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Confirmatory Validation and Measurement Equivalence of the Eating Loss of Control Scale in Binge Eating and Non-Clinical Samples

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Abstract
Although Loss of Control (LOC) is a transdiagnostic factor in eating pathology, there are few standalone assessments of LOC. The objective of this study was to evaluate the uni-dimensionality and measurement equivalence of the Eating Loss of Control Scale (ELOCS). Confirmatory factor analyses were used to achieve a well-fitting uni-dimensional model in clinical ($N = 226$) and non-clinical ($N = 476$) samples. Measurement equivalence was tested in a factor analytic framework, and effect sizes were computed to evaluate the impact of non-equivalence. A well-fitting model was achieved in both samples after the removal of 4 items. The instrument showed configural equivalence but not metric equivalence. Results suggest that the ELOCS is a reliable and valid measure of LOC in clinical and non-clinical samples. However, while the nature of the LOC construct is similar across binge eating and non-clinical participants, comparisons of ELOCS across these groups are affected by measurement non-equivalence. This research also revealed novel insights into the relative sensitivity of model fitting and effect size approaches to investigating measurement equivalence.

Keywords Loss of control · Measurement equivalence · Measurement invariance · Assessment · Eating disorder · Binge eating

Recurrent episodes of binge eating represent a core feature of eating disorders. From the perspective of the *Diagnostic and Statistical Manual of Mental Disorders* (DSM-5, APA 2013), these episodes involve eating unusually or objectively large amounts of food within a discrete period of time in the context of experiencing a subjective sense of loss of control over eating during the episode. Loss of control (LOC) is central to binge eating episodes. For instance, research suggests that LOC over eating is a risk factor for eating disorder severity, general psychopathology, and poorer quality life in diverse samples (Elder et al. 2008; Latner et al. 2007), and that it predicts obesity even after controlling for total amount of food consumption (Sonneville et al. 2013). LOC is also related to poor health (Tanofsky-Kraff et al. 2008) and negative response to bariatric surgery (White et al. 2010)

Until recently there were no assessment methods for measuring LOC over eating as a standalone uni-dimensional construct in clinical samples. LOC has typically been measured as an item or small set of items within more general eating disorder instruments (e.g., Cooper & Fairburn, 1993; Gormally, Black, Daston, & Rardin, 1982). Latner et al. (2014; Stefano et al. 2016) recently developed a multi-dimensional measure called the Loss of Control over Eating Scale (LOCES) that has yet to be validated in clinical samples. The focus of this study is on the *Eating Loss of Control Scale* (ELOCS; Blomquist et al. 2014), a questionnaire that taps a range of feelings, thoughts, and behaviors pertinent to LOC, which was originally validated in a sample of 168 treatment-seeking, obese, individuals diagnosed with Binge Eating Disorder (BED) with comorbid obesity. The ELOCS, which measures multiple aspects of LOC over eating, provides continuous data regarding both severity and frequency. In the initial validation study of the ELOCS, Blomquist et al. (2014) reported that a single principal component explained the majority of covariance among these items in that study, and all but two of the original 20 items had pattern coefficients > .40 on this dimension. Cronbach's alpha was 0.90 for the scale, which correlated

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moderately to strongly with measures of overall eating disorder severity, self-control, and depression.

This study had two specific aims. First, we sought to confirm the instrument's uni-dimensional structure in a clinical sample that included the participants from the original study as well as 58 new participants. Second, we sought to test the measurement equivalence (ME) of this structure across clinical and non-clinical samples. We tested configural, metric, and scalar equivalence. *Configural* equivalence would indicate that the pattern of factor loadings is the same across clinical and non-clinical samples. This finding would support the assumption that the scale is measuring the same latent construct across clinical and non-clinical populations. *Metric* equivalence would specifically indicate the similarity of factor loadings across samples. *Scalar* equivalence would indicate the similarity of latent intercepts given similar measured scores. Scalar and metric equivalence would support the direct comparison of distributions (e.g., means and standard deviations) across clinical and non-clinical samples.

