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# Confirmatory tetrad analysis in PLS path modeling

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**Abstract**

The authors propose a CTA-PLS assessment routine for measurement models. This routine applies confirmatory tetrad analysis (CTA) in a manner which is consistent with partial least squares (PLS) path modeling assumptions. The conceptualization employs a bootstrapping procedure to accomplish an appropriate statistical test examining vanishing tetrads in CTA-PLS. The approach allows distinguishing a formative indicator specification from a reflective indicator specification. Applications using experimental and empirical data demonstrate the usefulness and effectiveness of CTA-PLS. As a means of evaluating PLS path modeling results, the routine assists researchers in avoiding potentially unrepresentative consequences of measurement model misspecification.
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## 1. Reflective and formative measurement models in partial least squares path modeling

The partial least squares (PLS) path modeling methodology (Lohmöller, 1989) allows reflective and formative computations with respect to the measurement of latent variables. Although PLS path modeling represents a well-substantiated method for estimating complex cause–effect-relationship models in business research, limited work has been done on the assessment of the mode of measurement models in general, and the appropriateness of using formative measurement models in PLS path modeling in particular. Several tests for examining the reliability of reflective measurement models exist but the academic literature shows an inadequate emphasis on statistical methods that assist in evaluating formative measurement models and the manifest variables (indicators) that form those composite variables (i.e., indexes).

Formative measurement models (c.f. Diamantopoulos, 2006) come into use when an explanatory combination of indicator variables underlies the latent construct. Business research studies typically test formative indicator variables for their validity using theoretic rationale and expert opinion (e.g., Rossiter, 2002), while commonly examining reflective measures using a range of techniques of scale construction and measurement assessment including factor analysis (Spearman, 1904) and classical test theory (Lord and Novick, 1968). An evaluation of reflective measurement models concerns unidimensionality. However, this logic is to some extend inappropriate in the case of formative measurement models (Bollen and Lennox, 1991). In a similar vein, Diamantopoulos and Winklhofer (2001) point out that conventional procedures – which researchers commonly employ to examine the validity and reliability of measurement models of the reflective mode (e.g., confirmatory factor analysis and assessment of internal consistency) – are not suitable for the formative mode.

Much of the problem surrounding the absence of formative indicator testing is attributable to construct or measurement

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model misspecification (Jarvis et al., 2003). Misspecification of measurement models can bias inner model parameter estimation (e.g., Gudergan, 2005) and lead to incorrect assessments of relationships in PLS path modeling. The most suitable approach for avoiding misspecification for measurement models is to employ a-priori techniques such as Diamantopoulos and Winklhofer's (2001) approach to index construction, an examination of qualitative decision rules for determining whether a construct is formative or reflective (Jarvis et al., 2003), or the C-OAR-SE procedure (Rossiter, 2002), and to account for the commentary put forward by authors such as Diamantopoulos (2005), Finn and Kayande (2005), and Rossiter (2005), who provide additional insights into a-priori measurement model development.

Notwithstanding this theoretic foundation, few endeavors in the academic business literature stress techniques for statistically assessing the application of formative measurement models in PLS path modeling. For instance, authors such as Bucic and Gudergan (2004), Venaik et al. (2004), and Gudergan (2005) have applied Bollen and Ting's (1993) confirmatory tetrad analysis (CTA) for drawing conclusions about the appropriateness of using formative measurement models as compared to reflective measurement models. Within the context of those applications, the authors analyze the homogeneity of correlations among manifest variables in the measurement models to assist in making this determination. They also use CTA results to assess whether manifest variables in the measurement model are independent determinants of a latent variable rather than reflections of the latent construct in an effect indicator scale. In this manner, the application of CTA provides additional insights and represents a means for testing the mode of measurement models according to theoretical foundations with respect to empirical data (Rigdon, 2005).

This study provides both conceptual as well as practical guidelines for evaluating the appropriate application of outer models in PLS path modeling utilizing CTA. The general approach of this paper draws on (a) an initial theoretical indicator specification of latent variables as authors such as Diamantopoulos (1999, 2005), Diamantopoulos and Winklhofer (2001), Jarvis et al. (2003), and Rossiter (2002, 2005) suggest; (b) the CTA-PLS evaluation of measurement models applying CTA in a manner that is consistent with PLS path modeling assumptions; and (c) the straightforward application of the SmartPLS software application for PLS path modeling that includes the CTA-PLS module (Ringle et al., 2005). The focus of this paper is on the integrative evaluation of outer models and the application of the CTA-PLS module. This paper includes methodological advances that provide valuable insight assisting in evaluating the mode of measurement models and proposes an approach to distinguish formative indicators from reflective indicators.

