Original Article

Further Insights Into the German Version of the Multidimensional Assessment of Interoceptive Awareness (MAIA)

Exploratory and Bayesian Structural Equation Modeling Approaches

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Abstract: Interoception is defined as an iterative process that refers to receiving, accessing, appraising, and responding to body sensations. Recently, following an extensive process of development, Mehling and colleagues (2012) proposed a new instrument, the Multidimensional Assessment of Interoceptive Awareness (MAIA), which captures these different aspects of interoception with eight subscales. The aim of this study was to reexamine the dimensionality of the MAIA by applying maximum likelihood confirmatory factor analysis (ML-CFA), exploratory structural equation modeling (ESEM), and Bayesian structural equation modeling (BSEM). ML-CFA, ESEM, and BSEM were examined in a sample of 320 German adults. ML-CFA showed a poor fit to the data. ESEM yielded a better fit and contained numerous significant cross-loadings, of which one was substantial ($\geq$ .30). The BSEM model with approximate zero informative priors yielded an excellent fit and confirmed the substantial cross-loading found in ESEM. The study demonstrates that ESEM and BSEM are flexible techniques that can be used to improve our understanding of multidimensional constructs. In addition, BSEM can be seen as less exploratory than ESEM and it might also be used to overcome potential limitations of ESEM with regard to more complex models relative to the sample size.

Keywords: multidimensional assessment of interoceptive awareness (MAIA), interoception, Bayesian structural equation modeling, exploratory structural equation modeling

The concept of interoception has been proposed as an iterative process that involves receiving, accessing, appraising, and responding to signals from inside the body (Farb et al., 2015). Compared with interoceptive awareness as a sense of the physiological condition of the body (Craig, 2002), this broader definition implies that "interoception is a product of conscious perception, and as such is a psychobiological process that is modified by complex bidirectional interactive evaluative functions, which are influenced by appraisal, beliefs, past experience, expectations, and contexts" (Mehling et al., 2012, p. 2). Interoception has been shown to be critical for well-being, mainly due to its strong link to self-regulation and affect regulation (e.g., Füstös, Gramann, Herbert, & Pollatos, 2013) and as a mediator between chronic or acute stress and body-related mental disorders (Schulz & Vögele, 2015). Moreover, research on interoceptive sensitivity and awareness has demonstrated its crucial role in influencing health behaviors such as eating behavior (e.g., Koch & Pollatos, 2014).

To capture the broader definition of interoception, Mehling and colleagues (2009, 2012) developed a new instrument: the Multidimensional Assessment of Interoceptive Awareness (MAIA). The MAIA was developed by applying an extensive and systematic mixed-methods approach that involved reviewing the literature on multidimensional conceptual frameworks, evaluating existing instruments, and analyzing focus group responses. The resulting items were further refined by applying cognitive interview testing. In the following field test, the construct validity of the items was validated by applying an exploratory cluster factor analysis and a confirmatory factor analysis (CFA). The final instrument consisted of 32 items comprising eight scales: (1) Noticing: the awareness of uncomfortable, comfortable, or neutral body sensations;

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(2) Not Distracting: the tendency not to ignore or use distraction to cope with sensations of discomfort; (3) Not Worrying: the tendency not to worry or experience emotional distress with physical discomfort; (4) Attention Regulation: the ability to sustain and control attention to body sensations; (5) Emotional Awareness: the awareness of the connection between bodily signals and emotional states; (6) Self-Regulation: the ability to regulate distress by paying attention to body sensations; (7) Body Listening: the tendency to actively listen to the body for insights; and (8) Trusting: experiencing one's body as safe and trustworthy (Mehling et al., 2012).

Taking into account the relevance of the construct (cf. a special issue in *Frontiers in Psychology*, 2015), the extensive and rigorous development of the scale, and the translation of the original English version into 13 languages, there is a need to evaluate the psychometric quality of the scale in more detail. Besides the original publication of the MAIA (Mehling et al., 2012), to our knowledge, only two studies have explored the psychometric properties of the adaptations: Bornemann, Herbert, Mehling, and Singer (2015) evaluated the German version, and Valenzuela-Moguillansky and Reyes-Reyes (2015) evaluated the Spanish version. Bornemann and colleagues conducted an exploratory factor analysis (EFA) with varimax rotation ($n = 1{,}076$) and replicated the eight-factor solution proposed by Mehling et al. (2012) except for Item 19. Valenzuela-Moguillansky and Reyes-Reyes (2015) reduced the scale to 30 items on the basis of the results of an EFA. In addition, the authors encountered estimation problems with the Not Worrying and Not Distracting subscales. In a subsequent CFA, an acceptable model fit was achieved with additional modifications of the measurement model.

