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Brief Report

Evaluating the Factor Structure of the MIDI Personality Scale Using Exploratory Structural Equation Modeling

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Abstract: This study investigated the factor structure of the 26-item Midlife Development Inventory (MIDI) Personality Scale in a sample of 2,720 Americans. It was found that whereas confirmatory factor analysis (CFA) did not provide an acceptable fit to the data, exploratory structural equation modeling (ESEM) provided an acceptable fit. The results of ESEM revealed that the a priori five-factor structure of personality was generally consistent with the data, and all items had salient loadings on their target factors. ESEM also revealed that some of the items contributed significantly to more than one personality factor. The results are in line with previous research, and indicate that ESEM is more suitable than CFA for the study of personality traits.

Key words: Midlife Development Inventory (MIDI) Personality Scale, exploratory structural equation modeling (ESEM), confirmatory factor analysis (CFA), Big Five, Midlife in the United States (MIDUS).

The five-factor model of personality traits is recognized as the dominant paradigm in personality research. This model posits that most personality traits can be classified into five broad domains: Extraversion (E), Openness to Experience (O), Neuroticism (N), Agreeableness (A), and Conscientiousness (C). There has been a constant demand for short Big Five measures. This need is most salient in contexts in which the respondents' time or energy is limited. The Midlife Development Inventory (MIDI) Personality Scale (Lachman & Weaver, 1997) is among the briefest Big Five measures.[1] The scale has been developed based on a need to measure personality traits in less than 5 min to be used in national surveys where time is usually limited. The authors of the scale created a list of adjectives commonly used in prior personality scales to measure the five personality traits. In pilot studies, the items that had low variances, factor loadings, or item-to-total-scale correlations were omitted, and new items were added to increase reliabilities on some scales (Lachman & Weaver, 1997).

The resulting scale has been included in the National Study of Midlife in the United States (MIDUS), and over 110 publications have used it so far. Lachman (2005) reports correlations ranging from .42 to .81 between the subscales of the MIDI Personality Scale and those of the 60-item NEO-Five Factor Inventory (NEO-FFI; Costa & McCrae, 1989). For four of the traits, the correlations were

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[1]The scale also measures a sixth trait called *agency*, which is not of interest in the present study.

high, indicating high conceptual overlaps across the corresponding scales. However, the correlation between the Agreeableness subscales was relatively low (.42). This may be due to the fact that the MIDI Agreeableness items are largely focused on trust and altruism, whereas the NEO Agreeableness subscale has a broader conceptual coverage (Lachman, 2005).

Applying confirmatory factor analysis (CFA), Zimprich, Allemand, and Lachman (2012) investigated the factor structure of the scale using the first wave of the MIDUS data (collected between 1995 and 1996). They found that the fit of the original five-factor model to the data was not acceptable. After removing one of the items, and allowing five cross-loadings and six item residual covariances, the fit of the model met the conventional criteria. That traditional CFA has failed to support the a priori structure of the MIDI Personality Scale is consistent with a large body of evidence showing CFA's constant failure to support the five-factor model across measures, populations, and languages (e.g., Chiorri, Marsh, Ubbiali, & Donati, 2016; Rosellini & Brown, 2011).

CFA's failure to represent personality traits results from the assumption that each indicator should load on a single factor, and non-target factor loadings should be fixed at zero. This assumption has been found to be too restrictive in practice (Marsh et al., 2010). What available data show is that many indicators of complex constructs have significant relationships with more than a single factor. Exploratory structural equation modeling (ESEM; Asparouhov & Muthen, 2009) has proved to be a useful substitute for CFA, because it allows all indicators to load freely on all factors. This results in more accurate estimates and better fit. Prior research comparing CFA and ESEM has shown that ESEM represents the factor structure of personality traits considerably better than CFA (e.g., Booth & Hughes, 2014; Chiorri et al., 2016; Marsh et al., 2010; Rosellini & Brown, 2011).

