Three Approaches to Estimate Latent Interaction Effects: Intention and Perceived Behavioral Control in the Theory of Planned Behavior

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Abstract

Interaction effects between explanatory constructs are an important part of many social theories. Analyses of interaction effects between variables using regression techniques have low power because they do not control for measurement errors. Therefore, latent interaction modeling using structural equation modeling (SEM) has been proposed as a better alternative to test for interaction effects. In contrast to traditional and complicated ‘constrained’ SEM approaches, two recent developments, the unconstrained approach and the residual centering approach, are especially attractive for applied researchers as they are much easier to implement. However, applied researchers still seem to be unsure about how to apply these approaches. In this study, we illustrate the use of the unconstrained and the residual centering approach and compare these approaches with the constrained approach of Algina and Moulder (2001) using data from a field study of 1,442 students. Theoretical background is the theory of planned behavior (Ajzen, 1991) in which we test the proposed interaction between an individual’s intention to perform a behavior and perceived behavioral control (PBC) on behavior. The illustration should assist researchers interested in testing interaction effects using structural equation modeling.

Keywords: Interaction effects; structural equation modeling; constrained and unconstrained approaches; residual centering approach; theory of planned behavior; perceived behavioral control; intention

Introduction

Theoretical models in the social sciences often postulate interaction effects between explanatory variables. Social scientists often expect individual variables such as education or income to display stronger effects in certain regions compared to others, values to have a stronger effect on attitudes or behavior for particular age groups, or state policies to have a stronger effect in particular contexts. Typical analyses of such interactions rely on methods like moderated regression with observed variables. These models include multiplicative
terms of the interacting variables. For example, in the examples above, education is then multiplied with a dummy variable indicating a certain region, values are multiplied with the age variable, or a dummy variable indicating a particular policy is multiplied with another dummy variable indicating a particular social context to build the interaction term.

One of the main problems with such typical analyses of interactions between explanatory variables is that they suffer from low power. In other words, such analyses do not control for measurement errors of explanatory variables, and thus interaction effects are blurred and as a result cannot be detected (Busemeyer & Jones, 1983). As a better alternative, latent interaction modeling has been proposed for more than 10 years now, since it can control for measurement errors. Latent variables are variables which are not directly observed but are rather inferred from other observed variables. These observed variables are often called indicators or manifest variables (Bollen, 1989). A typical approach in regression analyses to compute a scale is to create a sum index of several manifest variables. One of the main advantages of using latent variables and structural equation modeling instead of a sum index and simple regression is the possibility to control for different kinds of random and nonrandom measurement errors. As a result, parameter estimates in the model are more accurate (For further details, see Bollen, 1989).

In the last years, there have been many developments for estimating interactions between latent variables in structural equation modeling (Armingher & Muthén, 1998; Bollen & Paxton, 1998; Coenders et al., 2008; Jaccard & Wan, 1995, 1996; Jöreskog, 1998; Jöreskog & Yang, 1996; Klein & Moosbrugger, 2000; Marcoulides & Schumacker, 2001; Ping, 1998; Schermelleh-Engel et al., 1998; Schumacker & Marcoulides, 1998; Wall & Amemiya, 2000; Yang-Jonsson, 1997; Yang-Wallentin & Jöreskog, 2001). Although these approaches differ in details, most of them agree that a latent product variable is included in the model to represent the interaction term. The indicators of the latent product variable (the so-called product indicators) are computed by multiplying the indicators of the latent variables which interact with each other (the indicators of the so-called first-order effect variables).

A technical consequence of this procedure, which is described in several of the studies mentioned above, is that it requires various nonlinear constraints to be incorporated in the model to express the mathematical relationships between the product indicators and the first-order effect indicators. Consequently, these approaches have been summarized as constrained approaches (Marsh et al., 2004, 2006).

For the applied researcher, this abundance of different complicated approaches has led to a state of confusion. Additionally, the necessity to incorporate the complicated constraints is a burden for many applied researchers and increases the probability of erroneously specifying a model. The reason is that these constraints include a list of several complex equations that have to be introduced into the syntax of the model and that constitute a source of potential specification errors in the model. As a result, applied researchers almost never use structural equation modeling for the analysis of interaction effects and continue to rely on traditional methods like moderated regression with observed variables. These methods, as we have just mentioned, are simple to use but have low power to detect the interaction effect and are, therefore, highly disadvantageous.

