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PLS FAC-SEM: an illustrated step-by-step guideline to obtain a unique insight in factorial data

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Abstract

Purpose – The purpose of this paper is to provide an illustrated step-by-step guideline of the partial least squares factorial structural equation modeling (PLS FAC-SEM) approach. This approach allows researchers to assess whether and how model relationships vary as a function of an underlying factorial design, both in terms of the design factors in isolation (i.e. main effects) as well as their joint impact (i.e. interaction effects).

Design/methodology/approach – After an introduction of its building blocks as well as a comparison with related methods (i.e. *n*-way analysis of variance (ANOVA) and multi-group analysis (MGA)), a step-by-step guideline of the PLS FAC-SEM approach is presented. Each of the steps involved in the PLS FAC-SEM approach is illustrated using data from a customer value study.

Findings – On a methodological level, the key result of this research is the presentation of a generally applicable step-by-step guideline of the PLS FAC-SEM approach. On a context-specific level, the findings demonstrate how the predictive ability of several key customer value measurement methods depends on the type of offering (feel-think), the level of customer involvement (low-high), and their interaction (feel-think offerings × low-high involvement).

Originality/value – This is a first attempt to apply the factorial structural equation models (FAC-SEM) approach in a PLS-SEM context. Consistent with the general differences between PLS-SEM and covariance-based structural equation modeling (CB-SEM), the FAC-SEM approach, which was originally developed for CB-SEM, therefore becomes available for a larger amount of and different types of research situations.

Keywords Interaction effect, Factorial design, Main effect, Multi-group analysis (MGA), *n*-way ANOVA, PLS FAC-SEM

Paper type Research paper

1. Introduction

Partial least squares structural equation modeling (PLS-SEM) is a versatile and often applied technique in business and social sciences that allows researchers to assess inter-construct relationships as well as relationships among constructs and their respective indicators (see Henseler *et al.*, 2016 for an excellent state-of-the-art introduction and overview of PLS-SEM). In its most basic form PLS-SEM assumes that the data stem from a single population, meaning that a single model represents all observations well (Sarstedt *et al.*, 2011). Very often, researchers face a heterogeneity of observations, meaning that for different subpopulations, different parameters hold. In those cases, partial least squares multi-group analysis (PLS-MGA) is a useful approach to tackle this heterogeneity (Henseler *et al.*, 2009). In general terms, a PLS-MGA involves estimating separate models for each subpopulation and subsequently assessing whether significant differences exist between the sets of parameter estimates.

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A special type of multi-group data occurs when the data are organized according to a so-called factorial design. A factorial design is a statistical experimental design consisting of two or more factors (comparable to grouping variables in PLS-MGA), each with discrete possible values or levels. For each of the resulting combinations of these levels across all of the factors involved (i.e. treatments), data are collected. Due to its specific nature, a factorial design allows researchers to examine the effect of the factors in isolation (i.e. main effects) as well as in combination (i.e. interaction effects), thereby making factorial designs[1] a useful and efficient approach for business and management researchers (Neter *et al.*, 1996; Montgomery, 2012).

Regular PLS-MGA analysis, which analyses the effect of a single grouping variable, may be used to assess the main effects but is incapable of assessing interaction effects that stem from the use of a factorial design. In this paper a new approach called partial least squares factorial structural equation modeling (PLS FAC-SEM) is introduced that enables researchers to assess the main and interaction effects resulting from an underlying factorial design on PLS-SEM parameter estimates. Compared to the existing arsenal of PLS-SEM analyses, the PLS FAC-SEM approach offers its users an additional and unique insight in their (experimental) data.

As can be concluded from the opening paragraphs, the introduction of PLS FAC-SEM involves a methodological contribution to the PLS-SEM domain. However, a methodological contribution is only truly valuable if it advances researchers' possibilities to gain novel insights from their data. Therefore, the best way to demonstrate the added value of PLS FAC-SEM is to use an example showing a particular situation that is recognizable for managers and researchers alike. Moreover, to illustrate how PLS FAC-SEM relates to other existing approaches we explicate the relevant links where necessary throughout the example.

A question of high practical relevance for a (marketing) manager of an airline concerns whether and how complaint handling perceptions depend on situational (e.g. attribution complexity; is it clear who is to blame? Yes: low-attribution complexity vs No: high-attribution complexity) and customer characteristics (e.g. type of customer: private vs business). This question can be tackled by conducting a (scenario-based) factorial experimental design in which both design factors (i.e. attribution complexity and type of customer) are crossed, resulting in a factorial design of four independent cells or groups: low-attribution complexity – business customer; low-attribution complexity – private customer; high-attribution complexity – business customer; and high-attribution complexity – private customer. Regardless of the combination of design factor levels, each respondent is asked to fill out a survey containing items tapping their perceptions regarding constructs such as distributive justice (i.e. fairness of compensation), procedural justice (i.e. perceived fairness of complaint handling procedure), and satisfaction with complaint handling. These perceptions are generally assessed by means of Likert scales resulting in metric data.

Typically, this kind of factorial data are analyzed using *n*-way analysis of variance (ANOVA) allowing the researcher to address questions such as:

> Is satisfaction with complaint handling/distributive justice/procedural justice higher for situations in which there is high attribution complexity compared to situations in which there is low attribution quality? (Main effect design factor "attribution complexity").

> Is satisfaction with complaint handling/distributive justice/procedural justice higher for business customers than for private customers? (Main effect design factor "type of customer").

> Does the difference in satisfaction with complaint handling/distributive justice/procedural justice between business and private customers diminish when attribution complexity increases? (Interaction effect attribution complexity × type of customer).

Despite its undisputable value, an important shortcoming is that *n*-way ANOVA only focuses on the mean value of a single outcome (i.e. complaint handling satisfaction/distributive justice/procedural justice). That is, *n*-way ANOVA does not provide an answer to the question how model relationships vary as a function of the underlying factorial design. Put differently, *n*-way ANOVA is incapable of answering research questions such as:

> Does procedural justice have a larger impact on complaint handling satisfaction in situations where attribution complexity is high? (Main effect design factor "attribution complexity").

> Does distributive justice have a larger impact on complaint handling satisfaction for private customers than for business customers? (Main effect design factor "type of customer").

> Does the greater impact of distributive justice over procedural justice on complaint handling satisfaction for private customers diminish when attribution complexity increases? (Interaction effect attribution complexity × type of customer).

Indeed, PLS-MGA (see also Henseler *et al.*, 2009) can be used to address the effects of the design factors on the relationships in isolation (i.e. main effects), but this analysis would leave the question regarding of how the effect of one design factor on the inter-construct relationships depends on the other design factor (i.e. interaction effect) unanswered.

To address the last research questions involving the combined impact of design factors (i.e. interaction effect) on relationships[2], Iacobucci *et al.* (2003) proposed an approach called factorial structural equation models (FAC-SEM). That is, FAC-SEM combines the strengths of *n*-way ANOVA (i.e. ability to analyze interaction effects) and MGA (i.e. focus on relationships) in a single approach. Although the FAC-SEM approach allows researchers to obtain a deeper and unique understanding of factorial data, it is hitherto only available in a covariance-based structural equation modeling (CB-SEM) context.

The aim of the current study is to extent the FAC-SEM approach to a PLS-SEM context and to provide a step-by-step guideline that shows how to apply the PLS FAC-SEM approach in practice. The significance of introducing PLS FAC-SEM in addition to the originally developed CB FAC-SEM can be seen from two perspectives. First, given the general, manifold advantageous features of PLS-SEM over CB-SEM (see also Sarstedt *et al.*, 2014; Hair *et al.*, 2011), the introduction of PLS FAC-SEM will make the FAC-SEM methodology applicable in a larger number of practical research situations. Second, given the differences in underpinnings of PLS-SEM and CB-SEM (see also Rigdon, 2012, 2014), an extension of the FAC-SEM approach in a PLS-SEM context offers possibilities to apply the approach to more prediction-oriented research contexts.

The remainder of this paper is structured as follows. Section 2 provides a brief introduction of the key building blocks of the PLS FAC-SEM approach and discusses it added value. Section 3 is the core of the paper and contains a detailed illustrated step-by-step guideline of the PLS FAC-SEM approach. Finally Section 4 summarizes the main conclusions.

