ISSN: 1309 – 6575
Eğitimde ve Psikolojide Ölçme ve Değerlendirme Dergisi
Journal of Measurement and Evaluation in Education and Psychology
Research Article; 2022; 13(3); 244-255

Bifactor and Bifactor S-1 Model Estimations with Non-Reverse-Coded Data

Fulya BARIŞ PEKMEZCİ*

Abstract

The bifactor model is an extension of Spearman's two-factor theory. The bifactor model has a strict assumption, which is named orthogonality. The bifactor S-1 model was developed by stretching the orthogonality assumption of the bifactor model. The bifactor S-1 model, contrary to the bifactor model, allows correlation between specific factors and enables items that do not form a common specific factor to be loaded only on the general factor. In psychology, data are mostly multidimensional due to the nature of psychological constructs. The Positive and Negative Affect Schedule (PANAS) which is one of the psychological tests and has two dimensions named positive affect and negative affect. In the literature studies on PANAS, negative affect dimensions were not reverse coded while implementing the bifactor model. Therefore, negative path coefficients were revealed. The purpose of this study is to ascertain whether or not the items in the negative affect factor should be reverse coded in the PANAS. Within the scope of the current study, bifactor and bifactor S-1 model analyses were implemented for the two data sets, which were reverse coded and non-reverse coded. As a result of this study, with reverse-coded data, the bifactor S-1 model was seen as the better model for the PANAS. Additionally, in the modeling of unique variances of items with specific factors, the bifactor S-1 model performed well and also resolved the problem of negative loading on the general factor. The point to take into consideration, which should be noted by researchers who will study the PANAS, is that negative items should be reverse coded.

Keywords: PANAS, bifactor S-1, reverse coding

Introduction

The bifactor model and methods were introduced by Holzinger and Swineford (1937) as an extension of Spearman's two-factor theory. According to Spearman's two-factor (g-factor) theory, individuals have a single cognitive capacity, named "g". The "g", which does not change throughout life, consists of abstract thinking and problem-solving skills, and the ability to perform complex mental processes. The factor named "s", consists of the individual's specific skills concerned with mathematical and verbal ability. According to Spearman's conceptualization of cognitive skills, all variables are related to a general factor and at least one specific factor. Figure 1 shows the bifactor model that items can be loaded on two different factors, named the general and specific factors (Canivez, 2016; Reise et al., 2010). All items loaded on general factor and items shared common content are loaded at the same specific factor. The bifactor model, which is used to separate the contributions of specific facets/factors to the general factor, is frequently used for scaling psychological constructs. In addition, the bifactor model is used to create a short unidimensional scale from a multidimensional or unidimensional scale (Stucky & Edelen, 2015; Stucky et al., 2014) and is useful in terms of using subscale scores (Cucina & Byle, 2017). Besides these advantages, in addition to Item Response Theory (IRT) assumptions, the bifactor model has a strict assumption, which is named orthogonality. The orthogonality assumption requires that the specific factors are orthogonal to each other and the general factor, in other words, there is no correlation between these factors. However, the bifactor S-1 model (Figure 1) was developed as a result of stretching the orthogonality assumption of the bifactor model. Contrary to the bifactor model, the bifactor S-1 model enables correlation between specific factors. Besides, the bifactor S-1 model enables items that do not form a common specific factor to

* Assoc. Prof. Dr., Yozgat Bozok University, Faculty of Education, Yozgat-Turkey, fulya.baris@bozok.edu.tr, ORCID ID: 0000-0001-6989-512X

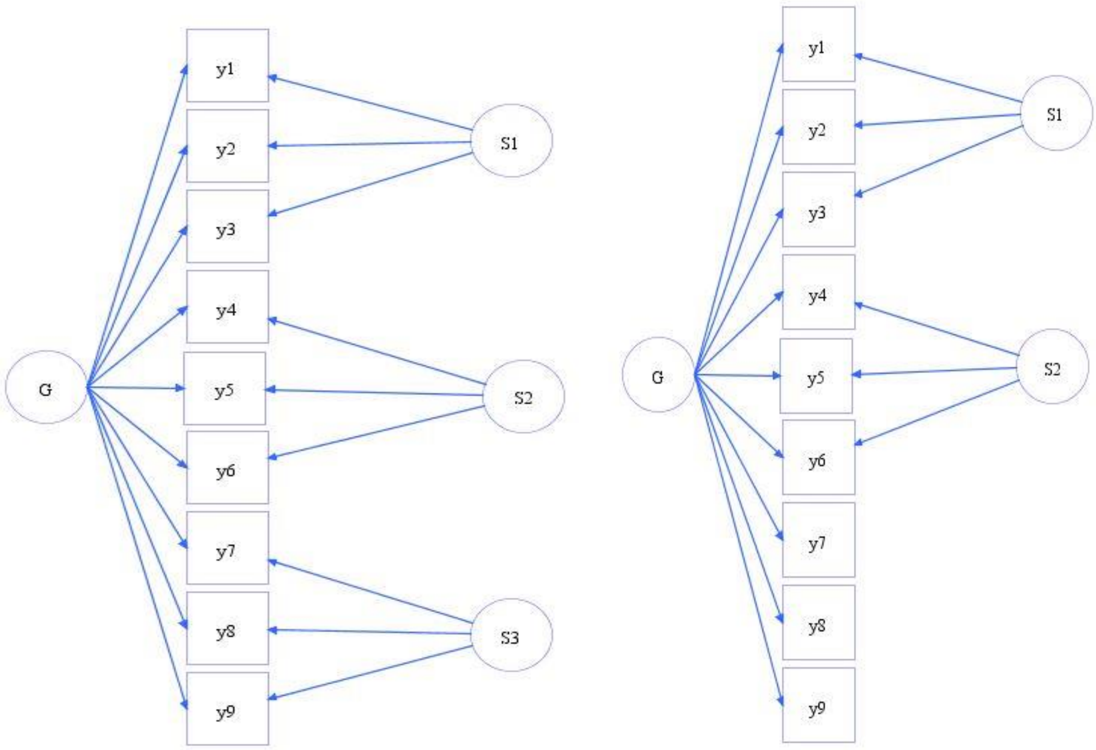
To cite this article:
Baris-Pekmezci, F., (2022). Bifactor and bifactor S-1 model estimations with non-reverse-coded data. *Journal of Measurement and Evaluation in Education and Psychology, 13*(3), 244-255. https://doi.org/10.21031/epod.1135567

