

# Cognitive Abilities Explain Wording Effects in the Rosenberg Self-Esteem Scale

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## Abstract

There is consensus that the 10 items of the *Rosenberg Self-Esteem Scale* (RSES) reflect wording effects resulting from positively and negatively keyed items. The present study examined the effects of cognitive abilities on the factor structure of the RSES with a novel, nonparametric latent variable technique called *local structural equation models*. In a nationally representative German large-scale assessment including 12,437 students competing measurement models for the RSES were compared: a bifactor model with a common factor and a specific factor for all negatively worded items had an optimal fit. *Local structural equation models* showed that the unidimensionality of the scale increased with higher levels of reading competence and reasoning, while the proportion of variance attributed to the negatively keyed items declined. Wording effects on the factor structure of the RSES seem to represent a response style artifact associated with cognitive abilities.

## Keywords

structural equation modeling, self-esteem, cognitive abilities, factor structure, dimensionality

The *Rosenberg Self-Esteem Scale* (RSES; 1965) is a popular self-report instrument measuring a respondent's global self-worth and self-respect with 10 items. Due to its brevity and face validity, the RSES has dominated the literature on self-esteem since its introduction (see Donnellan, Trzesniewski, & Robins, 2011; Zuckerman, Li, & Hall, 2016). The RSES has been widely used in clinical (Salerno, Ingoglia, & Coco, 2017) and educational contexts (Diseth, Meland, & Breidablik, 2014) as well as in large-scale social survey research (Marsh, Scalas, & Nagengast, 2010). The concomitant discussion about the dimensionality of the measure is almost as old as the measure itself (for recent summaries, see Donnellan, Ackerman, & Brecheen, 2016; Reise, Kim, Mansolf, & Widaman, 2016). In line with its original conceptualization that conceives self-esteem as a unitary concept describing the feeling that “one's good enough” (Rosenberg, 1965, p. 31), many authors confirmed the unidimensionality of the RSES (e.g., Chao, Vidacovich, & Green, 2017; Franck, De Raedt, Barbez, & Rosseel, 2008; Pullmann & Allik, 2000; Schmitt & Allik, 2005). For example, an international large-scale study that translated the RSES into 28 languages and administered the instrument to almost 17,000 participants across 53 nations found a single factor underlying the 10 items in most samples (Schmitt & Allik, 2005). However, because the RSES assesses positive self-appraisals (e.g., “I feel that I have a number of good qualities.”) and negative self-appraisals (e.g., “At times, I think I am no good at all.”) with opposing keyed items, other researchers identified

some form of multidimensionality (e.g., DiStefano & Motl, 2009; Donnellan et al., 2016; Gnambs, Scharl, & Schroeders, 2018; Quilty, Oakman, & Risko, 2006; Reise et al., 2016). It seems that although the RSES items are dominated by a common factor, the negatively keyed items capture systematic residual variance over and above general self-esteem. The structural ambiguity of the RSES resulted in a series of factor analytical studies within the past decades that explored whether the RSES scores reflect a single trait or represent a composite of different latent traits. In this discussion, potential moderating influences that might explain the divergent findings regarding the RSES's dimensionality have been somewhat neglected. Therefore, the present study scrutinized individual differences in potentially relevant cognitive abilities (i.e., reasoning, reading competence, vocabulary) to explain the multidimensionality of the RSES. On a more general stance, *local structural equation models* (LSEM; Hildebrandt, Lüdtke, Robitzsch, Sommer, & Wilhelm, 2016) are applied as a method for moderator analyses of latent structures to study wording effects along continuous context variables.

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## Are Wording Effects in the RSES More Substance or Style?

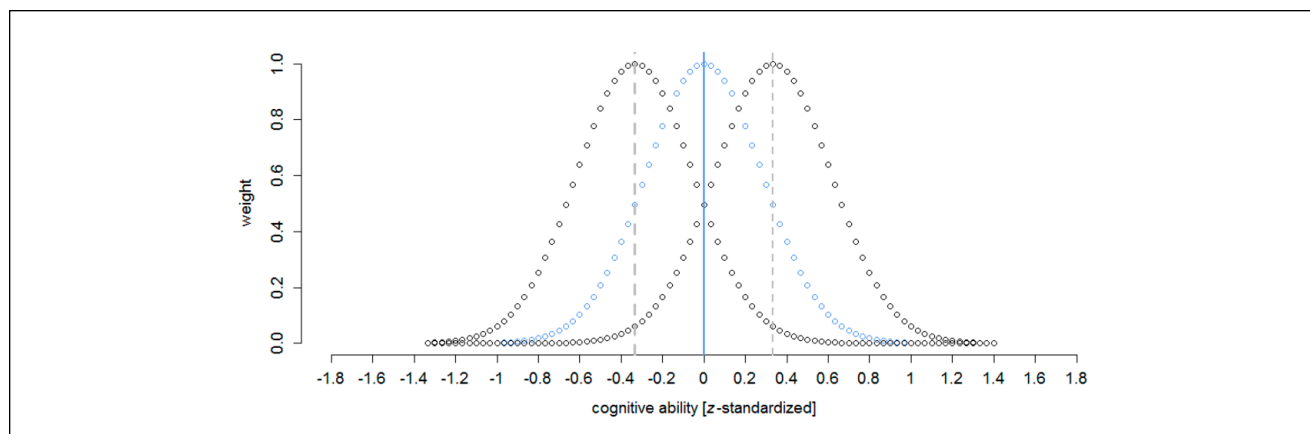
The nature and interpretation of wording effects in the RSES is subject to an ongoing debate. On the one hand, some authors considered them mere noise without substantial meaning (Marsh, 1996; Tomás & Oliver, 1999). According to this view, the residual variance captured by negatively keyed items represents a methodological artifact that needs to be controlled for in empirical analyses because it contaminates the measurement of self-esteem. Findings from an experimental study (Greenberger, Chen, Dmitrieva, & Farruggia, 2003) that administered three versions of the RSES, one with all items rephrased in a positive direction, one with all items written in the negative direction, and the original version, provided support for this view: Whereas the original RSES was best represented by a two-dimensional model, the RSES versions including items keyed in only one direction were essentially unidimensional. On the other hand, some authors considered the existence of wording effects the result of systematic response styles such as acquiescence (DiStefano & Motl, 2006; Tomás, Oliver, Galiana, Sancho, & Lila, 2013). In this view, in addition to the focal construct of self-esteem negatively keyed items also capture a conceptually distinct trait representing a respondent's response consistency independent of the scales' content. In line with this assumption, wording effects in the RSES have been found to be stable across measurement occasions (Gana et al., 2013; Marsh et al., 2010; Michaelides, Koutsogiorgi, & Panayiotou, 2016; Motl & DiStefano, 2002) and subgroups (DiStefano & Motl, 2009; Lindwall et al., 2012; Michaelides, Zenger, et al., 2016; Salerno et al., 2017), they were identified in different language versions (Tomás et al., 2013; C. H. Wu, 2008; Y. Wu, Zuo, Wen, & Yan, 2017), and have been replicated across similar instruments (DiStefano & Motl, 2006; Horan, DiStefano, & Motl, 2003). Furthermore, because criterion-related validity studies associated the RSES scores for positively and negatively keyed items with distinct personality traits and motivational tendencies (e.g., Donnellan et al., 2016; Quilty et al., 2006), some authors even argued that these subdimensions imply a substantive distinction between two unique, albeit correlated, personality traits, positive and negative self-esteem (e.g., Alessandri, Vecchione, Eisenberg, & Laguna, 2015; Owens, 1994; Roth, Decker, Herzberg, & Brähler, 2008). According to this perspective, the negatively keyed items of the RSES measure self-derogation or self-deprecation, whereas the positive items capture self-competence. Hence, differently keyed items of the RSES form two subscales reflecting different forms of self-esteem.