A number of methodological problems are noteworthy in the previous studies on the MAIA. First, the internal consistencies for some subscales (e.g., Not Worrying and Not Distracting) were not satisfactory. However, the consistencies may have been underestimated because the assumptions behind the use of Cronbach's α had not yet been tested. One such assumption is an essentially τ-equivalent model (Dunn, Baguley, & Brunsden, 2014; Jöreskog, 1971), which implies that all indicators are restricted to assessing the same latent construct with the same units of measurement (i.e., equal factor loadings). In cases in which the assumptions are not met, the ω reliability index (Dunn et al., 2014; Raykov, 2004) provides more precise estimates of internal consistency. Second, previous evaluations of the fit of the MAIA models have been satisfactory at best. For instance, the models with several residual correlations showed a Comparative Fit Index (CFI) $\leq .92$ (Bornemann et al., 2015; Valenzuela-Moguillansky & Reyes-Reyes, 2015) or $\leq .89$ (Mehling et al., 2012). Mehling and colleagues (2012; n = 309) as well as Valenzuela-Moguillansky and Reyes-Reyes (2015; n = 250) reported significant chi-square tests. Researchers often ignore significant chi-square statistics on the basis of the chi-square test's oversensitivity to irrelevant discrepancies between model-implied and sample covariance matrices (Schermelleh-Engel, Moosbrugger, & Müller, 2003) even though a significant χ^2 should not be automatically assumed to indicate trivial model misspecifications and may perform well for the identification of misspecified models at least in terms of a χ^2/df-ratio (Marsh, Hau, & Wen, 2004). Finally, modification indices have been used to improve model fit. However, modification indices formalize the improvement in model fit to be gained from freeing only one parameter at a time. On the one hand, a sequence of model modifications needed to improve model fit often lacks theoretical justification and may capitalize on specific sample characteristics (MacCallum, Roznowski, & Necowitz, 1992), thus hampering replicability (Wagenmakers, Wetzels, Borsboom, & Van Der Maas, 2011). On the other hand, researchers have argued that "analyses using maximum likelihood (ML) and likelihood-ratio chi squared testing apply unnecessarily strict models to represent hypotheses derived from substantive theory" (Muthén & Asparouhov, 2012, p. 313). As a consequence, the requirements of ML estimation may lead to an unnecessary rejection of the model with distorted factors and biased factor correlations (Marsh et al., 2009, 2010).

To overcome these problems, Muthén and Asparouhov proposed a Bayesian Structural Equation Modeling (BSEM) approach (Asparouhov, Muthén, & Morin, 2015; Muthén & Asparouhov, 2012) that can be considered a blending of exploratory and confirmatory methods (Rindskopf, 2012). The main goal of this method of estimation is "not to confirm or disconfirm the CFA model but to evaluate the sources of the differences between the hypothesized CFA model and the data" (Asparouhov et al., 2015, p. 6). The main idea underlying this approach is that the strict assumptions of zero cross-loadings and zero residual covariances are substituted by values of approximately zero. That is, informative priors with a mean of zero and a normal distribution with a small variance are specified instead of the exact-zero assumption (Muthén & Asparouhov, 2012). In models that are based on ML estimation, freeing these parameters would result in a nonidentified model. In BSEM, small variance priors for nontarget cross-loadings as well as residual covariances inform the estimation process so that identification issues can be avoided. In the frequentist approaches to estimation, exploratory structural equation modeling (ESEM) also allows users to avoid fixing cross-loadings to zero and can thus be seen as a modeling strategy that is a generalization of both exploratory and confirmatory factor analyses. In contrast to exploratory factor analysis, ESEM is a more confirmatory approach