2. PLS FAC-SEM: its building blocks and introduction

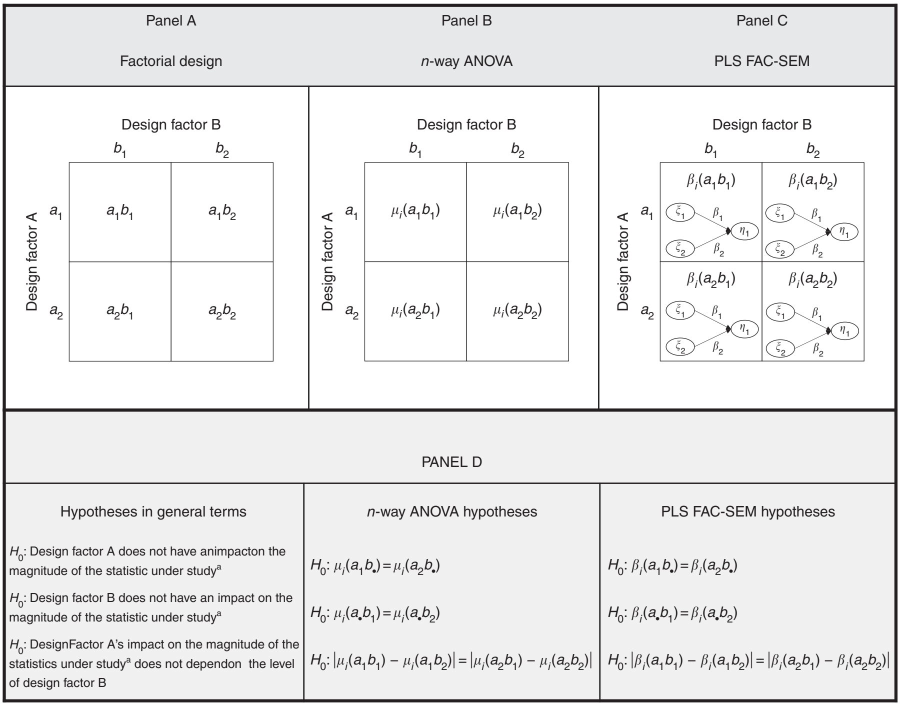
In order to fully appreciate the merits of PLS FAC-SEM, it is necessary to explain what is meant by factorial designs, main effects, and interaction effects. Furthermore, the characteristics of the two methodological approaches to which PLS FAC-SEM is closely linked, that is, n-way ANOVA and MGA, need to be understood. Finally, the merits of PLS FAC-SEM over CB FAC-SEM are underscored.

2.1 Factorial designs

A factorial design is a statistical experimental design used to assess the effects of two or more design factors[3] simultaneously. Each design factor consists of a (not necessarily equal) number of levels. The treatment conditions in a factorial design are combinations of the factor levels. Figure 1 panel A provides a graphical overview of a factorial design consisting of two design factors (i.e. A and B), each having two levels (i.e. a_1, a_2, b_1, and b_2), resulting in four cells (i.e. a_1b_1, a_1b_2, a_2b_1, and a_2b_2)[4].

2.2 Main and interaction effects

The arrangement of a factorial design is such that information can be obtained about the influence of each of the design factors separately (i.e. main effects) and about how the design factors combine to influence relevant outcomes (i.e. interaction effects). Each design factor's main effect involves the impact of that design factor on a particular



Notes: For n-way ANOVA the statistic under study is the mean value of a dependent variable or construct denoted by μ_i in Panel D. For PLS FAC-SEM the relevant statistic is the structural or measurement model parameter which is denoted in Panel D by β_i. Finally, it should be noted that the hypotheses for CB FAC-SEM are equal to those listed in Panel D under PLS FAC-SEM. [a]The general term "statistic under study" is used here as the actual statistic depends on the analytical tool applied

Figure 1.
General overview of PLS FAC-SEM and its building blocks

outcome disregarding the impact of the other design factor. The interaction effect assesses how the impact of a design factor on an outcome depends on the level of the other design factor. Put differently, the presence of a significant interaction effect indicates that the impact of a design factor is not constant across levels of the other factor. For an extensive treatment of main and interaction effects the interested reader is referred to Keppel (1991) and Montgomery (2012). As can be seen in Figure 1 panel D factorial designs imply hypotheses for each separate main effect as well as their interaction effect.

2.3 n-way ANOVA

Typically, *n*-way ANOVA is used to assess how the mean value of an outcome variable differs as a result of the design factors making up the factorial design (see also Figure 1 panel B). Consistent with the distinct nature of factorial designs, a pivotal feature of *n*-way ANOVA is its ability to unravel the variance present in some metric outcome variable to determine whether the mean value of this outcome can be explained by the design factors separately (i.e. main effects) and/or the design factors in combination (i.e. interaction effects). For an overview of the statistical hypotheses underlying associated with *n*-way ANOVA, see Figure 1 Panel D. For illustrative questions that can be addressed with *n*-way ANOVA, see also the first set of research questions mentioned in the introduction of this study.

It should be noted that ANOVAs can also be conducted using standard PLS-SEM software as explained and illustrated by Streukens *et al.* (2010).

2.4 MGA

Despite *n*-way ANOVA's key feature to assess both main effects and interaction effects, a notable shortcoming is its focus on an outcome's mean value, rather than on relationships. As such, research questions involving the impact of design factors on parameters associated with the relationships among different constructs (see e.g. the second set of question in the introduction) and/or relationships among constructs and their respective measures cannot be assessed using *n*-way ANOVA.

Traditional MGA, regardless of whether it is applied in a PLS-SEM context or not, is only capable of assessing the impact of design factors on inter-construct relationships in isolation (i.e. main effects), thereby failing to take into account possible interaction effects that may exist between design factors. Failing to take into account possible interaction effects may lead to erroneous conclusions regarding the main effects as interaction effects per definition mean that the main effect of one design factor is not constant for different levels of the other design factor.

2.5 FAC-SEM

Originally developed by Iacobucci *et al.* (2003), FAC-SEM is as special kind of MGA in which the different groups represent the different cells of a factorial design. The purpose of FAC-SEM is to statistically test whether and how model relationships vary significantly as a function of the underlying factorial design, both in terms of main and/or interaction effects. As also shown in Figure 1 panel C, FAC-SEM's scope of investigation involves model parameters describing relationships rather than construct means.

Table I illustrates the added value of FAC-SEM relative to *n*-way ANOVA and MGA. Basically, FAC-SEM combines the ability to assess the influence of both main and interaction effects of design factors (cf. *n*-way ANOVA) with a focus on relationships (cf. MGA). As a result FAC-SEM is capable of tackling research questions that are left unanswered by opting for n-way ANOVA or traditional MGA thereby allowing researchers to gain a new and unique insight in their factorial data. In terms of the example put forward in the introduction, the unique type of research question FAC-SEM can address involves how design factors in combination (i.e. interaction effect) have an impact on model relationships (see also the last research question put forward in the introduction).

2.6 PLS FAC-SEM

Similar to the general distinction between PLS-SEM and CB-SEM (see also Henseler *et al.*, 2016; Sarstedt *et al.*, 2014), extending the principles of the FAC-SEM approach as originally developed by Iacobucci *et al.* (2003) for CB-SEM to a PLS-SEM context opens up a plethora of new possibilities to apply the FAC-SEM approach. More specifically, the introduction of PLS FAC-SEM makes FAC-SEM analysis a realistic option for studies that involve more complex models, models that contain composites or a combination of composites and common factors, and situations which do not meet the stringent distributional assumptions and sample size requirements associated with CB-SEM. In a similar vein, PLS FAC-SEM is suitable for research contexts that focus on prediction rather than explanation (cf. Hair *et al.*, 2011). Finally, it needs to be stressed that PLS FAC-SEM can also be used in combination with consistent partial least squares (PLSc) estimation as developed by Dijkstra and Henseler (2015a, b). PLSc introduces a correction for structural model estimates when PLS is applied to reflectively measured constructs (i.e. common factors) thereby avoiding inflation of the path coefficients and thus reducing the probability of type I errors. PLSc is applicable to models that contain both common factors and composites, yet PLSc only corrects those constructs that are reflective (see also Dijkstra and Henseler, 2015a, b).