Method

Participants

Data from two samples were used in this study. The *Clinical sample* comprised 226 treatment-seeking individuals with DSM-IV-TR (APA 2000) BED and comorbid obesity (average BMI = 38.82, SD = 5.76). BED diagnoses were determined by trained and monitored doctoral-level research clinicians based on the *Structured Clinical Interview for DSM-IV Axis I Disorders* (First, Spitzer, Gibbon, & Williams 1997). The average age was 47.24 years (SD = 10.88); 163 were women and 63 were men; 149 were White, 46 were Black/African-American, 15 were Hispanic/Latina, 2 were Asian-American, and 14 reported mixed or other racial/ethnic category. The *non-clinical sample* comprised 476 college students aged 18–22 participating in an online survey study for course credit. Of those who reported demographic characteristics ($N = 461$), 345 were women and 116 were male; 326 were White, 38 were Black/African-American, 28 were Asian-American, 9 were Hispanic/Latino, and 60 reported belonging to another racial/ethnic category. Both samples were collected with the approval of local Institutional Review Boards and all participants consented.

Measures

All 20 items of the original ELOCS (Blomquist et al. 2014) were administered to all participants in both samples.

Analyses

The first step in our analyses was to evaluate the fit of a unidimensional model in the ELOCS items in the clinical sample. We first conducted principal components analyses in both samples, following the original validation study (Blomquist et al. 2014). We then fit confirmatory models in each sample independently. We expected to identify a robust single factor, and considered the removal of items based on modification indices and residual correlations in order to achieve unidimensionality and good model fit. Model fit conventions from Hu and Bentler (1999) of .06 for RMSEA, .95 for TLI and CFI, and .08 for SRMR guided interpretation of overall model fit.

To test for measurement equivalence (ME), responses to the ELOCS were compared across clinical and non-clinical samples. For these analyses, the clinical sample was treated as the reference group and an equivalent referent item was identified using the constrained baseline approach suggested by Stark, Chernyshenko, and Drasgow (2006). With this approach, both the factor loadings and the intercepts were constrained to be equivalent across groups for all of the items in the scale. Then, the parameters for a single item at a time were unconstrained and changes in the fit of the model were evaluated. If the model fit improved substantially, the item was considered nonequivalent and was not appropriate to use as the referent item. This process continued until an equivalent item was identified that could be used as the referent.

Once an appropriate referent item was identified, ME was tested by sequentially constraining parameters for a single item at a time and checking for decrements in fit. Although the constrained baseline approach provides high power for detecting nonequivalence, it also results in high Type I error rates (Stark et al. 2006). In contrast, the approach used here to test for ME, called the free baseline approach, provides lower Type I error rates while maintaining high power. Therefore, this approach provides more accurate estimates of ME (Stark et al. 2006). Using this approach, nonequivalence was identified if changes in the CFI were greater than .002 (cf. Meade, Johnson, & Braddy 2008) when the factor loadings and intercepts were constrained to be equivalent across groups. Finally, the effect sizes of nonequivalence proposed by Nye and Drasgow (2011) were also estimated to provide additional information about the magnitude of differences across groups.

Results

Uni-Dimensionality

We began by conducting a principal components analysis on the ELOCS items. As in the original validation study (Blomquist et al. 2014), both the eigenvalues and

the scree plot indicated a strong first factor. Therefore, we next estimated a uni-dimensional confirmatory factor analysis (CFA) model. Results of these analyses indicated that the model did not fit particularly well (RMSEA = .09, CFI = .83, TLI = .80, SRMR = .06). Examining the model, residuals, and modification indices suggested that a number of items were highly correlated after accounting for the general factor. Neither the principal components analysis nor the results of the CFA indicated a potential second factor. Instead, the results indicated the presence of correlated residuals between several of the items. As in the original validation study (Blomquist et al. 2014), two items ("Ate unhealthy food choices" and "Feel out of control when you have not eaten an unusually large amount of food") were problematic. In the original study, these items had low factor loadings. In the current CFA results, the residuals for these two items were correlated with a number of factors, suggesting that they were measuring multiple unique constructs other than the general loss of control factor. To avoid overfitting the model with a number of correlated residuals, these two items were removed from the CFA model. The results of the CFA model also indicated that two additional items had unmodeled shared variance ("Feel disgusted, depressed, or very guilty while eating" and "Give up even trying to control eating"). Given the shared content of these two items (i.e., aspects of helplessness), respecifying the model to free the residuals for these items to correlate seemed justified. The resulting uni-dimensional model fit the data well (RMSEA = .065, CFI = .92, TLI = .90, SRMR = .05). In the end, we removed four items from the original 20-item scale (items 6, 12, 16, 20 in Blomquist et al. 2014) to achieve good fit in the clinical sample. The Cronbach's alpha for these remaining 16 items was .88 (item average = 6.29, SD = 1.74).