(Marsh et al., 2010), in particular due to the use of target rotation. Muthén and Asparouhov (2012) argues that BSEM can be considered a generalization of ESEM because, whereas the optimal rotation in the latter is determined solely on the basis of the unrotated loadings, the optimal rotation in BSEM is determined by all parts of the model (Muthén & Asparouhov, 2012, p. 330). Also, BSEM overcomes the potential limitations of ESEM with regard to more complex models relative to the sample size because, in such cases, ML estimation might not be appropriate (Marsh, Morin, Parker, & Kaur, 2014). However, these advantages come at the price that BSEM analyses depend heavily on the choice of appropriate priors (cf. Depaoli & van de Schoot, 2015). Nonetheless, with appropriate priors, BSEM might provide researchers with new insights, also with regard to well-validated scales such as the Wechsler Intelligence Scale for Children Fourth Edition (WISC-IV; Golay, Reverte, Rossier, Favez, & Lecerf, 2013).

In a multidimensional instrument such as the MAIA, numerous cross-loadings may be assumed to be slightly greater than zero. For example, Mehling and colleagues (2012) argue that the three subscales of Emotional Awareness, Self-Regulation, and Body Listening pertain to an awareness of mind-body integration and thus more developed levels of body awareness. Similarly, the Not Distracting and Not Worrying subscales refer to emotional reactions and attentional responses to bodily sensations. Clearly, assuming zero cross-loadings on related factors in a maximum likelihood confirmatory factor analysis (ML-CFA) may result in misspecification because even very reliable psychometric indicators are assumed to seldom be perfectly pure construct indicators (Asparouhov et al., 2015). Asparouhov et al. (2015) argue that "although 'pure' indicators of a single construct may exist, we surmise that such indicators remain at best a convenient fiction and that, in practice, most indicators will present both some level of random noise and also some level of construct-relevant association with other constructs" (p. 3). In a similar vein, scholars argue that, when based on current standards of the basic independent clusters model of CFA, many psychological instruments do not meet the minimum criteria for acceptable fit (Marsh et al., 2014; Morin, Arens, & Marsh, 2015).

Another part of BSEM is the estimation of residual covariances. Equivalent to cross-loadings, residual covariances in an ML-CFA are constrained to a mean and a variance of zero. The covariance of residual terms refers to shared variance in the indicators that is not related to the respective factors. Such shared variance may pertain to the context (i.e., culture, life domain) or to the wording (i.e., parallel wording). For example, in the MAIA, the negatively worded Items 4–9 may share variance that is not influenced by their respective factors. The advantage of BSEM is that a multivariate prior (an inverse Wishart prior) is used to allow for a simultaneous estimation of a full residual variance-covariance matrix. By contrast, in the ESEM approach, researchers must rely on modification indices for the modeling of residual covariances.

In sum, the present study was conducted to reinvestigate the structure of the German version of the MAIA by applying the recently proposed BSEM approach and by comparing it to results obtained with ESEM. The extensive MAIA development reflects growing interest in the concept of interoception (cf. Farb et al., 2015), but the factor structure of the scale may need further improvement (Valenzuela-Moguillansky & Reyes-Reyes, 2015). As demonstrated by recent studies on the underlying structure in several instruments (e.g., Fong & Ho, 2013, 2015; Golay et al., 2013), BSEM appears to be a framework that is adequate enough to provide additional insights into the dimensionality of the MAIA.

Method

Participants and Measure

The participants in this study were 320 German adults (70% female). The mean age of participants was 41.3 years = 12.6; *n* = 28 missing). They were recruited through articles in local newspapers, flyers, and links on different websites and online discussion boards. Data collection was implemented with an online survey, and the 32 MAIA items (0 = *never,* 5 = *always*) were presented in a random order. Table 1 presents the means and standard deviations for all subscales as well as the reliability coefficients per scale. The data and code are available at the Open Science Framework OSF: https://osf.io/8hpb8/

Models and Analyses

The 8-factor model of the MAIA was examined by applying the three approaches: ML-CFA, ESEM, and BSEM in Mplus (Version 7.2). To estimate the sample size needed for the ML-CFA, we computed a Monte Carlo simulation. Because we did not have starting values from a previous study on the German version of the MAIA, we derived them theoretically: We assumed reasonable factor loadings of .80, moderate factor correlations of .25, and residual variances of the indicators equal to .36. In addition, we specified four different cross-loadings of .30. The sample size required to detect these or a larger cross-loading with a power of .95 at an α level of .05 ranged from 65 to 148. All models were computed at the item level. Consistent with previous research on the MAIA, the items were treated as