3. The PLS FAC-SEM methodology: a step-by-step guide and illustration

Performing a PLS FAC-SEM analysis requires a sequence of steps that is summarized below in Figure 2. Although not explicitly mentioned in Figure 2, it is important to emphasize that before conducting the actual PLS FAC-SEM analysis, data on the underlying factorial design (i.e. variables denoting of the factors (and the treatments)) need to be included in the dataset. Furthermore, similar to traditional PLS-MGA, the data collection procedures as well as the model need to be identical across the cells of the factorial design under study.

The remainder of this section provides a detailed explanation of these steps. In order to further clarify the steps involved in PLS FAC-SEM we start in Paragraph 3.1 with the introduction of a real-life example that will be used throughout the remainder of this section.

	Parameter of interest	Interaction effects
n-way ANOVA	Means	Yes
MGA	Structural/measurement model parameters (i.e. relationships)	No
FAC-SEM	Structural/measurement model parameters (i.e. relationships)	Yes

Notes: Interaction effect in this context refers to the interaction effect as the joint influence of the design factors of the underlying factorial design, not the interaction effect between two constructs as in a moderator analysis. The statements made in Figure 2 hold regardless of whether the analyses are performed in a PLS-SEM context or not

Table I. FAC-SEM, n-way ANOVA, and MGA

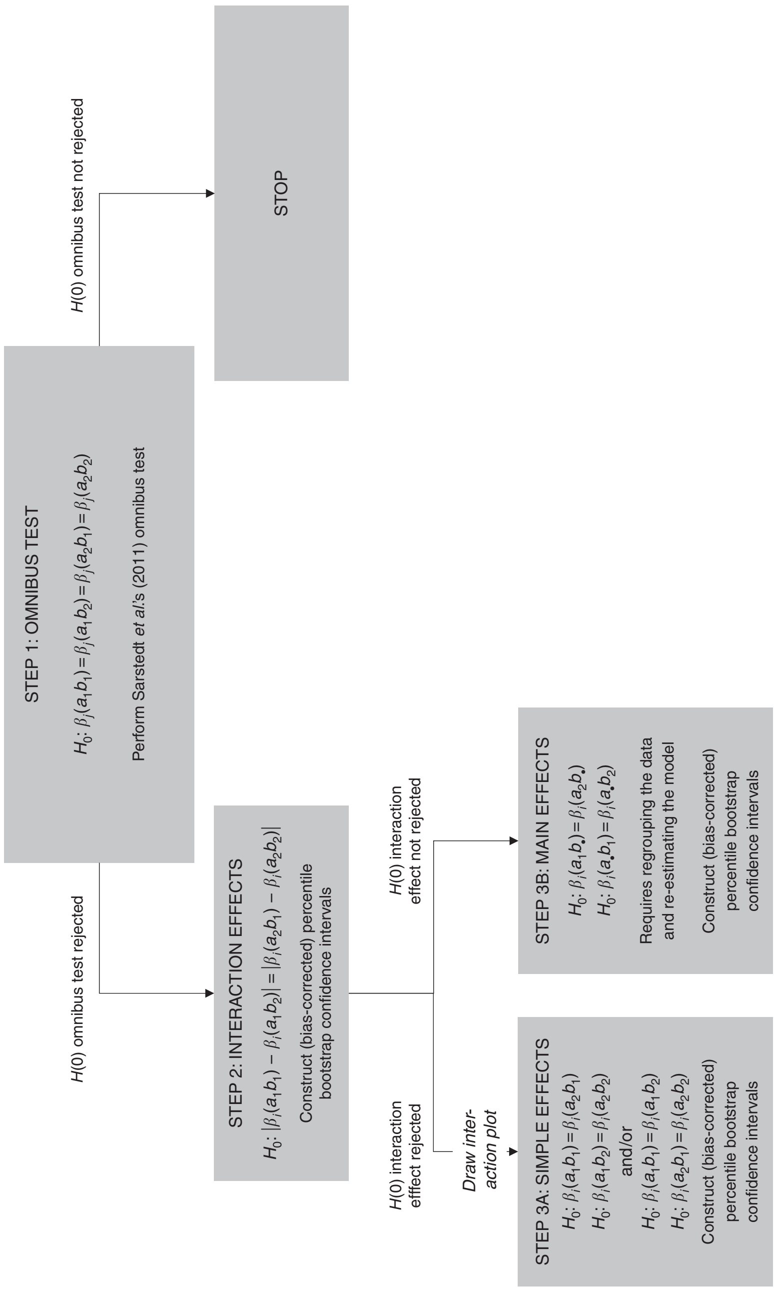


Figure 2.
PLS FAC-SEM
step-by-step

3.1 PLS FAC-SEM data: the relative performance of different customer value methods[5]

Perceived customer value is a key determinant of customer behavior. Research by Leroi-Werelds *et al.* (2014) assessed the performance of the four alternative measurement methods that are most commonly used in empirical studies (i.e. the value measurement methods proposed, respectively, by Dodds *et al.*, 1991; Gale, 1994; Woodruff and Gardial, 1996; Holbrook, 1999). Their performance was assessed in terms of their predictive ability of customer's word-of-mouth intentions. Here, a customer value measurement method's predictive ability of word-of-mouth intentions was measured by the R^2 value of the latter construct with the particular customer value measurement method acting as a predictor.

Closer inspection of Leroi-Werelds *et al.*'s (2014) results indicate that the differences in the predictive ability of customers' word-of-mouth intentions between the four value measurement methods vary across settings (see for an overview of these results Table AI). In this context, differences in predictive ability or relative performance reflect the differences in the amount of variance explained (i.e. R^2 value) for the criterion constructs (i.e. customer's word-of-mouth intent) for two customer value measurement methods. For example, the relative predictive ability of Gale's (1994) method compared to Holbrook's (1999) method in terms of customer's word-of-mouth thus involves assessing the difference in R^2 values for the latter construct obtained when Gale's (1994) method was used as a predictor and when Holbrook's (1999) method was used as a predictor.

The aim of the current empirical study is to assess whether the relative performance of the four customer value measurement methods varies structurally as a function of product involvement and type of product. Besides the effect of level of product involvement and product type in isolation (i.e. main effects), we question whether the effect of product involvement on relative predictive ability is dependent on product type (i.e. interaction effect).

To address the abovementioned research question, the data collection is structured as a factorial design composed of two design factors. The first design factor is the level of involvement and consists of two levels (i.e. low and high). The second design factor is the type of offering, which also consists of two levels (i.e. think and feel). Figure 3 provides a graphical presentation of this factorial design as well as the abbreviation used throughout the remainder of this paper. Furthermore, Figure 3 provides

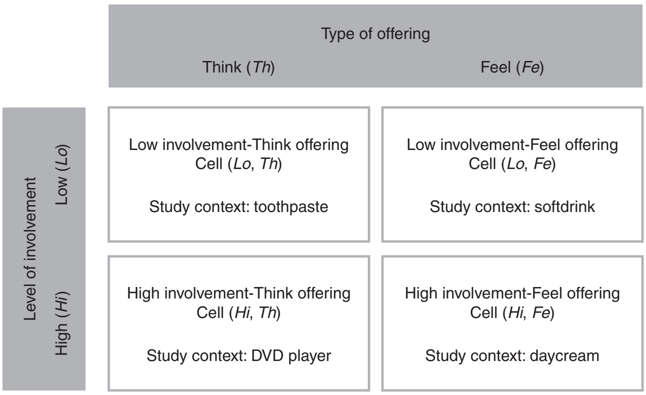


Figure 3. Factorial design empirical illustration PLS FAC-SEM

information about the study contexts used to operationalize the different cells of the factorial design. The relevant PLS FAC-SEM substantive hypotheses as well as the relevant theoretical background can be found in the Appendix 1. Appendix 1 also contains a detailed explanation of how the substantive hypotheses translate into relationship parameters which will be central to the PLS FAC-SEM approach.

The remainder of this section focuses on the relevant PLS FAC-SEM statistical hypotheses both in general terms as well as applied to the illustrative example.

3.2 PLS FAC-SEM: an illustrated step-by-step guideline

The results of the PLS FAC-SEM analysis accompanying this step-by-step guideline are summarized in Table II and will be discussed in detail for each of the steps below.