## 2. Confirmatory tetrad analysis for measurement model evaluation in structural equation modeling

The covariance-based structural equations modeling (CBSEM; c.f. Diamantopoulos and Siguaw, 2000) methodology allows researchers to hypothesize and test a theory about relationships by taking measurement errors into account (Bollen, 1989). The structural model usually includes latent constructs which researchers do not directly observe and which they measure in terms of one or directly observable indicator variable. CTA facilitates the evaluation of cause–effect relationships for latent variables and their specification of indicators in measurement models. Referring to four indicator variables, a tetrad is the difference of the product of a pair of covariances and the product of another pair of covariances. The six covariances of four indicator variables permit formation of three tetrads:

$$\begin{aligned} \tau_{1234} &= \sigma_{12}\sigma_{34} - \sigma_{13}\sigma_{24}, \\ \tau_{1342} &= \sigma_{13}\sigma_{42} - \sigma_{14}\sigma_{32}, \quad \text{and} \\ \tau_{1423} &= \sigma_{14}\sigma_{23} - \sigma_{12}\sigma_{43}. \end{aligned} \tag{1}$$

While the construction of tetrads according to Eq. (1) requires four indicator variables at a time, CTA is also applicable to measurement models of more or less than four indicators as Bollen and Ting (1993) describe in detail. These authors propose the concept of vanishing tetrads using a covariance or correlation data matrix in CBSEM applications to complement standard procedures of model evaluation, and provide methods for selecting model-implied non-redundant vanishing tetrads, significance testing, and estimating the power of the test statistic. A vanishing tetrad equals zero and all model-implied non-redundant tetrads vanish in reflective measurement models (Bollen and Ting, 2000).

Bollen and Ting (2000) propose the use of CTA as a means to distinguish causal from effect indicators in measurement models of latent variables in CBSEM (CTA-SEM) by testing between the hypothesis $H_0$: $\tau=0$ and the alternative hypothesis $H_1$: $\tau\neq 0$. A non-significant test statistic supports $H_0$ involving consistency of the sample data with the vanishing tetrads implied by a reflective measurement model. In contrast, a significant test statistic supports $H_1$ that casts doubt on the effect indicator model in favor of the alternative cause indicator model. Researchers may reject this hypothesis at the conventional alpha level (type I error rate) but do not control committing a type II error (failure to reject $H_0$ when $H_1$ is true). Bollen and Ting (2000) provide several numerical examples that demonstrate the usefulness of CTA-SEM evaluation of measurement models to distinguish causal from effect indicators.

Applications of CTA macros (e.g., Ting, 1995; Hipp et al., 2005) support this statistical argument. They provide results for every single tetrad and their *t*-values of the Student's *t* distribution as well as $\chi^2$, *df* (degrees of freedom) and the *p* (probability)-value for the simultaneous vanishing tetrad test. The simultaneous tetrad test (Bollen, 1990) is consistent with and complements the CBSEM method by (1) providing a test of under-identified models, (2) comparing the fit of models that are not nested in the conventional likelihood ratio test, (3) not showing convergence problems since numerical minimization (starting from specific values) is not entailed, and (4) providing an assessment on the likelihood ratio test fit (Bollen and Ting, 1993). CTA, in its original conception, assumes continuous normal and non-normal observed variables. In the CBSEM context, Hipp and Bollen (2003) attend to the vanishing tetrad test for working with censored, ordinal, or dichotomous indicator variables.