When there are no outcomes and/or predictors for the factors in a factor analytic model, an ESEM is basically identical to an exploratory factor analysis (EFA). However, ESEM offers a lot of advantages over EFA. Specifically, it

> shares many characteristics with CFA that fundamentally distinguish it from traditional approaches to EFA, such as tests of predictive relations between latent constructs adjusted for measurement error, method factors, correlated uniquenesses, complex error structures, bifactor models, full measurement invariance over groups or occasions, latent mean structures, differential item functioning (i.e., noninvariance of item intercepts), extension of factor analysis to SEMs, auto-regressive path models of causal ordering, and multiple-indicator multiple-cause (MIMIC) models of relations of latent factors with background and predictor variables (Marsh, Morin, Parker, & Kaur, 2014, p. 88).

Of crucial importance in the context of the present study is that ESEM yields model fit indices that can be compared across ESEM and CFA models.

Building on the recent developments in the field of personality research, the present study sought to reinvestigate the factor structure of the MIDI Personality Scale with a recently collected American data set, using both CFA and ESEM. Given that ESEM has never been used with short measures of the Big Five, the present study is expected to contribute evidence on the potential usefulness of ESEM for brief measures of personality.

Methods

Participants

The MIDUS III data set (Ryff et al., 2014) was used. The data were collected between 2013 and 2014. The overall MIDUS III sample consists of 3,294 American respondents (54.9% females) with a mean age of 63.64 years (*SD* = 11.35 years). Of the participants, 574 were excluded because of missing

Table 1 The items and internal consistencies

Dimension	α	Item
E	.756	Outgoing, Friendly, Lively, Active, Talkative
N	.714	Moody, Worrying, Nervous, Calm (R)
C	.668	Organized, Responsible, Hardworking, Careless (R), Thorough
A	.773	Helpful, Warm, Caring, Softhearted, Sympathetic
O	.774	Creative, Imaginative, Intelligent, Curious, Broad-minded, Sophisticated, Adventurous

data on all of the personality items. Hence, the final sample consisted of 2,720 participants.

Measure

The scale has 26 items, which are presented in Table 1. Respondents indicate how well the items describe them, on a scale from 1 (*a lot*) to 4 (*not at all*). The items were reverse-coded such that higher scores indicated higher levels of the traits. As shown in Table 1, internal consistencies ranged from .668 (C) to .774 (O).

Statistical analysis

The CFA model was specified based on the a priori factor structure of the scale. In CFA, because the items are constrained to a single factor, only 26 factor loadings were freely estimated, and the 104 non-target loadings were constrained to zero. In contrast, all possible factor loadings are freely estimated in ESEM. The mean- and variance-adjusted weighted least squares (WLSMV) estimator was used, because the indicators are categorical. An oblique geomin rotation (ε = .5) was used in ESEM. A minimum cutoff of .90 for the comparative fit index (CFI) and a maximum cutoff of .08 for the root mean square error of approximation (RMSEA) were considered as indicative of acceptable fit. The conventional cutoff point of .30 for size of loading was used to identify salient loadings to be emphasized in defining constructs (e.g., Joshanloo, 2016; Rosellini & Brown, 2011).

Results

Fit indices for both the CFA and ESEM models are presented in Table 2. As can be seen, whereas the fit of the CFA model was unacceptable, the ESEM model provided acceptable fit. The Bayesian information criterion (BIC) serves as an important index to compare the fit of the CFA and ESEM models because it imposes penalties for model complexity. Hence, we can make sure that the fit advantage of ESEM is not merely due to having more free parameters. However, the BIC is not reported in Mplus when the WLSMV is used. Therefore, separate analyses were conducted comparing the same CFA and ESEM models using a robust ML estimator (MLR) to obtain the BIC. The BIC value of the ESEM model (144,983.39) was substantially smaller than that of the CFA model (147,114.32), indicating that the fit advantage of the less constrained ESEM model is enough to offset the penalty for having more free parameters than the CFA model. Five alternative ESEM models were also tested with different numbers of factors. As shown in Table 2, the fit of the one- to four-factor models was not acceptable. The six-factor model fitted the data better than the five-factor model. However, one of the factors in the six-factor model had only two salient indicators (Creative and Imaginative). It is recommended to restrict the number of factors to those having at least three salient variables, because two variables lack reliable variance to form a nontrivial construct (Gorsuch, 1997; Tabachnick & Fidell, 2013). In addition, the five-factor model is more theoretically sensible. Therefore, the five-factor model was considered as superior.