## Moderating Influences on the Structure of the RSES

Despite an abundance of research on the RSES, little is known about moderators that might explain why some studies supported an essentially unidimensional structure,

whereas others advocated for a multidimensional structure. Some authors attributed aberrant responses for negatively keyed items to respondents' cognitive abilities (Cordery & Sevastos, 1993; Marsh, 1996; Weems, Onwuegbuzie, & Collins, 2006; Williams & Swanson, 2001). For example, Marsh (1996) suggested that responses to the RSES might be affected by the verbal skills of the respondents because responding to negatively worded items requires more complex cognitive processes than responding to positively keyed items. Individuals lacking the necessary competencies to properly understand grammatical negations might perceive negatively worded items differently. Along this line, Sliter and Zickar (2014) demonstrated that negatively keyed items functioned differently and, on average, exhibited higher category thresholds (i.e., they were more difficult) than positively keyed items. Moreover, Marsh (1996) showed—by dividing a sample into different ability groups—that wording effects decreased for students with higher reading competence. Thus, the RSES seems to be a relatively unidimensional scale among verbally competent respondents, whereas the negatively keyed items capture systematic residual variance among respondents with limited verbal skills. These results were replicated in some samples (Corwyn, 2000; Dunbar, Ford, Hunt, & Der, 2000), but not in others (von Collani & Herzberg, 2003b).

A fundamental problem with this sort of analysis is how moderating effects were modeled. Although reading competence was measured on a continuous scale, the variable was post hoc classified into different categories to create artificial competence groups. However, this artificial categorization of a naturally continuous context variable is associated with several methodological problems (MacCallum, Zhang, Preacher, & Rucker, 2002; Preacher, Rucker, MacCallum, & Nicewander, 2005; Rucker, McShane, & Preacher, 2015): First, in the framework of *multiple-group mean and covariance structure* (MGMCs) analyses that are widely used and accepted for investigating factorial invariance across categorical context variables (van de Schoot, Lugtig, & Hox, 2012; Wicherts & Dolan, 2010), creating artificial subgroups increases the risk of missing nonlinear trends and interaction effects. Unless a large number of groups are used, they do not allow the identification of the onset of a parameter change (Hildebrandt, Wilhelm, & Robitzsch, 2009). Second, categorization leads to a loss in information on individual differences within a given group. When observations that differ across the range of a continuous variable are grouped, respondents within groups are assumed homogenous and potential variations within these groups are ignored. Third, when splitting a continuous distribution of a moderator into several distinct sections, the selection of cutpoints is frequently rather arbitrary. Thus, neither the number of groups nor their ranges along the context variables are unique. Critically, in case of nonlinear parameter changes the selected ranges can



**Figure 1.** Weighting functions for cognitive ability as moderator.

Note. Focal moderator points are  $-1/3$ ,  $0$ , and  $1/3$ . Gray dashed lines indicate the value of the moderator at which an observation will receive a weight of .50 for focal point  $0$ .

influence the results of MGCMS analyses and increase the likelihood of Type II errors (Hildebrandt et al., 2009; MacCallum et al., 2002).

### Local Structural Equation Modeling

To overcome shortcomings of categorizing continuous context variables, the present study capitalizes on a recently developed nonparametric structural equation modeling (SEM) technique called LSEM (Hildebrandt et al., 2009; Hildebrandt et al., 2016), which allows studying variance-covariance structures contingent on a continuous context variable. In principle, LSEMs are traditional SEMs that weight observations around focal points (i.e., specific values of the continuous moderator variable) with a Gaussian kernel function (Gasser, Gervini, & Molinari, 2004). Thus, in contrast to grouping participants according to a moderator variable (as is the custom in MGCMS), in LSEM participants are weighted depending on their value of the moderator. The core idea is that observations near the focal point provide more information for the corresponding SEM than more distant observations. Figure 1 exemplifies three weight functions using the cognitive ability of the respondents ( $z$  standardized) as moderator at focal points of  $z = -1/3$ ,  $0$ , and  $1/3$ . Observations exactly at the focal point receive a weight of 1; observations with moderator values higher or lower than the focal point receive smaller weights. For example, if the difference between the focal point and moderator is  $|1/3|$ , the weight is about .50 (see the gray dashed lines in Figure 1). For each focal value of the context variable, a separate SEM is estimated resulting in a series of models that provide gradients of model parameters. A more formal introduction into LSEM is given in the Appendices.

An advantage of LSEM is the opportunity to study any model parameter (e.g., means, factor loadings, or variances) across a continuous context variable. It is even conceivable

to explore changes in model fit indices (e.g., comparative fit index [CFI]) or other indices such as composite reliability that is derived from estimated factor loadings (Rodriguez, Reise, & Haviland, 2016). Because LSEM does not require an a priori function regarding change, the approach is also viable when there are no explicit assumptions regarding the onset or the trajectories of parameter change.

Generally, each local SEM will utilize more observations than a SEM that is limited to respondents with a specific value of the context variable. The weighting scheme used in LSEM results in an effective sample size at each focal point that depends on the available observations near the value of the context variable. In the case of a normally distributed context variable, focal points in the midrange will integrate the information of many respondents, resulting in a larger effective sample size. In contrast, focal points in the extremes of the moderator range will rely on less observations. As a consequence, the effective sample size will be smaller at the lower and upper ends of the moderator distribution and, thus, result in less precise parameters estimates and larger confidence intervals.

LSEMs allow for the visual inspection of gradients of SEM parameters. For example, examining the trajectories of factor loadings or latent means can help in identifying the onset of parameter changes or in describing developmental aspects (e.g., curvilinear trends). Traditional model fit indices or statistical likelihood-based tests to evaluate the effect of the moderator are not available since the moderator is no explicit parameter in the model, but influences the SEM only indirectly through the weighting function. Statistical inferences can be made using so-called permutation tests that evaluate if a SEM parameter is constant across different values of the context variables (initially described in Hülür, Wilhelm, & Robitzsch, 2011; see also Hildebrandt et al., 2016). For this test, a large number of data sets are generated from the observed data (e.g., 1,000 permutations) that

each randomly assigns the observed values of the moderator to the individuals. This approach ensures that the data in the permuted data set are completely independent of the context variable and, thus, allows to test whether changes of the gradients in the real data set are connected to the moderator variable. More specifically, through the random assignment, the results of the permutation test are adjusted for a main effect of the moderator. Therefore, the *shape* of the parameter estimates is compared between the observed and the permuted data sets rather than *absolute values* (see also Schroeders, Schipolowski, & Wilhelm, 2015).