## 3. Confirmatory tetrad analysis for measurement model evaluation in PLS path modeling

PLS path modeling (c.f. Falk and Miller, 1981; Lohmöller, 1989; Tenenhaus et al., 2005) represents a non-traditional alternative to CBSEM for structural equation modeling (Rigdon, 2005). However, compared to CBSEM (Fornell and Bookstein, 1982; Schneeweiß, 1991), Wold's (1982) PLS method of soft modeling is rather a different than an alternative statistical methodology for estimating these models. The PLS methodology rests on predictor specification (Wold, 1988) which adopts the assumptions for a linear conditional expectation relationship between independent and dependent variables in the inner and outer path models (Chin, 1998; Lohmöller, 1989). Given these properties, the vanishing tetrad test analysis also applies to PLS path modeling. The use of CTA in PLS (CTA-PLS), in principal, follows Bollen and Ting's (2000) confirmatory approach of testing model-implied vanishing tetrads and the application of CTA to help distinguish between formative and reflective measurement models in PLS path modeling. Although CTA-PLS uses a similar evaluation process, the approach differs from CTA-SEM for PLS methodological assumptions in both the single tetrad testing approach and the simultaneous tetrad testing procedure.

Firstly, CTA-PLS builds on the statistical test for every single model-implied vanishing tetrad. To overcome the limitations regarding distributional assumptions of the single tetrad test, CTA-PLS follows Bollen's (1990) suggestion and includes a bootstrapping routine. Asymptotic distribution theory justifies using bootstrap estimators for this test but requires some moment conditions and some degree of smoothness regarding the given statistic. The weakness of these assumptions underlying the bootstrapping approach does not restrict the distributions of the data to a special distributional family as, for example, normal distributions (Shao and Tu, 1995). The more general setting is what makes the bootstrapping approach suitable for testing the statistical significance of single vanishing tetrads in a way which is consistent with the assumptions underlying the PLS methodology (Tenenhaus et al., 2005). This kind of bootstrapping differs from the routine that Bollen and Ting (1998) present to generate a bootstrap distribution for their simultaneous tetrad test statistic $T$ to obtain the bootstrap probability value ($p$-value).

Secondly, results for the single non-redundant vanishing tetrad significance tests per measurement model provide a basis for deciding whether a reflective operationalization does not conform to the empirical data. A rejection of the reflective mode provides support for a formative indicator specification. As this analysis usually includes several single tetrads per measurement model, CTA-PLS involves the multiple testing problem (Miller, 1981). Bollen (1990) accounts for this problem by Bonferroni adjustments of the significance levels. The Bonferroni method assures that the familywise error rate does not exceed the level $\alpha$ for all $n$ desired tests. In compliance with PLS methodological assumptions, the non-parametric nature of the Bonferroni approach does not require certain assumptions about the data and the dependence between comparisons. Consequently, the method applies to almost any test statistic and multiple testing situation (e.g., for multiple tests based on individual confidence intervals).

The present research uses Bonferroni adjustments as a satisfactory means to address the multiple testing problem within the PLS path modeling context. However, "[a]n alternative simultaneous test of whether all tetrad differences strongly implied by the model are zero is possible" (Bollen, 1990, p. 89) and represents the methodological foundation for CTA-SEM evaluation (Bollen and Ting, 1993). The resultant test statistic, however, asymptotically approaches a $\chi^2$ distribution with the degrees of freedom equal to the number of tested tetrads. This test criterion builds on asymptotic theory which, in contrast to PLS path modeling, is in compliance with CBSEM approaches. "Unlike conventional SEM, PLS does not aim to test a model in the sense of evaluating discrepancies between empirical and model-implied covariance matrices. Eschewing assumptions about data distributions or even sample size, PLS does not produce an overall test statistic like conventional SEM's $\chi^2$." (Rigdon, 2005, p. 1935). Moreover, Ting (1995) outlines a note of caution regarding asymptotic theory. For instance, the asymptotic distribution-free estimator requires very large sample sizes so that the asymptotic properties are an appropriate approximation of finite samples. Bollen and Ting (1998) showed that the sampling distribution of the test statistic can significantly deviate from $\chi^2$ when samples' sizes are small. These authors present a bootstrap estimation of the $p$-value for their simultaneous tetrad test statistic $T$ and demonstrate that "the bootstrap distribution of the vanishing tetrad test statistic provides a useful check on the results using the $\chi^2$ distribution for calculating $p$ values" (Bollen and Ting, 1998, p. 100) – an approach that Johnson and Bodner (2007) further elaborated.