In Table II, the results mentioned under the heading "estimates per cell" are the average parameter values per cell. They can be used as descriptives to further unravel the nature of the main and/or interaction effects that take central stage in the PLS FAC-SEM analysis.

Step 1 PLS FAC-SEM: the omnibus test. The first step in PLS FAC-SEM is to assess whether the structural model parameters are indeed different across the cells of the factorial design. In general terms (as also employed in Figures 1 and 2), this involves testing the following null hypothesis:

$$H_0 : \beta_i(a_1b_1) = \beta_i(a_1b_2) = \beta_i(a_2b_1) = \beta_i(a_2b_2)$$

To test this null hypothesis Sarstedt *et al.*'s (2011) omnibus test of group differences is needed. Note that Sarstedt *et al.*'s (2011) omnibus test cannot be conducted using regular PLS-SEM software packages. In order to perform this test a SAS-code was written which can also be found in the Appendix 2.

Rejection of the omnibus test's null hypothesis indicates that the model relationships (denoted by β_i) vary as a function of the underlying factorial design. Whether the differences are due to significant interaction effects and/or main effects needs to be assessed in the remaining PLS FAC-SEM steps. If the omnibus test's null hypotheses cannot be rejected, the parameter under investigation is equal across all cells of the factorial design implying that the underlying factorial design does not have an impact on the parameter's magnitude. In this case, the PLS FAC-SEM analysis stops.

In terms of the empirical illustration at hand, the first step of the PLS FAC-SEM approach involves testing three[6] omnibus tests. That is, one omnibus test for each pair of customer value methods that we compare (i.e. comparison Woodruff and Gardial vs Gale; Holbrook vs Gale; Holbrook vs Woodruff and Gardial). Specifically, this boils down to the three null hypotheses presented in Figure 4.

In Figure 4, Δ refers to the difference in predictive ability or relative performance (i.e. difference in R^2 values for customer's word-of-mouth intentions as predicted by the different value measurement methods) and the letters *WG*, *GA*, and *HB*, respectively, denote the customer value measurement methods of Woodruff and Gardial, Gale, and Holbrook. Furthermore, the cell of the factorial design is denoted by the abbreviations in parentheses. Similar as in Figure 3, *Lo* indicates low involvement and *Hi* indicates high involvement. Whereas *Fe* and *Th*, respectively, indicate feel and think offerings.

As shown in Table II, the results of the omnibus tests reveal that for each of the three customer value method-comparisons the null hypothesis can be rejected (all $p < 0.001$).

	Value measurement method comparison		
	Woodruff and Gardial vs Gale	Holbrook vs Woodruff and Gardial	Holbrook vs Gale
Estimates per cell			
Δ(*Hi*,*Fe*)	0.13 [0.07;0.20]	−0.09 [−0.16;−0.03]	0.04 [−0.05;0.12]
Δ(*Hi*,*Th*)	0.00 [−0.05;0.06]	−0.14 [−0.14;−0.09]	−0.14 [−0.20;−0.08]
Δ(*Lo*,*Fe*)	0.01 [−0.05;0.07]	0.03 [−0.03;0.09]	0.04 [−0.02;0.11]
Δ(*Lo*,*Th*)	0.02 [−0.03;0.08]	0.10 [0.04;0.15]	0.12 [0.07;0.16]
Step 1: omnibus test (see Figure 4 for H_0)			
p-value omnibus test	$p < 0.001$	$p < 0.001$	$p < 0.001$
Conclusion	H_0 rejected	H_0 rejected	H_0 rejected
Step 2: interaction effect (see Figure 5 for H_0)			
Δ(*Hi*,*Fe*)−Δ(*Hi*,*Th*)	−0.01 [−0.09;0.07]	0.05 [−0.02; 0.13]	−0.07 [−0.16;0.01]
Δ(*Lo*,*Fe*)−Δ(*Lo*,*Th*)	0.12 [0.04;0.22]	−0.06 [−0.15;0.01]	0.17 [0.07;0.28]
Difference	*0.14 [0.02;0.25]*	*0.11 [−0.01;0.23]*	*0.24 [0.11;0.38]*
Conclusion	H_0 rejected	Failed to reject H_0	H_0 rejected
Step 3A: simple effects (see Figure 7 for H_0)			
Low involvement			
Δ(*Lo*,*Fe*)−Δ(*Lo*,*Th*)	0.12 [0.04;0.22]	–	0.17 [0.07;0.28]
Conclusion	H_0 rejected	–	H_0 rejected
High involvement			
Δ(*Hi*,*Fe*)−Δ(*Hi*,*Th*)	−0.01 [−0.09;0.07]	–	−0.07 [−0.16;0.01]
Conclusion	Failed to reject H_0	–	Failed to reject H_0
Step 3B: main effects (see Figure 8 for H_0)			
Involvement			
Δ(*Hi*,•)	–	−12 [−0.21;−0.03]	–
Δ(*Lo*,•)	–	0.07 [−0.02;0.15]	–
Difference	–	*−0.19 [−0.31;−0.06]*	–
Conclusion	–	Failed to reject H_0	–
Type of offering			
Δ(•,*Th*)	–	−0.03 [−0.11;0.05]	–
Δ(•,*Fe*)	–	−0.03 [−0.13;0.06]	–
Difference	–	*−0.01 [−0.11;0.13]*	–
Conclusion	–	Failed to reject H_0	–

Notes: *Hi*, high involvement; *Lo*, low involvement; *Fe*, feel offering; *Th*, think offering. The term "Difference" refers to the difference between parameter estimates in the preceding rows. For the exact calculation of the Δ-parameter see Appendix 1. En dashes are printed at locations where a particular hypothesis test was not applicable. The simple effects appear twice in this table (i.e. in Steps 2 and 3A). This is a deliberate choice made for reasons of clarity

Table II. Estimation results PLS FAC-SEM illustration

This indicates that the parameter estimates across the cells of the factorial design are not equal. In terms of the application at hand, the rejection of the omnibus null hypotheses implies that the relative performance of two value measurement methods differs as a function of the level of involvement, the type of offering, and/or their interaction. The subsequent steps are needed to further assess the nature of the across-cells parameter differences.

Step 2 PLS FAC-SEM: assessing interaction effects. Similar to *n*-way ANOVA, upon rejection of the omnibus test's null hypothesis, the PLS FAC-SEM analysis continues with the assessment of the highest order statistically significant interaction (cf. Keppel, 1991). The rationale for this lies in the fact that a significant nth-order interaction effect implies that the lower (n−1)th effect is not constant and therefore can only be meaningfully interpreted when the higher order interaction effect is ignored. For example, in a $2 \times 2 \times 2$ factorial design, a significant third-order the interaction effect implies that the magnitude and/or nature of a second-order interaction effect depends on the level of a third design factor. Ignoring the significant third-order interaction, would lead to the false conclusion that there is a particular second-order interaction effect that is the same for all levels of the third design factor, whereas in reality it might be that a second-order interaction exists for a particular level of the third design factor and there is no (or different) second-order interaction effect for another level of the third design factor. In turn, significant second-order interaction effects indicate that a factor's main effect depends on the level of the other factor involved in the second-order interaction effect. Again, ignoring the interaction effect may lead to erroneous conclusions about the magnitude and/or presence of the lower level effects. Empirical studies by Hui *et al.* (2004) and Van Dolen *et al.* (2008) provide examples of how significant higher order interaction effects influence the interpretation of lower order effects.

To examine whether an interaction effect exists, the bootstrap estimates obtained in the first step of Sarstedt *et al.*'s (2011) omnibus test are used to construct bias-corrected percentile confidence intervals to test the null hypothesis whether the difference in parameter estimate stemming from one design factor remains unaffected by the other design factor. For a detailed explanation of how to construct bias-corrected percentile bootstrap confidence intervals see Streukens *et al.* (2010) and Streukens and Leroi-Werelds (2016). For this study, all confidence intervals were constructed in Microsoft Excel using the relevant bootstrap output from SmartPLS 3.0 (Ringle *et al.*, 2015) as a starting point.