## Present Study

In order to shed light on the question whether the negatively worded items of the RSES capture trait-specific variance or if they simply add trait-irrelevant variance to an otherwise unidimensional scale, we studied the dimensionality of the RSES along a range of cognitive abilities in a representative sample of German students. If negatively keyed items formed a substantive trait independent of general self-esteem, the factor structure should remain invariant independent of the verbal ability of the students. In contrast, if negatively keyed items represented response artifacts associated with cognitive abilities, we would expect the method factor to account for a larger proportion of item variance among less competent respondents, whereas the proportion of explained variance should decline for more competent respondents. Thus, the goal of the study is the examination of the factor structure of the RSES across potentially relevant continuous moderators. More specifically, we study changes in selective model parameters across different levels of reading abilities, vocabulary, and reasoning by means of LSEM.

## Method

### Participants

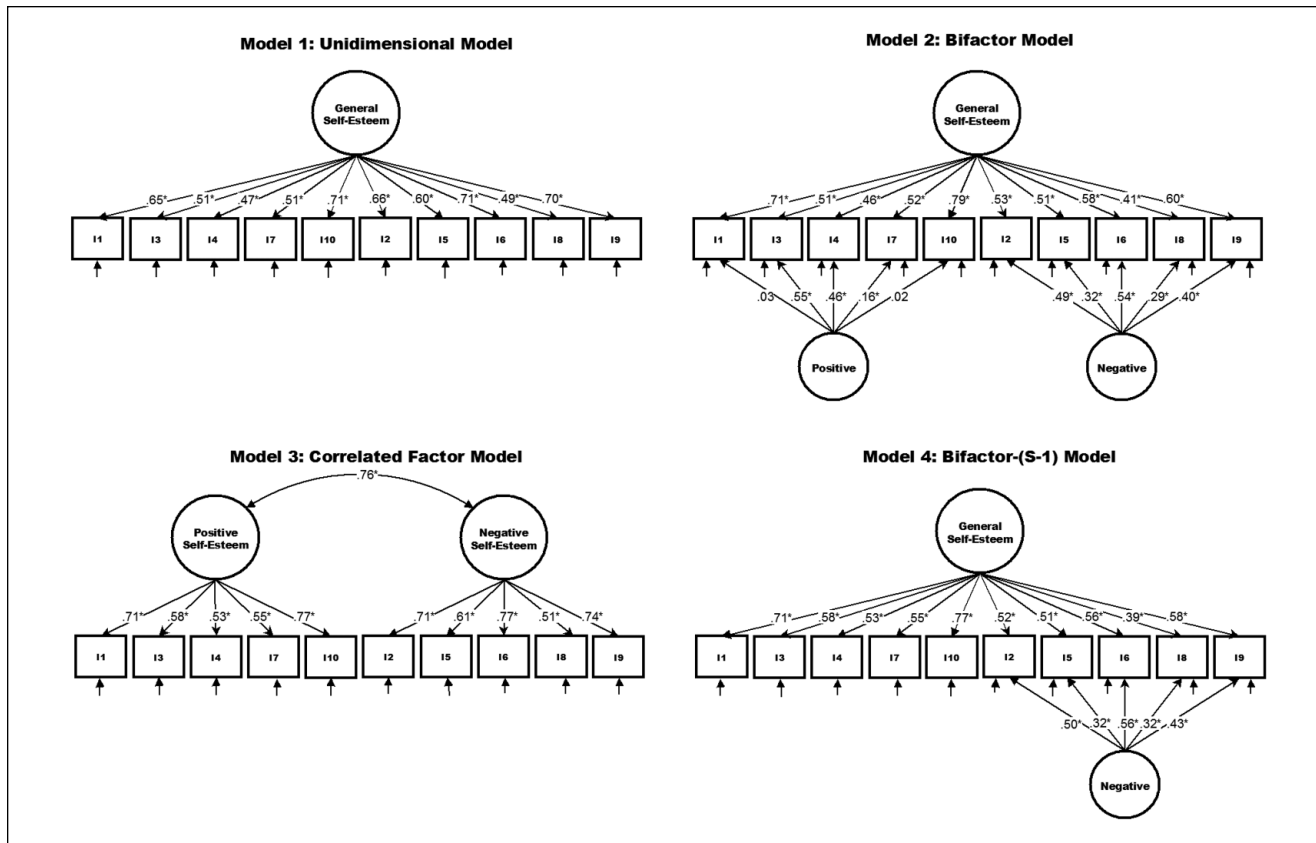
The respondents ( $N = 12,437$ ; 50% girls) were part of a representative sample of German students in the National Educational Panel Study (see Blossfeld, Roßbach, & von Maurice, 2011) that attended ninth grade at various schools across rural and urban localities. To reach a diverse sample of students, all major school types were included (see Steinhauer, Aßmann, Zinn, Goßmann, & Rässler, 2015, for details on the sampling procedure), about 54% attended general or intermediate secondary schools, 39% went to higher secondary schools, and the remaining 7% encompassed students from several specialized school branches. Their mean age was  $M = 14.68$  ( $SD = 0.69$ ) years. Data collection was conducted in small groups at the students' respective schools by a professional survey institute (for details on the data collection process, see the field reports provided at <http://www.neps-data.de>).

### Instruments

*Self-esteem* was measured with a German translation (von Collani & Herzberg, 2003a) of the Rosenberg (1965) scale using 10 items on 5-point response scales from 1 (*strongly disagree*) to 5 (*strongly agree*; see the Appendices). The negatively keyed items (2, 5, 6, 8, 9) were recoded so that higher scores indicate higher self-esteem. For each item between 1% and 3% of the respondents exhibited missing values. The means, standard deviations, and correlations between all items are summarized in Table S1 of the supplemental material. The average score of the 10 RSES items had a mean of 3.94 ( $SD = 0.63$ ) and a reliability  $\omega_{\text{total}}$  of .85 (McNeish, 2018). *Vocabulary* was measured with an adapted German version of the Peabody Picture Vocabulary Test (Dunn & Dunn, 2004) including 89 items. For each item, the respondents had to select one out of four pictures that corresponded to a spoken word. The sum score of correctly answered items ( $M = 57.76$ ,  $SD = 10.25$ ) had a reliability categorical  $\omega_{\text{total}}$  of .87 (Green & Yang, 2009). *Reading competence* was measured with an achievement test ( $M = 0.03$ ,  $SD = 1.25$ ) including 31 items that required either multiple-choice or short constructed responses (see Haberkorn, Pohl, Hardt, & Wiegand, 2012). The test was scaled using a unidimensional item response model (Rasch, 1960). Competence scores for each respondent were derived as weighted maximum likelihood estimates (Warm, 1989) with a reliability of .75. *Reasoning* was measured with a matrices test including 12 items. Matrices tests are good proxies for fluid intelligence, because the figural content is seen as prototypical for the construct (Wilhelm, 2005). For each item, respondents had to identify a missing element from several response options that logically completed a geometrical pattern. The number of correctly solved items ( $M = 8.74$ ,  $SD = 2.40$ ) had a reliability of categorical  $\omega_{\text{total}} = .70$ .