In consideration of PLS path modeling assumptions, aspects of general applicability for hypothesis testing, and simplicity of routines, CTA-PLS follows Bollen's (1990) suggestions. More specifically, the routine includes the single-stage Bonferroni method to compute simultaneous confidence intervals for multiple tetrad tests. "When a confidence interval for a difference does not include zero, the hypothesis that the difference is zero is rejected. Testing with confidence intervals has the advantage that they give more information by indicating the direction and something about the magnitude of the difference or, if the hypothesis is not rejected, the power of the procedure can be gauged by the width of the interval" (Shaffer, 1995, p. 575). The use of multiple tetrad tests has some limitations in comparison with the alternative simultaneous testing routine. For example, the latter is more powerful. The use of multiple tests in this study, however, is more conservative and reliably rejects $H_0$. Miller (1986) supports this notion and points out that only when the test does not reject the null hypothesis a detailed analysis employing a test with greater power might be useful. Conservative testing routines can correctly depict if a statistical test is significant or not significant for a given $\alpha$ level. In the latter situation, more elaborated and powerful testing routines will unlikely produce significant results. Detailed analyses by tests with higher power might be useful in those very few situations in which results are insignificant but appear to be "almost" significant. However, modifications of the Bonferroni approach for gaining power in multiple testing, for example the Holm (1979) or the Hochberg (1988) procedure, provide the same conclusions when evaluating the mode of a measurement model via model implied non-redundant vanishing tetrads.

Although the routines differ, the systematic application of CTA-PLS for the assessment of measurement models is similar to the one for CTA-SEM (Bollen and Ting, 2000). CTA-PLS involves the following steps:

1. Form and compute all vanishing tetrads for the measurement model of a latent variable.
2. Identify model-implied vanishing tetrads.
3. Eliminate redundant model-implied vanishing tetrads.
4. Perform a statistical significance test for each vanishing tetrad.
5. Evaluate the results for all model-implied non-redundant vanishing tetrads per measurement model by accounting for multiple testing issues.

Step 1 involves the selection of the measurement model for CTA evaluation and computation of the vanishing tetrads. Four manifest variables in a measurement entail a set of three vanishing tetrads (Eq. 1). A measurement model that includes five manifest variables entails five different combinations of four variables and each of these sets involves three vanishing tetrads resulting in a total of fifteen vanishing tetrads. In general, $n!/(n-4)!4!$ sets of four variables, each resulting in three vanishing tetrads, exist for measurement models with $n$ manifest variables. Measurement models with less than four manifest variables require an inclusion of indicators from another latent variable to form a set of four manifest variables to carry out CTA-PLS. The procedure follows the precise description which Bollen and Ting (1993) provide. In contrast to CBSEM, PLS path modeling does not account for certain kinds of covariances in the model structure, for example covariances of error terms of manifest variables in a reflective measurement model, that result in a lower number of model-implied vanishing tetrads in CTA-SEM. For this reason, CTA-PLS implies all vanishing tetrads for a reflective measurement model with four and more manifest variables. In accordance with Bollen and Ting's (1993, 2000) explications and with respect to PLS methodological assumptions, a reduction of the number of vanishing tetrads in CTA-PLS predominantly ensues for latent variables that have two manifest variables in a reflective measurement model. However, the expectations for formative indicator specifications are different: None of the tetrads shall vanish in formative measurement models. Table 1 presents examples for the measurement of a latent variable (within a PLS path model) that includes four or less reflective or formative indicators and its particular model-implied vanishing tetrads in CTA-PLS.

In Step 3 of CTA-PLS, algebraic substitution allows excluding all redundant model-implied vanishing tetrads from the analysis (Bollen and Ting, 1993). This redundancy exists, for example, whenever the same pair of variances appears in two model-implied vanishing tetrads. Elimination of those redundant tetrads considerably improves the performance of Step 4 and is necessary for Step 5. In Step 4, for every single model-implied non-redundant vanishing tetrad CTA-PLS determines whether the value is significantly different from zero. Several authors (e.g., Kenny, 1974; Spearman and Holzinger, 1924; Wishart, 1928) have proposed appropriate statistical tests for this assessment but all of them require a multivariate normal distribution for the observed variables (Bollen, 1990). This assumption is not consistent with the non-parametric character of PLS. For this reason, statistical significance tests for evaluating PLS path modeling results employ a bootstrapping procedure (Chin, 1998). To introduce an appropriate statistical test for vanishing tetrads, CTA-PLS follows one of Bollen's (1990) suggestions and utilizes a bootstrapping routine on raw data (Davison and Hinkley, 1997). This method complies with the approach for evaluating the significance of PLS estimates for path coefficients (Tenenhaus et al., 2005). Generating a sufficient number of bootstrap subsamples (e.g., 5000), and computing their relevant tetrads allows obtaining the bootstrap estimated standard error (se) for every tetrad ($\tau$) and the $t$-value of the Student's $t$ distribution ($t$-value$=\tau/$se). The null hypothesis is $H_0$: $\tau=0$ and a $t$-value (two-tailed test) above or