Received: 24.06.2022
Accepted: 26.09.2022

load only on the general factor and can be applied to many psychological constructs (Burns et al., 2020; Eid, 2020).

Figure 1

Example of Bifactor and Bifactor S-1 model



G: General factor; S: Specific factor; y: items

In psychology, data obtained from any constructs are mostly multidimensional, and these dimensions correlated with each other. The Positive and Negative Affect Schedule (PANAS) is one of the scales in psychology, developed by Watson et al. (1988). It has two dimensions, named *positive affect* (PA) and *negative affect* (NA). Watson et al. (1988) proved that two factors are orthogonal. Since then, the PANAS has been developed and is widely used with clinical and non-clinical samples (Flores-Kanter et al., 2021; Rush & Hofer, 2014). However, the construct validity of the PANAS has been debated for almost 30 years (e.g., Ebesutani et al., 2011; Gaudreau et al., 2006; Watson et al., 1988). Also, there are various studies that have different interpretations and findings about the factor structure of the PANAS (Huebner & Dew, 1995; Killgore, 2000; Leue & Beauducel, 2011; Mihić et al., 2014; Ortuño-Sierra et al., 2015; Pires et al., 2013; Seib-Pfeifer et al., 2017; Vera-Villarroel et al., 2017). Besides, the PANAS factor structure is more suitable for bifactor model analysis due to its consisting of two orthogonal factors, which are PA and NA. In the literature, studies that modelled PANAS according to the bifactor model used naming affective *polarity* (AF) for general factor (Leue & Beauducel, 2011), and in this study, the same terminology was used.

In studies (Leue & Beauducel, 2011; Seib-Pfeifer et al., 2017) that used a bifactor model to examine the PANAS factor structure, negative path coefficients were revealed due to non-reverse coding of negative items. However, Brown and Marshall (2001) and Zampetakis et al. (2015) stated that those who work with PANAS should reverse code the items regarding the NA factor.

According to DiStefano et al. (2009), an item with a negative factor loading means a negative correlation between the item and factor, and the raw score of the item should be subtracted rather than added. From the factor analytical perspective, in exploratory factor analysis (EFA), factor scores mean correlation coefficients between the item and factor (Bernard, 2013; Kline, 2005), while for confirmatory factor analysis (CFA), factor scores mean path coefficients.

Negative factor loadings show that the items measure the opposite trait of the determined factor. At this point, the general factor loses its importance for the bifactor model. Although the general factor consists of all scale items, the negative correlation between an item and the general factor shows that the specific item measures a different trait from the general factor. So, the debate arises as to whether the negatively correlated items should be included in the general factor. According to DiStefano et al. (2009), negatively correlated items should be subtracted from the related factor. This means that negatively correlated items will not contribute to the explained variance in the general factor. In this situation, the existence of the general factor becomes questionable. If negative items are not reverse coded, can the bifactor model be used?

From this point of view, the purpose of this study is to ascertain whether or not the items in the NA factor should be reverse coded in the PANAS while using bifactor models. With this purpose in mind, the PANAS items were modeled with both the bifactor and bifactor S-1. In the literature, there were two studies that the PANAS were modelled according to the bifactor model. To compare the results with the literature in addition to bifactor s-1, bifactor model analyses were implemented too. The Bifactor s-1 model was used because it is not required an orthogonality assumption and enables avoiding estimation bias arising from correlation. It is hoped that this research will contribute to a deeper understanding of reverse coding of negative items. In line with this purpose, the following research questions were asked:

1) What are the factor loadings and model fit statistics according to the bifactor model when the items in the NA factor are not reverse coded?
2) What are the factor loadings and model fit statistics according to the bifactor model when the items in the NA factor are reverse coded?
3) What are the factor loadings and model fit statistics according to the bifactor S-1 model when the items in the NA factor are not reverse coded?
4) What are the factor loadings and model fit statistics according to the bifactor S-1 model when the items in the NA factor are reverse coded?

Methods

Participants

In this study, data were obtained from the Dutch Longitudinal Internet Studies for the Social Sciences (LISS) panel (www. lissdata.nl). The survey research data of the LISS Core Study of Personality Wave 11 were used in this study. The sample of Wave 11 consisted of 5075 participants aged 16 or older.