### Statistical Analyses

The dimensionality of the RSES was examined by confirmatory factor analyses using a full information maximum likelihood estimator with heteroskedasticity-consistent standard errors (Freedman, 2006) and a robust test statistic (Yuan & Bentler, 2000) in *lavaan* version 0.5-23.1097 (Rosseel, 2012). Simulation studies indicate that linear factor analyses allow for valid inferences as long as all variables have at least five response categories (Beauducel & Herzberg, 2006; Rhemtulla, Brosseau-Liard, & Savalei, 2012). Model fit was evaluated in line with conventional standards (see Schermelleh-Engel, Moosbrugger, & Müller, 2003) using the CFI, the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). Models with  $CFI \geq .95$ ,  $RMSEA \leq .08$ , and  $SRMR \leq .10$  are interpreted as "acceptable" and models with  $CFI \geq .97$ ,  $RMSEA \leq .05$ , and  $SRMR \leq .05$



**Figure 2.** Factor models for the Rosenberg Self-Esteem Scale with standardized factor loadings.

\* $p < .05$ .

as “good” fitting. We tested four structural models for the RSES that have been frequently adopted in the literature (see Figure 2). In all models, factor loadings and residual variances were freely estimated. For identification purposes, the latent factor variances were fixed to 1. Moreover, the residual variances for all items were uncorrelated. Model 1 was strictly unidimensional and assumed a single general factor explaining the covariances between the RSES items. Model 2 specified a bifactor structure (see Brunner, Nagy, & Wilhelm, 2012; Reise, 2012) including a general factor for all items of the RSES and two specific factors for the positively (1, 3, 4, 7, 10) and negatively keyed items (2, 5, 6, 8, 9). In this model, the two method factors capture the residual variance that is attributed to the positively and negatively keyed items after accounting for the shared variance of all items. Trait and method factors were uncorrelated. Model 3 specified two correlated latent factors representing positive and negative self-esteem. The latter was indicated by the five negatively keyed items, whereas the former was specified by the positively keyed items. This model is mathematical equivalent to a bifactor model with proportional constraints on the factor loadings (Reise, 2012). Thus, Model 3 is more parsimonious than Model 2. Finally, Model 4

specified a bifactor-(S-1) structure (see Eid, Geiser, Koch, & Heene, 2017) that included a general factor for all items and a single specific latent factor for the negatively keyed items. In the factor analytical literature, such models have previously been termed nested factor models (Schulze, 2005). In this model, the general factor can be understood as general self-esteem which is instantiated by the positively keyed items and orthogonal to a method factor capturing the residual variance of the negatively keyed items.

A recent simulation study (Gu, Wen, & Fan, 2017) highlighted that wording effects might have a detrimental effect on the homogeneity of a scale, that is, ignoring negative wording effects leads to biased estimates of reliability and criterion-based validity. Therefore, the focal parameter in our analyses pertained to the percentage of variance in total scores attributable to the general factor (i.e., general self-esteem) in terms of omega hierarchical ( $\omega_H^2$ ; Rodriguez et al., 2016). For a bifactor model (Model 2 in Figure 2),  $\omega_H^2$  is given in equation [1] with  $\lambda_{gen}$  representing the standardized factor loadings on the general factor,  $\lambda_{pos}$  the respective loadings on the positive factor,  $\lambda_{neg}$  the respective loadings on the negative factor, and  $h^2$  the explained item variance.

$$\omega_H = \frac{\left(\sum_{i=1}^{10} \lambda_{gen,i}\right)^2}{\left(\sum_{i=1}^{10} \lambda_{gen,i}\right)^2 + \left(\sum_{i=1}^5 \lambda_{pos,i}\right)^2 + \left(\sum_{i=1}^5 \lambda_{neg,i}\right)^2 + \sum_{i=1}^{10} (1-h_i^2)} \quad [1]$$

Moreover, because some authors advocated the interpretation of subscales in the RSES (e.g., Alessandri et al., 2015; Owens, 1994), we also examined  $\omega_H$  subscale (see Rodriguez et al., 2016) for the negatively keyed items which reflects the proportion of unique variance in the subscale score after accounting for the general factor. For the five items of the negative self-esteem subscale  $\omega_{HS.NEG}$  is given as follows:

$$\omega_{HS.NEG} = \frac{\left(\sum_{i=1}^5 \lambda_{neg,i}\right)^2}{\left(\sum_{i=1}^5 \lambda_{gen,i}\right)^2 + \left(\sum_{i=1}^5 \lambda_{neg,i}\right)^2 + \sum_{i=1}^5 (1-h_i^2)} \quad [2]$$

Moderating effects of cognitive abilities on  $\omega_H$  and  $\omega_{HS.NEG}$  were studied using LSEMs with robust full information maximum likelihood estimation (Hildebrandt et al., 2016), implemented in the R package *sirt*, version 2.0-25 (Robitzsch, 2017). We selected 37 equally spaced focal points between -1.8 and 1.8 on the *z* standardized scale of each moderator. Because fewer participants achieved extreme scores on the moderators (i.e.,  $\leq -2$  or  $\geq 2$ ) and the robustness of estimated SEM parameters is affected by the sample size (Wolf, Harrington, Clark, & Miller, 2013), the analyses were limited to focal points resulting in an effective sample size of at least 400. This resulted in effective sample sizes across the 37 focal points between 421 and 3,969 (*Mdn* = 2,310 to 2,486 for the different values of the moderators). Gradients of  $\omega_H$  and  $\omega_{HS.NEG}$  were derived by reestimating a confirmatory factor model at different focal points of the moderator using appropriate sample weights. Permutation tests on the derived vectors of  $\omega$  allow for statistical inferences on the variability and potential trends of  $\omega$  across the continuous moderators (Hildebrandt et al., 2016; Hülür et al., 2011).

### Open Data

The variance-covariance matrix between the 10 items of the RSES is provided in the supplemental material (Table S1). Moreover, researchers accepting the respective legal and confidentially agreement can download the complete data set analyzed in this study (<http://www.neps-data.de>). We also provide all R scripts (R Core Team, 2017) in an online repository of the *Open Science Framework* (<https://osf.io/bkzjy>) to make the present analyses as transparent and reproducible as possible (Nosek et al., 2015).

**Table 1.** Exploratory Factor Analysis of the Rosenberg Self-Esteem Scale.

	Factor 1	Factor 2	$h^2$
Item 1	.30	.43	.44
Item 3	-.13	.78	.49
Item 4	-.12	.71	.40
Item 7	.13	.45	.30
Item 10	.34	.45	.52
Item 2	.75	-.07	.50
Item 5	.49	.15	.36
Item 6	.85	-.10	.62
Item 8	.53	-.04	.26
Item 9	.71	.02	.53
Eigenvalue	2.63	1.79	
Explained variance	26%	18%	

Note. *N* = 12,437. Full information maximum likelihood factor analysis with oblimin rotation (factor correlation: .67). Gray cells indicate salient pattern coefficients of positively keyed items (1, 3, 4, 7, 10) and negatively keyed items (2, 5, 6, 8, 9).