Table 1
Examples for the selection of model-implied vanishing tetrads

| | $\xi_1$ | | Model-implied vanishing tetrads |
|---|---|---|---|
| Latent variable $\xi_1$ and a measurement model with four manifest variables | Reflective | | $\tau_{1234}$, $\tau_{1342}$, $\tau_{1423}$ |
| | Formative | | None |
| | $\xi_1$ | $\xi_2$ | Model-implied vanishing tetrads |
| Latent variable $\xi_1$ with three manifest variables and latent variable $\xi_2$ with one manifest variable in the measurement model; for a path relationship from $\xi_1$ to $\xi_2$ (and the reverse case) | Reflective | Reflective | $\tau_{1234}$, $\tau_{1342}$, $\tau_{1423}$ |
| | Reflective | Formative | None |
| | Formative | Reflective | None |
| | Formative | Formative | None |
| | $\xi_1$ | $\xi_2$ | Model-implied vanishing tetrads |
| Latent variables $\xi_1$ and $\xi_2$ each with two manifest variables in the measurement model; for a path relationship from $\xi_1$ to $\xi_2$ (and the reverse case) | Reflective | Reflective | $\tau_{1342}$ |
| | Reflective | Formative | $\tau_{1342}$ |
| | Formative | Reflective | $\tau_{1342}$ |
| | Formative | Formative | None |

below a critical value for the conventional $\alpha$ level supports rejection of the null hypothesis.

The statistical test builds on a test statistic $T$ which measures the discrepancy between the data and the null hypothesis. The significance probability $p=\Pr(T \geq t \mid H_0)$ measures the level of evidence against $H_0$: $\theta=\theta_0$ whereby $t$ denotes the value of the observed test statistic. An application of the bootstrapping procedure for single tetrad tests, however, needs to account for the distribution of $T$ under $H_0$ which is the null distribution of $T$. This distribution provides the basis for determining the $p$-value. When the null distribution is unknown, an assumption that the test statistic is asymptotically normal is common. Bootstrapping provides a non-parametric alternative but must account for the problem that the generation of the data follows the alternative hypothesis $H_1$: $\theta \neq \theta_0$. An examination of the statistical correspondence between tests of significance and confidence intervals when the null hypothesis concerns a particular parameter value allows addressing this problem. Bootstrapping confidence intervals is an appropriate approach for this purpose (Davison and Hinkley, 1997; Efron and Tibshirani, 1993). The corresponding approximate $1-\alpha$ (two-tailed) confidence interval for the bootstrap estimates of bias ($b_B$) and variance ($v_B$) is

$$t - b_B \pm v_B^{1/2} z_{1-\alpha/2}. \qquad (2)$$

Only if the corresponding $(1-\alpha)$ confidence interval includes (or does not include) the parameter value $\theta_0$, an acceptance (or rejection) of a null hypothesis $H_0$: $\theta=\theta_0$ at a given level $\alpha$ is adequate. The bias correction of the bootstrap confidence interval in Eq. (2) provides an appropriate means to test the model-implied non-redundant vanishing tetrads in CTA-PLS.