Instrument

The PANAS is an adjective-based scale which has 10 items for NA and 10 items for PA (Magyar-Moe, 2009). Participants indicate "*To what extent do you feel in general?*" (1=*not at all*, 5=*extremely*) for each item. The whole data set had 5201 cases. In structural equation modelling, there is always the risk of accepting invalid models with very "large" sample sizes and of rejecting valid models with very "small" sample sizes (Molwus et al., 2013). Kline (2011) stated that for more complicated models sample size is at least 200 and Hair et al.

(2008) suggest a minimum of 200 and a maximum of 400 as appropriate sample size. According to Lacobucci (2010), 50 can be sufficient for minimum sample size and 100 can be sufficient for maximum sample size, and the rules of thumb suggesting required sample sizes to be at least 200 are “conservative” and “simplistic. To eliminate the large sample effect on the model fit indices, whole data were not used and two samples which have 1000 cases were drawn. Before bifactor and bifactor s-1 analysis, outliers were detected and deleted from the data. The sample size was 572 for reverse-coded data and 732 for non-reverse-coded data. Final samples have differences in sample sizes due to the number of outliers.

Analysis

Before starting the analysis, two samples have 1000 cases were drawn from downloaded data (n=5210). Then, data were recoded to obtain reverse-coded data for the bifactor model and bifactor s-1 model analyses. Then, both reverse-coded and non-reverse-coded data were cleaned for missing values and outliers to meet the assumptions of confirmatory factor analysis models (Kline, 2011). All data analyses were carried out with Mplus 7 software.

Some goodness-of-fit indices for confirmatory models were used to decide the best model fit. The fit indices and reference ranges which were obtained from Mplus 7 and used in this study are given in Table 1.

Table 1

Goodness-of-fit indices for confirmatory models

	Acceptable fit	Good fit
Chi-square (X^2)[3]	$2df<X^2\leq 3df$	$0\leq X^2\leq 2df$
Standardized root mean square residual (*SRMR*)[1]	$0.05<SRMR\leq 0.10$	$0.00\leq SRMR\leq 0.05$
The comparative fit index (*CFI*)[1]	$0.90\leq CFI<0.95$	$0.95\leq CFI\leq 1.00$
Tucker Lewis fit index (*TLI*)[1]	$0.90\leq TLI<0.95$	$0.95\leq TLI\leq 1.00$
Root mean square error of approximation (*RMSEA*)[2]	$0.05<\mathrm{RMSEA}\leq 0.08$	$0.00\leq \mathrm{RMSEA}\leq 0.05$

Note: [1]For SRMR, CFI, and TLI, cutoff values were obtained from Hu and Bentler (1999) and Schermelleh-Engel, Moosbrugger & Müller (2003; p.52)

[2]For RMSEA, cutoff values were obtained from Brown (2015).

[3]For, $\mathcal{X}^2$ Schermelleh-Engel, Moosbrugger & Müller (2003).

For $\mathcal{X}^2$, insignificant values indicate that the model-data fit is provided. However, $\mathcal{X}^2$, is always affected by the sample size (Distefano & Hess, 2005; Kline, 2011). With large samples, $\mathcal{X}^2$ tends to be significant (Zimmer & Odum Institute, 2019).

In the scope of this study, firstly bifactor analysis was performed for both non-reverse coded data and reverse-coded data. Bifactor analysis results were used to determine which items (Positive or negative items) were to be used for loading in the AF factor.

Results

As aforementioned, two data sets were prepared which are reverse coded and non-reverse coded data. Bifactor analysis was performed for both non-reverse coded data and reverse-coded data for PANAS. The results of the bifactor model analysis are given in Table 2.

Table 2

Bifactor analysis for reverse coded and non-reverse coded data

Coding type	Models	RMSEA	RMSEA CI		CFI	TLI	SRMR	Chi-Square
non-reverse coded data	Without modification	0.116	0.111	0.121	0.875	0.843	0.397	1639.831 (151)
	With modification	0.104	0.099	0.110	0.900	0.873	0.397	1337.046 (149)
Reverse coded data	Without modification	0.099	0.093	0.105	0.910	0.887	0.367	1001.044 (151)
	With modification	0.085	0.080	0.091	0.934	0.916	0.368	771.100 (149)

When the model fit statistics in Table 2 were examined, it was seen that the model data fit was not achieved. To improve model fit, correlation of error terms can be used. Therefore, modifications were made through error term correlations. Error term modifications show that there is some common issue, which is not specified within the model, which causes covariation (Gerbing & Anderson, 1984). From this point of view, to provide model data fit, certain modifications (correlations of item PA9 with item PA8, and item PA9 with item PA6 in the PA factor were allowed) were made. Nevertheless, the model data fit was not achieved. Additionally, one of the modifications was remarkable, which suggests correlation between PA and AF (general factor) of the model. Besides, the bifactor model is rigid for factor correlations and does not allow correlation between general and specific factors. Thus, the fact that this remarkable modification could not be implemented. However, it can be evaluated as a preliminary finding for the compatibility of the bifactor S-1 model for the PANAS.