We next estimated the same model in the undergraduate sample using the reduced set of 16 items included for the final model in the clinical sample. The Cronbach's alpha for the 16 items in this sample was .91 (item average = 1.57, SD = 1.49). Again, the principal components analysis indicated a strong general factor. However, fitting the same CFA model as in the clinical sample resulted in poor model fit (RMSEA = .092, CFI = .87, TLI = .85, SRMR = .05). Adding the correlated residual from the clinical sample (i.e., between items with aspects of helplessness) had virtually no effect on model fit (RMSEA = .093, CFI = .87, TLI = .85, SRMR = .05). However, two additional items ("Afraid of losing control over eating" and "Feel upset by the feeling that you couldn't stop eating") did appear to share unique variance and adding this correlation improved fit substantially (RMSEA = .079, CFI = .90, TLI = .89, SRMR = .05).

Equivalence

Note that differences in the covariances among the uniqueness of the CFA model are not generally considered a form of measurement nonequivalence (Vandenburg & Lance 2000). Although past studies have examined the equivalence of error variances, even this test is now considered overly stringent and unnecessary (Bentler 1995; Jöreskog 1971; Vandenberg 2002). Therefore, despite apparent differences in the covariances among the uniquenesses across groups, we continued to test for more traditional forms of measurement nonequivalence.

The results of the measurement equivalence analyses are reported in Table 1. As shown here, configural equivalence was achieved. When the uni-dimensional models examined above were tested simultaneously in the clinical and non-clinical samples, the model fit the data well. Therefore, we next tested for the equivalence of the factors loadings and intercepts across groups. There was significant evidence for scalar variance for several items. When the factor loadings and intercepts of five items were constrained to be equivalent across groups, the CFI for the model decreased by more than .002, indicating nonequivalence.

The effect sizes (d_{MACS}) presented in Table 2 suggest that the nonequivalence identified in these five items was substantial. However, these effect sizes also suggested substantial nonequivalence in the other items in the scale as well. Although traditional methods of identifying nonequivalence (e.g., ΔCFI) suggested that these items were equivalent, the effect sizes for all of these items ranged from .32 to 1.02, indicating relatively large effects. This suggests that the dMACS procedure may have been more sensitive to nonequivalence than the comparative fit statistics, and that there was substantial evidence of metric and scalar nonequivalence in the ELOCS items.

To investigate these effects further, we examined the raw differences between the factor loadings and the intercepts of these items in the configural model where the item-level parameters were freely estimated in both groups. These parameter differences are illustrated in Table 2 along with the effect sizes of these differences calculated using the same pooled standard deviation that was used for d_{MACS}. As shown in Table 2, there were substantial differences in the factor loadings and intercepts across clinical and non-clinical samples. In many cases, the differences in the factor loadings across groups were relatively small. However, differences in the intercepts were substantial, both for the items identified as nonequivalent and for those that were not identified using traditional methods. Given that nonequivalence is defined as differences in the item-level parameters across groups, the differences illustrated in Table 2 seem to support the effect size results suggesting nonequivalence in many of the ELOCS items.

Table 1 Measurement equivalence results across clinical and non-clinical samples

	χ^2 (df)	RMSEA	CFI	TLI	SRMR
Configural invariance model	614.39	.075	.907	.89	.05
Scalar invariance models					
Go out of your way to get food you were craving.[a]	–	–	–	–	–
Feel helpless to control eating urges.	617.05	.075	.906	.89	.05
Give up control over what you ate BEFORE started to eat.	618.82	.075	.906	.89	.05
Give in to an impulse to eat even though not hungry.	625.07	.076	.905	.89	.06
Ignore an interruption to keep eating.	624.82	.076	.905	.89	.05
Keep eating even though you thought you should stop. [b]	628.83	.076	.904	.89	.06
Eat much more rapidly than normal.	618.41	.075	.906	.89	.05
Eat until you feel uncomfortably full.	622.03	.075	.905	.89	.05
Ate large amount of food when not physically hungry. [b]	628.23	.076	.904	.89	.06
Feel embarrassed about how much you were eating. [b]	634.44	.076	.903	.89	.06
Afraid of losing control over eating.	617.09	.075	.906	.89	.05
Feel driven or compelled to eat.	618.65	.075	.906	.89	.05
Hard to stop eating once started. [b]	633.95	.076	.903	.89	.06
Feel upset by the feeling that you couldn't stop eating.	619.13	.075	.906	.89	.05
Hard to stop thinking about food you were craving.	616.20	.075	.907	.89	.05
Feel out of control when you have eaten an unusually large amount of food. [b]	632.74	.076	.903	.89	.06

