Caveats of non-ipsatization of basic values: A review of issues and a simulation study

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Abstract

Ipsatization, or a correction of variables by their common component, is routinely applied to measures of basic values. Although ipsatization has been criticized, the consequences of non-ipsatization are rarely discussed. We show that the ipsatization of values is intertwined with their definition. A common factor involved in ipsatization was suggested to represent a nuisance variable, a response style, social desirability, or other constructs. A simulation study illustrated that within-individual centering revealed more accurate value scores when the common factor was in the data, with exception of the situation when values were consistently and positively correlated with each other. We conclude that in different conditions both applying and failing to apply ipsatization can cause bias. Therefore, no general advice in regard to ipsatization can be provided.

Keywords: basic values, method factor, centering, ipsatization, ipsatizing, ipsated measures.

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Introduction

Basic values are an increasingly popular concept in psychology, sociology, political science, and management research, and they have been widely used to explain and predict various kinds of behavior, attitudes, and choices (Maio, 2016). Values have been measured in a number of ways, which may be crudely divided into ranking and rating scales. Ranking requires respondents to order values by importance, forcing them to prioritize one value over another even if participants think some values are actually of similar importance for them (e.g., Rokeach, 1973). Ranking produces so-called ipsatized (ipsated, ipsative) measures, that is, measures which reflect within-individual preferences; their mean is a constant across all individuals, and all the variables in the set are inherently interrelated. These features of ipsatized measures violate assumptions of many conventional methods of statistical analysis and complicate interpretation, thereby spreading confusion for decades. Some researchers claimed that the ipsatized measures were incomparable across individuals (e.g., Hicks, 1970), while others worked on methods that deal with the specifics of ipsatized scores (e.g., Chan & Bentler, 1993).

Following these critiques of ranking, more recent value measurement instruments have adopted independent ratings of values (e.g., Schwartz & Bilsky, 1987). It was suggested that value preferences do not have to be indicated by participants themselves; rather, the preferences can be inferred by researchers from the ratings of each value. Thereby, participants can rate each value item independently, and researchers can use these ratings to convert them into preferences. In one of the most popular value theories and its accompanying instruments (Schwartz, 1992), the value scores were suggested to be ipsatized by within-individual centering, which reveals the scores by a subtraction of an overall individual mean of all value items from every specific value index based on subsets of these items. The ipsatization procedure was recommended by Schwartz, 1992, Schwartz, 2005, Schwartz et al., 2001) and has been widely applied (Roccas et al., 2017).

Ipsatization was claimed to have different purposes, including a conversion of ratings to preference scores, and a correction for response styles, social desirability, and a general level of motivation (Schwartz et al., 1997, Schwartz, 2003, Borg and Bardi, 2016, Danioni and Barni, 2020). Despite popularity and widespread use of ipsatization of values, the meaning and consequences of ipsatization have been rarely discussed. Furthermore, several papers

challenged the practice of ipsatization (Fischer, 2004, Fischer and Milfont, 2010) and recommended avoiding the use of ipsatization (He and van de Vijver, 2015, Borg and Bardi, 2016). Other studies suggested equivalent external validity for ipsatized and non-ipsatized scores (Baron, 1996). Yet it is still unclear if value ipsatization or failure to ipsatize value scores leads to bias. Thus, the issue of ipsatization remains highly ambiguous. Therefore, the aims of the current paper are to (1) clarify popular interpretations of a general factor standing behind the ipsatization, (2) revisit various criticisms of the value ipsatization procedure, and (3) summarize statistical issues with an illustration by means of a simulation study.

Background

Basic values “(1) are concepts or beliefs, (2) pertain to desirable end states or behaviors, (3) transcend specific situations, (4) guide selection or evaluation of behavior and events, and (5) are ordered by relative importance” (Schwartz, 1992, p. 4). Measurement of values usually aims at retrieving true value scores using a set of observed variables by distinguishing between the target scores (i.e., substantive value factors) and the residual variance. Ipsatization involves a correction of each value score by a common variance of a whole set of observed variables. It can be embedded in a questionnaire (i.e., ranking) or conducted by researchers on the responses to rating scales. Ipsatization assumes that there is some common factor that affects all participants’ responses. It is supposed to reduce or eliminate the common factor thereby reducing error in value scores.

The common factor can be considered a byproduct of the measurement procedure, yet it can vary across individuals and groups in a systematic way reflecting some non-random characteristic. There are, however, differing theories about this common factor.

We have identified three general ways of attributing a meaning to the common factor: as (1) an arbitrary level to which the raw value scores should be adjusted; (2) a substantive construct theoretically related to values (e.g., social desirability, value guidedness); and (3) a methodological artifact conceptually independent of values (e.g., response set, acquiescence, and other method influences). In the following sections, we explicate these interpretations of the common factor as well as characteristics of the underlying measurement model, and then discuss statistical issues related to ipsatization.

Common factor as an arbitrary level of adjustment

From the infancy of empirical value research, values were defined in terms of preferences because every value was viewed as part of a larger system rather than independently of each other (Parsons et al., 1951, Kluckhohn and Strodtbeck, 1961, Allport et al., 1970). Ipsatized value scores fit well into the system view of values, because every ipsatized value includes information about all the other values in a system, and they are interdependent. Therefore, the ipsatized value score (e.g., value ranking) was a desirable measure because it reflected a relative importance, or preference, of a value compared to the other values. Early on, Kluckhohn and Strodtbeck (1961) discussed cultural or value dilemmas, from which every human (as well as a survey respondent) has to choose. Allport et al. (1970) developed a theory and corresponding instruments of value preferences, which forced participants to choose from multiple occupation-related dichotomies. The resulting scores were purposefully ipsatized, emphasizing the relative rather than absolute value importance. The prominent Rokeach value survey (1973) involved the ordering of cards with values by their importance. Moreover, the very definition of values formulated by Rokeach included preferences, so that beliefs that do not express preferences were not considered a part of value domain. A methodological discussion ensued, questioning if explicit ordering of cards, or ranking, was necessary for value measurement, with some concluding that it was (Rankin & Grube, 1980), and others claiming that independent ratings were better measures (Braithwaite and Law, 1985, Maio et al., 1996) or that both had their advantages (Krosnick and Alwin, 1988, Ovadia, 2004). The problem with ranking (and more generally with forced-choice questions) is that respondents are not allowed to choose the same importance for two or more values. Following this critique, Schwartz combined both ranking and rating in his value survey (Schwartz, 1992), and he later on opted for ratings only (various versions of Portrait Value Questionnaire – PVQ, Schwartz et al., 2001). Yet Schwartz emphasized the relative importance of values:

“What really interests us is the relative importance of the ten values to a person, the person’s value priorities. This is because the way values affect attitudes, feelings and behaviour is through a trade-off or balancing among the different values that are simultaneously relevant to action... Behaviours often have opposing implications for the relevant values (e.g., implications of rock climbing for stimulation vs. security). If we make predictions with the absolute importance of any single value for an

individual or group, without considering the importance of this value relative to the individual's or group's other values, we will fail to take account of the fact that values function as a system.” (Schwartz, 2005)

Since ipsatization can essentially transform value ratings to indicators of relative within-individual importance, it was recommended by Schwartz, 1992, Schwartz, 2005, Schwartz et al., 2001).

Hicks (1970) and later Closs (1996) criticized “ipsative” scores¹ for being incomparable across individuals, mostly due to the difficulty of interpretation. It is indeed more complex than interpretation of non-ipsatized scores. However, for value research it seems to be less problematic because most definitions of values included preference as a key attribute of values. Some studies directly implied the individual priorities of one value over the other, for example, a value dimension representing the degree of preference of openness over conservation values (Schwartz, 1992).

Many other popular measures of values followed the preference feature by using ranking (“List of Values” by Kahle and Kennedy [1988]), varieties of forced-choice questions (e.g., postmaterialism by Inglehart [1997]; best-worst basic values instrument by Lee et al., 2008, Lee et al., 2019)), or bipolar dimensions which implicitly represented individual preference of one value over another (e.g., Inglehart’s [1997] survival vs. self-expression or Gouveia’s [see Fischer et al., 2011] humanistic vs. thriving dimension). Individual factor scores derived from a factor analysis with bipolar factors implicitly involves preference scores (Van Schuur & Kiers, 1994). Thus, virtually all major approaches to measurement of values followed the ordered nature of values in one way or another.²

Therefore, interpretation of difference scores is not an issue. However, the common factor removed by ipsatization was rarely conceptualized and thus was implicitly treated as an

¹ In psychometrics, “ipsative” or “ipsated” scores (which we consider synonymous to “ipsatized”) are opposed to normative scores in the sense that ipsative scores are standardized within an individual, whereas normative scores are standardized at the population level so that the mean or median represents a statistical norm (e.g., Baron, 1996).