### Results

All items of the RSES were moderately correlated (Table S1). An exploratory maximum likelihood factor analysis with oblimin rotation ( $\delta = 0$ ; see Table 1) resulted in a clearly interpretable two-factor solution (first four eigenvalues: 4.31, 1.20, 0.74, 0.72) explaining about 44% of the item variance. Negatively keyed items had average pattern coefficients on the first factor of *Mdn*( $\lambda$ ) = .71 (*Min* = .49, *Max* = .85); positively keyed items exhibited average pattern coefficients on the second factor of *Mdn*( $\lambda$ ) = .45 (*Min* = .43, *Max* = .78). The correlation between both factors amounted to  $r = .67$ . The three cognitive measures showed rather negligible associations with the RSES scores. Vocabulary, reading competence, and reasoning correlated ( $p < .001$ ) with self-esteem at .11, .05, and .04, respectively.

### Dimensionality of the Rosenberg Self-Esteem Scale

The goodness-of-fit indices for the competing factor models are summarized in Table 2, whereas the respective standardized parameter estimates are included in Figure 2. A unidimensional factor model (Model 1) for the RSES exhibited an unsatisfactory fit (CFI = .87, RMSEA = .09, SRMR = .06), although all items showed substantial factor loadings, *Mdn*( $\beta$ ) = .63 (*Min* = .47, *Max* = .71). In contrast, a bifactor model (Model 2) that also included specific factors for the positively and negatively keyed items resulted in a significantly ( $p < .05$ ) better fit (CFI = .99, RMSEA = .04, SRMR = .02). Standardized loadings were larger than .40 on the general factor, *Mdn*( $\beta$ ) = .53 (*Min* = .41, *Max* = .79). In addition, the negatively keyed items had nonignorable loadings on the

**Table 2.** Fit Statistics for Different Factor Models for the Rosenberg Self-Esteem Scale.

Model	Model fit								Model comparison		
	$\chi^2$	<i>df</i>	<i>c</i>	CFI	SRMR	RMSEA	90% CI	BIC	Comp.	$\Delta\chi^2$	$\Delta df$
M1 General factor model	3765.00*	35	1.251	.871	.055	.093	[.090, .095]	302055.41			
M2 Bifactor model	438.04*	25	1.205	.986	.017	.036	[.034, .039]	297967.87	M1	3059.90*	10
M3 Correlated factor model	1528.73*	34	1.238	.948	.035	.059	[.057, .062]	299247.54	M2	1026.00*	9
M4 Bifactor-(S-1) model	1409.90*	30	1.215	.952	.033	.061	[.058, .063]	299106.68	M2	934.07*	5
M5 Bifactor-(S-1) model with correlated residuals	565.50*	29	1.216	.981	.021	.039	[.036, .041]	298090.19	M4	856.87*	1

Note.  $N = 12,437$ ;  $c$  = scale correction factor (Yuan & Bentler, 2000); CFI = comparative fit index; SRMR = standardized root mean residual; RMSEA = root mean square error of approximation; BIC = bayesian information criterion; Comp. = comparison model;  $df$  = degrees of freedom; CI = confidence interval for RMSEA. Robust full information maximum likelihood estimation. M5 includes correlated residuals between Items 3 and 4.

\* $p < .05$ .

method-specific factor,  $Mdn(\beta) = .40$  ( $Min = .29$ ,  $Max = .54$ ). However, only two positively keyed items (3, 4) exhibited substantial loadings on the respective factor,  $Mdn(\beta) = .16$  ( $Min = .01$ ,  $Max = .55$ ); in contrast, one item (7) had a significant ( $p < .05$ ) but nonsubstantial loading and two items (1, 10) exhibited no significant ( $p > .05$ ) factor loadings on the method factor. These results fall in line with previous findings (e.g., Donnellan et al., 2016; Marsh et al., 2010) that demonstrated more pronounced method effects for negatively keyed items and unclear loading patterns (i.e., nonsignificant or even negative) for the positively keyed items. This pattern of result matched with the respective reliability estimates: The negative factor accounted for about 10% of the test score variance, whereas only about 4% were attributable to the positive factor. However, the general factor accounted for most of the variance ( $\omega_H = .79$ ). Thus, the RSES was dominated by a single general factor.

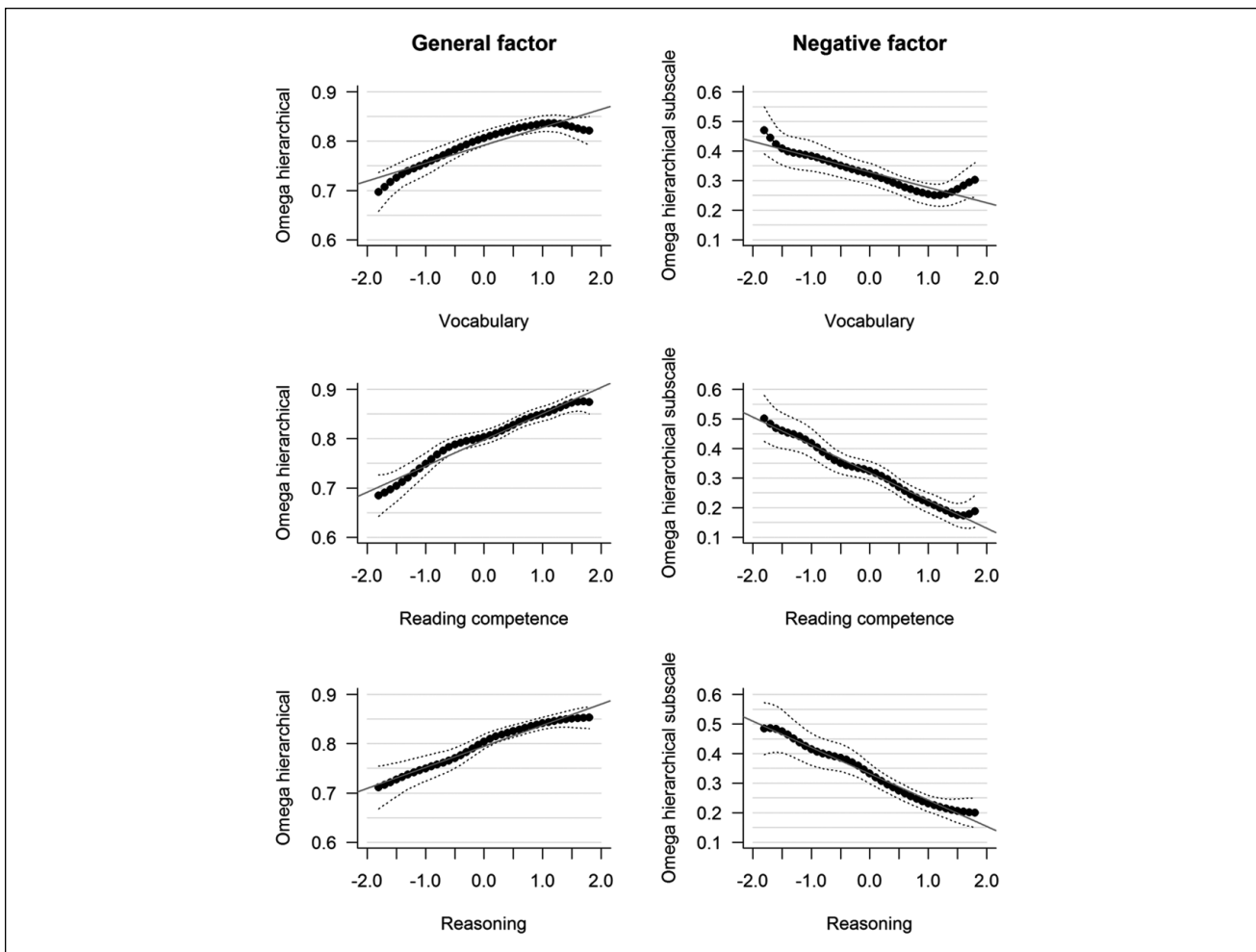
We also examined whether more parsimonious models might adequately describe the data. A model with two correlated factors reflecting positive and negative self-esteem (Model 3) showed a notable decline in fit (see Table 2). Similarly, the bifactor-(S-1) model (Model 4) that included only a single specific factor for the negatively keyed items exhibited a worse fit than the full bifactor model. Finally, because the positive factor in Model 2 was primarily defined by two items (3, 4), we extended the bifactor-(S-1) model and allowed the residuals between these items to correlate freely. The respective model (Model 5 in Table 2) showed a negligible decline in fit as compared with the full bifactor model. All goodness-of-fit indices indicated an excellent fit (CFI = .98, RMSEA = .04, SRMR = .02). Moreover, all standardized loadings on the general factor were substantial,  $Mdn(\beta) = .54$  ( $Min = .40$ ,  $Max = .78$ ), which also holds true for the negative factor,  $Mdn(\beta) = .41$  ( $Min = .30$ ,  $Max = .55$ ). Again, most of the test score variance was attributable to the general factor ( $\omega_H = .79$ ) as compared with the negative factor (11%). The two residuals correlated at  $r = .31$  ( $p < .001$ ).<sup>1</sup> Therefore, all subsequent analyses were based on