Table 1. Descriptive statistics for the original eight MAIA subscales

Subscale	*M* (*SD*)	ω (95% bca CI)	α (95% bca CI)
Noticing	3.37 (0.91)	.75 [.68, .79]	.74 [.66, .79]
Not distracting	2.25 (0.95)	.66 [.57, .72]	.64 [.54, .70]
Not worrying	2.51 (1.06)	.65 [.56, .72]	.67 [.57, .73]
Attention regulation	2.69 (1.07)	.91 [.88, .92]	.91 [.88, .92]
Emotional awareness	3.49 (0.98)	.84 [.80, .88]	.84 [.80, .88]
Self-regulation	2.47 (1.22)	.88 [.84, .90]	.88 [.84, .90]
Body listening	2.32 (1.19)	.86[.83, .89]	.86 [.83, .89]
Trusting	3.13 (1.16)	.87 [.83, .89]	.86 [.82, .88]

Notes. N = 257. *M* = mean; *SD* = standard deviation; bca CI = bias corrected and accelerated confidence interval.

continuous. The ML-CFA and the ESEM were evaluated with a χ^2-statistic and its associated *p*-value, the CFI $\geq$ .95 and Tucker-Lewis Index (TLI) $\geq$ .95, the Root Mean Square Error of Approximation (RMSEA) $\leq$ .08 and its associated *p*-value for test of close fit, and the Standardized Root Mean Square Residual (SRMR) $\leq$ .10 (Schermelleh-Engel et al., 2003). To examine the assumptions behind Cronbach's α (i.e., essential τ-equivalency), the unstandardized factor loadings for each factor were set equal to each other in the ML-CFA.

In this study, ESEM was used in a confirmatory manner: on the basis of the extensive development of the instrument, we used its theoretical assumptions for the measurement model. To account for this, although all items were allowed to cross-load on nontarget factors, the TARGET rotation setting in Mplus was used to make cross-loadings as close to the specified zeros as possible (Browne, 2001; Gucciardi & Zyphur, 2016). The fit of the ESEM solution was then compared with the τ-congeneric ML-CFA.

The BSEM models were computed with the Bayes estimator. Following Asparouhov et al.'s (2015) recommendations, we estimated a series of models with different prior specifications for both the cross-loadings and the residual covariances. In the first model (Model 1), diffuse priors were specified for the hypothesized factor loadings. In this model, as in the ML-CFA, the cross-loadings and residual covariances were restricted to zero. Second, in Model 2, we specified small-variance (i.e., 0.02) informative priors for the cross-loadings. On the basis of previous analyses on the MAIA, we assumed that the cross-loadings would not exceed .30, meaning that the loadings would be considered minor in an EFA approach. By specifying a prior variance of 0.02, we allowed for a 95% credibility interval for the cross-loadings of ±.28 (Muthén & Asparouhov, 2012). Finally, inverse Wishart priors IW (*dD*, *d*) were specified for the residual covariances (Model 3). On the basis of our sample size, we chose $d = 100$ for the starting value, whereas the *D* values were the residual variances estimated in the BSEM model with cross-loadings. The BSEM estimation was run with two independent Markov Chain Monte Carlo (MCMC) chains using the Gibbs sampler (Muthén & Asparouhov, 2012) and 50,000 iterations.

We evaluated the model's convergence through trace plots, checked whether convergence remained after doubling the number of iterations, visually checked the smoothness of the histograms for all parameters (Depaoli & van de Schoot, 2015), and applied the Kolmogorov-Smirnov (K-S) test to test for equal posterior distributions across chains. The K-S test uses 100 draws from each of the two MCMC chains and compares the two distributions: if convergence has been achieved, the two distributions should be similar, and the K-S test would not reject the hypothesis of equal distributions. The model fit was evaluated by means of posterior predictive checking (PPC). Posterior predictive *p*-values (PPP) refer to the proportion of times that the posterior predictive likelihood ratio test is larger than the observed statistic (Zyphur & Oswald, 2015). PPP values of about .50 imply a good model fit because observed and generated data are equally probable. Models were compared using the deviance information criterion (DIC). The DIC is recommended over the Bayesian information criterion (BIC) for BSEM analyses because its model complexity penalty is based on the estimated number of parameters (Asparouhov et al., 2015). Following Asparouhov et al.'s (2015) recommendations, we evaluated smaller and larger prior variances for the cross-loadings. A sensitivity analysis was also run with regard to the residual covariances.