Recently, two new approaches to interaction modeling aimed at delivering procedures which are easy to apply for researchers and possess the positive aspects of structural equation modeling (i.e., controlling for measurement error and providing a model fit) have been proposed: (1) The unconstrained approach (Marsh et al., 2004, 2006) suggests omitting most of the constraints. (2) The residual centering approach (Little et al., 2006) uses residuals as product indicators. The resulting specified interaction model contains no constraints at all. Marsh et al. (2004) as well as Little et al. (2006) provided evidence from Monte Carlo simulations showing that their approaches were comparable with traditional approaches in terms of Type I
error and parameter bias. Furthermore, both groups of authors recently showed that their approaches can be algebraically integrated (Marsh et al., 2007).

The present paper uses data from a field study to illustrate the application of the unconstrained and residual centering approach and compares the results of these approaches with one of the constrained approaches (Algina & Moulder, 2001). Thus, the main contribution of the present study is to present the application of the three approaches to an existing data set and to test a theoretically-driven interaction effect in the theory of planned behavior (which is described below in the next section) (Ajzen, 1991). This interaction effect is proposed between two variables in the theory of planned behavior: an individual’s intention to perform a behavior and the perceived behavioral control (PBC) about performing it on the execution of the behavior. In the empirical illustration we expect to detect a significant interaction effect using each of the three approaches. The following section describes the theory, its elements, and the expected interaction.

The theory of planned behavior

The theory of planned behavior (Ajzen, 1991; Ajzen & Fishbein, 1980, 2008; Fishbein & Ajzen, 2010) was developed to explain behavior in different domains. Indeed, over the last few decades it has been successfully used to explain behavior in various contexts, such as consumer behavior, ecological behavior, sexual behavior, and involvement in sports (for an overview see Armitage & Conner, 2001). In many of these studies the theory was able to provide a reasoned explanation of the behavior under consideration. Figure 1 depicts the main factors in the theory and the relations between them.

**Figure 1: The theory of planned behavior**

![Figure 1: The theory of planned behavior](image)

A central factor in the theory is the intention of individuals to perform a certain behavior. Intention indicates the extent to which an individual is willing to perform the behavior. According to the theory, the intention directly influences the behavior. The theory postulates that the stronger the intention to perform the behavior, the more likely it becomes that the behavior will be performed.

In addition, performing the behavior depends on the behavioral control, that is, the perceived availability of opportunities and resources to perform the behavior. In the present context the use of public transportation is investigated; in this case, the theory would propose that the use of public transportation depends on whether or not public transportation is perceived by the individual as available. This perception is called the perceived behavioral control (PBC) and reflects an individual’s perception of his or her control over the behavior. The theory postulates that the likely performance of a behavior increases with greater perceived behavioral control. However, the theory postulates that PBC also has a direct effect on intention. In other words, it is expected that with an individual’s increasing perceived behavioral control over the behavior, there is also a stronger intention to perform the behavior. Thus, intention partially mediates the effect of PBC on behavior.
In contrast to the intention and PBC, attitudes toward the behavior and subjective norms’ influence on behavior are fully mediated by intention and exert no direct effect on the behavior. The attitude toward the behavior indicates the extent to which an individual has a positive or a negative evaluation of the behavior. Subjective norms indicate the extent of perceived social pressure to perform the behavior. It is expected that the more positive the attitudes toward the behavior and the subjective norms, the stronger is the intention to perform the behavior. Attitudes and subjective norms are not considered in our empirical illustration.

Whereas intention and PBC are posited to have direct effects on behavior, the theory also suggests an interaction of both variables. Ajzen (1991) states that a ‘behavioral intention can find expression in behavior only if the behavior in question is under volitional control’ (p. 182). This notion is rooted in the traditionally postulated interaction between motivation and ability in predicting achievement, whereas ability in the theory of planned behavior reflects internal and external barriers or facilitation conditions. In other words, the theory expects intention to have a stronger effect on behavior when PBC is higher. The same idea can also be expressed by the expectation that PBC is expected to display a stronger effect on behavior when intention is high. The interaction is displayed in Figure 1.

So far, the interaction between intention and PBC has rarely been tested with real data and latent variables using structural equation modeling (e.g., Reinecke, 2002; Yang-Wallentin et al., 2001; for a meta-analysis on studies testing this interaction effect, see Yang-Wallentin et al., 2004). We believe the reason for the sparse number of studies testing this interaction effect using structural equation modeling techniques is because of the relative complexity of conducting such a test. Most of the studies that tried to test this interaction used moderated regression with observed variables. Moreover, only a small number of these studies found a significant interaction effect between these two constructs (Yang-Wallentin et al., 2004). As we have mentioned earlier, it could well be the case that no significant interaction effect was detected because of the low power of traditional methods to test interaction effects that use no latent variables. Van den Putte and Hoogstraten (1997) conducted a test of the theory in a SEM framework, estimating most of the relationships formulated in the theory. However, these authors did not test the interaction effects in the theory. Applying sophisticated methods to interaction modeling is essential for drawing conclusions with regard to the hypothesized theoretical interaction in the theory. In the next sections we will present three of these methods: the constrained and unconstrained approaches and the residual centering approach.