² In fact, many studies beyond basic values used derived preference scores (e.g., difference scores or scores that reflect preference—explicitly or implicitly—of one item over the other) and did not find it problematic to compare them across individuals. For instance, the prominent semantic differential procedure (Osgood et al., 1957) revealed scores which represented the within-individual tendency to lean toward one of the poles as compared to this same individual’s scores on the opposite pole. Essentially, these scores represented a degree of individual preference of some characteristic over all or some of the others.

arbitrary level of adjustment. Essentially, the common factor was treated as a completely random variable unrelated to values and equally distributed across value indicators. As we show below, these two assumptions may be unreasonable and may bring a bias into value scores.

Common factor as a substantive variable

Schwartz et al. (1997) hypothesized that a common value factor represents an overall level of social desirability, since all values are desirable—to some degree. They studied the relations between value scores and the Marlow-Crowne Social Desirability Scale. The results indicated that the common value factor had little to do with social desirability. A mean value rating representing common factor showed a weak positive correlation with the social desirability score (0.17 and 0.27 in two samples). Moreover, social desirability positively correlated with social-focus values such as conformity, and these were only weakly affected by the correction for an overall value rating, that is, ipsatization. Therefore, social desirability was not found to be a confounder, but it rather substantially related to values. Indeed, if some people tend to respond in a socially desirable way, it may represent their susceptibility to act in a socially desirable way in general; thereby, their responses to value questions are as useful as responses of respondents who do not tend to be socially desirable.

In contrast, Cieciuch et al. (2013) found that the correlations of the common factor with social desirability (i.e., its impression management component, Stöber, 2001), as well as with moralistic and egoistic bias were quite strong (0.60, 0.64, and -0.40 , respectively). These contradictory conclusions might have occurred due to the different measurement instruments used in these studies: Schwartz et al. (1997) used the Schwartz Value Survey (SVS), which combined ranking and rating procedures and therefore might have partly removed the common factor. The SVS first requests respondents to choose the most important values from a list of values, and then to rate the rest of them as guiding principles in their life. Cieciuch et al. (2013) applied the Revised Portrait Values Questionnaire (PVQ-RR), which uses only ratings: It allows respondents to rate the similarity between a described person and themselves. The latter might have induced socially desirable responding through activating

social comparison.³ If this is the case, then the common factor behind values may reflect slightly different constructs depending on the specific instrument. In addition, both studies found that social desirability had positive correlations with social-focus values, such as conformity, and negative correlations with person-focus values, such as hedonism.

More recently, in a sample of Italian students, Danioni and Barni (2020) found a weak, positive correlation between the common factor and the two measures of social desirability: impression management and self-deceptive enhancement. Similar to the abovementioned studies, these results were found only for the PVQ, but not for values measured with the SVS. The two components of social desirability exhibited different relations with values: Impression management was related to conformity and the other conservation values whereas self-deceptive enhancement was related to self-enhancement values. These findings point to the ambiguity of the social desirability concept in its relation to value measurement. Different components of social desirability can be seen individually as motivational goals or values, one of which is close to conformity and the other functioning through self-enhancement values. It implies that if a common factor is fully determined by social desirability, this factor can be a consequence or part of conformity and self-enhancement values rather than their measurement bias. It follows that it might be unreasonable to try to separate social desirability from these values. At the same time, ipsatization might reduce the bias imposed on the other values, increasing their discriminant validity. As we discussed above, the effects of social desirability on a common factor were found to be either weak or strong depending on specific instruments, and it is unknown if this part of the common factor is sufficient to crucially bias the value scores.

Other interpretations of the common factor that is related to values were suggested as well. Harman (2018) followed the wording of the response options in the PVQ, which involve evaluation of similarity with a set of given value portraits (e.g., “Very much like me”). A mean rating based on all the responses indicated how strongly respondents referred to “external role models to guide their own conduct” (Harman, 2018, p. 7). In a similar vein, Borg and Bardi (2016) suggested that a common value factor may represent a personal value guidedness, that is, a general susceptibility of a person to follow their values. However, the concepts of external role guidedness and value guidedness were not theoretically developed

³ Another explanation is the outdated content of the Marlow-Crowne Social Desirability Scale used by Schwartz and colleagues (1997), see Stöber (2001). The two studies also included different samples: Finnish students and Israeli general population sample (Schwartz et al. 1997) and the general population samples of Poland (Cieciuch et al., 2013).

nor supported with empirical evidence so far. Further research should follow up on this. Still, it is conceivable that both interpretations may be linked to some values: external role guidedness may represent conformity, and a general value guidedness may relate to self-direction. Similar to social desirability, such interpretations of the common factor pose some problems for ipsatization practice, since the removal of a common factor that overlaps with some values may bias their true scores (but at the same time adjust for bias of the other values).

Common factor as a methodological artifact

As long as values are measured in surveys with batteries of similar questions, the value scores are likely to be affected by response styles (response sets), which in turn might manifest a common factor. Response styles appear when a respondent demonstrates a systematic response tendency reacting to a format rather than to the substance of the questions. There is abundant evidence on the susceptibility of Likert-type scales to various response styles, for example, the individual tendency to choose responses situated at a certain location on the response scale (e.g., Van Herk et al., 2004, Weijters et al., 2010).⁴ Multiple studies demonstrated that the preferred way of responding to the survey questions differs across cultures and individuals (e.g., He et al., 2014, Smith, 2004, Smith, 2011). Moreover, response styles were found to be interrelated across measurement methods, regardless of whether behavior, traits, attitudes, or values were measured (He et al., 2014, He and van de Vijver, 2015). This implies that response style, unlike social desirability, is external in relation to values and constitutes a separate concept.

At the same time, some evidence suggests that response style can be associated with values. He and van de Vijver (2013) found a fair-sized correlation of a general response style with personality traits (mostly with the “Big One” and agreeableness) which in turn are related to values (Parks-Leduc et al., 2015). It might imply that the response style is also related to values, in particular to conformity and benevolence values. At the cultural level, response

⁴ Various determinants were theorized to cause response sets/styles: motivation to participate in a survey (which causes low differentiation between items, less attention, and cognitive effort in responding, satisficing), communication styles (midpoint vs. extreme options scale answering), and personality traits (acquiescence or “yeah”-saying), to name a few.

style was found to correlate to cultural conformity values, or more precisely, the value of embeddedness (He et al., 2014).

Thereby, values such as conformity may share some substantive content with both social desirability and some response styles (e.g., acquiescence). Since response style is a reaction to a format rather than the substance of questions, the association of the specific basic values with response style is likely to be weaker than the one with social desirability. For the same reason, the response style is likely to affect all the responses in a similar degree which makes it easier to separate from the value scores. Moreover, response styles are behaviors, thus they are conceptually distinct from values (which are beliefs). Values may affect responding behavior, but by no means is the behavior a part of values. This makes it theoretically possible to disentangle values from response style. Thus, a part of the common factor determined by the response style can effectively be separated from values by means of ipsatization.

Overall, social desirability and response styles are not mutually exclusive interpretations of the common value factor. They can overlap, contributing to a common factor and correlate to values. This implies that the effect of the common factor on responses to value items can be heterogeneous, that is, the common factor might have differing effects on different items and different values. In such a situation, both ipsatization and non-ipsatization can have unknown effects on the value scores.

A rare attempt to study the effect of ipsatization showed that after partialing out the common factor across many measures, “the patterning of all correlations remained the same but the values became slightly weaker” (He and van de Vijver, 2015, p. 133). Based on that, the authors advised against ipsatization (or “score corrections to deal with response style”) because they believed that “a response style is part and parcel of one’s psychological makeup” (p. 134). Yet it is unclear whether the true value scores had higher correlations with the external variables; therefore, a slightly higher correlation by no means implies higher validity.

Borg and Bardi (2016) demonstrated correlations of ipsatized and non-ipsatized basic values with a set of external variables and found slightly lower correlations for ipsatized values. Based on this, they recommended that “routinely discarding the respondents’ mean value ratings as response style artifacts is premature” (p. 101) both in multidimensional scaling to study interrelations between values and for predicting external variables. Again, it is unclear

if the true correlations should have been higher. Interestingly, the non-ipsatized values correlated more strongly with the four mental health items which came from the questions in a battery format (which is prone to response style bias) but did not correlate with responses to the standalone questions. This finding suggests that the higher correlations of non-ipsatized values were caused by the common response style. Hence, although these studies showed the presence of a common value factor, they did not provide evidence that ipsatization brings bias to the value scores. Similarly, the opposite suggestions that ipsatization, in contrast, provides “a clearer picture of the relationships” (Parks-Leduc et al. 2015, p. 21) are equally questionable.

Since it is impossible to make reliable conclusions about the consequences of the ipsatization and non-ipsatization based on empirical data, we conducted a simulation study that illustrates the accuracy of both ipsatized and non-ipsatized scores in different conditions. The simulation study can make such conclusions because the true values are known.