After obtaining the non-fitting model for the non-reverse data, bifactor analysis was performed for the reverse-coded data. As seen in Table 2, like with the non-reverse data, model data fit was not achieved. Some modifications (correlations of item PA4 with item PA5, and of item PA9 with item PA6 in the PA factor were allowed) were made to ensure model-data fit. However, the model data fit could not be achieved and it was observed that items NA3, NA4, and NA5 gave negative path coefficients with the NA factor. In addition to this, as a result of reverse coding, item PA2 resulted in a negative path coefficient with the general factor. In accordance with this result, previous studies demonstrated that item PA2 had a negative factor loading (Leue & Beauducel, 2011; Seib-Pfeifer et al., 2017). As with the data that were non-reverse coded, the correlation between PA and AF was seen as a remarkable modification for the model. Also, it is an important finding that the reverse-coded data showed a better fit than the non-reverse data. By obtaining the same results as for the non-reverse data, the preliminary finding was strengthened for the suitableness of the bifactor S-1 model.

When the factor loadings were analyzed according to bifactor analysis for the non-reverse data (see Appendix for detailed information), the factor loadings of four items in the NA factor and one item in the PA factor were lower than 0.32 (Comrey & Lee, 1992). Lower factor loadings in specific factors (PA and NA) were an indication of inadequate variance explained by the items. For reverse-coded data, only PA2 had a negative factor loading on the general factor (AF). Except for two items, all items in the NA factor had factor loadings lower than 0.32. Besides, three items had negative factor loadings in the NA factor. Modifications did not change the results.

As a result of obtaining the same finding for non-reverse and reverse-coded data, which showed a strong correlation between the PA factor and general factor (AF) and gave a remarkable modification coefficient (Sörbom, 1989), bifactor S-1 model analysis was implemented. Therefore, items which were in the PA factor were only loaded on the AF factor. In light of these findings, the bifactor S-1 model analysis was performed for both reverse-coded and non-reverse data sets. The results of the bifactor S-1 model analysis were given in Table 3.

Table 3

Bifactor S-1 model analysis for reverse coded and non-reverse coded data

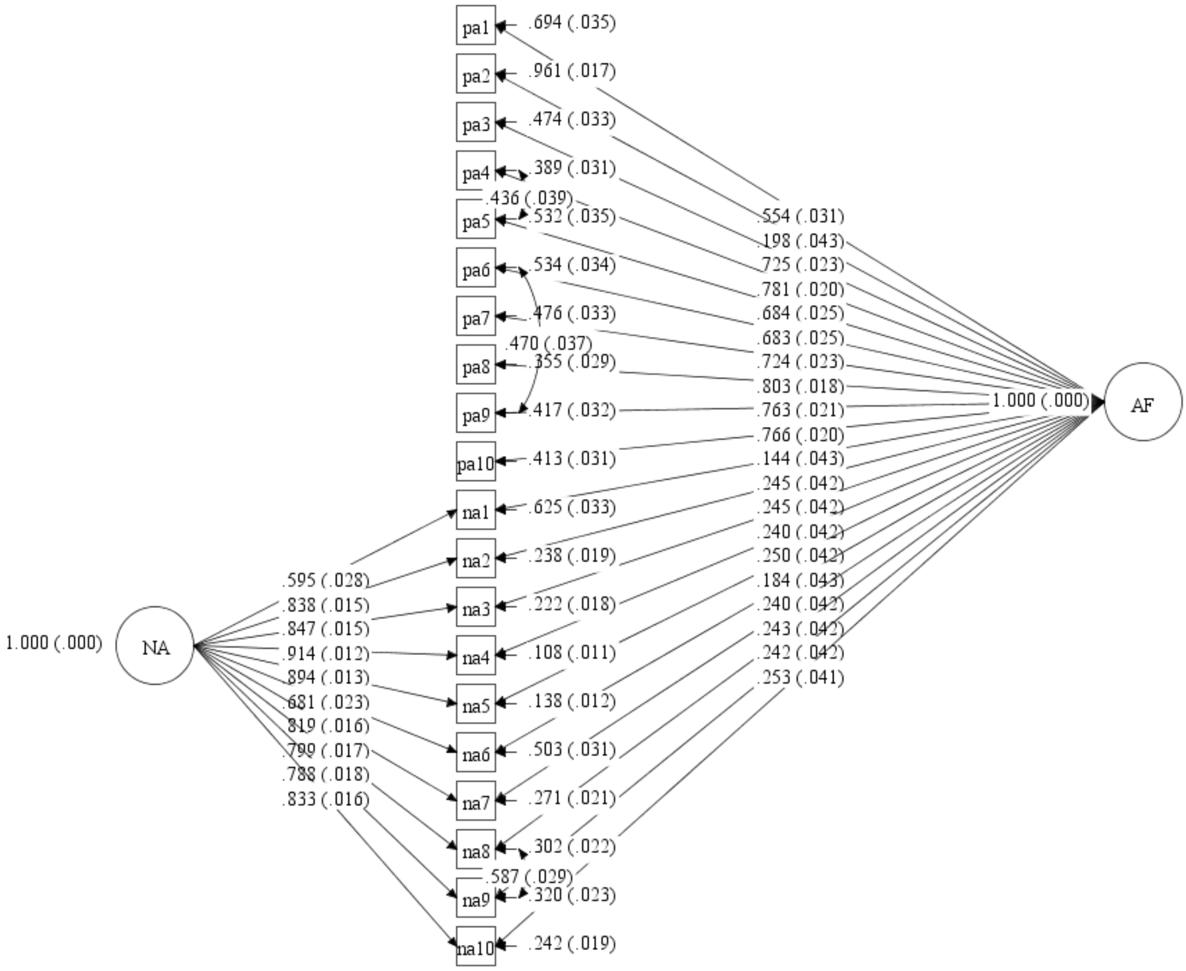
Coding type	Models	RMSEA	RMSEA CI		CFI	TLI	SRMR	Chi-Square
Non-reverse coded data	Without modification	0.111	0.106	0.116	0.880	0.857	0.102	1592.078 (160)
	With modification	0.087	0.082	0.092	0.927	0.912	0.100	1020.594 (156)
Reverse coded data	Without modification	0.113	0.107	0.118	0.877	0.854	0.097	9683.840 (190)
	With modification	0.089	0.084	0.095	0.924	0.908	0.095	876.259 (157)