Step 5 concludes with an assessment of the conformity of a reflective indicator specification with the empirical data. A reflective measurement model does not conform to the empirical data if at least one of the model-implied vanishing tetrads is significantly different from zero. CTA-PLS employs a procedure for testing $n$ hypotheses $H_1$, $H_2$..., $H_i$ with test statistics $T_1$, $T_2$..., $T_i$ for a single measurement model. Each single tetrad test bases on an experiment-wise significance level that is smaller than a specific value $\alpha$. A multiple tetrad testing problem, however, exists in that some of the tests might be significant by chance (Glymour et al., 1987, p. 103). Thus, to account for multiple testing issues, the probability of rejecting the null hypothesis requires adjustment. "Perhaps the simplest correction for this problem is a *Bonferroni* adjustment" (Bollen, 1990, p. 88), which consists of rejecting $H_i$, for any $i=1,\ldots, n$, if the associated test statistic $T_i$ is significant at the $\alpha'=\alpha/n$ adjusted level of the test, where $n$ is the number of hypotheses to be tested. "If we have, for example, 10 vanishing tetrads to test, and we wish the $\alpha$ level for the group of hypotheses to be maintained at no more than a 0.05 significance level, then for each individual test we should use a critical value that corresponds to an $\alpha$ level of 0.005 (=0.05/10)" (Bollen, 1990, p. 88). CTA-PLS uses the Bonferroni method to address multiple testing issues and, thereby, adjusts the $\alpha$ level of the confidence intervals for testing the model-implied vanishing in Eq. (2). The procedure concludes with a sensitivity analysis which provides additional assurance that the tetrad substitution does not affect the initial statistical test results and, thus, a reliable foundation for evaluating the analytical results (Bollen and Ting, 2000).

## 4. CTA-PLS application using simulated data

A primary application of CTA-PLS to evaluate the mode of measurement models in PLS path modeling employs a set of simulated data. Albers and Hildebrandt (2006) present the experimental design which underlies this part of the study. These authors use simulated data for a PLS path model with predetermined relationships in the inner model (Fig. 1) and a correlation matrix (Table 2) with the following pattern:

- Manifest variables A1, A2, and A3 have high correlations while A4 and A5 each have rather low correlations with all other manifest variables in the measurement model of latent variable A. However, A4 and A5 (A1, A2 and A3) have significant (insignificant) correlations with the manifest variables in the outer models of the latent endogenous variables E1 and E2.
- A similar pattern holds for the measurement model of the latent exogenous variable B. Here, the manifest variables B4 and B5 have a high correlation value while the correlations of these variables with the indicators of the latent variables E1 and E2 are at a level which is close to zero. In contrast, B1, B2, and B3 each have low correlation values with all other manifest variables in this measurement model as well as with the manifest variables of E1 and significant correlations with the manifest variables of E2.
- The manifest variables in the measurement model of latent variable C have relatively low to moderate correlations. Here, the correlations of all five manifest variables with the indicators of latent variable E2 (E1) are at a moderate level (at a level which is close to zero).

The analytical purposes of this study require a modification of the original correlation matrix. Absolute correlation values of manifest variables in the outer models below 0.1 become subject to a systematical increase in their absolute value by 0.1

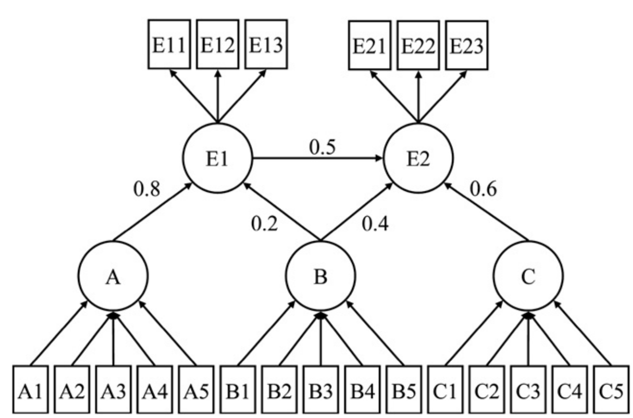


Fig. 1. PLS path model for the experimental CTA example.