Results

ML-CFA Model Results

In a first step, we computed a τ-congeneric model. This model is the least restrictive measurement model and yielded a model fit that was acceptable as indicated by the SRMR = .06 but questionable with regard to the other indices: CFI = .90; TLI = .89; RMSEA = .06, p = .001, and the chi-square test, $\chi^2(436) = 939.4$, $p < .001$. Consequently, the more restrictive essentially τ-equivalent model showed a model fit that was even less satisfactory (CFI = .87; TLI = .86; RMSEA = .07, $p < .001$; SRMR = .13; $\chi^2(468) = 1171.9$, $p < .001$), and the model comparison indicated that the τ-equivalent model fit the data significantly worse than the τ-congeneric model, $\Delta\chi^2(32) = 232.5$, $p < .001$. These results have two implications: first, the German version of the MAIA did not meet the criteria for the Cronbach's α reliability index, so McDonald's ω should be used to estimate its internal consistency (Dunn et al., 2014). Second, the ML-CFA

Table 2. Comparison of the BSEM models

Model	#	p_D	PPP	2.5% PP limit	97.5% PP limit	DIC	BIC
Model 1							
8-Factor model with no informative priors	124	138.52	0.000	261.44	538.65	27,433.63	27,871.73
Model 2							
8-Factor model with cross-loadings (priors variance = 0.02)	348	235.67	0.005	28.01	217.71	22,230.61	23,752.34
Model 3							
8-Factor model with cross-loadings (0.01) and residual covariances (d = 100)	844	393.70	0.780	−129.21	61.24	22,189.46	26,262.92
Model 4							
7-Factor model with cross-loadings (0.01) and residual covariances (d = 100)	805	397.85	0.780	−128.88	57.57	22,192.65	26,034.50

Notes. # = Number of free parameters; p_D = estimated number of parameters; PPP = posterior predictive p-value; PP limit = posterior predictive limit; DIC = deviance information criterion; BIC = Bayesian information criterion.

analysis indicated that the 8-factor structure proposed by the model did not fit the observed data well. Therefore, in the next step, we performed the ESEM and BSEM analyses to identify the sources of the differences between the hypothesized CFA model and the observed data.

ESEM and BSEM Results

The ESEM with target rotation yielded an excellent fit (SRMR = .02; RMSEA = .04, p = .93; CFI = .97; and TLI = .94). However, the chi-square test still indicated that the model should be rejected, $\chi^2(268) = 427.6$, $p < .001$. Also, although the AIC was slightly lower for the ESEM as compared with the τ-congeneric CFA (27,207.5 for ESEM vs. 27,551.7 for CFA), the penalty for increased model parameters inherent in the BIC favored the parsimonious CFA model (28,307.8 for ESEM vs. 27,898.4 for CFA). Overall, ESEM identified 54 significant cross-loadings, of which only one was substantial. Item 8 (“When I feel physical pain, I become upset”) loaded not only on the intended Not Worrying factor (.36) but also on the Not Distracting factor (.45). All factor loadings and also the correlations between the latent factors can be found in Table 3 (presented side by side with the BSEM loadings).