Standardized factor loadings for the 5-factor models are presented in Table 3. In CFA, all of the factor loadings were over .30 with the exception of Careless. In ESEM, all of the items had loadings over .30 or very close to

Table 2 Fit indices

Model	χ^2	*df*	CFI	RMSEA	90% CI for RMSEA	
					Low	High
5-factor CFA	6,929.164	289	.841	0.092	0.090	0.094
6-factor ESEM	1,545.118	184	.967	0.052	0.050	0.055
5-factor ESEM	2,357.241	205	.948	0.062	0.060	0.064
4-factor ESEM	4,513.891	227	.897	0.083	0.081	0.085
3-factor ESEM	7,249.566	250	.832	0.101	0.099	0.103
2-factor ESEM	10,630.972	274	.752	0.118	0.116	0.120
1-factor ESEM	15,885.427	299	.626	0.138	0.137	0.140

Note. All χ^2 values are significant at $p < .001$. CI = confidence interval.

.30 on their target factor. In addition, the results of ESEM revealed 78 significant non-target loadings. However, the target loadings were considerably stronger than the non-target loadings. More specifically, disregarding the direction of the loadings, the 26 target loadings averaged .591, whereas the 104 non-target loadings averaged .101. Seven of the secondary loadings exceeded or were very close to the cutoff point of .30. These included: Warm, Sophisticated, and Adventurous on E; Careless on N; Active and Intelligent on C; and Friendly on A. The factor correlations are presented in Table 4. The ESEM correlations (irrespective of the direction) averaged .18, whereas the CFA correlations averaged .41, indicating that CFA yielded decreased factor orthogonality.

In sum, ESEM provided better fit and revealed a large number of non-trivial cross-loadings, which are fixed at zero in CFA. Thus, ESEM provided more nuanced and comprehensive information on the relationships between the items and factors.

Discussion

Consistent with many previous studies with other personality measures (e.g., Chiorri et al., 2016; Marsh et al., 2010; Rosellini & Brown, 2011), the ESEM model provided a better fit than did CFA. Inspection of the factor loadings (Table 3) suggests that the emerging factors in ESEM correspond to the five personality factors, in that each factor is clearly dominated by items related to one of the Big Five. All of the factors are predominantly loaded by their target items. To a considerably smaller degree, the factors are also loaded by non-target items. Thus, based on the results of ESEM, it can be concluded that the five-factor model of personality is largely compatible with the data in the present sample.

O had no salient loadings from non-target items. The other four factors, however, had factor loadings from non-target items that were larger than or close to .30 (i.e., three non-target loadings on E, one on N, two on C, and one on A). These salient secondary loadings should be considered when interpreting these factors. It is also important to note that five items had larger secondary than primary loadings, or their primary and secondary loadings were almost equal. These items include Sophisticated, Adventurous, Intelligent, Active, and Friendly. Each of these items is contributing almost equally to two personality traits. If these results are replicated in future large-scale studies, researchers may consider removing these five items or replacing them with other items.

CFA models of the personality traits have regularly been found to provide poor fit (Church & Burke, 1994; Lee & Ashton, 2007), and the present CFA model did not fare any better. In fact, many researchers have questioned “the adequacy of CFA in the study of personality structure” (Rosellini & Brown, 2011, p. 28), and have concluded that CFA is “too restrictive to