DF for Configural Invariance model was 206, for Scalar Invariance Model was 208

[a] This item was used as the referent item based on the constrained baseline analyses. Therefore, no effect size or fit indices are reported for the scalar invariance model of this item

[b] Nonequivalent based on CFI difference test

These results suggest that the means and variances of the ELOC scale should not be compared across clinical and non-clinical samples. Given the nonequivalence in the measure, these comparisons would be misleading and differences in scale scores could be due to nonequivalence in the measure rather than true differences in the latent construct. However, these results do not necessarily preclude comparisons of the validity of the scale across groups. Although nonequivalence in the measure can influence the relationship between a scale and an external variable (Drasgow 1984), past studies have indicated that this effect is generally negligible in both field samples (Nye 2011) and in simulation studies (Nye and Bialko 2014; Nye et al. 2010).

Discussion

The purpose of this study was to evaluate psychometric characteristics of the Eating Loss of Control Scale (ELOCS). Although LOC is a transdiagnostic construct relative to several variants of eating pathology, few well-validated measures focusing on this construct currently exist in the literature. Those that exist are either brief (e.g., 1-item) assessments embedded in multi-dimensional instruments or have only been validated thus far in non-clinical samples. The initial ELOCS validation study suggested uni-dimensionality using principal components analyses and indicated criterion validity with respect to eating-relevant variables in a clinical sample. However, it also identified four problematic items in the original 20-item pool. This study extended those findings, resulting in a revised, 16-item version of the ELOCS.

Revised 16-Item ELOCS

Two further items were eliminated in order to establish uni-dimensionality in a confirmatory model. The end result is a uni-dimensional 16-item scale with excellent reliability (see items with means and standard deviations in Table 3). This version of the ELOCS offers a useful tool for researchers interested in studying LOC as it relates to eating pathology, and a promising measure for understanding individuals with eating problems, change as a function of interventions, and other aspects of LOC.

Measurement equivalence analyses revealed a somewhat complicated relationship between the ELOCS measurement properties and sampling. Data supported configural equivalence, meaning that the measure assesses the same general *structure* of ELOCS across clinical and non-clinical samples. However, data indicated non-equivalence of the loadings and intercepts. In applied settings, this suggests interpretive problems in ELOCS score comparisons of individuals from clinical and non-clinical samples, and indicates the need for

Table 2 Parameter differences and effect sizes for measurement equivalence analyses