In terms of the factorial design presented in Figure 1, the following general null hypothesis applies for the interaction effect:

$$H_0 : \left|\beta_i(a_1b_1) - \beta_i(a_1b_2)\right| - \left|\beta_i(a_2b_1) - \beta_i(a_2b_2)\right| = 0$$

Rejection of the interaction effect's null hypothesis (i.e. the confidence interval contains the value 0), implies that a design's factor effect on the structural relationships under study depends on the level of the other design factor.

Omnibus test hypothesis for the comparison Woodruff and Gardial vs Gale

$$H_0: \Delta_{WG-GA}(Lo,Fe) = \Delta_{WG-GA}(Hi,Fe) = \Delta_{WG-GA}(Lo,Th) = \Delta_{WG-GA}(Hi,Th)$$

Omnibus test hypothesis for the comparison Holbrook vs Woodruff and Gardial

$$H_0: \Delta_{HB-WG}(Lo,Fe) = \Delta_{HB-WG}(Hi,Fe) = \Delta_{HB-WG}(Lo,Th) = \Delta_{HB-WG}(Hi,Th)$$

Omnibus test hypothesis for the comparison Holbrook vs Gale

$$H_0: \Delta_{HB-GA}(Lo,Fe) = \Delta_{HB-GA}(Hi,Fe) = \Delta_{HB-GA}(Lo,Th) = \Delta_{HB-GA}(Hi,Th)$$

Figure 4.
Exhibit 1:
null hypotheses
omnibus tests

When a significant interaction effect is evidenced, the researcher is advised to create a so-called interaction plot to gain further insight in the nature of the interaction effects. An interaction plot is a graph containing the mean parameter values for each cell of the factorial design. The *x*-axis of the interaction plot contains the different levels of one design factor. The interaction plot contains lines (equal to the number of levels of the other design factor) that connect the mean parameter values of the cells corresponding to a particular level of the other design factor (see Keppel, 1991; Chapter 9 for a detailed overview of the construction of interaction plots). Note that the in-depth inspection of the interaction effect is strongly driven by theoretical considerations (i.e. what does the substantive literature hypothesize in terms of an interaction effect). That is, which design factor is used to represent the lines in an interaction plot and which factor is placed on the *x*-axis, is a decision that should be in line with the underlying substantive theory.

For the empirical study at hand, three (second-order) interaction effects are relevant (i.e. one for each of the three pair-wise customer value methods comparisons), leading to the three null hypotheses presented in Figure 5 (same notation applies as used in Figure 4).

As can also be seen in Table II, a significant interaction effect is present for two out of the three comparisons (Woodruff and Gardial vs Gale: 0.14 $CI_{0.95} = [0.02; 0.25]$; Holbrook vs Gale: 0.24 $CI_{0.95} = [0.11; 0.38]$). This implies that the difference in relative performance of the value measurement method of Woodruff and Gardial (Holbrook) compared to that of Gale between think and feel offerings depends on the level of involvement.

For these significant interaction effects, the corresponding interaction plots were constructed to gain a better understanding of the interaction effect. These interaction plots are shown in Figure 6. Inspection of the interaction plots shows that the interactions are disordinal in nature as the lines of the plot cross each other. To fully understand the exact nature of the interaction effects, an analysis of the relevant simple effects is needed (see also Step 3A).

It is important to note that the third and final step of the PLS FAC-SEM approach depends on the outcome of Step 2. If there is a significant interaction effect, the researcher proceeds by assessing the relevant simple effects (Step 3A). In case there is no significant interaction effect, the researcher continues by assessing the design factor's main effects (Step 3B).

Step 3A PLS FAC-SEM: simple effects. The existence of a significant interaction effect (i.e. assessed in Step 2), implies that the effect of one design factor depends on the level of the other design factor. Put differently, a significant interaction effect means

Interaction effect hypothesis for the comparison Woodruff and Gardial vs Gale

$$H_0: |\Delta_{WG-GA}(Lo,Fe) - \Delta_{WG-GA}(Lo,Th)| = |\Delta_{WG-GA}(Hi,Fe) - \Delta_{WG-GA}(Hi,Th)|$$

Interaction effect hypothesis for the comparison Holbrook vs Woodruff and Gardial

$$H_0: |\Delta_{HB-WG}(Lo,Fe) - \Delta_{HB-GW}(Lo,Th)| = |\Delta_{HB-WG}(Hi,Fe) - \Delta_{HB-WG}(Hi,Th)|$$

Interaction effect hypothesis for the comparison Holbrook vs Gale

$$H_0: |\Delta_{HB-GA}(Lo,Fe) - \Delta_{HB-GA}(Lo,Th)| = |\Delta_{HB-GA}(Hi,Fe) - \Delta_{HB-GA}(Hi,Th)|$$

Figure 5.
Exhibit 2: null hypotheses interaction effects

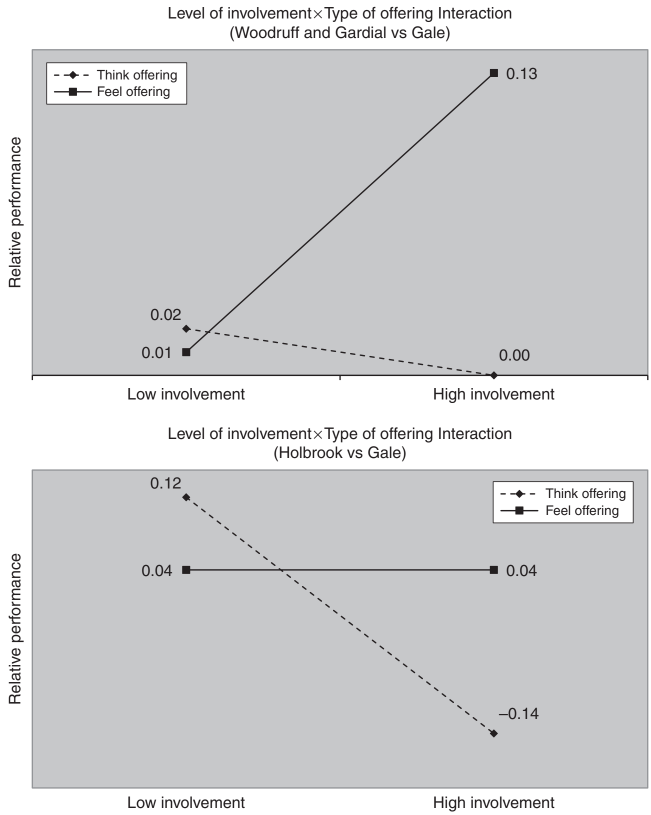


Figure 6.
Interaction plots

that the main effect of a design factor is non-constant across the level of the other design factor. As such, it is generally not meaningful to refer to main effects, even if they are statistically significant, when a significant interaction effect is present (cf. Zar, 1999). Rather, the simple effects need to be assessed.

Simple effects involve the analysis of the effects of one design factor at one level of the other design factor (Keppel, 1991). In general terms (and conform the design depicted in Figure 1), analysis of simple effects for design factor A involves testing:

$$H_0 : \beta_i(a_1b_1) = \beta_i(a_2b_1) \text{ and } H_0 : \beta_i(a_1b_2) = \beta_i(a_2b_2)$$

Similarly, the general null hypotheses accompanying the analysis of the simple effects for design factor B are:

$$H_0 : \beta_i(a_1b_1) = \beta_i(a_1b_2) \text{ and } H_0 : \beta_i(a_2b_1) = \beta_i(a_2b_2)$$

Bias-corrected percentile bootstrap confidence intervals need to be constructed to assess whether the simple effects are statistically significant. Similar as to the analysis of the interaction effect, the nature of the simple effects' tests need to be guided by theoretical considerations.

For the empirical study at hand, simple effects are assessed for the customer value method comparison Woodruff and Gardial vs Gale and the customer value method comparison Holbrook vs Gale. In doing so, the levels of the design factor "involvement" are kept constant, meaning that a simple effect needs to be assessed for each level of the design factor "involvement". The null hypotheses that apply to the assessment of the simple effects are shown below in Figure 7 (again, the same notation applies as in Figure 5). Note that these hypotheses are only developed and tested for the significant interaction effects.