the bifactor-(S-1) model with correlated residuals for Items 3 and 4. In addition, all analyses were also replicated using the full bifactor specification (Model 2). But, these yielded no significantly and substantially different results (see supplemental material).

### Moderating Effects of Cognitive Abilities

Neither the general factor nor the negative factor was substantially correlated with vocabulary, reading comprehension, or reasoning ( $r$ s between  $-.06$  and  $.11$ ; see Table S2 in the supplement material). To study potential moderating effects of individual differences in cognitive abilities on the dimensionality of the RSES and the homogeneity of the general factor, LSEMs were conducted. We investigated the influence of vocabulary, reading competence, or reasoning as a continuous moderator of the factor structure in three separate LSEMs. All models indicated good model fits: The average CFI was  $Mdn = .979$  ( $Min = .962$ ,  $Max = .982$ ), the average RMSEA was  $Mdn = .049$  ( $Min = .040$ ,  $Max = .071$ ), and the average SRMR was  $Mdn = .022$  ( $Min = .020$ ,  $Max = .029$ ). The variability of  $\omega_H$  for the general factor along the  $z$  standardized ability scores is summarized in Figure 3 (left column). Overall,  $\omega_H$  gradually increased along the values of all three cognitive measures. Moreover, permutation tests (see Table 3) corroborated that  $\omega_H$  for the general factor was not constant across different values of the moderators, but demonstrated significant variation along values of vocabulary ( $SD = 0.03$ ,  $p < .001$ ), reading competence ( $SD = 0.04$ ,  $p = .01$ ), and reasoning ( $SD = 0.04$ ,  $p < .001$ ). A regression of the estimated  $\omega_H$  on the different values of the moderators identified significant linear trends for vocabulary ( $B = .04$ ,  $p < .001$ ), reading competence ( $B = .05$ ,  $p < .001$ ), and reasoning ( $B = .05$ ,  $p < .001$ ). Thus, a difference of 1 standard deviation on either cognitive measure corresponded to an increase of about 4% to 5% in variance explained by the general factor. In the same vein, the percentage of variance in subscale scores attributed to the negatively keyed items





**Figure 3.** Reliability (black dots) for general and negative factors in the Rosenberg Self-Esteem Scale across z-standardized cognitive abilities with 95% confidence intervals (dashed lines) and regression line (gray solid line).

**Table 3.** Results of Permutation Tests for LSEM on Factor Reliabilities.

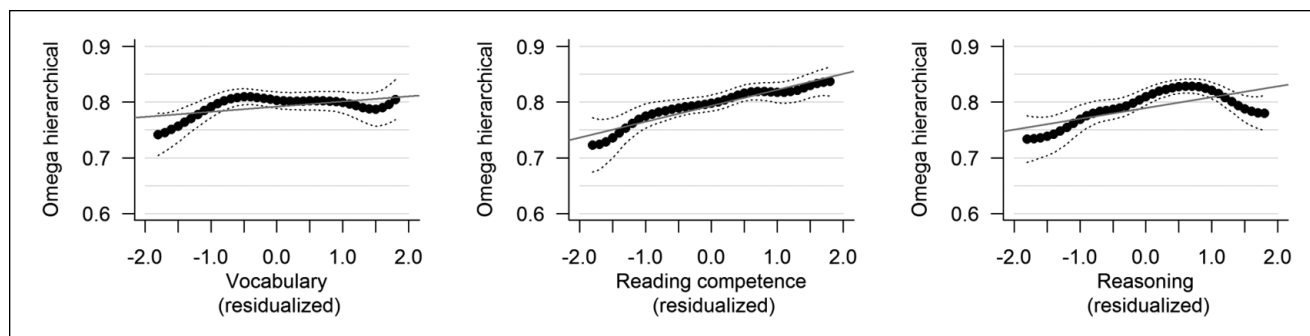
	General factor ( $\omega_H$ )					Negative factor ( $\omega_{HS,NEG}$ )				
	M	SD	p(SD)	B	p(B)	M	SD	p(SD)	B	p(B)
<i>Bivariate effects</i>										
Vocabulary	.800	.033	<.001	.037	<.001	.320	.049	<.001	-.055	<.001
Reading competence	.801	.044	<.001	.052	<.001	.318	.080	<.001	-.095	<.001
Reasoning	.805	.037	<.001	.045	<.001	.314	.078	<.001	-.094	<.001
<i>Partial effects</i>										
Vocabulary	.798	.014	.02	.006	.34	.325	.024	.14	.005	.52
Reading competence	.797	.023	<.001	.027	<.001	.328	.051	<.001	-.058	<.001
Reasoning	.802	.026	<.001	.023	<.001	.320	.052	<.001	-.052	<.001

Note. N = 12,437; M = average  $\omega$  across values of the moderator (range: [-1.8, 1.8]); SD = variation of  $\omega$  across values of the moderator; p(SD) = p-value of the permutation test for SD; B = linear effect of the moderator on  $\omega$ ; p(B) = p-value of the permutation test for B. Based on the bifactor-(S-1) model with correlated residuals between Items 3 and 4. Partial effects are based on the residualized values of the moderators.

mirrored the results for the general factor (see right column of Figure 3):  $\omega_{HS,NEG}$  gradually decreased along the values

of all three cognitive measures. A 1 standard deviation difference on vocabulary, reading competence, or reasoning





**Figure 4.** Reliabilities (black dots) for the general factor in the Rosenberg Self-Esteem Scale across residualized cognitive abilities with 95% confidence intervals (dashed lines) and regression line (gray solid line).

was accompanied by a decrease of about 5% to 10% in unique variance explained by the negative factor.