	Loadings				Intercepts					
	Clinical	Non-Clinical	Difference	Effect Size	Clinical	Non-Clinical	Difference	Effect Size	Pooled SD	dMACS
Go out of your way to get food you were craving.[a]	1	1	0	0.00	0	0	0	0.00	2.47	–
Feel helpless to control eating urges.	1.56	1.89	−0.33	−0.13	−1.31	−3.56	2.26	0.89	2.54	0.55
Give up control over what you ate BEFORE started to eat.	1.26	1.60	−0.34	−0.12	−0.37	−2.94	2.57	0.94	2.73	0.62
Give in to an impulse to eat even though not hungry.	0.94	1.81	−0.88	−0.33	3.05	−1.94	4.99	1.85	2.69	1.02
Ignore an interruption to keep eating.	1.25	0.58	0.67	0.26	−3.30	−1.00	−2.30	−0.89	2.59	0.32
Keep eating even though you thought you should stop. [b]	0.94	1.93	−0.99	−0.41	2.90	−3.13	6.02	2.50	2.41	1.44
Eat much more rapidly than normal.	1.18	1.20	−0.03	−0.01	−0.73	−1.84	1.12	0.42	2.67	0.39
Eat until you feel uncomfortably full.	0.99	1.87	−0.88	−0.31	2.16	−2.17	4.33	1.53	2.83	0.76
Ate large amount of food when not physically hungry. [b]	0.70	1.06	−0.36	−0.17	2.47	−0.66	3.13	1.47	2.12	1.03
Feel embarrassed about how much you were eating. [b]	1.49	0.74	0.75	0.31	−3.16	−1.51	−1.65	−0.68	2.42	0.33
Afraid of losing control over eating.	1.62	1.57	0.05	0.02	−2.60	−3.33	0.73	0.28	2.61	0.33
Feel driven or compelled to eat.	1.57	1.47	0.10	0.04	−1.23	−1.99	0.76	0.27	2.77	0.37
Hard to stop eating once started. [b]	1.54	1.47	0.07	0.03	−0.51	−3.10	2.59	1.20	2.15	1.29
Feel upset by the feeling that you couldn't stop eating.	1.72	1.75	−0.04	−0.01	−2.31	−3.82	1.51	0.60	2.50	0.57
Hard to stop thinking about food you were craving.	1.57	1.83	−0.26	−0.10	−1.63	−3.45	1.82	0.68	2.68	0.43
Feel out of control when you have eaten an unusually large amount of food. [b]	1.51	1.43	0.08	0.04	−0.60	−2.96	2.36	1.07	2.21	1.17

[a] This item was used as the referent item based on the constrained baseline analyses. Therefore, no effect size or fit indices are reported for the scalar invariance model of this item

[b] Nonequivalent based on CFI difference test

caution in using the instrument as a diagnostic tool. Although scores within either a clinical (BED) or non-clinical sample would reliably indicate LOC severity, the use of ELOCS scores in a non-clinical sample to infer membership in a clinical population (i.e., to "diagnose" LOC) could be problematic. We note that this issue has not been consistently examined in eating disorder assessment tools, so it is possible that there would be similar interpretive problems with those measures as well. Empirically, loading and intercept non-equivalence implies that the meaning of LOC behaviors is somewhat different in clinical and non-clinical samples. This finding suggests that a pathological loss of control over eating may be qualitatively different than everyday overeating.

New Insights Regarding Equivalence Testing

From a methodological perspective, the finding that the effect sizes of nonequivalence for some items were substantial despite fit indices suggesting equivalence is interesting. Past research has demonstrated the accuracy of using the change in CFI as an indicator of nonequivalence (Meade et al. 2008). However, in the present study, results based on this method conflicted with the effect size results. In addition, examining the parameter differences across groups suggested that the change in CFI was insensitive to substantial parameter differences across groups in some cases. Given the promising findings from past simulations, more research is needed to clarify the conditions in which the change in CFI will be less accurate.

The findings in the present study suggest two potential explanations for the divergent results across effect sizes and traditional indicators of nonequivalence. First, the inaccuracy of traditional methods could be due to the relatively small sample size in the clinical sample. Although Nye (2011) found the change in CFI to be the most accurate indicator of nonequivalence, these criteria were slightly less effective in sample sizes of 250. Specifically, the power to detect nonequivalence in samples of this size was relatively low, indicating that the change in CFI may not identify nonequivalence even if it is actually present under these conditions. A second potential explanation for the seeming inaccuracy of the change in CFI in the present study could have been related to the parameter

Table 3 ELOCS item means and standard deviations in clinical and non-clinical samples