Our results (see also Table II) reveal that for the comparison Woodruff and Gardial vs Gale a significant simple effect for the type of offering exists for high-involvement products (0.12 $CI_{0.95} = [0.04; 0.22]$), but not for low-involvement products (−0.01 $CI_{0.95} = [-0.09; 0.07]$). A similar pattern is found for the comparison Holbrook vs Gale (respectively, 0.17 $CI_{0.95} = [0.07; 0.28]$ and −0.07 $CI_{0.95} = [-0.16; 0.01]$). Thus, in terms of the substantive hypotheses, the relative performance of Woodruff and Gardial's method (Holbrook's method) over Gale's method in equal for low involvement think offerings and low involvement feel offerings. In contrast, relative performance of Woodruff and Gardial's method (Holbrook's method) over Gale's method is different for high-involvement think offerings and high-involvement feel offerings.

Step 3B PLS FAC-SEM: main effects. As stated above in Paragraph 2.2 a design factor's main effect refers to the design factor's effect on an outcome collapsed over the levels of the other design factors. The number of main effects is equal to the number of design factors.

As also can be concluded from the hypotheses in Figure 1 panel D, testing a factor's main effect involves aggregating the data over other factor's different levels (this is indicated by the dots in the subscript). In terms of Figure 1 panel C, to test for the main effect factor A the data over cells a_1b_1 and a_1b_2 are merged into a single group $a_1b_\bullet$ (i.e. $a_1b_1+a_1b_2=a_1b_\bullet$) and the data over cells a_2b_1 and a_2b_2 are merged into a single group $a_{2.}b_\bullet$ (i.e. $a_2b_1+a_2b_{21}=a_2b_\bullet$). The null hypothesis concerning the main effect of design factor A equals:

$$H_0 : \beta_i(a_1b_\bullet) = \beta_i(a_2b_\bullet)$$

In a similar vein, to test for the main effect of design factor B the data in the different cells are merged such that $a_1b_1+a_2b_1=a_\bullet b_1$ and $a_2b_1+a_2b_2=a_\bullet b_2$. The accompanying null hypothesis for the main effect of design factor B is:

$$H_0 : \beta_i(a_\bullet b_1) = \beta_i(a_\bullet b_2)$$

Simple effect hypotheses for the comparison Woodruff and Gardial vs Gale

Low involvement	H_0: $\Delta_{WG-GA}(Lo,Fe)=\Delta_{WG-GA}(Lo,Th)$
High involvement	H_0: $\Delta_{WG-GA}(Hi,Fe)=\Delta_{WG-GA}(Hi,Th)$

Simple effect hypotheses for the comparison Holbrook vs Gale

Low involvement	H_0: $\Delta_{HB-GA}(Lo,Fe)=\Delta_{HB-GA}(Lo,Th)$
High involvement	H_0: $\Delta_{HB-GA}(Hi,Fe)=\Delta_{HB-GA}(Hi,Th)$

Figure 7.
Exhibit 3A: null hypotheses simple effects

In order to be able to test the main effects' null hypotheses the data needs to be regrouped and for the resulting groups the model needs to be re-estimated. For the actual testing of the null hypotheses, bias-corrected percentile bootstrap confidence intervals need to be constructed.

For the situation at hand, two main effects need to be assessed for the customer value method comparison Holbrook vs Woodruff and Gardial (i.e. no significant interaction effect). That is, a main effect of level of involvement and a main effect for type of offering. Figure 8 summarizes the relevant null hypotheses. Again, the notation used in Figure 8 is equal to that used in Figure 7.

Having re-arranged the data as outlined above and re-estimated the models, bias-corrected bootstrap percentile intervals were construct to test the main effect null hypotheses. As can be concluded from Table II, a significant main effect is found for the design factor involvement (-0.19 $CI_{0.95} = [-0.31; -0.06]$), but not for the design factor type of product (-0.01 $CI_{0.95} = [-0.13; 0.11]$). This result means that the relative performance of Holbrook's method compared to Woodruff and Gardial's method varies as a function of the level of involvement, but not as a function of type of offering (i.e. feel-think).

4. Conclusion

The aim of this paper was to provide and illustrate a step-by-step guideline of the PLS FAC-SEM approach. The PLS FAC-SEM approach, which can be considered as a special kind of MGA, offers researchers the ability to obtain alternative and unique insights in their factorial data as it allows researchers to assess whether and how model relationships vary as a function of an underlying factorial design. More specifically, consistent with the logic underlying *n*-way ANOVA, PLS FAC-SEM assesses whether differences in inter-construct relationships depend on the design factors both in isolation (i.e. main effects) and in combination (i.e. interaction effect).

So far, the FAC-SEM approach, as originally developed by Iacobucci *et al.* (2003), was only available in a CB-SEM context. With the introduction of PLS FAC-SEM the virtues of the FAC-SEM approach now become applicable for a larger variety of research and modeling situations. We believe that the PLS FAC-SEM approach is a valuable addition to the PLS-SEM analysis toolbox.

As a final remark, it is important to note that the PLS FAC-SEM approach as discussed in this paper was limited to 2×2 factorial designs and inter-construct relationships. This choice was made for the ease of exposition of the PLS FAC-SEM approach. Following the principles of *n*-way ANOVA (see also Keppel, 1991), the PLS FAC-SEM approach can be extended to larger factorial designs without any problem. Likewise the PLS FAC-SEM approach can be used to assess the impact of the underlying factorial design on PLS-SEM parameters other than the structural model parameters.

Main effect hypothesis "Involvement" for the comparison Woodruff and Gardial vs Holbrook

H_0: $\Delta_{HB-WG}(Lo,\bullet) = \Delta_{HB-WG}(Hi,\bullet)$

Main effect hypothesis "Type offering" for the comparison Woodruff and Gardial vs Holbrook

H_0: $\Delta_{HB-WG}(\bullet, Fe) = \Delta_{HB-WG}(\bullet, Th)$

Figure 8.
Exhibit 3B: null hypotheses main effects

Notes

1. The use of factorial designs in high-quality studies in leading journals across different domains such as supply chain management (e.g. Singh and Kumar, 2012), information systems (e.g. Gan *et al.*, 2013), software design (e.g. Mangalaraj *et al.*, 2014), IT-enabled learning (e.g. Park *et al.*, 2015), and marketing (e.g. Eggert *et al.*, 2015) further illustrates the value of factorial designs.
2. Note that the focus of this paper is on inter-construct or structural model relationships. Yet, the FAC-SEM approach can also be applied on measurement model relationships.
3. It is important to explicitly note that the term factor in the context of a factorial design, and thus PLS FAC-SEM, has a different meaning than what is usually implied by this term in PLS-SEM (i.e. a construct as implied by the common factor model). In order to avoid unnecessary confusion, we therefore decide to refer to the factor in a factorial design as design factor.
4. Without loss of generalizability we focus on 2×2 factorial designs. Factorial designs with more than two factors are possible as well as factorial designs in which factors have more than two levels. Moreover, no restrictions apply to whether the number of levels per factor need to be equal. The proposed PLS FAC-SEM approach can also be applied to factorial designs that deviate from the 2×2 format employed in this paper.
5. Details pertaining to the actual empirical study can be found in Appendix 1 as well as in Leroi-Werelds *et al.* (2014). This paragraph only pays attention to those details of the study related to the PLS FAC-SEM approach.
6. As explained in Appendix 1 as well as in the work of Leroi-Werelds *et al.* (2014) the value measurement method put forward by Dodds *et al.* (1991) does not possess favorable psychometric properties and will therefore be excluded from the PLS FAC-SEM analysis.

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Appendix 1. Background information empirical study

The aim of this appendix is to provide more detailed information about the empirical study used to illustrate the PLS FAC-SEM approach.

Perceived customer value and predictive ability

Perceived customer value has been of continuing interest to marketing researchers and practitioners alike. Moreover, it has been recognized as one of the most significant factors in the success of organizations (Slater, 1997). In line with Zeithaml's (1988, p. 4) definition that "perceived value is the consumer's overall assessment of the utility of a product based on perceptions of what is received and what is given", there has been a general consensus that customer value involves a trade-off between benefits and costs. Given the academic and practical relevance of customer value, there is a pressing need for further understanding of how this construct should be measured (e.g. Sánchez-Fernández *et al.*, 2009).