Within-individual centering and its assumptions

Centering is probably the most popular ipsatization method in the value research literature, as it was recommended early on by Schwartz (1992). Although there are other methods of ipsatization (e.g., partialing, residualization, rationing, bifactor models, etc.), here we focus on centering.

Since ipsatization assumes the presence of a common factor, raw non-ipsatized scores are products of the true score and a common factor (which has a zero variance if not present), as well as some random error. Suppose there are n items ($V_{1_1}, V_{1_2}, \dots, V_{k_n}$) that are supposed to measure k values ($F_1 \dots F_k$):

$$F_{k_observed} = F_{k_true} + F_{common} + error_{k_n}$$

where $F_{k_observed}$ is an observed value, F_{k_true} is the true value, F_{common} is a common factor, and $error_{kn}$ are measurement errors of items. Fig. 1 shows the diagram of this general model. It is then theoretically possible to reveal a true factor score (mixed with measurement error) by removing an estimated common factor from each item or several items combined to an index:

$$F_{k_true} = F_{k_observed} - F_{common} = F_{k_true} + error_{k_n}$$

Centering measures a common factor with a mean rating, that is, an arithmetic mean of individual responses on all value items:

$$\text{Mean rating} = (V_{1_1} + V_{1_2} + \dots + V_{k_n})/n$$

Thus, the centered value score involves the subtraction of an overall individual mean of all the items in a measurement set from each value index, which in turn is computed as an individual mean of all value items (mean rating):

$$F_{k_centered} = F_{k_observed} - \text{Mean rating} = F_{k_true} + error_{k_n}$$

It shows that centering involves a number of assumptions. First of all, it assumes that the common factor exists, because if it does not, the centering would remove a meaningful variance and cause bias in the resulting scores (assumption 1).

Second, the true factor F_{k_true} and the common factor F_{common} represented by the mean rating are uncorrelated (assumption 2). If it is not true, the subtraction of the mean rating would remove part of the substantive variance of the true value. If it is not true, the subtraction of the mean rating would remove part of the substantive variance of the true value. If the common factor is believed to be related to values (e.g., social desirability or value-guidedness), this assumption cannot be accepted.

Moreover, the value factors should not all be correlated with each other positively (assumption 3), otherwise the mean rating would mistakenly include the variance of all of the measured values, and the centering would remove this true variance from the value scores. If theory implies strong correlations between values, it will violate this assumption. Similarly, this assumption would be too strong if the set of items is not balanced enough, that is, a set that does not describe opposite constructs or does not contain the same number of direct- and reverse-coded items.⁵ It leads to a non-zero sum of correlations across substantive factors; thus, centering may lead to a confounding between substantive factors and a common one.

These three assumptions apply to many ipsatization methods, whereas centering involves another two. In centering, both mean rating and specific value indices are the unweighted averages, therefore, they have weights (e.g., factor loadings) of 1 on each item (assumption 4). This assumption can be problematic, for example, if the common factor represents social desirability because different value items are likely to vary in their social desirability.

⁵ Balanced set of items can be defined as a set of items whose intercorrelations sum approximately to zero. Ideally, it includes approximately the same number of straight- and reverse-coded items; or, as is the case with Schwartz's PVQ, it includes several subsets of values referring to the opposite motivational content.

Ipsatization in this case may “overcorrect” part of the value scores and “undercorrect” others, introducing bias to all of them. Finally, centering involves the subtraction of an overall mean from the particular value scores, so it follows the additive (rather than, e.g., the multiplicative) model (assumption 5).

Overall, ipsatization can bias the results when some of these assumptions are violated. On the other hand, ipsatization, and centering in particular, is able to correct the scores in the presence of a common factor, and a lack of ipsatization may result in the scores that include a variance of the common factor. In case the latter has a large variance, the non-ipsatized scores can be substantially biased. However, it is not clear how serious the bias would be under different conditions and whether centering or non-centering brings a higher bias. The simulation study presented next illustrates the behavior of centered and non-centered scores under conditions violating these assumptions.

Figure 1. The representation of a general model with various true factors $F_{1_true} - F_{k_true}$ and a single common factor F_{common} . $V_{1,1} - V_{k,n}$ are observed value indicators of corresponding factors; $b_{1,1} - b_{k,n}$ are loadings of the common factor, $a_{1,1} - a_{k,n}$ are loadings of value factors, and “cov” indicates covariances.

Methods

The simulations aimed to illustrate how the violation of the statistical assumptions determine bias in centered and non-centered scores. We generated data that conformed and deviated from assumptions 1, 2, and 3: First, we manipulated the variance of the common factor as well as the variance of substantive factors and item residuals to demonstrate their relative impact on the replication of true scores with centered and non-centered scores. Next, we manipulated correlations between the common factor and substantive factors as well as between the substantive factors to show how a violation of assumptions 2 and 3 can affect the performance of centered and non-centered scores.⁶ Correspondingly, the first set of manipulations can relate to a mere existence of the common factor, manipulations related to assumption 2 can be tied to the social desirability or value-guidedness content of the common factor, and the manipulation related to assumption 3 represents differences in a theoretical structure of value interrelations.

The data was generated in several steps. First, the true factor scores (both substantive and the common factor) were generated as random normal variables with specified variances and covariances. Second, using these true factor scores and random errors (normally distributed with a zero mean and a given variance), the indicator variables were generated. Third, these indicator variables were used to compute composite value indices, centered and non-centered. Finally, we computed a replication rate as a squared Pearson correlation of the true scores with the centered and non-centered value indices (signed R^2). If the average correlation was negative, a negative sign was added. A squared correlation represents a share of the true variance detected by centered and non-centered scores. It can be thought of as the chances of success in recovering the true relations between values and external variables, for example, in regression analysis. The replication rate was reported for the first substantive factor.

For simplicity, we used a four-factor model with five continuous indicators for each factor.⁷ For each combination of manipulations, the base R engine simulated 1,000 datasets with 1,000 observations each. The replication R codes are available as supplementary material.

⁶ Violations of assumption 4 were also explored. Unequal loadings of a common factor negatively affected replication rates of centered scores, and variances of item residuals in general decreased replication rates of both centered and non-centered scores, see details in Appendix 2.

⁷ In summative indices, the number of items per factor and the number of factors can affect replication rates when it increases relative size of residual variances compared to substantive factor variances (e.g., Table 1). Likewise, the summative indices include item measurement errors, which are implicitly assumed to be zero or to

Results

Variance of factors and residuals

In the true model of the first set of simulations, the factors were weakly correlated (± 0.1), did not correlate to a common factor, all the factor loadings were 1, and the standard deviations (SDs) of the common and substantive factors as well as item residuals were manipulated. The results are presented in Table 1.

Expectedly, the non-centered scores showed the best replication rates when the common factor was not present in the data or had a smaller SD than each of the substantive factors (i.e., < 1 ; conditions 1–3, 7–9, 16–17). Performance of the non-centered indices deteriorated proportionally to the amount of the common factor's SD as compared to residual and substantive factor SDs. Non-centered scores approached perfect replication rate when the common factor and residuals were nearly absent (conditions 1–20) and dropped below 10% when the common factor's SD was 3 times higher than the SDs of each of the substantive factors (conditions 6, 12, and 13).

Replication rate of centered scores was at 75% and 62% depending on low or medium residual variance respectively but did not depend on the presence and variance of the common factor, even when it was zero (conditions 1–12). The centered scores' replication rate became higher than the one for non-centered scores when the SD of each substantive factor was larger than 10% of the common factor's SD (given the constant error variance, conditions 4–6, 10–12, and 14–17). Therefore, the relative magnitude of a common and substantive factors' variances was the key to the performance of the centered and non-centered scores. Overall, the non-centered scores outperformed centered scores only when the residual variance was nearly zero and when the common factor's variance was relatively small.

cancel each other. Since these issues are not related to the ipsatization problems, we do not discuss them in the current paper.

Table 1. Replication rates (signed R^2) of centered and non-centered scores of the true values under conditions of varying on the variances of a common factor, substantive factors, and residuals

Condition #	Common factor <i>SD</i>	Factors' <i>SD</i>	Item residuals <i>SD</i>	Score replication (R^2)	
				Non-centered	Centered
1	0	1	0.1	1.00(0.000)	0.75(0.001)
2	0.1	1	0.1	0.99(0.000)	0.75(0.001)
3	0.5	1	0.1	0.80(0.001)	0.75(0.001)
4	1	1	0.1	0.50(0.001)	0.75(0.001)
5	2	1	0.1	0.20(0.000)	0.75(0.001)
6	3	1	0.1	0.10(0.000)	0.75(0.001)
7	0	1	1	0.83(0.008)	0.62(0.012)
8	0.1	1	1	0.83(0.008)	0.62(0.012)
9	0.5	1	1	0.69(0.010)	0.62(0.012)
10	1	1	1	0.46(0.009)	0.62(0.012)
11	2	1	1	0.19(0.005)	0.62(0.012)
12	3	1	1	0.10(0.003)	0.62(0.012)
13	1	0.1	1	0.01(0.002)	0.03(0.011)
14	1	0.5	1	0.17(0.009)	0.40(0.019)
15	1	1	1	0.46(0.009)	0.62(0.012)
16	1	2	1	0.77(0.005)	0.71(0.006)
17	1	3	1	0.88(0.003)	0.73(0.004)

Note. The data were generated using 5 items per factor, 4 factors weakly correlated with each other ($\pm .1$), and did not correlate to a common factor. *SD* is standard deviation.