The three approaches for interaction modeling

The constrained and unconstrained approaches to interaction modeling

The main characteristic of the constrained approach(es) examination of an interaction between two latent variables is the specification of nonlinear constraints. These constraints determine that the parameters of the measurement model of the product latent variable (i.e., loadings of the indicators and error (co)variances) are not freely estimated but expressed in terms of the parameters of the measurement models of the first-order effect variables. In our example of the theory of planned behavior, this model implies that the parameters of the interaction latent variable (intention X PBC) will be expressed in terms of the parameters of the measurement models of the two first-order effect latent variables, intention and PBC. We will not describe these constraints in detail here because we focus in this study on the other methods which are easier to apply. Nevertheless, we list these constraints as formulated by Algina and Moulder (2001) in Figure 2 and the interested reader is referred to the original studies of Kenny and Judd (1984), Jöreskog and Yang (1996), and Algina and Moulder (2001).
Although there are several ways to set these constraints, they all originate from the classic study of Kenny and Judd (1984). Jöreskog and Yang (1996) provided a general model for the specification of constraints. Their model relied on uncentered indicators, that is, they used indicators in their original format whose means were not centered to zero. In 2001, Algina and Moulder revised and simplified the Jöreskog–Yang model by relying on centered indicators whose means were centered to zero. By centering the indicators, the Algina-Moulder approach allowed a researcher to ignore the intercepts and latent means (at least of the first-order effect variables). The authors found that this model showed better convergence rates and had less bias, lower Type I error rates, and greater power. Figure 2 depicts an interaction model according to the constrained approach (Algina & Moulder, 2001), with two first-order effect variables ($\xi_1$ and $\xi_2$) and a latent product variable ($\xi_1\xi_2$). In addition, the figure shows the nonlinear constraints which have to be incorporated. Later in the example we could think of $\xi_1$ and $\xi_2$ as the first-order effect variables intention and PBC and $\xi_1\xi_2$ as the interaction latent variable intention X PBC.

In 2004, Marsh et al. proposed omitting most of these constraints. The authors criticized that specifying these constraints would require normally distributed latent variables, a situation which is unlikely to be the case in reality. Even if the first-order effect variables ($\xi_1$ and $\xi_2$) are normally distributed, the product latent variable ($\xi_1\xi_2$) is nonnormal because the product of two normally distributed variables is not normal. Marsh et al. proposed relying on centered indicator variables and using the products of centered indicators as indicators of the latent product variable. In this respect his approach is similar to the Algina and Moulder model. However, Marsh et al. also proposed to omit most of the constraints that were required by Algina and Moulder. As the only remaining constraints, the means of the latent first-order effect variables are fixed to zero (i.e., $\kappa_1 = \kappa_2 = 0$) and the mean of the latent product variable equals the covariance of the two first-order effect variables (i.e., $\kappa_3 = \phi_{13}$). In our example of the theory of planned behavior, the unconstrained model implies centering the indicators of intention and PBC before multiplying them. Their products will serve as indicators of the interaction latent variable (intention X PBC). In addition, the means of the latent variables intention and PBC will be fixed to zero and the mean of the interaction latent variable (intention X PBC) will equal the covariance between the latent variables intention and PBC. The first and maybe most important advantage of this model is the ease of use for applied researchers. The second is that this model does not impose any constraints derived from the multivariate normality assumption of the latent variables, in contrast to the constrained approach (Marsh et al., 2004).

Marsh et al. (2004) conducted four simulation studies that showed that the unconstrained approach had further important advantages. The estimates in the unconstrained approach were slightly less biased than in
the constrained approach, and solutions were somewhat more likely to converge when the indicators were normally distributed and sample size was small. Unfortunately, Marsh et al. did not test the influence of multicollinearity on model fit, convergence, and bias of estimates. Given that studies with real data often imply substantially correlated predictors, it is unclear if the unconstrained approach delivers efficient estimates and adequate test statistics to detect interaction effects.

*The residual centering approach*

The residual centering approach (Little et al., 2006) avoids any statistical dependency between indicators of first-order effect variables and those of the latent product variable. Instead, the researcher uses residuals to form the indicators for the product variable.