All BSEM models are presented in Table 2. The BSEM model with noninformative, diffuse priors was rejected by the data (PPP = .000; positive 95% lower PP limit of 361.44). Next, we specified small-variance (0.02) priors for the cross-loadings. The model with cross-loadings (Model 2) revealed a lower DIC than the Bayesian CFA model. However, the model was still rejected by the data with PPP = .005 and 95% lower PP limit of 28.01. In this model, we found six significant cross-loadings (i.e., loadings for which the highest posterior density [HPD] credibility interval did not include zero) of which only the loading of Item 8 on the Not Distracting factor was substantial (.38). Thus, in the next model, the prior of this item was set to diffuse (Muthén & Asparouhov, 2012). The model with residual covariance priors with d = 100 yielded a better fit to the data with PPP = .71 and the 95% lower limit at −122.33. The DIC for this model was 22,205.42. Also the K-S test did not reject the hypothesis of equal distributions. However, the sensitivity analysis showed that the model (Model 3) with cross-loadings’ prior variances of 0.01 demonstrated a reasonable fit to the data with PPP = .780 and DIC = 22,189.46. An interesting finding from this BSEM model was that the two factors Attention Regulation (AR) and Self-Regulation (SR) were as highly correlated as .88. This suggested combining AR and SR factors resulting in a 7-factor model. For this model (Model 4), the same priors were applied (i.e., 0.01 and d = 100). The model fit for this model was basically the same as for the 8-factor model (PPP = .780; DIC = 22,192.65). Thus, the comparison of the two models seemed arbitrary, and the theoretically grounded 8-factor model (Model 3) was retained as the final model. Four minor but significant residual correlations were identified in the final model (range from −.13 to .22). In this model, all 32 items loaded substantially on their respective factor (for a schematic overview of the model see Electronic Supplementary Material, ESM 1). Of the eight factors, Not Worrying was not significantly related to any other factor, and Not Distracting was related to four out of seven other subscales. The other six factors were consistently related to each other with Attention Regulation and Self-Regulation showing the highest correlation of .88 (see Table 3). Thus, the pattern of the latent factors’ correlations differed between BSEM and ESEM (see Table 3).

Discussion

The present study aimed to explore the structure of the German version of the Multidimensional Assessment of Interoceptive Awareness (MAIA) by applying the common

Table 3. Loadings and factor correlations in ESEM (E) and BSEM (B)

	NO		ND		NW		AR		EA		SR		BL		TR	
Item	E	B	E	B	E	B	E	B	E	B	E	B	E	B	E	B
								Loadings								
1	**.68***	**.64***	−.02	−.03	.06	.02	−.04	.00	.09	.02	.13*	.02	−.03	−.00	.02	−.02
2	**.54***	**.66***	.06	.01	−.13*	−.09	.16	−.04	.15*	.04	−.21*	−.07	.06	−.01	−.06	−.05
3	**.44***	**.56***	−.04	−.02	−.04	.02	.20*	.06	.03	−.01	.09	.05	−.01	.03	.24*	.10
4	**.28***	**.49***	.09	.04	−.09	.00	.23*	.03	.18*	.04	.19*	.04	−.17*	−.00	−.02	−.00
5	.04	.04	**.61***	**.63***	−.01	−.02	.14	.04	−.04	−.01	−.01	.03	.16*	.05	.04	.00
6	.09	.01	**.49***	**.43***	.05	−.01	−.11	−.05	.13*	.05	−.05	−.04	−.11	−.04	−.01	−.02
7	−.05	−.04	**.66***	**.67***	.11*	.05	−.07	−.03	.00	−.02	.08	.00	.04	−.00	.06	.01
8	−.06	−.01	.45*	.47*	**.36***	**.38***	.19*	.04	−.09	−.05	.03	−.01	−.05	−.01	.02	−.00
9	−.03	−.05	−.01	.06	**.88***	**.73***	−.15*	−.05	−.00	.00	.05	−.01	−.03	−.03	−.02	−.01
10	−.04	.05	−.17*	−.04	**.57***	**.55***	.24*	.06	.08	.01	−.01	.04	−.02	.04	.05	.03
11	−.04	−.01	−.03	−.01	.04	.01	**.70***	**.77***	.01	−.02	.15*	.03	.10	.03	−.08	−.05
12	.07	−.01	.03	.04	.07	.02	**.50***	**.62***	−.04	−.00	−.03	.01	.24*	.04	.11	.06
13	.17*	.01	−.06	−.01	.20*	.09	**.52***	**.63***	−.03	−.02	−.02	−.01	−.11	−.06	.07	.00
14	.10	−.02	−.01	−.02	.04	−.00	**.73***	**.89***	−.08	−.05	.05	−.01	.05	−.00	.07	.01
15	.19*	.02	.05	.00	.01	−.01	**.57***	**.80***	−.06	.00	.18*	.03	.03	−.02	.01	−.03
16	−.03	.02	.04	.02	.03	.01	**.67***	**.65***	.13*	.04	−.08	−.03	.06	.01	−.01	−.01
17	.07	.04	.07	.02	−.08	−.04	**.54***	**.70***	.07	.04	.23*	.03	−.02	.01	.09	.03
18	.25*	.04	.03	.02	.06	−.02	−.06	.01	**.39***	**.50***	−.15*	−.02	.25*	.04	.07	.03
19	.26*	.06	.03	−.00	−.00	−.06	−.06	.03	**.44***	**.55***	.00	.03	.26*	.04	−.14*	−.06
20	−.08	−.04	.01	−.00	−.03	.00	.03	.01	**.86***	**.87***	.10	.02	−.01	−.03	−.02	−.01
21	.07	.03	−.00	−.02	.04	.04	.04	.00	**.75***	**.75***	.10	.01	−.10	−.01	−.05	−.03
22	.02	−.03	.01	−.00	−.03	−.00	−.12	−.05	**.76***	**.80***	.02	−.03	.00	−.00	.16*	.06
23	.04	.00	−.01	.03	.14*	.06	.15	.03	.05	.02	**.28***	**.57***	.20*	.04	.22*	.10
24	−.05	−.02	.03	.01	−.02	−.01	.15	−.00	.15*	.04	**.46***	**.71***	.07	.01	.22*	.06
25	.04	.02	.01	−.02	.08	.01	.16*	−.00	.13*	.00	**.61***	**.85***	.00	−.03	.04	−.03
26	.13*	.01	.04	.00	.06	−.01	.07	.03	−.01	−.02	**.70***	**.84***	.22*	.04	−.05	−.07
27	.01	.01	.15*	.07	−.03	−.01	.15*	.01	.14*	.04	.10	.01	**.54***	**.72***	.08	.02
28	.04	−.01	.02	−.01	.01	−.00	−.00	−.01	.06	.00	.28*	.03	**.66***	**.83***	−.02	−.06
29	−.04	.01	.01	−.00	−.04	−.01	.20*	.01	.12*	.00	.00	−.00	**.51***	**.70***	.19*	.07
30	.16*	.02	.01	−.03	.02	−.00	−.07	.01	−.14*	−.06	.09	−.01	.06	.01	**.83***	**.85***
31	−.04	−.03	.02	−.01	.03	.03	−.01	−.03	.04	.00	.11*	.01	−.03	−.02	**.85***	**.92***
32	−.05	.03	.08	.05	.07	.01	.21*	.04	.25*	.11	−.13*	.02	.12	.05	**.47***	**.54***
								Factor correlations								
ND	.10	.35														
NW	−.01	.01	.21*	.22												
AR	.49*	.75*	.32*	.51*	.30*	.35										
EA	.50*	.72*	.22*	.35	−.02	−.02	.43*	.57*								
SR	.30*	.68*	.21*	.50*	.26*	.36	.63*	.88*	.36*	.61*						
BL	.42*	.69*	.27*	.53*	.08	.16	.51*	.80*	.41*	.67*	.34*	.82*				
TR	.25*	.51*	.23*	.45*	.36*	.42	.59*	.73*	.35*	.48*	.46*	.73*	.43*	.68*		