Correlations between factors

This set of simulations manipulated correlations between substantive factors and the common factor as well as between substantive factors, setting it to values in the range of -0.8 and 0.8 . Correlation matrices were constructed to be positive-definite, so only a correlation with the first factor was consistently manipulated. For the full list of correlations used for the data generation, see Appendix 1. The common factor SD was set to either 0.5 or 1.5 . The results are listed in Table 2.

Conditions 18–24 varied correlations between substantive factors while the correlation with the common factor was set to zero. The correlations between substantive factors did not affect the replication of non-centered scores because these are computed independently of each other. At the same time, as mentioned above, higher SD of the common factor caused the replication rate of non-centered scores to decrease from 69% to 29%. In contrast, the centered scores were robust to the presence of the common factor but were sensitive to intercorrelations between factors: Higher positive correlations led to lower replication rates whereas higher negative intercorrelations led to higher replication rates of centered scores.

Conditions 25–30 added positive correlation of substantive factors with the common factor and varied the intercorrelations between substantive factors. Higher correlations of substantive factors with a common factor increased replication of non-centered scores from 71% to 87% when the common factor SD was 0.5 and from 35% to 83% when the SD was 1.5 . The replication rate of centered scores did not depend on the correlations of the common factor with substantive factors (nor on the common factor's variance), but it was sensitive to intercorrelations between substantive factors, showing 41% replication when the intercorrelation was 0.3 , and about 85% when the intercorrelation of factors was negative (-0.3).

Conditions 31–36 simulated a situation in which a common factor correlated negatively with at least one substantive factor. Replication rates of non-ipsatized scores decreased when the negative correlation was stronger, and when combined with a higher variance of the common factor, the replication rate even became negative (-0.04), representing the inverted distribution of the true score.

Table 2. Replication rate (signed R^2 s) of centered and non-centered scores given different true correlation structures and variance of the common factor

Conditio n #	Correlation between factors	Correlation with common factor	Common factor $SD = .5$		Common factor $SD = 1.5$	
			non-centered	centered	non-centered	centered
18	0	0	0.69(0.010)	0.62(0.012)	0.29(0.007)	0.63(0.012)
19	0.1	0	0.69(0.010)	0.55(0.013)	0.29(0.007)	0.55(0.013)
20	0.5	0	0.69(0.010)	0.27(0.015)	0.29(0.007)	0.27(0.015)
21	0.8	0	0.69(0.010)	0.08(0.011)	0.29(0.007)	0.08(0.011)
22	-0.1	0	0.69(0.010)	0.70(0.010)	0.29(0.007)	0.70(0.010)
23	-0.5*	0	0.69(0.010)	0.84(0.006)	0.29(0.007)	0.84(0.006)
24	-0.8*	0	0.69(0.010)	0.92(0.004)	0.29(0.007)	0.92(0.004)
25	0.3	0.1	0.71(0.009)	0.41(0.014)	0.35(0.007)	0.41(0.014)
26	0.3	0.5	0.80(0.007)	0.41(0.014)	0.62(0.006)	0.41(0.014)
27	0.3	0.8*	0.87(0.005)	0.41(0.015)	0.83(0.004)	0.41(0.014)
28	-0.3	0.1	0.71(0.009)	0.85(0.007)	0.35(0.007)	0.85(0.007)
29	-0.3	0.5*	0.80(0.007)	0.85(0.007)	0.62(0.006)	0.85(0.007)
30	-0.3	0.8*	0.87(0.005)	0.84(0.007)	0.83(0.004)	0.84(0.006)
31	0.3	-0.1	0.67(0.011)	0.41(0.014)	0.23(0.007)	0.41(0.014)
32	0.3*	-0.5*	0.59(0.013)	0.46(0.015)	0.03(0.004)	0.46(0.015)
33	0.3*	-0.8*	0.55(0.015)	0.46(0.015)	-0.04(0.005)	0.46(0.015)
34	-0.3*	-0.1*	0.67(0.011)	0.75(0.008)	0.23(0.007)	0.75(0.008)
35	-0.3*	-0.5*	0.59(0.013)	0.75(0.009)	0.03(0.004)	0.75(0.009)
36	-0.3*	-0.8*	0.55(0.016)	0.75(0.008)	-0.04(0.006)	0.75(0.008)

Note. Four factors, 5 indicators per factor, factor means variance is 1, common factor mean is 0, indicator residuals are all 1. Negative sign of replication rate points to the negative relations with the true factor values.

* The largest correlation, the other correlations were made compatible to keep the covariance matrix positive definite. For the full correlation matrices, see Appendix 1.

Centered scores were again more robust to correlations between substantive factors and a common factor. They depended on the interrelations between substantive factors, showing higher bias when the substantive factors were related positively to each other and demonstrated higher accuracy when substantive factors correlated with each other negatively. Higher common factor variance combined with negative intercorrelations between all factors resulted in replication rates of centered scores of 75% whereas non-centered scores showed replication rates between 23% and negative 4%.

Discussion

The issue of ipsatization remains problematic and ambiguous in value research. It was criticized but the critique was applicable only to a limited range of situations and did not consider the consequences of non-ipsatization. The current paper aimed at clarifying issues arising from both ipsatization and non-ipsatization, reiterated the conceptualizations of the common factor, and illustrated how violation of several assumptions can lead to a bias in either centered or non-centered scores.

Ipsatization removes a common factor, but the nature of this common factor is questionable. Although the common factor was conceptualized in different ways, empirical evidence was provided only for the relations of the common factor with measures of social desirability and response style. There is no evidence of whether the common factor represented a general value guidedness, or an external role guidedness. Overall, the common factor is likely to be a combination of social desirability, response styles, and some general value factor, but its source and contents are largely unknown, and uncovering this is a task for future research.

Interpretations of the common factor allow theorizing of its potential impact. As we have shown, the nature and the effect of the common factor can differ across measurement instruments and samples, and perhaps across question formats, survey modes, and other characteristics of value measurement. The distinction between common factor and values is more problematic with social desirability and a general value guidedness, as its components can be directly treated as conformity, self-enhancement, or self-direction values.

We have identified several assumptions that would make it reasonable to apply within-individual centering, a popular ipsatization technique. The simulations illustrated how centering performs under violation of these assumptions. Expectedly, the presence of the

common factor and its higher variance biased the non-centered scores whereas the centered scores were resistant to it. The centered scores outperformed the non-centered scores in most conditions where the common factor variance was at least as large as the variance of one of the value factors. This seems a plausible scenario in most measurement situations involving batteries of questions.

When the value factors tended to intercorrelate positively, the centered scores were less accurate. When the intercorrelations between the values were negative, the centered scores were closer to the true ones compared to non-centered scores. Therefore, if there are good reasons to believe that the values are all positively intercorrelated, then centering might be a suboptimal option. In contrast, if theoretical relations between values are at least slightly negative, centered scores are more accurate. This is the case in the balanced sets of items.

Relations between values and a common factor are perhaps the most uncertain issue because the nature of the latter is understudied. More positive and higher correlations of the values with the common factor increased the accuracy of the non-centered scores; while the replication rate of the centered scores was not affected. Since it was shown that centered scores are insensitive to correlations of values with the common factor, it might be safer to apply centering, even when the common factor substantially overlaps with the values (e.g., if it is social desirability). On the other hand, if the common factor is highly correlated to values, non-centered scores might be similarly accurate. In sum, centering reveals more accurate value scores whenever the common factor is in the data, with exception of the situation where there are high, positive intercorrelations between values.

Implications for multiple group analysis

The simulations presented in the current study addressed only the replication rates of correlations (or regression slopes), ignoring the intercepts and means. These do matter, however, in multiple group analysis. The implications of ipsatization for the multiple-group analysis can be derived from the presented results. The multiple-group case can be thought of as a general case, with a special part of the factors' variances contributed by between-group differences in latent means. Given that common factor variance causes bias in non-centered scores, the higher between-group variance of the common factor would cause higher bias in non-centered group means, whereas means based on centered scores would be more reliable.

When the factor means are positively intercorrelated, the group means of factors measured with centered scores might be biased. Negative correlations between means of value factors would lead to a higher validity of the means based on centered scores.