Over the years several customer value measurement methods have been put forward in the literature, all using Zeithaml's definition as point of departure. In general, the customer value measurement methods of Dodds *et al.* (1991), Gale (1994), Woodruff and Gardial (1996), and Holbrook (1999) dominate the marketing literature. Although all of these methods have their merits, considerable differences among them exist. One key domain of difference involves the nature of the benefits and costs included in the model. Following Gutman's (1982) means-end chain model, customer perceived benefits and costs can be measured at the attribute and/or consequence level. Attributes are concrete characteristics or features of a product or service such as size, shape, or on-time delivery. Consequences are more subjective experiences resulting from product use such as a reduction in lead time or a pleasant experience (Gutman, 1982).

In a large-scale empirical study Leroi-Werelds *et al.* (2014) compared the predictive ability of these four commonly used customer value measurement methods (i.e. Dodds *et al.*, 1991; Gale, 1994; Woodruff and Gardial, 1996; Holbrook, 1999). The results of Leroi-Werelds *et al.* (2014) indicate that the relative predictive ability of the customer value measurement methods in terms of customers' word-of-mouth intentions is not consistent across settings that differ in terms of involvement (high-low) and type of offering (feel-think). Table AI summarizes the relevant results reported in the study by Leroi-Werelds *et al.* (2014).

Underlying factorial design

The FCB grid classifies customers' purchase decisions on two dimensions: involvement and type of offering. Involvement is defined as the attention of a customer to a product or a service because it is somehow important or relevant to him (Ratchford, 1987). Regarding the type of offering, the FCB grid discerns between think and feel offerings. Think offerings are products or services bought to satisfy utilitarian needs, while feel offerings represent products and services bought to satisfy emotional wants.

Hypothesis development

Below we develop hypotheses reflecting the main effects of involvement (*H1*) and type of offering (*H2*) as well as the interaction effect between involvement and type of offering (*H3*). In terms of structural model parameters, the hypotheses focus on the structural relationships between on the one hand customer value and on the other hand word-of-mouth intention. More specifically, the parameters of interest reflect the predictive ability (i.e. R^2) of customer value as measured by the different approaches in terms of customers' positive word-of-mouth intentions.

According to consumer research (e.g. Mulvey and Olson, 1994; Claeys *et al.*, 1995) the level of involvement and the type of product (feel-think) influence customers' means-end chains. Mulvey and Olson (1994) show that the higher the level of involvement, the more a person is aware of the consequences that stem from product use. Likewise, research by Claeys *et al.* (1995) reveals that, compared to think products, the means-end chains for feel products are characterized by a higher level of abstraction.

Table AI. Predictive ability of different customer value methods

	Toothpaste (low involvement, think offering)					Soft drink (low involvement, feel offering)			
	DO	GA	WG	HB		DO	GA	WG	HB
DO					DO	0.60 (0.36)			
GA		0.61 (0.37)	*		GA		0.58 (0.33)		
WG			0.63 (0.40)		WG			0.59 (0.35)	
HB		*		0.72 (0.52)	HB				0.62 (0.39)
	DVD player (high involvement, think offering)					Day cream (high involvement, feel offering)			
	DO	GA	WG	HB		DO	GA	WG	HB
DO					DO	0.56 (0.32)		**	
GA		0.76 (0.58)		**	GA		0.60 (0.36)	*	
WG			0.76 (58)	**	WG	**	*	0.73 (0.54)	
HB		**	**	0.62 (0.38)	HB				0.64 (0.41)

Notes: DO, Dodds *et al.*; GA, Gale; WG, Woodruff and Gardial; HB, Holbrook. This table displays the *R*-values with the R^2 in parentheses. $^*p < 0.10$; $^{**}p < 0.05$
Source: Leroi-Werelds *et al.* (2014)

A key dimension of difference among the four commonly used customer value measurement methods is the extent to which they assess customer value perceptions at the attribute or consequence level. On the one hand, the methods proposed by Holbrook (1999) and Woodruff and Gardial (1996) take into account the consequences customers experience from product use, whereas the other methods do not. On the basis of this theoretical foundation, it is conjectured that the relative performance of customer value measurement methods is influenced by the degree of correspondence between the level of abstraction of the benefits and sacrifices assessed by the customer value measurement method and the characteristics of the means-end chains that depend on the level of involvement and the type of product. This leads to the following hypotheses:

H1. The difference in ability to predict word-of-mouth intent between customer value measurement methods that assess benefits and sacrifices at the consequence level (i.e. Woodruff and Gardial and Holbrook) and customer value measurement methods that do not assess benefits and sacrifices at the consequence level (i.e. Gale and Dodds *et al.*) is larger for high-involvement offerings than for low-involvement offerings.

H2. The difference in ability to predict word-of-mouth intent between customer value measurement methods that assess benefits and sacrifices at the consequence level (i.e. Woodruff and Gardial and Holbrook) and customer value measurement methods that do not assess benefits and sacrifices at the consequence level (i.e. Gale and Dodds *et al.*) is larger for feel offerings than for think offerings.

Furthermore, Claeys *et al.* (1995) infer that under a high level of involvement the difference between think and feel offerings may become more prominent, because under high involvement conditions, the cognitive structure is better organized at the product-knowledge levels (i.e. the attributes) and the self-knowledge levels (i.e. the consequences). Accordingly, the following hypothesis is proposed:

H3. The suggested superiority in word-of-mouth predictability of customer value measurement methods that assess benefits and sacrifices at the consequence level (i.e. Woodruff and Gardial and Holbrook) over customer value measurement methods that do not assess benefits and sacrifices at the consequence level (i.e. Gale and Dodds *et al.*) for feel offerings will be even more pronounced in case of a high level of involvement

Settings and sampling

In order to test the hypotheses outlined above, data were collected across four different settings reflecting the structure of the FCB grid. The products selected as research contexts (see also Figure 3) for our study were soft drinks (low-involvement feel offering), toothpaste (low-involvement think offering), day cream (high-involvement feel offering), and DVD players (high-involvement think offering). To enhance the external validity of our research, data were collected using one of the largest marketing research panels in Belgium.

Questionnaire design

We opted to construct 16 different questionnaires (i.e. collected from 16 different [sub]samples), so that each questionnaire assesses one customer value measurement method in one setting. All questionnaires were identical in terms of the measurement instrument for customer word-of-mouth intentions and the manipulation checks (i.e. measurement of involvement and type of offering). What differed across the questionnaires was the customer value measurement method employed which, furthermore, needed to be adapted to the particular setting. The content of the questionnaires as well as a detailed explanation of how the different customer value measurement methods were operationalized can be found in Leroi-Werelds *et al.* (2014). Data collection continued until we obtained an effective sample size of 210 for each of the 16 questionnaires (i.e. setting-method combinations).

Analytical approach

Unless stated explicitly in the discussion of the results, all analyses were performed using SmartPLS 3 (Ringle *et al.*, 2015). To assess the statistical significance of parameter estimates and differences in parameter estimates, we constructed bootstrap percentile confidence intervals based on $J = 5{,}000$ bootstrap samples (cf. Preacher and Hayes, 2008).

Measurement model structure and properties

Following the work of Jarvis *et al.* (2003), the measurement model structures for the four customer value measurement methods used in this study are specified as follows. The scale suggested by Dodds *et al.* (1991) was modeled as a first-order factor model. A first-order composite model was used to operationalize Gale's (1994) approach. Here, the constructed market-perceived price and market-perceived quality scores act as indicators.

For the remaining two methods (i.e. Woodruff and Gardial, 1996; Holbrook, 1999) we specified second-order measurement models. For the Woodruff and Gardial (1996) approach, overall customer value is a second-order construct formed by two first-order constructs (i.e. benefits and sacrifices). In turn, the benefit construct is modeled as a composite and the sacrifice construct is modeled along the lines of a factor model. Regarding Holbrook's (1999) approach, overall customer value represents a second-order construct with the dimensions arising from his typology acting as first-order constructs that form overall customer value. The various first-order constructs are either a composite or a factor. For more details regarding the exact measurement model specifications, which reflects the theoretical foundations of the respective customer value measurement approaches, the reader is referred to Leroi-Werelds *et al.* (2014). To model customer value as a second-order construct, the two-stage approach suggested by Reinartz *et al.* (2004) was used. In the first stage, the latent variable scores were estimated without the second-order construct (i.e. customer value) present but with all of the first-order constructs (benefits and sacrifices for Woodruff and Gardial's method and the various value types for Holbrook's method) in the model. In the second stage, the latent variable scores of the first-order factors (i.e. benefits and sacrifices for Woodruff and Gardial's method and the various value types for Holbrook's method) were used as indicators of the second-order construct (i.e. customer value) in a separate higher order PLS model.

