	1	2	3	4	5	6	7	8
1. Knowledge - systems	53	44	46	19	34	50	36	48
	-							
2. Knowledge - solutions	**0.17**	73	43	27	41	67	40	64
	0.65	-						
3. Attitudes - barrier removal	**0.07**	-0.04	30	19	15	27	12	26
	0.78	0.64	-					
4. Attitudes - benefits	**0.36**	**0.12**	**0.02**	51	31	48	32	44
	0.78	**0.63**	**0.76**	-				
5. Attitudes - norms	-0.02	-0.12	-0.10	**0.38**	48	45	25	43
	0.59	0.47	0.77	**0.81**	-			
6. Interpersonal comm.	**0.05**	**0.47**	-0.03	**0.34**	**0.13**	79	44	71
	0.55	**0.76**	0.65	**0.74**	**0.63**	-		
7. Intention	**0.44**	**0.19**	-0.21	**0.56**	**0.40**	**0.31**	48	42
	0.82	**0.68**	0.80	**0.88**	**0.85**	**0.73**	-	
8. Behavior change	**0.40**	**0.01**	**0.02**	**0.47**	**0.33**	**0.18**	**0.62**	76
	0.76	**0.47**	**0.68**	**0.80**	**0.74**	**0.57**	**0.87**	-