Since the between-group variance can be independent from the one observed at the individual level, dealing with the multiple-group case should be accompanied by consideration of all the problems mentioned for the general case, but at the between-group level. Therefore, the assumptions that are reasonable at the individual level should not be automatically transferred to the group level, because it is likely to have a different structure.

Ipsatization and interrelations between values

As shown above, the ipsatization (within-individual centering) was able to improve the replication rate in diverse conditions involving a common factor. It is clear that if the value score is replicated well, its use in the regression, analyses of variance, and other statistical procedures is inherently more desirable. The problem is that ipsatized scores are necessarily interdependent (Cattell, 1944). Thus, Fischer (2004) advised “to refrain from using multivariate techniques with ipsative scores” (p. 276). Indeed, ipsatized measures are perfectly collinear, so when all measured values are used as predictors in a regression analysis, they do not require centering, as their effects are adjusted for each other in the regression itself. Moreover, the centered measures can be used as well, although it would require dropping at least one centered value from the analysis.

A special case we have not discussed is the application of ipsatization before studying the interrelations between values. Ipsatization forces at least one of the intercorrelations between values to be downward biased, that is, to be falsely (too) negative or less positive (Hicks, 1970, Fischer, 2004, Bartram, 1996). A higher number of indicators per factor, more factors, and their lower interdependence were shown to reduce or even eliminate these problems of ipsatized measures (e.g., Baron, 1996). When the common factor is not in the data, ipsatization may lead to a false detection of negative relations between values. At the same time, a failure to ipsatize in the presence of a strong common factor can affect correlations in the opposite direction, that is, this can reveal more positive correlations than there truly are. For instance, correlations between values that are theoretically opposed (e.g., conservation and openness values, see Schwartz, 1992) were positive when they were estimated with non-

centered scores (Rudnev et al., 2018, supplementary materials). Using simulated data, Groenvynck et al. (unpublished manuscript) demonstrated that the higher variance of the common factor led to biased correlations between non-ipsatized indices, but was correctly estimated by ipsatized ones, and especially so by a bifactor model (which can be considered an ipsatization method).

A related problem occurs with internal consistency reliability estimates, such as Cronbach's alpha. The presence of the common factor falsely boosts the reliability estimates based on non-ipsatized items, because it increases item consistency, especially if a common factor is strong and is not related to values. It is likely to be a reason for the previously reported higher reliability of non-ipsatized scores (Baron, 1996, Bartram, 1996, Saville and Willson, 1991). Mirroring this logic, the use of ipsatized scores in the absence of the common factor may lead to underestimation of reliability, especially when the substantive factors are weakly or negatively related, which is often the case with values.

Finally, the test-retest reliability of ipsatized scores is lower, because change in a single item affects all the ipsatized scores, while non-ipsatized scores are independent of each other and change in one item has impact only on the reliability of the specific value score. The ambiguity of the reliability estimates makes it problematic to use with the preference scores or variables that have been affected by a common non-substantive factor.

Many multivariate methods can handle non-ipsatized scores by removing the common factor. Within-individual centering did not show much impact on the results of multidimensional scaling (Borg & Bardi, 2016). The unfolding method revealed plausible structure after adding an additional dimension for representing a common factor (Borg & Bardi, 2016). Likewise, in exploratory factor analysis of non-ipsatized scores, the common factor is expectedly the first factor before rotation (see, e.g., Schwartz, 2003, Borg and Bardi, 2016), which is effectively redistributed (i.e., removed) after applying most automated rotation techniques such as "varimax" rotation. This makes ipsatization unnecessary (e.g., Closs, 1996). A bifactor model, which is a type of confirmatory factor analysis, can explicitly model a common factor, adjusting the substantive value factors. The inclusion of the common (method) factor to the model of Schwartz values demonstrated increased measurement invariance across countries (Lilleoja, Dobewall, Aavik, Strack, & Verkasalo, 2016).

Even if the data are already ipsatized, for instance, they were collected with ranking and other forced-choice measures, it still can be analyzed with principal component analysis (a set of

items should be well-balanced, see ten Berge, 1999) and several other methods specifically developed for ipsatized measures (e.g., Chan and Bentler, 1993, Cheung, 2006). In other words, although ipsatization may cause some difficulties in studies of value interrelations, many multivariate methods can deal with a common factor and work well with ipsatized scores.

Implications for the research practice

As we have shown, ipsatization is not necessarily problematic for studying values' relations to external variables (e.g., behavior). Moreover, even interrelations between values can be recovered with ipsatized scores if the proper methods of analysis are applied. Finally, a special problem of non-ipsatized value scores is their incompatibility with the definition of values as essentially ordered instances of preference. To consistently use non-ipsatized value scores, either the value definition should be modified or evidence should be provided that the raw ratings can represent preferences.

Therefore, a general recommendation of whether value measures should be ipsatized cannot be offered. Instead of either ignoring or automatically applying ipsatization, researchers are encouraged to theorize and reason the chosen way of dealing with value scores. The choice can be reasoned in every case based on the information at hand and the explication of situation-specific theory of a common factor. Note that non-ipsatization should be reasoned as well, because, as was shown above, it might lead to a severe bias in scores. Likewise, the (sometimes) recommended practice of reporting results based on both ipsatized and non-ipsatized value scores can add to the confusion. The fact that results based on ipsatized and non-ipsatized scores are different is not sufficient to conclude that one of them is more accurate than the other; in cases where these results are similar, both can be biased (e.g., when the measurement error is very high).

Overall, in order to decide if ipsatization should be applied to measures of basic values, one has to consider at least three questions: (1) Is there a common factor behind the measures of the basic values? (2) Does this common factor relate to basic values? (3) Do basic values intercorrelate in a balanced way? For example, low survey quality control is a reason to assume the presence of a strong common factor reflecting response tendencies, whereas assessing values during a job interview is likely to enhance social desirability. If the former

assumption is combined with a strong belief that values are measured by a balanced set of items, ipsatization rather than non-ipsatization seems a reasonable choice. In addition, if there are reasons to expect that the common factor has similar effects on all the items, within-individual centering would be a reasonable choice of ipsatization method.

Does the Schwartz value theory satisfy these conditions? First, most measurement instruments are in the form of a battery with a common question and the same response options for each item (see Roccas et al., 2017). It leads to a response style effect, which in turn increases the common factor's variance. Second, depending on the measurement instrument, this common factor might be weakly or strongly related to values. Third, the theory postulates value conflicts as well as value congruencies, which implies that it is not theoretically feasible to assume that all the values are positively related. Instead, there is a circular structure that crudely resembles a balanced set. Finally, Schwartz's definition of values requires indicators of preference, which can be obtained by ipsatization of value ratings. Therefore, in general, ipsatization is compatible with the Schwartz theory and measurement instruments.

The current paper is limited to the classical test theory because it revised existing practices in values research. Application of latent variable models, in particular, bifactor models, to represent both values and a common factor would resolve many of the mentioned issues, but it could involve other problems, such as weak model identification (e.g., Mansolf & Reise, 2017). Future research should discuss the other ipsatization methods as well.

Conclusion

Up to this moment, evidence is very scarce on how non-ipsatized value scores perform and whether ipsatized scores are actually biased. A large part of the substantive research focusing on the relations between values (measured with Schwartz's and other instruments) and various concepts (behaviors, attitudes, norms, etc.) applied the ipsatized value scores, and virtually no study, to the best of our knowledge, has demonstrated that ipsatization distorted the true relations of values with external variables. In other words, there is evidence of the validity of ipsatized scores, but the evidence of (either superior or inferior) validity of non-ipsatized value scores is very limited.

Our findings indicate that non-ipsatization of values is equally debatable as ipsatization. Under different conditions related mostly to a presence of a common factor and value

interrelations, both ipsatization and non-ipsatization can lead to bias or reveal true scores. The sources and the consequences of both are largely unexplored. Future research should further investigate the meaning of the common value factor in different value instruments and demonstrate if and to what degree it represents response styles, social desirability, a general motivation, value-guidedness, or some other construct. Further simulation studies should describe different methods of ipsatization, such as partialing, residualization, and bifactor models, as their potential to deal with statistical assumptions goes far beyond simple within-individual centering.

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APPENDICES

Appendix 1

True correlations used in simulation study presented in Table 2.