We evaluated the psychometric properties of all first-order constructs used in our study. In terms of psychometric properties, it is crucial to distinguish between composites and factors (MacKenzie *et al.*, 2005). Regarding the factor models, we assessed unidimensionality (procedure Sahmer *et al.*, 2006 and cut-off criteria proposed by Karlis *et al.*, 2003), internal consistency reliability (procedure Jöreskog, 1971), item validity (procedure Hulland, 1999), within-method convergent validity and discriminant validity (procedures Fornell and Larcker, 1981). Regarding the composites, the statistical significance of the items was assessed (cf. Diamantopoulos and Winklhofer, 2001) discriminant validity was assessed by examining whether the latent variable correlations fall within two standard errors of an absolute value of 1 (MacKenzie *et al.*, 2005). Detailed results regarding the constructs' psychometric properties can be found in Leroi-Werelds *et al.* (2014). All constructs possess favorable properties with exception of the customer value measurement method proposed by Dodds *et al.* (1991). Consequently, the Dodds *et al.* (1991) measurement approach will be left out of the remaining analyses.

Manipulation checks

To assess whether the chosen products indeed reflect the dimensions of the FCB matrix, manipulation checks were conducted. Following the procedure outlined by Streukens *et al.* (2010) it was assessed whether the average scores of the involvement items and the think/feel items included in the questionnaire differ for the relevant products. Regarding the level of involvement, we found significant differences between soft drink and day cream (mean SD = 4.26, mean DC = 4.94, $p < 0.001$) as well as between tooth paste and DVD player (mean TP = 4.14, mean DVD = 4.72, $p < 0.001$). With respect to the type of offering (think vs feel), significant differences were found between soft drink and tooth paste (mean SD = 4.91, mean TP = 4.39, $p < 0.001$) as well as between day cream and DVD player (mean DC = 4.76, mean DVD = 3.99, $p < 0.001$).

Comparing the predictive ability of different customer value methods

A key challenge in the current situation is to make four substantially different customer value measurement methods comparable. This challenge is magnified further by the fact that the operationalization of each value measurement method also differs per setting. The answer to this challenge is to find a common structural model that is identical (and thus comparable) across methods and settings.

To place all customer value measurement methods, across all settings, on an even footing we proceeded as follows:

- In total, 12 (four settings and three methods because Dodds *et al.* (1991) was not taken into account) structural models were estimated in which $y = f$(perceived customer value), in the current illustration y refers to the respondent's intention to engage in positive word-of-mouth.
- For each of the 12 models, the estimation results were used to obtain the predicted values ($\hat{y}$) of the endogenous construct under study (i.e. positive word-of-mouth).
- The predicted values ($\hat{y}$) were then regressed to the actual data (i.e. the latent variable scores) of the relevant construct (y). Thus, we estimated the following structural model: $y = f(\hat{y})$ which is identical for all methods and across all settings.
- Similar as in a bivariate regression context, the resulting path coefficient equals the coefficient of multiple correlation R and indicates the model's predictive ability. As can be seen above, predictive ability plays a central role in our hypothesis testing.

Appendix 2. SAS-code omnibus test group differences

This appendix presents the SAS-code written to conduct Sarstedt *et al.*'s (2011) omnibus test. The omnibus test plays a pivotal role in "PLS FAC-SEM Step 1: the omnibus test" as outlined in the paper. Following the work of Sarstedt *et al.*'s (2011), the omnibus test involves four stages which are briefly described.

Stage 1 (Sarstedt *et al.*, 2011): for each of the groups (i.e. cells) $B = 5{,}000$ bootstrap samples are generated. For each of these samples the model is estimated. This is all done using SmartPLS3 (Ringle *et al.*, 2015). The bootstrap results for the relevant model parameter under study are saved in a separate data file (e.g. Excel).

Stage 2-4 (Sarstedt *et al.*, 2011): for the remaining three stages a SAS-code was programmed based on Vickery's (2015) work. The code, together with comments to clarify its contents, is listed below in "Exhibit B1: SAS-code for omnibus test". The input data stem from the data file created in Stage 1 of the Sarstedt *et al.* (2011) procedure, which is also explained above.

Note that Sarstedt's *et al.* (2011) omnibus test can also be programmed in other software such as R or Gauss.

Exhibit B1: SAS-code for omnibus test

```
/* FAC-SEM USING PLS-SEM - SANDRA STREUKENS & SARA LEROI-WERELDS */
/* SASCODE FOR THE OTG TEST */

/*Start with reading the data file containing the bootstrap estimates of the model parameter
under study into SAS. The bootstrap results are generated using standard PLS-SEM software and
are subsequently saved in a separate file */


/* START OF THE CODE */

proc  iml ;
use Facsem;                                               /*Enter name of data file */
read all var {CELL01 CELL02 CELL03 CELL04} into xobs;    /*Read data into matrix format */
close Facsem;

/* USER-DEFINED MODULE NAMED FMOD(X) TO ENABLE SAS TO CALCULATE THE VARIANCE RATIO; SEE ALSO
EQUATION (13) SARSTEDT ET AL. (2011) */

start fmod(x);
        grandmean = x[:];       /*Grand mean scalar */
        n = nrow(x);            /*number of rows in data matrix (i.e, B in OTG test) */
        k = ncol(x);            /*number of columns in data matrix (i.e., G in OTG test */
        groupmean = x[:,];      /*Group mean; calculated for each of the G groups */

        SSB = (groupmean-grandmean)##2; /* Calculating SSB-The numerator of OTG test */
        SSB = SSB[+];

        SSW = (x-groupmean)##2;         /* Calculating SSW-The denominator of OTG test */
        SSW = SSW[+,];
        SSW = SSW[+];


        MSSB = (k*n*(1/(k-1)))*SSB;             /* F-value (variance ratio) computation */
        MSSW = (1/(n-1))*SSW;
        F=MSSB/MSSW;
        return (F);
        finish;

/* USER-DEFINED MODULE NAMED PERMUTEWITHINROWS */

        start PermuteWithinRows(m);             /* For more details see Vickery (2015) */
                colIdx = ranperm(1:ncol(m), nrow(m));
                f = (row(m)-1)*ncol(m);
                matIdx = f + colIdx;
                return( shape(m[matIdx], nrow(m)) );
                finish;

/*CALCULATING THE F-VALUE FOR THE ORIGINAL DATA FILE */

fobs = fmod(xobs);              /* Applies FMOD to original data */
print fobs;                     /* Shows you the output concerning the computed Fvalue */
call symputx('fobs',fobs);

/* GENERATING PERMUTATIONS AND CALCULATING THE ACCOMPANYING F-VALUES */

call randseed(12345);
B = 5000;                               /* Number of permutations */
fdist = j(B,1);                 /* Creation of vector containing the F-value for */
do      j = 1 to B;                     /* each of the permutations. In a later step this is */
        x = PermuteWithinRows(xobs);    /* also saved in a data file */
        F = fmod(x);
        fdist[j,] = F;
end;

/* COMPUTATION P-VALUE*/

pval = sum(fdist > abs(fobs)) / B;      /* Calculating the pvalue for the omnibus test */
print pval[label='P-value'];            /* Shows you the output concerning the computed Pvalue */
call symputx('p',pval);

/*CREATION OF DATASET */

create facsemotg var {fdist};           /* Creation of data file containing the F-value for */
append;                                 /* each of the permutations. Allows you to perform */
close facsemotg;                        /*additional (visual) inspections */

quit ;

/* AND YOU'RE DONE! */
```

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1. HenselerJörg Jörg Henseler Department of Design, University of Twente, Enschede, The Netherlands NOVA Information Management School, Universidade Nova de Lisboa, Lisbon, Portugal . 2016. Guest editorial. *Industrial Management & Data Systems* **116**:9, 1842-1848. [Citation] [Full Text] [PDF]

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