Notes. Values in bold indicate hypothesized major loadings. NO = Noticing; ND = Not Distracting; NW = Not Worrying; AR = Attention Regulation; EA = Emotional Awareness; SR = Self- Regulation; BL = Body Listening; TR = Trusting. For ESEM: *$p < .05$. For BSEM: cross-loadings marked with asterisks have a 95% credibility interval that does not cover zero.

ML-CFA approach, the ESEM approach, and a more recently developed BSEM approach. The results of the ML-CFA showed that both the τ-congeneric and the more restrictive essentially τ-equivalent measurement models did not fit the data well. These analyses provided information about two things: first, McDonald's ω should be used to estimate the reliability of the MAIA subscales (Dunn et al., 2014). In fact, the ω values reported in this study ranged from .66 to .91 and showed that the Cronbach's α indices reported in the original study (Mehling et al., 2012) underestimated the reliability of most subscales except the Not Distracting and Not Worrying scales. Second, the ML analyses showed that the proposed 8-factor structure of the MAIA needed some modifications. The poor fit reported for the ML-CFA may have been the result of the restrictive constraints of exactly zero cross-loadings and exactly zero residual covariances. In the ESEM and BSEM approaches, the concerns about the highly restrictive nature of CFA can be alleviated, and researchers can acknowledge that indicators are likely to encompass true variance shared with multiple constructs, an idea that is in line with the reflective logic of factor analyses (Morin et al., 2015). Both ESEM and BSEM have the potential to improve researchers' understanding of the underlying structure, thus providing an improvement over the practices of sweeping the sources of misfit under the rug and of estimating and reporting models that have questionable fits to the data. However, researchers should be aware that ESEM and BSEM differ in several ways: first, Bayesian estimation is based on a fundamentally different probability paradigm in which probability is considered the subjective experience of uncertainty rather than long-run frequency (van de Schoot et al., 2014). Hence, BSEM allows researchers to implement prior knowledge, whereas ESEM does not. Second, BSEM analyses are feasible in smaller samples in which ESEM analyses might not converge, in particular with more complex models. However, this advantage comes at the price that BSEM estimates depend on the appropriate specification of (informative) priors. Third, although ESEM enables researchers to model cross-loadings for all parameters, modification indices are required for the modeling of residual covariances. In the BSEM approach, informative priors provide some "wiggle room" (van de Schoot et al., 2013) for both cross-loadings and residual covariances that are restricted to zero in an ML-CFA. Hence, in contrast to modification indices, BSEM allows researchers to estimate all sources of possible misfit simultaneously.