Condition #	Correlations between substantive factors $f1$ - $f4$ and common factor fc									
	$f2,f1$	$f3,f1$	$f3,f2$	$f4,f1$	$f4,f2$	$f4,f4$	$fc,$ $f1$	$fc,$ $f2$	$fc,$ $f3$	$fc,f4$
18	0	0	0	0	0	0	0	0	0	0
19	.1	.1	.1	.1	.1	.1	0	0	0	0
20	.5	.5	.5	.5	.5	.5	0	0	0	0
21	.8	.8	.8	.8	.8	.8	0	0	0	0
22	-.1	-.1	-.1	-.1	-.1	-.1	0	0	0	0
23	-.5	-.5	.1	-.5	.1	.1	0	0	0	0
24	-.8	-.8	.5	-.8	.5	.5	0	0	0	0
25	.3	.3	.3	.3	.3	.3	.1	.1	.1	.1
26	.3	.3	.3	.3	.3	.3	.5	.5	.5	.5
27	.3	.3	.3	.3	.3	.3	.8	.4	.4	.4
28	-.3	-.3	-.3	-.3	-.3	-.3	.1	.1	.1	.1
29	-.3	-.3	-.3	-.3	-.3	-.3	.5	-.1	-.1	-.1
30	-.3	-.3	-.3	-.3	-.3	-.3	.8	-.3	-.3	-.3
31	.3	.3	.3	.3	.3	.3	-.1	0	0	0
32	.3	.3	.1	.3	.1	.1	-.5	0	0	0
33	.3	.3	.1	.3	.1	.1	-.8	-.3	-.3	-.3
34	-.3	-.3	.1	-.3	.1	.1	-.1	0	0	0
35	-.3	-.3	.1	-.3	.1	.1	-.5	0	0	0
36	-.3	-.3	.1	-.3	.1	.1	-.8	.3	.3	.3

Appendix 2

Effects of unequal factor loadings and item residuals

Table A1 lists the replication rates of the centered and non-centered scores under conditions manipulating between-item differences in factor loadings. Non-ipsatized scores were only slightly affected by differences in factor loadings because they estimated each value score independently. Differences in substantive factor loadings slightly decreased replication rates of centered scores but differences in the standard errors (reliability) of estimates increased substantially. Differences in factor loadings of the common factor deteriorated replication rates of centered scores, especially when the common factor's variance was large. In addition, higher inequality of factor loadings made standard errors of replication rate increase pointing to its lower reliability.

Table A1. Replication rate (R2 of the true score) of the ipsatized and non-ipsatized scores given different true between-item differences in factor loadings

Common factor standard deviation	Substantive factor loadings' variance	Common factor loadings' variance	Non-centered	Centered
0.1	0	0	0.99(0.000)	0.75(0.001)
0.1	.5	0	0.99(0.011)	0.72(0.116)
0.1	1	0	0.95(0.203)	0.65(0.235)
0.1	0	.5	0.99(0.004)	0.75(0.001)
0.1	0	1	0.99(0.009)	0.75(0.003)
1	0	0	0.45(0.009)	0.62(0.012)
1	.5	0	0.45(0.115)	0.60(0.124)
1	1	0	0.43(0.202)	0.54(0.236)
1	0	.5	0.46(0.090)	0.60(0.031)
1	0	1	0.47(0.165)	0.55(0.083)
3	0	0	0.10(0.003)	0.62(0.012)
3	.5	0	0.10(0.039)	0.59(0.122)
3	1	0	0.11(0.074)	0.56(0.226)
3	0	.5	0.11(0.050)	0.49(0.120)
3	0	1	0.16(0.166)	0.36(0.182)

Another set of conditions manipulated the differences across item residuals within every substantive factor while an average residual variance was 1 within every factor. All the factors were uncorrelated. The standard deviation of residuals within every factor was set to 0 (same residuals for every item), 0.5, 1, or 1.5 (very large differences). Replication rate for these conditions are listed in Table A2. The higher differences of residuals decreased replication rate of both centered and non-centered scores in all the cases because it violated the assumption of summative indices stating that all the residuals are equal. The centered scores were slightly more affected by unequal residuals because every centered score reflects assumptions taken for every item, whereas non-centered scores are independent of each other.

Table A2. Replication rate (R^2 of the true score) of the centered and non-centered scores given unequal item residuals (average item residual is 1)

Common factor standard deviation	Standard deviation of item residuals across items	Non-centered	Centered
0.1	0	0.83(0.008)	0.62(0.012)
0.1	.5	0.79(0.009)	0.59(0.013)
0.1	1	0.72(0.012)	0.53(0.016)
0.1	1.5	0.63(0.015)	0.46(0.018)
0.5	0	0.69(0.010)	0.62(0.012)
0.5	.5	0.66(0.011)	0.59(0.013)
0.5	1	0.61(0.013)	0.53(0.015)
0.5	1.5	0.55(0.016)	0.46(0.018)
1	0	0.46(0.009)	0.62(0.012)
1	.5	0.44(0.010)	0.59(0.014)
1	1	0.42(0.012)	0.53(0.015)
1	1.5	0.39(0.015)	0.46(0.018)

Supplementary Material (R code)

```
library("reshape2")
library("magrittr")
library("dplyr")
library("ggplot2")
library("matrixcalc")
library("lavaan")
library("MASS")

# Generate data function ####

generate_data <-
  function(n=1000,
    factor.means = scale(c(1,2,3,4)),
    factor.sds = c(1,1,1,1),
    factor.cors = 0, # or c(2.1,
      #      3,1, 3.2,
      #      4.1, 4.2, 4.3,
      #      5.1, 5.2, 5.3, 5.4) lower triangle, last line
    is a method factor

    method.factor.mean = 0,
    method.factor.sd = 0,

    items.per.factor = c(4,4,4,4), # For each factor
    item.residuals = c(1,1,1,1), # Variance of residuals across factors
    return.list=F,

    f.loadings.var = 0, # Loadings are drawn from normal distr with a mean
1 and this variance.
    m.loadings.var = 0 # Loadings are drawn from normal distr with a mean
1 and this variance.

  ) {

    n.factors <- length(factor.means)
```

```

if(length(factor.cors) == 1) {

  # generate n independent variables (factors) with mean and sd
  factors <- lapply(1:n.factors, function(x) rnorm(n, mean=factor.means[x], sd
= factor.sds[x]))
  names(factors) <- paste0("f", 1:n.factors)

  # generate independent common/method factor
  method.factor <- rnorm(n, method.factor.mean, method.factor.sd)

  # merge variables in a matrix
  factors <- cbind(Reduce( "cbind", factors), method.factor)

} else { #if correlations between factors shouldn't be zero

  # create full correlation matrix from a vector
  true.cor.matrix <- lavaan::lav_matrix_lower2full(factor.cors, diagonal = F)
  diag(true.cor.matrix) <- rep(1, n.factors+1)
  true.cov.matrix <- true.cor.matrix * tcrossprod(c(factor.sds,
method.factor.sd))

  # check if true correlation matrix is NPD
  if(!matrixcalc::is.positive.definite(true.cov.matrix) #&
    # !sum(factor.cors==0)==length(factor.cors)
    ) {
    message("Cov matrix is NPD, check ", paste(factor.cors, collapse=";"))
    )
    print("True cov matrix")
    print(true.cov.matrix, digits=2)
    # print(lavaan::lav_matrix_lower2full(factor.cors, diagonal = F))

  }

  # simulate factor variables that correlate with `true.cov.matrix`
  factors <- MASS::mvrnorm(n=n, mu=c(factor.means,method.factor.mean),
                           Sigma=true.cov.matrix, empirical=TRUE)

  colnames(factors) <- c(paste0("f", 1:n.factors), "method.factor")

}

```

```

# create items based on simulated `factors` and factor-specific
`item.residuals`
items <- lapply(1:n.factors, function(f.id) {

  sapply(1:items.per.factor[f.id], function(i) {

    rnorm(1, 1, f.loadings.var) * factors[,f.id] + #loadings and
factor
    rnorm(1, 1, m.loadings.var) * factors["method.factor"] +
    rnorm(n, 0, item.residuals[i])
    #rnorm(n, 0, item.residuals[f.id])

  })
})

# prepare resulting output
if(return.list) {

  out <- list(factors, items)

} else {

  out <- cbind(factors, Reduce( "cbind", items))

  dimnames(out)[[2]] <- c(
    paste0("f", 1:n.factors),
    "method.factor",
    as.vector(sapply(1:length(items.per.factor), function(f.id) {
      sapply(1:items.per.factor[f.id], function(item.id) paste0("f", f.id,
".item", item.id))
    })))
  )

  out <- as.data.frame(out)
  attr(out, "n.factors") <- n.factors

```

```

    }

    return(out)

}

# Analyze generated data #####
analyze_generated <- function(gen.dat=generate_data(), ipsatize=T) {

  a <- gen.dat

  # compute individual mean if ipsatization is requested
  if(ipsatize) {
    a$mrat <- rowMeans(a[,names(a)[grep("item", names(a))]])
  } else {
    a$mrat <- rep(0, nrow(a))
  }

  # extract the factor id from the names of items
  varnames.for.iterations <- cbind(Reduce("rbind", strsplit(names(a)[grep("item",
names(a))], "[.]")),
                                   names(a)[grep("item", names(a))])

  # compute factor means (indices, averaged items)
  factors.computed <- sapply(unique(varnames.for.iterations[,1]), function(x) {
    nonips =
rowMeans(as.matrix(a[,varnames.for.iterations[varnames.for.iterations[,1]==x,
3]]))
    nonips - a$mrat
  })

  list(
    corrs = sapply(paste0("f", 1:attr(a, "n.factors")), function(i) cor(a[,i],
factors.computed[,i]))
  )
}