The three cognitive measures were substantially ( $p < .001$ ) correlated. Vocabulary and reading competence correlated at  $r = .56$  and reasoning correlated with the two former at  $r = .41$  and  $r = .45$ , respectively. Therefore, we also studied the partial effects of each measure on  $\omega_H$ , that is, vocabulary, reading competence, and reasoning were residualized to cancel out their shared variance. In the following, we report the results of analyses replicated with these residualized scores. The variability of  $\omega_H$  for the general factor across the residualized cognitive measures is summarized in Figure 4 (see also Table 3). Vocabulary had no substantial partial effect on the variance explained by the general factor. Despite some variability of the estimated  $\omega_H$  ( $SD = 0.01$ ,  $p = .02$ ) across different values of vocabulary, there was no systematic linear trend ( $B = .01$ ,  $p = .22$ ). In contrast, the residualized reading competence ( $SD = 0.02$ ,  $p < .001$ ) and reasoning scores ( $SD = 0.03$ ,  $p < .001$ ) both replicated the linear trends identified previously,  $B = .03$  ( $p < .001$ ) and  $B = .02$  ( $p < .001$ ), respectively. Similarly, whereas vocabulary showed no partial effects for  $\omega_{HS,NEG}$  ( $B = .00$ ,  $p = .84$ ; see Table 3) it gradually decreased with higher residualized reading competence ( $B = -.02$ ,  $p < .001$ ) or reasoning scores ( $B = -.02$ ,  $p < .001$ ). Thus, the factor saturation in the subscale for the negatively keyed items was most pronounced for lower levels of reading competence and reasoning, whereas it gradually decreased for higher levels of these scores. Overall, for verbally more competent students, the negatively worded items captured little unique variance beyond general self-esteem.

## Discussion

In applied measurement, it is a common finding that psychological measures often have a dominant general factor capturing the commonality between all items, but also some evidence of multidimensionality. As a consequence, such “structural ambiguity leads to seemingly endless ‘confirmatory’ factor

analytic studies, in which the research question is whether scale scores can be interpreted as reflecting variation on a single trait” (Reise, Moore, & Haviland, 2010, p. 544). More than 50 years of research on the dimensionality of the RSES has not settled this dispute: Many authors concur that the RSES is not strictly unidimensional but also captures wording effects from negatively keyed items (Alessandri et al., 2015; Donnellan et al., 2016; Gnambis et al., 2018; Reise et al., 2016), while others found wording effects to be seemingly negligible and unlikely to distort the measurement of self-esteem (e.g., Chao et al., 2017; Franck et al., 2008; Schmitt & Allik, 2005).

With the present study, we took a different approach arguing that the extent of wording effects depends on the verbal and cognitive abilities of the test takers. More precisely, we explored potential moderating influences on the dimensionality of the RSES by means of LSEM. In line with previous research (Corwyn, 2000; Dunbar et al., 2000; Marsh, 1996), we showed that respondents with poor reading competences and reasoning abilities provided biased responses to negatively keyed items. Whereas the RSES was essentially unidimensional among skilled readers, the responses of students with difficulties in adequately understanding negatively keyed items also reflected a secondary trait beyond self-esteem. Such an interaction with test takers’ reading abilities seems particularly troublesome if RSES subscales are interpreted as representing different types of self-esteem (Alessandri et al., 2015; Owens, 1994). The unique variance among the five items forming a putative negative self-esteem scale gradually decreased with increasing reading abilities. As a consequence, the factor saturation has been halved for skilled readers as compared with less-skilled readers. Thus, distinguishing between qualitatively different aspects of self-esteem (i.e., positive and negative self-esteem) is not warranted, because differently keyed items measure essentially the same construct among gifted readers. Given that the interpretation of scale scores depends on the respondent’s cognitive abilities, it seems questionable to view positive and negative self-esteem as substantially different traits of personality.

### *Prospects of Local Structure Equation Modeling*

On a more general note, this study presented LSEM as a versatile and powerful method to examine changes in variance–covariance structures depending on continuous context variables. Until now, LSEM has been mainly applied to study age-related changes in cognitive abilities such as the differentiation–dedifferentiation of intelligence in childhood and adolescence (Hülür et al., 2011; Schroeders et al., 2015) or the development of face cognition abilities across the life span (Hildebrandt, Sommer, Herzmann, & Wilhelm, 2010; Hildebrandt, Wilhelm, Herzmann, & Sommer, 2013). However, LSEM has a greater potential, whenever moderating hypotheses pertain to continuous context variables. Unfortunately, all too often the set of available statistical methods shapes the way researchers conceptualize and study human behavior. For example, in cross-cultural research group differences between different ethnic groups are studied with MGMCS, when, more appropriately, the variable of interest should be cultural values or national identity. Thus, instead of analyzing the influence of membership to a salient group, it would be more informative to examine the underlying psychological mechanisms that are hypothetical and continuous in nature. Furthermore, the statistical methods and not the nature of the variables affect the way in which we analyze data. For instance, group designs are frequently used in research on aging, although the underlying context variable age is continuous (e.g., Gnambs & Buntins, 2017; Marsh, Nagengast, & Morin, 2013). Similar limitations pertain to previous studies on reading abilities and wording effects (Corwyn, 2000; Dunbar et al., 2000; Marsh, 1996; von Collani & Herzberg, 2003b). In these studies, researchers artificially and arbitrarily created ability groups, albeit ability was measured on a continuous scale. Although most studies corroborate the present findings—since the observed effect was nearly linear—such split-design analyses always run the risk of masking potential nonlinear changes.<sup>2</sup> Thus, LSEMs offer a flexible opportunity to study parameter changes in the mean and the variance–covariance structure across a continuous context variable. In particular, LSEM can also be used as an exploratory approach for situations when little is known about the onset and precise form of moderating effects.

### *Limitations and Future Research*

The present findings offer various avenues for future studies. For one, it is rather disconcerting that even in such a plain measure as the RSES, which is praised for its simple language and the brevity of its items, we were able to show that there is substantial construct–irrelevant variance associated with negatively keyed items. Most likely, similar issues apply to the majority of measurement instruments using negative items. Therefore, it should be investigated to what degree the

reported results also translate to other measurement instruments. In particular, it would be interesting to know whether the observed cognitive effects are more severe for instruments that include linguistically more complex items and if they are still identifiable in simplistic items including only one or two words (e.g., adjective lists). Second, a number of studies observed that respondents with lower educational attainment were more prone to acquiescence than those with higher levels of education (e.g., Meisenberg & Williams, 2008; Rammstedt & Farmer, 2013; Rammstedt, Kemper, & Borg, 2013). Even cognitive abilities have been identified as a pivotal source of individual differences in acquiescence responding (Lechner & Rammstedt, 2015). Therefore, the identified moderating effects of cognitive differences might represent indirect effects of systematic response style: Respondents that are unable to properly understand and evaluate the content of an item might more frequently resort to acquiescent responding instead of processing the item and elaborating a response and, thus, introduce multidimensionality in an otherwise unidimensional scale. Thus, it could be informative to scrutinize potential mediating mechanisms between cognitive abilities and acquiescence responding for the study of dimensionality issues in self-report scales. Finally, our results pertain to a rather specific population in the form of teenaged students in Germany. Future research is encouraged to extend these results to other age groups and language versions. For example, stronger individual differences in acquiescent responding have been observed among younger age groups (Soto, John, Gosling, & Potter, 2008) and in societies emphasizing collectivistic values (Johnson, Kulesa, Cho, & Shavitt, 2005). Therefore, it might be fruitful to contrast wording effects in different age groups and study the effects of negatively keyed items across the life span. Because cognitive abilities typically show age-related changes (e.g., reading competences are likely to increase in childhood and adolescence, whereas reasoning abilities tend to decline in old age), it could even be worthwhile to consider moderating effects for both variables including their interactions simultaneously.