In our MAIA analyses, ESEM and BSEM revealed one substantial cross-loading: Item 8 strongly contributed to the Not Distracting Factor. Therefore, we replicated the finding by Valenzuela-Moguillansky and Reyes-Reyes (2015) who excluded Item 8 from the Not Worrying subscale on the basis of its contribution to the Not Distracting scale instead of the intended factor. Consequently, adding this item to this subscale improved the internal consistency of Not Distracting (from $\omega = .66$ for the three items to .71 for the four items). This cross-loading, which cannot be estimated within an independent clusters model CFA approach, is one of the sources of MAIAs poor fit. Therefore, researchers should either consider moving Item 8 to the Not Distracting subscale or to drop it in future studies. Moreover, it seems important to add further items for the assessment of Not Worrying given that Items 9 and 10 are not sufficient to provide a reliable assessment. The reliability of both, the Not Distracting subscale and the Not Worrying subscale, was remarkably low. This finding was consistent with those of previous studies (Bornemann et al., 2015; Mehling et al., 2012; Valenzuela-Moguillansky & Reyes-Reyes, 2015). Notably, the correlations between the Not Worrying and Not Distracting factors were inconsistent in the ESEM in comparison with the BSEM analyses: in BSEM, the Not Worrying scale was unrelated to all other MAIA factors, a finding that is unusual for a multidimensional concept. In ESEM, at least some of the correlations between Not Worrying and the other factors were significant (cf. Table 3). Also, the correlation between Attention Regulation (AR) and Self-Regulation (SR) was .63 in ESEM, whereas it was .88 in BSEM. Therefore, the BSEM analyses clearly indicated that at least in our sample, AR and SR may form only one factor instead of two. Indeed, our model with seven factors instead of the eight original factors showed basically the same fit (see Table 2). We retained the original eight-factor solution due to its theoretically grounded measurement model. Although AR and SR refer to different aspects of the multidimensional conceptual framework (Mehling et al., 2012), it is possible that, in particular, individuals who are less experienced with regard to mind-body approaches may encounter difficulties in distinguishing between these two aspects. As a consequence, future studies should explore the degree to which the MAIA demonstrates measurement invariance across individuals familiar with a mind-body technique versus less experienced individuals.

In sum, in the present paper, we used ESEM and BSEM to analyze the structure of the German version of the MAIA (Mehling et al., 2012) and to illustrate both approaches. Both ESEM and BSEM allowed us to identify the sources of the differences between the hypothesized CFA model and the data that contributed to the poor fit of the MAIA. Taking into consideration the substantive theoretical work underlying the MAIA, we agree with other researchers who have argued that the Not Distracting and Not Worrying factors in particular require revising (Valenzuela-Moguillansky & Reyes-Reyes, 2015). In addition, the BSEM analyses showed that participants might not differ between Attention Regulation and Self-Regulation. Given the relevance that interoception and body awareness are gaining in both clinical and scientific fields, some of the underlying constructs in the MAIA may need some adaptation. This might be a crucial point for the scale's sensitivity to change processes in the context of mindfulness interventions.

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Electronic Supplementary Material

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ESM 1. Table and Figure (PDF).
The Table shows the MAIA items in German and in English. The Figure depicts the schematic overview of the BSEM model with one additional cross-loading and four residual covariances.

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