```

```

### Simulation: generate and analyze function ###

sim <- function(
  n.fac = 4,
  factor.means.sd = 1, # mean of each factor
  factor.sds.sd = 1,   # sd of each factor
  items.per.fact = 3,
  item.residuals.sd = 1,
  factor.cors = 0,      # see above (lower triangle )
  method.factor.mean = 0,
  method.factor.sd = 0,
  f.loadings.var = 0,   # factor loadings within factor variance
  m.loadings.var = 0,   # factor loadings within factor variance
  n=1000,
  datasets=1000,
  report = "corrs"
) {

  cat("Generating and analyzing", datasets, "datasets \n")
  pb <- txtProgressBar(style=3)

  a<- sapply(1:datasets, function(x) {

    # GENERATE
    b<-generate_data(factor.means = scale(c(1:n.fac))*factor.means.sd,
                     factor.sds = rep(factor.sds.sd, n.fac),

                     items.per.factor = rep(items.per.fact, n.fac),
                     item.residuals = if(length(item.residuals.sd) == 1)
                      rep(item.residuals.sd, items.per.fact) else
item.residuals.sd,
                     factor.cors = factor.cors,
                     method.factor.mean = method.factor.mean,
                     method.factor.sd = method.factor.sd,

```

```

        f.loadings.var = f.loadings.var,
        m.loadings.var = m.loadings.var,
        n=n)
setTxtProgressBar(pb, x/datasets)

# ANALYZE with ipsatized and non-ipsatized approach and report
if(report=="corrs") {

  # average correlations for the first factor
  c(mean(analyze_generated(b, ipsatize=T)[["corrs"]][1] ),
    mean(analyze_generated(b, ipsatize=F)[["corrs"]][1] )
  )

} else if(report == "r2") {
  # average R2s for the first factor
  cors=c(mean(analyze_generated(b, ipsatize=T)[["corrs"]][1] ),
    mean(analyze_generated(b, ipsatize=F)[["corrs"]][1] )
  )
  rsq = cors^2
  rsq[cors<0] = -rsq[cors<0]
  rsq
}

})
close(pb)
# format results
out <- data.frame(
  ipsatized= paste0(format(round(mean(a[1,], na.rm=T ), 2), nsmall=2), "(" ,
format(round(sd(a[1,], na.rm=T ), 3), nsmall=3), ")"),
  non.ipsatized=paste0(format(round(mean(a[2,]), 2), nsmall=2), "(" ,
format(round(sd(a[2,]), 3), nsmall=3), ")"),
  stringsAsFactors = F
)

return(out)

```

```
}
```

```
# Conditions ####
```

```
## . Correlation manipulated ####
```

```
cors <- list(
```

```
  zero = c(0,  
            0, 0,  
            0, 0, 0,  
            0, 0, 0, 0),
```

```
  plus1 = c(.1,  
             .1,.1,  
             .1,.1,.1,  
             0, 0, 0, 0),
```

```
  plus2 = c(.2,  
             .2,.2,  
             .2,.2,.2,  
             0, 0, 0, 0),
```

```
  plus3 = c(.3,  
             .3, .3,  
             .3, .3, .3,  
             0, 0, 0, 0),
```

```
  plus4 = c(.4,  
             .4,.4,  
             .4,.4,.4,  
             0, 0, 0, 0),
```

```
  plus5 = c(.5,  
             .5,.5,  
             .5,.5,.5,  
             0, 0, 0, 0),
```

```
  plus6 = c(.6,  
             .6,.6,  
             .6,.6,.6,
```

```

0, 0, 0, 0),

plus7 = c(.7,
          .7,.7,
          .7,.7,.7,
          0, 0, 0, 0),

plus8 = c(.8,
          .8,.8,
          .8,.8,.8,
          0, 0, 0, 0),

minus1 = c(-.1,
           -.1,  -.1,
           -.1,  -.1, -.1,
           0,    0, 0, 0),

minus2 = c(-.2,
           -.2,  -.2,
           -.2,  -.2, -.2,
           0,    0, 0, 0),

minus3 = c(-.3,
           -.3,  -.3,
           -.3,  -.3, -.3,
           0,    0, 0, 0),

minus4mix = c(-.4,
              -.4,  .1,
              -.4,  .1, .1,
              0,    0, 0, 0),

minus5mix = c(-.5,
              -.5,  .1,
              -.5,  .1, .1,
              0,    0, 0, 0),
minus6mix = c(-.6,
              -.6,  .1,
              -.6,  .1, .1,
              0,    0, 0, 0),

```



```

minus7mix = c(-.7,
              -.7,   .3,
              -.7,   .3, .3,
              0,    0, 0, 0),

minus8mix = c(-.8,
              -.8,   .5,
              -.8,   .5, .5,
              0,    0, 0, 0),

all13.method.1 = c( .3,
                   .3,   .3,
                   .3,   .3, .3,
                   .1,   .1, .1, .1),

all13.method.2 = c( .3,
                   .3,   .3,
                   .3,   .3, .3,
                   .2,   .2, .2, .2),

all13.method.3 = c( .3,
                   .3,   .3,
                   .3,   .3, .3,
                   .3,   .3, .3, .3),

all13.method.4 = c( .3,
                   .3,   .3,
                   .3,   .3, .3,
                   .4,   .4, .4, .4),

all13.method.5 = c( .3,
                   .3,   .3,
                   .3,   .3, .3,
                   .5,   .5, .5, .5),

all13.method.6 = c( .3,
                   .3,   .3,
                   .3,   .3, .3,
                   .6,   .6, .6, .6),

```

```

all13.method.7 = c( .3,
                    .3,   .3,
                    .3,   .3, .3,
                    .7,   .4, .4, .4),

all13.method.8 = c( .3,
                    .3,   .3,
                    .3,   .3, .3,
                    .8,   .4, .4, .4),

allminus3.method1 = c(-.3,
                      -.3,  -.3,
                      -.3,  -.3, -.3,
                      .1,   .1, .1, .1),

allminus3.method2 = c(-.3,
                      -.3,  -.3,
                      -.3,  -.3, -.3,
                      .2,   .1, .1, .1),

allminus3.method3 = c(-.3,
                      -.3,  -.3,
                      -.3,  -.3, -.3,
                      .3,   .1, .1, .1),

allminus3.method4 = c(-.3,
                      -.3,  -.3,
                      -.3,  -.3, -.3,
                      .4,   -.1, -.1, -.1),

allminus3.method5 = c(-.3,
                      -.3,  -.3,
                      -.3,  -.3, -.3,
                      .5,   -.1, -.1, -.1),

allminus3.method6 = c(-.3,
                      -.3,  -.3,
                      -.3,  -.3, -.3,
                      .6,   -.3, -.3, -.3),

```

```

allminus3.method7 = c(-.3,
                      -.3,  -.3,
                      -.3,  -.3, -.3,
                      .7,   -.3, -.3, -.3),

allminus3.method8 = c(-.3,
                      -.3,  -.3,
                      -.3,  -.3, -.3,
                      .8,   -.3, -.3, -.3),

all3mix.methodminus1 = c(.3,
                          .3,  .3,
                          .3,  .3, .3,
                          -.1, .0, .0, .0),

all3mix.methodminus5 = c(.3,
                          .3,  .1,
                          .3,  .1, .1,
                          -.5, .0, .0, .0),

all3mix.methodminus8 = c(.3,
                          .3,  .1,
                          .3,  .1, .1,
                          -.8, -.3, -.3, -.3),

all5mix.methodminus1 = c(.5,
                          .5,  .1,
                          .5,  .1, .1,
                          -.1, .0, .0, .0),

all5mix.methodminus2 = c(.5,
                          .5,  .1,
                          .5,  .1, .1,
                          -.2, .0, .0, .0),

all5mix.methodminus3 = c(.5,
                          .5,  .1,
                          .5,  .1, .1,
                          -.3, .0, .0, .0),

```

```

all5mix.methodminus4 = c(.5,
                        .5, .1,
                        .5, .1, .1,
                        -.4, .0, .0, .0),

all5mix.methodminus5 = c(.5,
                        .5, .1,
                        .5, .1, .1,
                        -.5, .0, .0, .0),
all5mix.methodminus6 = c(.5,
                        .5, .1,
                        .5, .1, .1,
                        -.6, .0, .0, .0),

all5mix.methodminus7 = c(.5,
                        .5, .1,
                        .5, .1, .1,
                        -.7, -.1, -.1, -.1),

all5mix.methodminus8 = c(.5,
                        .5, .1,
                        .5, .1, .1,
                        -.8, -.3, -.3, -.3),

minus3mix.methodminus1 = c(-.3,
                        -.3, .1,
                        -.3, .1, .1,
                        -.1, .0, .0, .0),
minus3mix.methodminus5 = c(-.3,
                        -.3, .1,
                        -.3, .1, .1,
                        -.5, .0, .0, .0),

minus3mix.methodminus8 = c(-.3,
                        -.3, .1,
                        -.3, .1, .1,
                        -.8, .3, .3, .3),

minus5mix.methodminus1 = c(-.5,