When Table 3 was examined, it was seen that the bifactor S-1 model for reverse-coded data fitted with some modifications. As modifications, correlations of item PA4 with item PA5, item PA9 with item PA6, and item NA8 with item NA9 were allowed. Except for the RMSEA value, the model had an acceptable fit. Also, the chi-square values always had a problematic fit because of the sample size (Zimmer & Odum Institute, 2019). Therefore, at this point, for acceptable model-data fit, at least three model-data fit indices were considered. The big difference between the bifactor and bifactor S-1 models for reverse-coded data is that all path coefficients were positive in the bifactor S-1 model. This is an important finding for the compatibility of the bifactor S-1 model for the PANAS. The Bifactor s-1 model for PANAS was given in Figure 2.

In addition to the model-fit statistics, the factor loadings were examined. For the non-reverse coded data, items in the NA factor had negative factor loadings on the general factor (AF). This result shows that these items measure a feature opposite to the general factor (AF). However, in the bifactor S-1 analysis, items had higher loadings on their factors and increased unique variance. With the reverse-coded data, negatively loaded items in the NA factor were turned to positive. Moreover, items in the NA factor had lower factor loadings than 0.32 on the general factor (AF), which is in accordance with the studies on PANAS in the literature (Leue & Beauducel, 2011; Seib-Pfeifer et al., 2017). The path diagram in Figure 2 shows that there is not any negative factor loading. Only item PA2 had a lower factor loading among the PA items. This item also had a negative factor loading in existing studies in the literature (Leue & Beauducel, 2011; Seib-Pfeifer et al., 2017).

Figure 2

Bifactor S-1 model for reverse coded data



Conclusion, Discussion, And Recommendations

This study aims to ascertain whether or not the items in the NA factor should be reverse coded in the PANAS. Therefore, bifactor and bifactor S-1 model analyses were implemented. According to the results, for reverse-coded items, the bifactor S-1 model was seen as the better model for the PANAS. Additionally, in modeling unique variances of items with specific factors, the bifactor S-1 model performed well and also resolved the negative loading problem of the items on the general factor. Contrary to the bifactor S-1 model, the bifactor model had a poor fit for the PANAS. In accordance with the present result, in the studies using the bifactor model, better fit indices were obtained in most cases, while in a controversial study, it was seen that this model had a poor fit for the PANAS (for detailed information, see Flores-Kanter et al., 2021). Also, in the literature, studies which found a better fit with the bifactor model for the PANAS had a big problem, which was negative factor loadings (Leue & Beauducel, 2011; Seib-Pfeifer et al., 2017).

In this research, negative factor loadings were not obtained with the bifactor model, but the model fit could not be achieved. Therefore, in consideration of modification suggestions, the bifactor S-1 model analysis was made, the negative coefficients were eliminated, and the model fit was obtained. Besides, lower factor loadings were obtained with the bifactor model than with the bifactor s-1 model. The increase in factor loadings showed that the items in the specific factor had a remarkable contribution.

The lower factor loadings of the items in the specific factor reduced the importance of the specific factor.

A remarkable finding of this study is that the bifactor model revealed lower factor loadings on NA factor. According to Kula Kartal et al.'s (2022) research, the wording effect can cause lower factor loadings of negative items. In this study, lower factor loading may have arisen from the wording effect too.

Even though the items in the NA factor were reverse coded in the bifactor model analysis, the PA2 item belonging to the positive affect factor had a negative loading, as in other studies in the literature (Leue & Beauducel, 2011; Seib-Pfeifer et al., 2017). This may be because the expression "distressed" in the PA2 item might have been perceived negatively by the group. The adjective for this item should be reexamined in other studies.

One of the modification suggestions is to establish a correlation between the PA factor and the general factor. The need for reverse coding of negative items has emerged as a finding. The point to take into consideration with this finding, which should be noted by researchers who will bifactor model with PANAS, is that negative items should be reverse coded. In this research, modifications were implemented to obtain model-data fit. However, modified models need to estimate with an independent sample. In this way, the model can truly be termed "confirmed" technically. With new studies, the bifactor S-1 model for the PANAS should be reanalyzed with different samples.