The residual centering approach consists of a two-step procedure: In the first step, two respective uncentered indicators of the first-order effect variables (in our example, an uncentered indicator measuring intention and an uncentered indicator measuring PBC) are multiplied and the resulting product is then regressed on all first-order effect indicators. The residuals of these regression analyses are saved in the data set. In the second step, the residuals are used as indicators of the product variable in the latent interaction model. As an illustration, consider two first-order effect variables intention and PBC, measured by two indicators, Int1 and Int2, and PBC1 and PBC2, respectively. In the first step, the product term Int1pbc1 is regressed on Int1, Int2, PBC1, and PBC2. The residual of this regression analysis is saved as a new variable. This procedure is repeated for the product terms Int1pbc2, Int2pbc1, and Int2pbc2. The resulting four new variables (the residuals in the four regressions) are used as indicators of the latent interaction variable. The advantage of this approach is the ease of implementation. The residuals can be computed using simple regression analyses and a conventional statistical software package such as SPSS or Stata. Simulations have shown that the residual centering approach performs well and demonstrates reasonable model fit and standard errors (Little et al., 2006, p. 512).

Both the unconstrained approach and the residual centering approach are valuable alternatives to the traditional constrained approaches and are much easier to use. In the next section, we demonstrate their application on real data.

*Method*

*Sample*

The sample consisted of 1,442 students that were surveyed in the first wave of a 4-year panel field study at the University of Giessen, Germany. Aim of the survey was to evaluate the effect of a semester ticket on travel mode choice and reduction of car use. A semester ticket allows students to use local public transportation for a very low price paid at the beginning of each semester. Introduction of the semester ticket plan was preceded by considerable discussion and publicity beginning about one year prior to the first wave of data collection. About five months prior to the final decision to launch the new semester ticket, a vote was taken among the student population. Sixty-five percent voted in favor of the semester ticket plan, which required students to pay 39 German marks (about $23) each term as part of their tuition. The data collection took place in February 1994, about two months before the introduction of the new semester ticket. Over a period of eight days, a nonsystematic sample of students who came to the registration offices were approached and handed a questionnaire (this sample was not representative of the student population at the University of Giessen). They were asked to return the completed questionnaire via campus mail. Of the 3,491 questionnaires that were distributed among students, 1,874 (54%) were completed and returned. Forty-one percent of the respondents were males. After eliminating missing values (listwise) in the analyzed variables,
the actual sample size was reduced to 1,442\(^3\). For further information about the original study, see Bamberg and Schmidt (1998).

**Measures**

Several items were included in the questionnaire to measure each construct. These items were approved by Icek Ajzen to represent reasonable measures of the constructs of the theory. Two items for each of our theoretical constructs of interest, intention and PBC, worked best, that is, had the highest correlation between each other and the highest factor loadings. Therefore, these items were used for the illustration. One of the reasons to choose only two indicators to measure each latent variable is that it is much easier to illustrate the methods when two (rather than more) items per construct are used. However, the same procedures may be applied when more than two items are used to measure each of the theoretical constructs of interest.

**Intention.** The intention to use public transportation was measured by the two items: ‘Next time, I intend to use public transportation when I go to the university’ (Int1; response options ranged from 1 [unlikely] to 5 [likely]) and ‘My intention to use public transportation when I go to the university is low [high]’ (Int2; response options ranged from 1 [low] to 5 [high]). These items are very similar to each other, and this similarity resulted in a high correlation between them.

**PBC.** We measured PBC with two items that requested respondents to indicate their expected control on a scale ranging from 1 (difficult, small) to 5 (easy, large). The two items were ‘using public transportation to go to the university is very difficult [easy] for me’ (PBC1); ‘my autonomy to use public transportation to go to the university is very small [large]’ (PBC2). These items were proposed by Ajzen (2002) to measure self-efficacy, which is a component of PBC.

**Behavior.** The behavior which reflects the travel mode choice, that is, using the bus or other means of transportation, was measured by the use of a standardized protocol of all routes a person traveled on one day in chronological order (Spiegel Documentation, 1993). From these journeys, we computed the percentage of public transport use from the total use of public transport and car on the reported day to all reported destinations. Thus, unlike intention and PBC, behavior is measured by a single indicator.

**Procedure**

**Constrained approach.** The constrained approach was conducted based on the Algina and Moulder (2001) reformulation of the Jöreskog and Yang (1996) approach that we described earlier. We used centered items to calculate the product indicators of intention and PBC. Since we had two intention and two PBC items, we ended up with four (two times two) product indicators for the latent interaction variable IntPBC. The item measuring behavior was kept in its original scale. The covariance matrix of the four centered indicators, four product indicators, and one behavior item as presented in Table 1 were used as input for the model. For the analysis we used the program LISREL 8.54 (Jöreskog et al., 2000). The syntax for the constrained approach may be obtained from the first author upon request.