Item	Clinical		Non-Clinical	
	Mean	SD	Mean	SD
On average, during these times, how much did you go out of your way to get the food you were craving?	5.18	2.50	2.69	2.27
On average, during these times, how helpless did you feel to control your eating urges?	6.80	2.76	1.54	2.43
On average, during these times, how much control did you give up over what you ate before you started to eat?	6.14	3.45	1.35	2.32
On average, during these eating occasions, how much did you give in to an impulse to eat even though you were not hungry?	7.91	2.15	2.94	2.90
On average, during these times, how much did you ignore the interruption (such as a phone call) to keep eating?	3.17	3.88	.57	1.69
On average, during these times, how much did you keep eating even though you thought you should stop?	7.76	2.03	2.08	2.56
On average, during these times, how much more rapidly than normal did you eat?	5.40	3.30	1.40	2.32
During the past four weeks, how many times did you keep eating even though you thought you should stop?	7.29	2.43	2.85	2.98
On average, during these times, how large was the amount of food you ate when you didn't feel physically hungry?	6.09	2.40	2.19	1.98
On average, during these times, how embarrassed have you felt about how much you were eating when you ate alone?	4.55	3.65	.49	1.55
During the past four weeks, how many times did you keep eating even though you thought you should stop?	5.76	3.37	.90	2.18
On average, during these times, how driven or compelled to eat have you felt?	6.89	2.63	1.97	2.85
On average, during these times, how hard has it been to stop eating once you've started?	7.44	2.50	.87	1.96
On average, during these times, how upset were you by the feeling that you couldn't stop eating or control what or how much you were eating?	6.58	3.01	.90	2.22
On average, during these times, how hard was it for you to stop thinking about the food you were craving?	6.53	3.00	1.50	2.51
On average, during the past four weeks, when you have eaten an unusually large amount of food (for example, eating two full meals; or eating three main courses; or eating an unusually large amount of one food or combination of foods) in a short period of time (1–2 h), how have you felt?	7.25	2.59	.90	2.00

Items anchors range from 0 (not at all) to 10 (extremely or completely)

differences reported in Table 2. In many cases, the items with large effect sizes that were not identified as nonequivalent had lower intercepts in the non-clinical sample but higher factor loadings. This combination of differences could result in effects that cancel out at the group level. Although the effect size was designed to address this issue and identify any differences across groups (Nye and Drasgow 2011), it is possible that the change in CFI is less sensitive to group differences under these conditions. Again, more research is needed to explore these issues with the methods used to identify nonequivalence.

Limitations and Future Directions

Our non-equivalence finding is worthy of further research on eating LOC and other aspects of eating pathology, given previous evidence for qualitative differences in eating symptoms in clinical and non-clinical samples (Williamson et al. 2002) and the importance of identifying screening indicators for LOC and other forms of pathological eating behavior. It is also the case that there were more differences in our samples than clinical status, including weight, age, and geographical location, and it is possible that these factors contributed to non-equivalence. Research using matched controls would be useful for testing this hypothesis. It would also be interesting to test the model from this study in other samples that vary in other meaningful factors, such as ethnicity, gender, or eating disorder diagnosis. Similarly, ME testing would be useful in retest or pre-post treatment studies to determine whether the ELOCS could be used to measure change as a function of treatment or in naturalistic designs within the same participants.

Perhaps it is possible to create a questionnaire measure of LOC that would show scalar and metric equivalence across clinical and non-clinical groups, which would be useful for determining clinical status in non-clinical populations. However, given that nearly all of the ELOCS items showed large differences in intercept equivalence across clinical and non-clinical samples in this study, and that the ELOCS items

are fairly representative of standard definitions of the construct, this seems challenging. It is possible that the nature of the eating LOC construct is such that individuals in clinical and non-clinical samples approach questions about LOC in a qualitatively different manner that impacts measurement issues (Gleaves et al. 2000). A similar kind of pattern might also apply to other eating disorder assessment tools. This is an important question worthy of future investigation.

At a broader level, future research should test further the possible multidimensionality and correlates of eating LOC using different instruments. It is possible that the important features of eating LOC coalesce within a single dimension; however, if distinct dimensions can be reliably identified within in the eating LOC construct, a multidimensional measure would be needed for effective and comprehensive assessment. Conversely, if eating LOC truly is unidimensional, even fewer than 16 items may be needed to capture it. Overall, there is significant work yet to be done to determine the best assessment approach for capturing this relatively new and clinically important factor in eating pathology.

Conclusion

In summary, the ELOCS is a brief, uni-dimensional measure of eating LOC that is reliable and valid, independently in BED/clinical and college student/non-clinical samples. The measure has significant potential for assessing symptom severity in research and practice. The ELOCS is a useful tool for applied practice with BED patients and its availability should promote research on LOC as an important transdiagnostic construct in eating pathology.

Compliance with Ethical Standards

Conflict of Interest Christopher J. Hopwood, Christopher D. Nye, Kerstin K. Blomquist, and Carlos M. Grilo declare that they have no conflict of interest.

Experiment Participants Informed consent was obtained from all individual participants included in this study. All procedures were in accordance with ethical standards of the institutions where the research was conducted and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

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