In this study, negative items were reverse coded. But in the literature, there was a majority of views on reverse coding. Greenberger et al. (2003) recommend not to mix negative items with positive items because it creates a two-factor structure of the instrument based on the item wording difference (positively and negatively worded items), which is a threat to construct validity. Ibrahim (2001) also recommends not mixing negatively and positively worded items. Salazar (2015) states that although mixing can reduce the acquiescence bias, it causes a method effect, impairs factorial validity, and hurts internal consistency. Hartley (2013) also recommend that if researchers mix positively and negatively items, they should present results obtained from negatively worded items separately, instead of reverse-coding the data and combining them with the data obtained from positively worded items. Locker et al. (2007) recommend that when using a mixed format with the intent to reverse-code negatively worded items, make sure to use a symmetrical response scale with an equal number of anchors on the positive and negative sides of the scale.

Literature about reverse coding is debatable. Also, PANAS should not be used with negative factor loadings both general and specific factors. If researchers hesitate to use reverse coding, it is not recommended to use bifactor models with PANAS. Kula Kartal et al. (2022), in their studies recommended using the bifactor model to examine the wording effect of items. A further study should asses the wording effect of the NA factor on PANAS with the bifactor model.

Declaration

Conflict of Interest: No potential conflict of interest was reported by the authors.

Ethical Approval: Secondary data were used in this study. Therefore, ethical approval is not required.

References

Bernard, H. R. (2013). *Social research methods: Qualitative and quantitative approaches*. Sage.

Brown, T. A. (2015). *Confirmatory factor analysis for applied research*. Guilford.

Brown, J. D., & Marshall, M. A. (2001). Self-esteem and emotion: Some thoughts about feelings. *Personality and Social Psychology Bulletin*, *27*(5), 575–584. https://doi.org/10.1177/0146167201275006

Burns, G. L., Geiser, C., Servera, M., Becker, S. P., & Beauchaine, T. P. (2020). Application of the Bifactor S − 1 model to multisource ratings of ADHD/ODD symptoms: An appropriate bifactor model for symptom ratings. *Journal of Abnormal Child Psychology, 48*(7), 881-894. http://dx.doi.org/10.1007/s10802-019-00608-4

Canivez, G. L. (2016). Bifactor modeling in construct validation of multifactored tests: Implications for understanding multidimensional constructs and test interpretation. *Principles and Methods of Test Construction: Standards and Recent Advancements*. Hogrefe Publishers.

Comrey, A. L., & Lee, H. B. (1992). *A first course in factor analysis* (2nd ed.). Erlbaum and Associates.

Cucina, J., & Byle, K. (2017). The bifactor model fits better than the higher-order model in more than 90% of comparisons for mental abilities test batteries. *Journal of Intelligence, 5*(3), 27. http://dx.doi.org/10.3390/jintelligence5030027

DiStefano, C., & Hess, B. (2005). Using confirmatory factor analysis for construct validation: An empirical review. *Journal of Psychoeducational Assessment*, *23*(3), 225-241. https://doi.org/10.1177/073428290502300303

DiStefano, C., Zhu, M., & Mindrila, D. (2009). Understanding and using factor scores: Considerations for the applied researcher. *Practical Assessment, Research, and Evaluation*, *14*(1), 20.

Ebesutani C., Smith A., Bernstein A., Chorpita B. F., Higa-McMillan C., & Nakamura B. (2011). A bifactor model of negative affectivity: Fear and distress components among younger and older youth. *Psychological Assessment, 23*(3), 679–691. http://dx.doi.org/10.1037/a0023234

Eid, M. (2020). Multi-faceted constructs in abnormal psychology: Implications of the bifactor S − 1 model for individual clinical assessment. *Journal of Abnormal Child Psychology, 48*(7), 895-900. http://dx.doi.org/10.1007/s10802-020-00624-9

Flores-Kanter, P. E., Garrido, L. E., Moretti, L. S., & Medrano, L. A. (2021). A modern network approach to revisiting the Positive and Negative Affective Schedule (PANAS) construct validity. *Journal of Clinical Psychology, 77*(10), 2370-2404. http://dx.doi.org/10.1002/jclp.23191

Gaudreau, P., Sanchez, X., & Blondin, J.-P. (2006). Positive and negative affective states in a performance related setting. *European Journal of Psychological Assessment*, *22*(4), 240–249. https://doi.org/10.1027/1015-5759.22.4.240

Gerbing, D. W., & Anderson, J. C. (1984). On the meaning of within-factor correlated measurement errors. *Journal of Consumer Research*, *11*(1), 572-580. http://dx.doi.org/10.1086/208993

Greenberger, E., Chen, C., Dmitrieva, J., & Farruggia, S. P. (2003). Item-wording and the dimensionality of the Rosenberg Self-Esteem Scale: Do they matter? *Personality and Individual Differences, 35*(6), 1241–1254. https://doi.org/10.1016/S0191-8869(02)00331-8

Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (2008). *Multivariate data analysis*. Prentice Hall Publisher.

Hartley, J. (2013). Some thoughts on Likert-type scales. *International Journal of Clinical and Health Psychology*, *13*(1), 83–86. https://doi.org/10.1080/13645570802648077

Holzinger, K. J., & Swineford, F. (1937). The Bi-Factor method. *Psychometrika, 2*(1), 41-54.

Huebner, E. S., & Dew, T. (1995). Preliminary validation of the positive and negative affect schedule with adolescents. *Journal of Psychoeducational Assessment, 13*(3), 286–293. https://doi.org/10.1177/073428299501300307

Ibrahim, A. M. (2001). Differential responding to positive and negative items: The case of a negative item in a questionnaire for course and faculty evaluation. *Psychological Reports, 88*, 497–500. https://doi.org/10.2466/pr0.2001.88.2.497

Jöreskog, K. G., & Sörbom, D. (1989). *LISREL 7 user's reference guide*. Scientific Software.