### **Conclusions**

Many previous studies observed that the negatively keyed items in the RSES distorted its factor structure. The present study on a representative sample of German young adults showed that the structural ambiguity of the scale is subject to individual differences in cognitive abilities. Respondents with poor reading skills or reasoning abilities showed systematic response styles associated with the negatively keyed items, whereas good readers showed limited wording effects. Among others, these results highlight the need for taking into account acquiescence in latent variable modeling of the RSES. Conversely, we found no evidence for negative self-esteem as a substantive personality trait.

## Appendix A

### Rosenberg (1965) Self-Esteem Scale

To what extent do the following statements apply to you?

1. On the whole, I am satisfied with myself. (P)
2. At times, I think I am no good at all. (N)
3. I feel that I have a number of good qualities. (P)
4. I am able to do things as well as most other people. (P)
5. I feel I do not have much to be proud of. (N)
6. I certainly feel useless at times. (N)
7. I feel that I'm a person of worth, at least on an equal plane with others. (P)
8. I wish I could have more respect for myself. (N)
9. All in all, I am inclined to feel that I am a failure. (N)
10. I take a positive attitude toward myself. (P)

Response scale: 1 = *strongly disagree*, 2 = *disagree*, 3 = *partly*, 4 = *agree*, 5 = *strongly agree*, P = positively keyed, N = negatively keyed (reverse scored for creating a sum score).

## Appendix B

### Local Structural Equation Modeling

Formally, a LSEM is given as follows (see also Hildebrandt et al., 2016): Assume for each person a vector of variables  $(M, Y_1, \dots, Y_i, \dots, Y_I)$ , where  $M$  denotes a moderator variable and  $Y_i$  ( $i = 1, \dots, I$ ) represents the person's responses to the  $I$  items of a test. At the population level, the conditional means  $\mu_i(m) = E(Y_i | M = m)$  and the conditional covariances  $\sigma_{ii}(m) = \text{Cov}(Y_i, Y_i | M = m)$  of the items are studied, where  $m$  denotes a specific value of the continuous moderator variable. To exemplify LSEM for a common factor model, the conditional covariance matrix  $\Sigma(m)$ , including the conditional variances and covariances  $\sigma_{ii}(m)$ , are represented by a unidimensional common factor model as follows:

$$\Sigma(m) = \Lambda(m)\Lambda(m)^T + \Psi(m) \quad [3]$$

In Equation 3,  $\Lambda(m)$  is a column vector of loadings (at a specific point  $m$  of the moderator variable  $M$ ) and  $\Psi(m)$  is an  $I \times I$  matrix of error variances and covariances assumed to be diagonal and conditional on  $m$ . In the formalization of the commonly used factor model, the model for item  $i$  that is conditional on  $m$  can be written as,

$$Y_{im} = v_i(m) + \lambda_i(m) \cdot \eta_m + \varepsilon_{im} \quad [4]$$

The intercepts  $v_i$ , factor loadings  $\lambda_i$ , and residual variances  $\varepsilon_{im}$  are all assumed to vary at specific values of  $M$  (see

Equation 4). LSEM aims to estimate a factor model or SEM for each possible value of the continuous moderator variable  $M$  and to inspect the course of the model parameter estimates across  $M$ . Ideally, SEMs are fitted in steps that are as narrow as possible on the scale of the continuous variable. However, the grading depends on the sample size over the moderator and the applied weighting function. An often used and theoretically sound weighting function of observations around focal points is the Gaussian kernel function (see Gasser et al., 2004). Using the Gaussian kernel function, weights around each focal point of  $M$  are normally distributed. Since the normal density function is not restricted, all observations will enter all models at each focal point in LSEM, but observations that are far away from the focal points have very small values and will have no practical influence on the model parameter estimation at a given focal point.

$$bw = \frac{h \cdot SD_M}{\sqrt[5]{N}} \quad [5]$$

The bandwidth ( $bw$ ) of the weighting function is calculated using Equation 5, where  $h$  denotes the  $bw$  factor,  $SD_M$  is the standard deviation of the moderator variable  $M$  and,  $N$  represents the total sample size. Then, the  $bw$  parameter  $bw$  is the standard deviation of the normal density function around the focal points. In the literature on nonparametric density estimation, the factor  $h = 1.1$  has been proposed as being adequate for many context variables, which has been confirmed with a recent simulation study in the context of LSEM (Hildebrandt et al., 2016). In general, the larger the  $bw$ , the smoother the resulting parameter function along the values of  $M$  will be. For each observation,  $M$  is standardized using the  $bw$  according to Equation 6 and weights ranging between 0 and 1 are derived using the Gaussian kernel function in Equation 7.

$$z(m, m_0) = \frac{m - m_0}{bw} \quad [6]$$

$$W(m, m_0) = \exp\left(-z(m, m_0)^2 / 2\right) \quad [7]$$

From the above description, it becomes apparent that MGMCS analyses can be seen as a special case of LSEM. Basically, MGMCS could be described as employing a weighting scheme in which several focal points along the scale of the moderator (as many as included in one group defined for the analysis) are fully weighted, and all other observations are allocated a weight of 0.

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### Notes

1. Because the correlated residual between Item 3 (“I feel that I have a number of good qualities”) and Item 4 (“I am able to do things as well as most other people”) was not a priori theorized, all interpretations of the observed local dependency have to remain speculative. Potentially, the two items more strongly capture ability-based self-views such as self-perceived skills and competences. In contrast, the other items (e.g., “I take a positive attitude toward myself”) might more strongly reflect attitudinal or affective self-perceptions.
2. MGMCS mirrored the presented results of the LSEM analyses because the wording effect of cognitive abilities was approximately linear. We created three ability groups using cut scores at  $M - 1 SD$  and  $M + 1 SD$  for each cognitive measure and estimated the reliability within each group. The sample sizes for these groups fell between  $N = 1,088$  and  $9,182$ . For reading competence, the reliabilities were  $\omega_H = [.69, .80, .86]$  and  $\omega_{HS.NEG} = [.51, .32, .21]$ , respectively. Thus, the reliability of the common factor increased with higher reading groups, whereas the reliability of the negative factor decreased. Similar patterns emerged for vocabulary,  $\omega_H = [.70, .80, .83]$  and  $\omega_{HS.NEG} = [.48, .33, .26]$ , and reasoning,  $\omega_H = [.71, .81, .85]$  and  $\omega_{HS.NEG} = [.49, .32, .21]$ .

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