**Unconstrained approach.** The unconstrained approach was based on the same data as the constrained approach. The model specification was simpler and contained only two constraints that are left in the unconstrained approach, as we previously outlined. First, the means of the latent variables intention and PBC were fixed to zero. Second, the mean of the latent product term IntPBC was constrained to be equal to the covariance of the latent variables intention and PBC. Further, all of the exogenous variables (intention, PBC, and the latent product variable) were allowed to correlate. The intercepts of the indicators of the exogenous variables were fixed to zero but the intercept of the behavior item was estimated. Finally, we estimated error
covariances between several product indicators - those which have a common component. In other words, the errors of the product indicators Int1pbc1 and Int1pbc2 covaried, as well as those of the product indicators Int2pbc1 and Int2pbc2, Int1pbc1 and Int2pbc1, and Int1pbc2 and Int2pbc2. The error covariance between Int1pbc1 and Int2pbc2 was fixed to zero because these two product indicators had no common component. The syntax for the unconstrained approach may be obtained from the first author upon request.

*Residual centering approach.* We conducted the analyses in two steps (see Little et al., 2006). First, we multiplied an *uncentered* indicator of intention with an uncentered indicator of PBC. This resulted in four product terms: Int1pbc1, Int1pbc2, Int2pbc1, and Int2pbc2. We regressed each of the four products on all indicators (i.e., Int1, Int2, pbc1, and pbc2). The residual of this regression was saved in the data file. For example, the residual resulting from the regression of Int1pbc1 on the four indicators Int1, Int2, pbc1 and pbc2 was named ‘res 1 1’. We produced the other three residuals in a similar manner and named them ‘res 1 2’, ‘res 2 1’, and ‘res 2 2’. Since we had two intention items and two PBC items, the procedure resulted in four products, four multiple regression analyses, and, therefore, four residuals. The four residuals were used for the measurement of the latent product term variable.

In the second step, we specified a latent interaction model. In this model, the two intention items were used as indicators of a latent intention variable, the two PBC items as indicators of a latent PBC variable, and the four residuals as indicators of a latent product variable. For each latent variable (intention, PBC, and the latent product IntPBC), one factor loading was fixed to one to provide a scale for the respective latent variable. In addition, we specified four error covariances between four pairs of residual product indicators: the error of ‘res 1 1’ covaried with the error of ‘res 1 2’, the error of ‘res 2 1’ covaried with the error of ‘res 2 2’, the error of ‘res 1 1’ covaried with the error of ‘res 2 1’, the error of ‘res 1 2’ covaried with the error of ‘res 2 2’. The covariance between the error of ‘res 1 1’ and ‘res 2 2’ was fixed to zero. In other words, an error correlation was freed for the residual product indicators resulting from the multiplication of the same first-order effect items as is illustrated in Figure 2. The syntax for the residual centering approach may be obtained from the first author upon request.

We followed Finney and Distefano’s (2006) recommendation and conducted all the analyses with robust maximum likelihood (RML) and Satorra-Bentler corrected standard errors (Satorra & Bentler, 1994). RML adjusts the chi-square (resulting in the Satorra-Bentler corrected chi-square; SBchi-square) for its upward bias in the case of nonnormally distributed data. As we have previously mentioned, the latent product variable is not normally distributed. RML corrects the standard errors which are underestimated in nonnormal data (Hoogland & Boomsma, 1998). Several Monte Carlo studies have shown the benefits of using RML (e.g., Finney & Distefano, 2006). To use RML, we included the covariance matrix of the indicators and, in addition, the asymptotic covariance matrix as input of the model.

**Results**

*Descriptive statistics*

Table 1 reports the correlations, means, standard deviations, skewness, and kurtosis of the centered indicators of intention and PBC and their product terms. All correlations are significant ($p < .01$). They are relatively high and support convergent and discriminant validity of the constructs. In other words, items belonging to the same construct correlate more strongly than items that belong to different theoretical constructs. Furthermore, the product indicators are nonnormally distributed. As can be seen in Table 1, both intention indicators and all of the product indicators display a significant skewness to the left side of the distribution. However, the indicators of PBC are considerably less skewed.
Table 1: Intercorrelations among the Centered Indicators and their Product Terms