Kula Kartal, S., Aybek, E. C., & Yaşar, M. (2022). Investigating the wording effect in scales based on different dimension reduction techniques. *Journal of Uludağ University Faculty of Education, 35*(1), 44-67. https://doi.org/10.19171/uefad.1033284

Killgore, W. D. S. (2000). Evidence for a third factor on the positive and negative affect schedule in a college student sample. *Perceptual and Motor Skills, 90*(1), 147–152. https://doi.org/10.2466/pms.2000.90.1.147

Kline, T. (2005). *Psychological testing: A practical approach to design and evaluation*. Sage.

Kline, R. B. (2011). *Principles and practice of structural equation modelling*. Guilford.

Lacobucci, D. (2010). Structural equations modelling: Fit indices, sample size, and advanced topics. *Journal of Consumer Psychology, 20*(1), 90-98. https://doi.org/10.1016/j.jcps.2009.09.003

Leue, A., & Beauducel, A. (2011). The PANAS structure revisited: On the validity of a bifactor model in community and forensic samples. *Psychological Assessment*, *23*(1), 215-225. http://dx.doi.org/10.1037/a0021400

Locker, D., Jokovic, A., & Allison, P. (2007). Direction of wording and responses to items in oral health-related quality of life questionnaires for children and their parents. *Community Dentistry and Oral Epidemiology, 35*(4), 255–262. https://doi.org/10.1111/j.1600-0528.2007.00320.x

Magyar-Moe, J. L. (2009). *Therapist's guide to positive psychological interventions*. Academic press.

Mihić, L., Novović, Z., Čolović, P., & Smederevac, S. (2014). Serbian adaptation of the Positive and Negative Affect Schedule (PANAS): Its facets and second-order structure. *Psihologija, 47*(4), 393–414. http://dx.doi.org/10.2298/PSI1404393M

Molwus, J. J., Erdogan, B., & Ogunlana, S. O. (2013). Sample size and model fit indices for structural equation modelling (SEM): The case of construction management research. In *ICCREM 2013: Construction and Operation in the Context of Sustainability* (pp. 338-347). http://dx.doi.org/10.1061/9780784413135.032

Ortuño-Sierra, J., Santarén-Rosell, M., de Albéniz, A. P., & Fonseca-Pedrero, E. (2015). Dimensional structure of the Spanish version of the positive and negative affect schedule (PANAS) in adolescents and young adults. *Psychological Assessment, 27*(3), e1–e9. https://doi.org/10.1037/pas0000107

Pires, P., Filgueiras, A., Ribas, R., & Santana, C. (2013). Positive and negative affect schedule: Psychometric properties for the Brazilian Portuguese version. *The Spanish Journal of Psychology, 16*, e58. https://doi.org/10.1017/sjp.2013.60

Reise, S. P., Moore, T. M., & Haviland, M. G. (2010). Bifactor models and rotations: Exploring the extent to which multidimensional data Yield Univocal Scale Scores. *Journal of Personality Assessment, 92*(6), 544-559. http://dx.doi.org/10.1080/00223891.2010.496477

Rush, J., & Hofer, S. M. (2014). Differences in within and between person factor structure of positive and negative affect: Analysis of two intensive measurement studies using multilevel structural equation modeling. *Psychological Assessment, 26*(2), 462–473. https://doi.org/10.1037/a0035666.

Salazar, M. S. (2015). The dilemma of combining positive and negative items in scales. *Psicothema, 27*(2), 192–199. https://doi.org/10.7334/psicothema2014.266

Schermelleh-Engel, K., Moosbrugger, H., & Müller, H. (2003). Evaluating the fit of structural equation models: Tests of significance and descriptive goodness-of-fit measures. *Methods of Psychological Research Online, 8*(2), 23-74.

Seib-Pfeifer, L.-E., Pugnaghi, G., Beauducel, A., & Leue, A. (2017). On the replication of factor structures of the Positive and Negative Affect Schedule (PANAS). *Personality and Individual Differences, 107*(1), 201–207. https://doi.org/10.1016/j. paid.2016.11.053

Stucky, B. D., & Edelen, M. O. (2015). Using hierarchical IRT models to create unidimensional measures from multidimensional data. In S. P. Reise & D. A. Revicki (Eds.), *Handbook of item response theory modeling: Applications to typical performance assessment* (pp. 183–206). Routledge/Taylor & Francis Group.