```

```

        -.5,   .1,
        -.5,   .1, .1,
        -.1,   .0, .0, .0),

minus5mix.methodminus2 = c(-.5,
        -.5,   .1,
        -.5,   .1, .1,
        -.2,   .0, .0, .0),

minus5mix.methodminus3 = c(-.5,
        -.5,   .1,
        -.5,   .1, .1,
        -.3,   .0, .0, .0),

minus5mix.methodminus4 = c(-.5,
        -.5,   .1,
        -.5,   .1, .1,
        -.4,   .0, .0, .0),

minus5mix.methodminus5 = c(-.5,
        -.5,   .1,
        -.5,   .1, .1,
        -.5,   .1, .1, .1),
minus5mix.methodminus6 = c(-.5,
        -.5,   .1,
        -.5,   .1, .1,
        -.6,   .1, .1, .1),
minus5mix.methodminus7 = c(-.5,
        -.5,   .1,
        -.5,   .1, .1,
        -.7,   .1, .1, .1),
minus5mix.methodminus8 = c(-.5,
        -.5,   .1,
        -.5,   .1, .1,
        -.8,   .3, .3, .3)

)

# "REALISTIC" cors
cor1 <- c(-.1,

```

```

        .1,    -.1,
        .1,    .1, -.1,
        .0,    .0, 0, .0) # lower triangle, last line is a method factor

# . Other conditions ####
conditions <- matrix(
  dimnames = list(NULL,
    c("items.per.fact",
      "method.factor.sd",
      "method.factor.mean",
      "factor.sds.sd",
      "factor.means.sd",
      "item.residuals.sd",
      "factor.cors")
  ),
  data = list(

    # Method factor variance
      5,  0,   0, 1, 1, 1, cor1, #1
      5,  .1,   0, 1, 1, 1, cor1,
      5,  .5,   0, 1, 1, 1, cor1,
      5,  1,    0, 1, 1, 1, cor1,
      5,  2,    0, 1, 1, 1, cor1,
      5,  3,    0, 1, 1, 1, cor1,

    # Method factor variance X Item residuals (sd)
      5,  0,   0, 1, 1, .1, cor1, #7
      5,  .1,   0, 1, 1, .1, cor1,
      5,  .5,   0, 1, 1, .1, cor1,
      5,  1,    0, 1, 1, .1, cor1,
      5,  2,    0, 1, 1, .1, cor1,
      5,  3,    0, 1, 1, .1, cor1, #12

    # Factor variance (sd)
      5,  1,   0, .1, 1, 1, cor1,  #13
      5,  1,   0, .5, 1, 1, cor1,
      5,  1,   0, 1, 1, 1, cor1,
      5,  1,   0, 2, 1, 1, cor1,
      5,  1,   0, 3, 1, 1, cor1

```

```

    ), ncol=7, byrow=T )

# RUN SIMULATIONS #####

# TAB1 - Run for variances #####
set.seed(1234)
a2<- apply(conditions[1:17,], 1, function(x)
  do.call(sim, append(x, list(n.fac=4, report="r2") )))

cbind(conditions[1:17,
      c("#items.per.fact",
        "method.factor.sd",
        "#method.factor.mean",
        "factor.sds.sd",
        "item.residuals.sd"
      )],
      non.ips=Reduce("rbind", a2)[,2],
      centered=Reduce("rbind", a2)[,1]
) %>%
  print(rownames = F, digits=3, quote=F)

# TAB2 - Run for correlations #####

# Different correlational structure
conditions.cor.structures.method.5 <- t(sapply(1:length(cors), function(x)
  list(5, .5, 0, 1, 1, 1, cors[[x]])))
dimnames(conditions.cor.structures.method.5)<-list(names(cors),
dimnames(conditions)[[2]])

conditions.cor.structures.method1.5 <- t(sapply(1:length(cors), function(x)
  list(5, 1.5, 0, 1, 1, 1, cors[[x]])))

```

```

dimnames(conditions.cor.structures.method1.5)<-list(names(cors),
dimnames(conditions)[[2]])

subs.cors = c('zero',
  'plus1', 'plus5', 'plus8',
  'minus1', 'minus5mix', 'minus8mix',
  'all3.method.1', 'all3.method.5', 'all3.method.8', 'allminus3.method1',
  'allminus3.method5', 'allminus3.method8', 'all3mix.methodminus1',
  'all3mix.methodminus5', 'all3mix.methodminus8', 'minus3mix.methodminus1',
  'minus3mix.methodminus5', 'minus3mix.methodminus8')

set.seed(1234)
a3.m.5<- apply(conditions.cor.structures.method.5[subs.cors,], 1,
  function(x) do.call(sim, append(x, list(n.fac=4, report="r2")) ))
set.seed(1234)
a3.m1.5<- apply(conditions.cor.structures.method1.5[subs.cors,], 1,
  function(x) do.call(sim, append(x, list(n.fac=4, report="r2")) ))

cbind(matrix(as.character(t(sapply(cors[subs.cors], function(x) c(x[1], x[7])))),
ncol=2,
  dimnames=list(names(cors[subs.cors]),
    c("Correlation between factors", "Correlation with
common factor"))),
  M1.non.ips =Reduce("rbind", a3.m.5)[,2],
  M1.centered=Reduce("rbind", a3.m.5)[,1],
  M1.non.ips =Reduce("rbind", a3.m1.5)[,2],
  M1.centered=Reduce("rbind", a3.m1.5)[,1]
) %>% print(quote=F)

# Appendix 1 - correlations used in Table 2 #####
Reduce("rbind", cors[subs.cors]) %>% matrix(ncol=10,
dimnames=list(names(cors[subs.cors]), c("f2,f1", "f3,f1", "f3,f2", "f4, f1",
"f4,f2", "f4, f4", "fc, f1", "fc, f2", "fc, f3", "fc,f4"))) %>% print(digits=1)

# Table A1 - Varying factor loadings #####

```



```

conditions.varying.loadings = data.frame(
  "f.loadings.var" = c(0, 0.5, 1, 0, 0, .5, 1),
  "m.loadings.var" = c(0, 0, 0, 0.5, 1, .5, 1)
)

# Combine conditions of the mfactor var and varying loadings
comb.cond <- Reduce("rbind", lapply(1:nrow(conditions.varying.loadings),
  function(x) cbind(conditions[c(2:4),],
    conditions.varying.loadings[x,]))))

set.seed(1234)
a<- apply(comb.cond, 1,
  function(x)
    do.call(sim, append(x, list(n.fac=4, report="r2") ))
)

a1 <- Reduce("rbind", a)
a2 <- cbind(comb.cond[, c("method.factor.sd",
  "f.loadings.var",
  "m.loadings.var")],
  a1)
print(a2[order(unlist(a2[,1])),], quote = F)

# Table A2 - Varying item residuals ####

conditions.varying.residuals = cbind(
  "f.loadings.var" = c(0, 0, 0, 0),
  "m.loadings.var" = c(0, 0, 0, 0),

  "item.residuals.sd" = list(c(1, 1, 1, 1, 1 ), #sd=0, mean=1
    c(0.5, 0.6, 1, 1.5, 1.6), #sd=0.5, mean=1
    c(0.4, 0.5, 0.2, 2.5, 1.7), #sd=1.0, mean = 1
    c(3.5, 0.1, 0.1, 0.1, 1.5) #sd=1.5 rgamma (n = 4,
shape = 1, scale = ?)
)
)

```

```

# Combine conditions of the mfactor var and varying loadings
comb.cond2 <- Reduce("rbind",
                    lapply(1:nrow(conditions.varying.residuals),
                           function(x) cbind(conditions[c(2:4),-
which(colnames(conditions)=="item.residuals.sd")],

f.loadings.var=conditions.varying.residuals[x,1],

m.loadings.var=conditions.varying.residuals[x,2],

item.residuals.sd=conditions.varying.residuals[x,3]))))

set.seed(1234)
a3<- apply(comb.cond2, 1,
           function(x)
             do.call(sim, append(x, list(n.fac=4, report="r2") ))
)

a1 <- Reduce("rbind", a3)
a2 <- cbind(comb.cond2[, c("method.factor.sd",
                           "f.loadings.var"
                           #"m.loadings.var",
                           #"item.residuals.sd"
                           )
            ],
            item.residuals.mean=sapply(comb.cond2[, "item.residuals.sd"], mean),
            item.residuals.var=sapply(comb.cond2[, "item.residuals.sd"], sd),
            a1)
print(a2[order(unlist(a2[,1])),], quote = F, digits=2)

```