Table 3 Standardized factor loadings for the 5-factor modified models

		ESEM					
		E	N	C	A	O	CFA
E	Outgoing	**.761*****	−.090***	−.044**	.081***	.019	**.706*****
	Friendly	**.563*****	−.144***	.028	**.535*****	−.039*	**.919*****
	Lively	**.635*****	−.029	.127***	.049**	.146***	**.742*****
	Active	**.358*****	−.055**	**.365*****	−.063**	.154***	**.598*****
	Talkative	**.665*****	.119***	−.068***	.090***	.064***	**.598*****
N	Moody	−.010	**.592*****	−.029	−.108***	.052**	**.586*****
	Worrying	−.035*	**.812*****	.070***	.100***	−.036*	**.750*****
	Nervous	−.016	**.822*****	.001	.099***	−.006	**.765*****
	Calm	−.041*	**−.449*****	.084***	.250***	.184***	**−.674*****
C	Organized	−.024	.010	**.704*****	−.034	−.011	**.600*****
	Responsible	−.030	−.071**	**.675*****	.217***	−.018	**.746*****
	Hardworking	.090***	−.005	**.570*****	.103***	.095***	**.740*****
	Careless	.179***	**.296*****	**−.358*****	−.115***	.127***	−.264***
	Thorough	.015	−.002	**.716*****	.018	.113***	**.784*****
A	Helpful	.183***	.004	.258***	**.464*****	.050*	**.698*****
	Warm	**.402*****	−.084***	.017	**.616*****	−.004	**.884*****
	Caring	.079***	.042*	.171***	**.727*****	.025	**.768*****
	Softhearted	−.077***	.122***	−.060**	**.699*****	.207***	**.581*****
	Sympathetic	.032	.068***	.048**	**.707*****	.136***	**.708*****
O	Creative	.050**	.036**	−.003	−.068***	**−.793*****	**−.733*****
	Imaginative	−.026*	−.017	−.071***	.094***	**.914*****	**.785*****
	Intelligent	.148***	−.074***	**.353*****	−.099***	**.365*****	**.622*****
	Curious	.231***	.034	.245***	−.049*	**.462*****	**.693*****
	Broad-minded	−.123***	.093***	−.113***	−.167***	**−.293*****	**−.536*****
	Sophisticated	**.311*****	.048*	.181***	−.092***	**.299*****	**.550*****
	Adventurous	**.373*****	−.098***	.152***	−.126***	**.364*****	**.648*****

Note. Loadings > .29 are shown in boldface.
* $p < .05$, ** $p < .01$, *** $p < .001$.

Table 4 Factor correlations

	E	N	C	A	O
E	—	−.229***	.470***	.771***	.636***
N	−.096***	—	−.235***	−.121***	−.236***
C	.232***	−.136***	—	.468***	.522***
A	.288***	−.033*	.208***	—	.465***
O	.325***	−.070***	.282***	.175***	—

Note. CFA and ESEM correlations are presented above and below the diagonal, respectively.
* $p < .05$, *** $p < .001$.

make it a useful tool for personality research" (Borkenau & Ostendorf, 1990, p. 523). CFA does not seem to be well suited for analyzing personality data because many believe that cross-loadings are actually expected in personality measures. For example, McCrae, Zonderman, Costa, Bond, and Paunonen (1996) state that "there is no theoretical reason why traits should not have meaningful loadings on three, four, or five factors" (p. 553). The present ESEM results and those of previous research with longer personality measures confirm that items with more than one salient loading are far from rare in the five-factor structure of personality traits (e.g., Chiorri et al., 2016; Marsh et al., 2010). Research in other fields of psychology also indicates that completely pure items of psychological constructs with no correlations with other constructs are hard to come by (Asparouhov, Muthén, & Morin, 2015; Joshanloo, 2016). Therefore, from both substantive and statistical standpoints, the restriction of zero cross-loadings imposed by CFA can often be considered unwarranted and misleading, which can also bias the estimation of non-constrained parameters. Thus, the present ESEM results converge with the bulk of previous research to intensify the concern over using CFA for analyzing measurement models of personality.

Previous CFA studies of personality traits have often relied on post hoc modifications to reach an acceptable fit. However, making exploratory use of CFA in personality research has been criticized. Post hoc adjustments are usually misleading unless the initial model provides a reasonably good fit (MacCallum, 1986). If the initial model is markedly different from the true model, as was the case in the present study and in many previous CFA studies of personality, post hoc adjustments are unlikely to lead to the correct measurement model (Brown & Moore, 2012). Given that the initial CFA models in prior research have been typically ill fitting, extreme caution should be exercised when interpreting the modified models. Moreover, it is usually ignored that constraining many non-trivial factor loadings to zero can make the discovery of truly misspecified loadings even more difficult. Even extensive post hoc adjustments of CFA models of personality may fail to provide an acceptable fit (Borkenau & Ostendorf, 1990). Therefore, to achieve simple structure, using rotation of the factor matrix (as in ESEM/EFA) seems to be more effective than relying on post hoc modification as commonly performed in CFA (Browne, 2001). ESEM usually provides better-fitting models, and reduces researchers' reliance on post hoc modifications.