Stucky, B. D., Edelen, M. O., Vaughan, C. A., Tucker, J. S., & Butler, J. (2014). The psychometric development and initial validation of the DCI-A short form for adolescent therapeutic community treatment process. *Journal of Substance Abuse Treatment, 46*(4), 516-521. https://doi.org/10.1016/j.jsat.2013.12.005

Vera-Villarroel, P., Urzúa, A., Jaime, D., Contreras, D., Zych, I., Celis-Atenas, K., Silva, J. R., & Lillo, S. (2017). Positive and Negative Affect Schedule (PANAS): Psychometric properties and discriminative capacity in several chilean samples. *Evaluation & the Health Professions, 42*(4), 473–497. https://doi.org/10.1177/0163278717745344

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology, 54*, 1063–1070. https://doi.org/10.1037/0022- 3514.54.6.1063

Zampetakis L. A., Lerakis M., Kafetsios, K., & Moustakis, V. (2015). Using item response theory to investigate the structure of anticipated affect: Do self-reports about future affective reactions conform to typical or maximal models? *Frontiers in Psychology, 6*, 1438. https://doi.org/10.3389/fpsyg.2015.01438

Zimmer, C., & Odum Institute (2019). Learn to perform confirmatory factor analysis in Stata with data from general social survey (2016). In SAGE research Methods Datasets Part 2. SAGE Publications. https://dx.doi.org/10.4135/9781529700091

Appendix

Appendix A

Table A1

Bifactor path coefficients for not reverse coded data

	Without modification			With modification		
Items	AF	PA	NA	AF	PA	NA
PA1	0.603	0.523		0.601	0.522	
PA2	0.638	0.247*		0.658	0.290*	
PA3	0.096	0.714		0.112*	0.747	
PA4	0.346	0.746		0.369	0.788	
PA5	0.261*	0.706		0.280*	0.744	
PA6	0.335	0.709		0.286*	0.651	
PA7	0.337	0.706		0.339	0.717	
PA8	0.277*	0.814		0.236*	0.768	
PA9	0.303	0.775		0.238*	0.707	
PA10	0.252*			0.240*	0.739	
NA1	0.699		0.143*	0.705		0.117*
NA2	0.822		0.373	0.839		0.337
NA3	0.790		0.491	0.814		0.455
NA4	0.833		0.491	0.856		0.451
NA5	0.772		0.563	0.800		0.524
NA6	0.820		0.162*	0.827		0.129*
NA7	0.810		0.374	0.828		0.339
NA8	0.948		0.140*	0.953		0.102*
NA9	0.939		0.140*	0.945		0.100*
NA10	0.846		0.326	0.861		0.289*

*<0.320

Table A2

Bifactor path coefficients for reverse coded data with modifications

	Without modification			With modification		
Items	AF	PA	NA	AF	PA	NA
PA1	0.699	0.401		0.699	0.408	
PA2	-0.383	0.358		-0.380	0.360	
PA3	0.559	0.596		0.561	0.592	
PA4	0.444	0.731		0.444	0.716	
PA5	0.444	0.651		0.439	0.621	
PA6	0.437	0.642		0.431	0.614	
PA7	0.390	0.674		0.398	0.684	
PA8	0.495	0.690		0.499	0.693	
PA9	0.500	0.669		0.499	0.654	
PA10	0.477	0.662		0.483	0.668	
NA1	0.687		0.172*	0.687		0.169*
NA2	0.915		0.005*	0.915		0.001*
NA3	0.925		-0.027*	0.925		-0.030*
NA4	0.967		-0.002*	0.967		-0.007*
NA5	0.961		-0.035*	0.961		-0.040*
NA6	0.771		0.224*	0.772		0.221*
NA7	0.901		0.039*	0.901		0.036*
NA8	0.876		0.387	0.878		0.383
NA9	0.869		0.380	0.871		0.376
NA10	0.906		0.169*	0.907		0.165*

*<0.320

Table A3

Bifactor S-1 path coefficients for non-reverse coded data

	Without modification		With modification	
Items	AF	NA	AF	NA
PA1	0.537		0.546	
PA2	0.141*		0.159*	
PA3	0.686		0.709	
PA4	0.748		0.768	
PA5	0.689		0.691	
PA6	0.712		0.662	
PA7	0.701		0.723	
PA8	0.825		0.783	
PA9	0.787		0.720	
PA10	0.737		0.748	
NA1	-0.108*	0.593	-0.113*	0.602
NA2	-0.218*	0.836	-0.223*	0.836
NA3	-0.221*	0.867	-0.220*	0.843
NA4	-0.265*	0.904	-0.270*	0.909
NA5	-0.243*	0.875	-0.248*	0.888
NA6	-0.159*	0.717	-0.169*	0.693
NA7	-0.197*	0.829	-0.203*	0.820
NA8	-0.233*	0.835	-0.239*	0.822
NA9	-0.255*	0.817	-0.262*	0.813
NA10	-0.243*	0.830	-0.251*	0.841

*<0.320

Table A4

Bifactor S-1 path coefficients for reverse coded data

	Without modification		With modification	
Items	AF	NA	AF	NA
PA1	0.543		0.554	
PA2	0.203*		0.198	
PA3	0.727		0.725	
PA4	0.799		0.781	
PA5	0.717		0.684	
PA6	0.717		0.683	
PA7	0.714		0.724	
PA8	0.798		0.803	
PA9	0.780		0.763	
PA10	0.756		0.766	
NA1	0.141*	0.602	0.144*	0.595
NA2	0.238*	0.836	0.245*	0.838
NA3	0.242*	0.843	0.245*	0.847
NA4	0.234*	0.909	0.240*	0.914
NA5	0.245*	0.888	0.250*	0.894
NA6	0.172*	0.693	0.184*	0.681
NA7	0.234*	0.820	0.240*	0.819
NA8	0.237*	0.822	0.243*	0.799
NA9	0.236*	0.813	0.242*	0.788
NA10	0.250*	0.841	0.253*	0.833

* <0.320