|       | Mean | SD  | Skew | Kurtosis | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|-------|------|-----|------|----------|-----|-----|-----|-----|-----|-----|-----|-----|
| (1) PBC 1 | .00  | 1.48 | .51  | -1.18    |     |     |     |     |     |     |     |     |
| (2) PBC 2 | .00  | 1.58 | .37  | -1.43    | .63**|     |     |     |     |     |     |     |
| (3) Int 1 | .00  | 1.22 | 1.69 | 1.56     | .55**| .43**|     |     |     |     |     |     |
| (4) Int 2 | .00  | 1.22 | 1.67 | 1.51     | .54**| .43**| .95**|     |     |     |     |     |
| (5) PBC1Int1 | 1.00 | 2.19 | 2.09 | 4.62     | .28**| .22**| .76**| .73**|     |     |     |     |
| (6) PBC2Int1 | .83  | 2.14 | 1.70 | 4.17     | .24**| .12**| .65**| .63**| .74**|     |     |     |
| (7) PBC1Int2 | .98  | 2.17 | 2.04 | 4.72     | .28**| .22**| .74**| .73**| .96**| .72**|     |     |
| (8) PBC2Int2 | .83  | 2.14 | 1.67 | 4.14     | .24**| .12**| .63**| .63**| .71**| .96**| .74**|     |
| (9) Behavior | .06  | .20  | 3.42 | 11.32    | .41**| .29**| .67**| .65**| .67**| .52**| .65**| .51**|

Note. ** p < .01; N = 1,442; PBC = Perceived behavioral control; Int = Intention; PBC1Int1 to PBC2Int2 = Product term indicators

Furthermore, the indicators of the first-order effect variables intention and PBC correlate significantly with the product variables. Most notably, the intention items correlate with the product indicators in the range from .63 to .76. These correlations emerge despite the attempt to reduce multicollinearity by centering both intention and PBC items prior to their multiplication and present a typical problem in interaction modeling.

Table 2: Intercorrelations among the Indicators Resulting from the Residual Centering Approach

|       | Mean | SD  | Skew | Kurtosis | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|-------|------|-----|------|----------|-----|-----|-----|-----|-----|-----|-----|-----|
| (1) PBC 1 | 2.49 | 1.48 | .51  | -1.18    |     |     |     |     |     |     |     |     |
| (2) PBC 2 | 2.63 | 1.58 | .37  | -1.43    | .63**|     |     |     |     |     |     |     |
| (3) Int 1 | 1.69 | 1.22 | 1.69 | 1.57     | .55**| .43**|     |     |     |     |     |     |
| (4) Int 2 | 1.69 | 1.22 | 1.68 | 1.52     | .54**| .43**| .95**|     |     |     |     |     |
| (5) Res 1 1 | .00  | 1.38 | -1.29| 5.50     | .00  | .00  | .00  | .00  | .00  | .00  | .91**|     |
| (6) Res 1 2 | .00  | 1.41 | -1.28| 5.64     | .00  | .00  | .00  | .00  | .00  | .00  | .47**| .44**|
| (7) Res 2 1 | .00  | 1.58 | -1.98| 12.40    | .00  | .00  | .00  | .00  | .00  | .00  | .47**| .44**|
| (8) Res 2 2 | .00  | 1.60 | -1.85| 11.13    | .00  | .00  | .00  | .00  | .00  | .00  | .43**| .49**| .93**|
| (9) Behavior | .07  | .20  | 3.30 | 10.47    | .41  | .29  | .66  | .65  | .27**| .25**| .12**| .12**|

Note. ** p < .01; N = 1,442; PBC = Perceived behavioral control; Int = Intention; Res = Residual resulting from a multiple regression of a product of one PBC item with one intention item on all items; the first index refers to the corresponding PBC item, the second index refers to the corresponding intention item.

Table 2 shows the means, standard deviations, correlations, skewness, and kurtosis of the indicators resulting from the residual centering approach. All of the indicators were nonnormally distributed, with the product indicators showing a substantially high kurtosis. Regarding the correlations between the indicators of the first-order effect variables intention and PBC and those of the product term, the residual centering approach
resulted in zero correlations in each case. This is not surprising because, by design, the residual centering approach reduces the correlation between the indicators of the first-order effect variables and those of the product term to zero. Since residuals, which are purged from the common variance between the first-order effect indicators of intention and PBC and the product indicators, are used for the interaction terms, they include no common variance with the first-order effect indicators.

**Findings of the three approaches**

In this section we provide the results of the three approaches. Table 3 provides the fit indexes for the specified models (i.e., constrained approach, unconstrained approach, and residual centering approach). Table 4 provides the estimated first-order and interaction effects.