The present ESEM results are different from the CFA results of Zimprich et al. (2012) in many important ways (it is notable that the item Thorough was not used in their analyses, because the item has been added in later versions of the scale). Zimprich et al. omitted the item Careless from the scale due to a small factor loading, which is consistent with the present CFA results. However, in the present ESEM analysis, this item had a salient loading on C, offering no justification for removing it. Secondly, Zimprich et al. permitted five cross-loadings in their CFA model based on CFA modification indices, of which only one matches the pattern of seven salient cross-loadings in the present ESEM model (i.e., Friendly on A). Third, Zimprich et al. also allowed six residual covariances to improve fit, which was not needed in the present ESEM analysis, because the fit of the model was already acceptable. This shows that if all of the cross-loadings are freely estimated, the need for specifying item residual covariances may be largely eliminated. Finally, they found the factor correlations to be considerably higher than those found in the present ESEM analysis. This elevation of factor correlations is a result of the constraints on secondary loadings in simple-structure CFA. Constraining non-trivial cross-loading enlarges the "burden on the factor correlations to reproduce the correlations among indicators loading on different factors because there are no cross-loadings to assist in these model-implied estimates" (Brown, 2015, p. 178). The result is that factor correlations are usually of greater magnitude in CFA than ESEM (Marsh et al., 2010).

In view of the pattern of factor loadings, researchers are encouraged to use ESEM when studying this personality measure to obtain more accurate estimates. The ESEM measurement model can be readily expanded to include predictive relations between the factors and directional relations between the factors and external variables (Marsh et al., 2014). If using ESEM is not possible, an alternative option would be to specify CFA models based on the results of previous ESEM analyses in the same population (Joshanloo, 2017). For example, researches can include the salient secondary loadings found in the present study in their future CFA models in American samples. The ESEM results can also be used when analyzing composite measures (e.g., sum scores). An item with two salient loadings can be used in calculating the scores of both of the traits on which the item loads. When using composite measures, some researchers may also choose to discard items with salient cross-loadings (Sass & Schmitt, 2010).

It is noteworthy that although simple-structure CFA has virtually always failed to support the measurement models of personality, CFA still has great potential in personality research. The general conclusion from studies that have used both ESEM and CFA in this field is that CFA should not be abandoned (Booth & Hughes, 2014; Furnham, Guenole, Levine, & Chamorro-Premuzic, 2013). Although ESEM has proved to be a better analytic strategy in the field of personality, it should be acknowledged that ESEM is an exploratory method, and is most useful in initial stages of model building and scale development (Booth & Hughes, 2014). After enough information on the loadings is accumulated by ESEM studies with large and diverse samples, CFA studies can utilize the emerging information to develop more parsimonious models. Therefore, the main concern is not the usage of CFA in the field. Instead, the main concern is that more exploratory techniques, such as ESEM, are underused. Accordingly, personality researchers are encouraged to use exploratory techniques until enough information is accumulated on various personality measures to ensure that a transition from exploratory to confirmatory analysis is warranted.

In sum, given that the a priori five-factor structure of the scale was replicated, and all of the items had salient loadings on their target factors, it can be concluded that the scale measures the intended constructs. This study also illustrates that ESEM can serve as a useful tool in the study of brief measures of personality traits. It will need to be borne in mind, however, that some of the items of the scale contribute substantially to non-target factors, as is the case with many other psychological scales (Joshanloo, 2016; Marsh et al., 2010). The presence of secondary loadings necessitates the use of ESEM in future research with the scale. These findings, if replicated in additional research, may also be considered as the main source on which to rely for optimizing the scale.

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