**Table 3: Fit Indexes of the Tested Models**

|                     | SB\(\chi^2\) (df) | RMSEA (pclose) | CFI  | SRMR |
|---------------------|---------------------|----------------|------|------|
| Constrained approach| 24.63 (30)          | .000 (1.00)    | 1.00 | .030 |
| Unconstrained approach| 27.08 (18)         | .019 (1.00)    | 1.00 | .009 |
| Residual centering approach| 1.59 (21)         | .000 (1.00)    | 1.00 | .004 |

*Note.* SB\(\chi^2\) = Satorra-Bentler corrected chi-square; RMSEA = root mean square error of approximation; CFI = comparative fit index; SRMR = squared root mean residual

**Constrained approach.** The constrained model according to Algina and Moulder (2001) showed a very good fit (SB\(\chi^2\)(30) = 24.63, RMSEA = .000, pclose = 1.0, CFI = 1.00, SRMR = .030). The latent product variable had, as expected, a significant positive effect on behavior (\(\gamma_3 = .059\), \(p < .01\)). The first-order effect of PBC on behavior was also significant but smaller (\(\gamma_1 = .029\), \(p < .01\)). Intention, however, had no significant effect.

**Unconstrained approach.** The fit of this model was very good as well (SB\(\chi^2\) (18) = 27.08, RMSEA = .019, pclose = 1.0, CFI = 1.00, SRMR = .009). The structural coefficients were similar to those in the constrained approach (see Table 4). PBC and the product variable also had significant positive effects on behavior with almost the same effects as in the constrained approach (\(\gamma_3 = .057\) and \(\gamma_1 = .029\); both \(p < .01\)). The effect of intention on behavior was also nonsignificant.

**Residual centering approach.** The resulting model had an excellent fit to the data (SB\(\chi^2\) (21) = 1.59, RMSEA = .000, pclose = 1.0, CFI = 1.000, SRMR = .004). The interaction effect was positive and significant (\(\gamma_3 = .040\), \(p < .01\)) and similar in its size to the one estimated in the constrained and unconstrained approaches. However, as Table 4 shows, intention had a significant positive first-order effect on behavior (\(\gamma_2 = .11\), \(p < .01\)) but PBC did not (\(\gamma_1 = .006\), \(p > .05\)). Thus, all the three approaches detect a significant interaction effect between intention and PBC as expected by the theory of planned behavior.
Table 4: Effects of PBC, Intention, and the Product Variable on Behavior

|                      | Unstandardized | Standard error | z-value |
|----------------------|----------------|----------------|---------|
| **Constrained approach** |                |                |         |
| PBC                  | $\gamma_1 = .029^{**}$ | .007           | 4.149   |
| Intention            | $\gamma_2 = .012$ | .017           | 0.729   |
| PBC*Intention        | $\gamma_3 = .059^{**}$ | .010           | 6.184   |
| **Unconstrained approach** |                |                |         |
| PBC                  | $\gamma_1 = .029^{**}$ | .007           | 4.118   |
| Intention            | $\gamma_2 = .015$ | .017           | 0.860   |
| PBC*Intention        | $\gamma_3 = .057^{**}$ | .009           | 6.106   |
| **Residual centering** |                |                |         |
| PBC                  | $\gamma_1 = .006$ | .004           | 1.606   |
| Intention            | $\gamma_2 = .110^{**}$ | .007           | 16.177  |
| PBC*Intention        | $\gamma_3 = .040^{**}$ | .004           | 9.010   |

Notes. ** $p < .01$ (two-tailed); PBC = perceived behavioral control

Discussion

Theoretical models often postulate interaction effects between explanatory latent variables. This is also the case in the theory of planned behavior, where an interaction between intention and PBC has been hypothesized but so far only rarely tested. The estimation of interaction effects between latent variables with structural equation modeling requires sophisticated methods, especially when the involved constructs are measured with multiple indicators, because the syntax includes a long list of complex constraints imposed on the model. Therefore, only a few of the studies that included an empirical test of the interaction effect used structural equation modeling with latent variables (Ridgon et al., 1998; Yang-Wallentin et al., 2004). This is unfortunate since such methods possess more power than conventional regressions to detect the interaction effect because they control for measurement error. In this study, we illustrated the use of three approaches to interaction modeling using structural equation modeling. One of the approaches, the constrained approach, is relatively complicated to apply, and the other two, the unconstrained approach and the residual centering approach are much easier to use. Our goal was to present their application and rigorously estimate the theoretically postulated interaction effect between intention and PBC in the theory of planned behavior (Ajzen, 1991).

All of the three approaches found a significant interaction effect. This effect was similar and moderate in size. In other words, the interaction between intention and PBC supposed by the theory of planned behavior was supported by the data using all three methods.

Whereas the interaction effect was significant in all of the analyses, the effect of intention on behavior was only significant in the residual centering approach, and the effect of PBC was only significant in the constrained and unconstrained approaches. The constrained and unconstrained approaches did not detect the effect of intention on behavior because of the multicollinearity on the latent level, indicated by the high correlation of $\phi = .82$ between intention and the latent product variable. By contrast, in the residual centering
approach, these correlations could be reduced to zero and there were no multicollinearity problems. Findings of no effect of PBC in the residual centering approach are in line with the theory, which does not expect any effect of PBC on behavior when the interaction effect between intention and PBC is introduced into the model.

As a limitation of our study we would like to note that using two indicators per latent variable and one single indicator for the behavior is not optimal, and it is recommended to use three or four indicators to measure each latent variable. The main reason for this is that with three or more indicators per latent variable, different types of random and nonrandom measurement errors may be controlled for. With only two items per latent variable, nonrandom measurement errors may be only partly controlled for (Bollen, 1989). However, the use of a small number of items enables us to present the methods in this study more easily. Using a larger number of items per latent variable should follow the same procedures. In addition, our data set relies on a self-report measure of behavior collected concurrently with the predictor variables. This may weaken the validity of the results. However, the indicators used in this study have performed well in numerous previous studies applying the theory of planned behavior (Ajzen, 2005) and, thus, provide no threat for validity. Furthermore, since this study has an applied focus, these limitations reflect realistic situations that applied researchers deal with.

Several other approaches, some of which we mentioned in our introductory section, have been developed in recent years to test for an interaction. Some of these approaches make an effort to be simple and more accessible to applied researchers. We could not review all of these methods and decided to focus on the two approaches in this study, which we find especially easy to use. Interested readers may further explore other available methods to test for interaction effects.

Concluding Comments

Overall, our illustration shows the ease of use of both the unconstrained and the residual centering approaches compared with the more complicated constrained approach to test for interaction effects. Furthermore, the two approaches can be comfortably implemented in many available software programs (i.e., LISREL, EQS, Amos, Mplus, and Mx). Using them can help researchers detect interaction terms that are formulated in their theories and that cannot be detected otherwise using traditional regression techniques due to their lower power. We hope that readers interested in testing for interaction effects using structural equation modeling will find the didactic approach taken in presenting this material to be helpful in fulfilling their endeavors.

Notes

1 Given an example of a regression equation containing two predictors X and Z and their product term XZ, a significant product term indicates that the effect of one predictor (e.g., X) is not constant but depends on the value of the other predictor (i.e., Z). The first-order effect of a certain predictor denotes the effect of the predictor at a level of zero of the other predictor (Cohen et al., 2003). In case of centered variables (where zero is the mean of the centered variable), the first-order effect of X thus is the effect of the predictor X at an average level of the other predictor Z. We would like to point out that methods other than product indicator procedures are now available for nonlinear SEM in existing software (maximum likelihood in Mplus and Bayesian in Winbugs). However, these were not the focus of the present study.

2 The $\theta$’s denote the variances and covariances of the indicators’ measurement error; the $\phi$’s refer to the variances and covariances of the latent variables $\xi$; the $\lambda$’s are the factor loadings, and the $\kappa$’s are the means of the latent variables. The two indexes following variance parameters (e.g., $\theta_{22}$ or $\phi_{11}$) refer to cells of the respective covariance matrix. For instance, $\theta_{22}$ refers to the error variance of the second item (X2) since it denotes the element of the main diagonal of the second row and second column. $\theta_{56}$ is an error covariance between the fifth (X1Z1) and sixth (X1Z2) indicator. The two
indexes following factor loadings denote the source of the aim of the loading (i.e., first index) and the target of the loading (i.e., the second index). $\lambda_{z2}$, for example, refers to the loading of the fourth indicator ($Z_2$) on the second latent variable $x_2$.

3 Although listwise deletion has been shown to be inferior compared to other missing data approaches (e.g., multiple imputation or full information maximum likelihood, see Schafer & Graham, 2002), it was sufficient for our purpose to create a common data set for all the investigated approaches to interaction modeling. In addition, the use of imputation techniques would have implied imputing data of four of the five indicators (both intention and PBC indicators) for around 25% of the respondents.

4 The high correlations occurring in the constrained and unconstrained approaches between the first-order effect indicators and the product indicators result partly from the severe level of nonnormality of the predictor variables in our study. Nonnormality is a typical problem in a model that includes interaction terms and is especially evident when Likert scales are used (Flora & Curran, 2004). Empirical tests of the theory of planned behavior are often based on Likert-scaled items.

5 $SB\chi^2 = \text{Satorra-Bentler Corrected Chi-Square}; \text{RMSEA} = \text{Root Mean Square Error of Approximation}; \text{pclose} = \text{Probability of Close Fit}; \text{CFI} = \text{Comparative Fit Index}; \text{SRMR} = \text{Standardized Root Mean Square Residual}$ (for further details, see Arbuckle, 1995–2009).

Author Note

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