Table 2
Correlation of manifest variables

| | A1 | A2 | A3 | A4 | A5 | B1 | B2 | B3 | B4 | B5 | C1 | C2 | C3 | C4 | C5 | E11 | E12 | E13 | E21 | E22 | E23 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A1 | 1.00 | | | | | | | | | | | | | | | | | | | | |
| A2 | 0.71 | 1.00 | | | | | | | | | | | | | | | | | | | |
| A3 | 0.72 | 0.65 | 1.00 | | | | | | | | | | | | | | | | | | |
| A4 | 0.18 | 0.14 | 0.19 | 1.00 | | | | | | | | | | | | | | | | | |
| A5 | −0.11 | −0.15 | −0.12 | 0.15 | 1.00 | | | | | | | | | | | | | | | | |
| B1 | 0.02 | 0.03 | −0.06 | 0.06 | −0.03 | 1.00 | | | | | | | | | | | | | | | |
| B2 | −0.02 | 0.03 | 0.08 | 0.08 | −0.02 | 0.13 | 1.00 | | | | | | | | | | | | | | |
| B3 | −0.11 | −0.12 | −0.06 | 0.00 | 0.02 | −0.11 | 0.15 | 1.00 | | | | | | | | | | | | | |
| B4 | −0.13 | −0.13 | −0.09 | −0.05 | 0.01 | 0.16 | −0.15 | 0.20 | 1.00 | | | | | | | | | | | | |
| B5 | −0.08 | −0.05 | −0.02 | −0.04 | 0.01 | −0.11 | 0.18 | 0.16 | 0.56 | 1.00 | | | | | | | | | | | |
| C1 | 0.02 | −0.03 | 0.00 | 0.06 | 0.00 | −0.02 | 0.07 | 0.10 | −0.05 | −0.06 | 1.00 | | | | | | | | | | |
| C2 | 0.01 | 0.07 | −0.01 | 0.03 | 0.12 | −0.03 | −0.05 | −0.02 | 0.06 | −0.01 | 0.12 | 1.00 | | | | | | | | | |
| C3 | −0.05 | 0.04 | −0.06 | 0.07 | 0.00 | 0.07 | 0.02 | 0.01 | 0.01 | −0.04 | 0.24 | 0.57 | 1.00 | | | | | | | | |
| C4 | 0.03 | 0.07 | −0.02 | 0.10 | 0.06 | −0.02 | −0.04 | 0.02 | 0.00 | −0.05 | 0.29 | 0.49 | 0.53 | 1.00 | | | | | | | |
| C5 | 0.03 | 0.05 | 0.01 | −0.01 | 0.01 | 0.05 | −0.02 | 0.00 | −0.02 | −0.01 | 0.13 | 0.20 | 0.29 | 0.27 | 1.00 | | | | | | |
| E11 | 0.06 | 0.06 | 0.05 | 0.54 | 0.61 | 0.15 | 0.14 | 0.19 | −0.02 | 0.01 | 0.08 | 0.08 | 0.03 | 0.06 | −0.02 | 1.00 | | | | | |
| E12 | 0.00 | 0.02 | 0.00 | 0.54 | 0.51 | 0.19 | 0.11 | 0.16 | 0.04 | 0.01 | 0.10 | 0.04 | 0.02 | 0.04 | −0.01 | 0.85 | 1.00 | | | | |
| E13 | 0.08 | 0.06 | 0.08 | 0.54 | 0.58 | 0.09 | 0.14 | 0.15 | 0.01 | 0.04 | 0.11 | 0.01 | 0.00 | 0.03 | 0.00 | 0.89 | 0.83 | 1.00 | | | |
| E21 | 0.06 | 0.07 | 0.04 | 0.33 | 0.30 | 0.29 | 0.31 | 0.36 | 0.02 | 0.04 | 0.33 | 0.37 | 0.39 | 0.42 | 0.32 | 0.58 | 0.53 | 0.55 | 1.00 | | |
| E22 | 0.00 | 0.01 | 0.01 | 0.31 | 0.28 | 0.26 | 0.31 | 0.40 | 0.06 | 0.09 | 0.29 | 0.35 | 0.38 | 0.35 | 0.34 | 0.54 | 0.51 | 0.52 | 0.83 | 1.00 | |
| E23 | 0.05 | 0.05 | 0.01 | 0.35 | 0.35 | 0.29 | 0.31 | 0.40 | 0.03 | 0.07 | 0.35 | 0.37 | 0.41 | 0.39 | 0.36 | 0.63 | 0.57 | 0.58 | 0.88 | 0.86 | 1.00 |

(e.g., 0.08 to 0.18 or −0.01 to −0.11). This modification is important because neither CTA-SEM nor CTA-PLS are applicable for correlations or covariances close to zero in the measurement model (Bollen and Ting, 2000). The CTA-PLS results report of SmartPLS provides the percentage of correlations with an absolute value of 0.1 or lower in a specific measurement model. Experience cautions against the use of CTA-PLS to assess a measurement model if more than three out of twenty relevant correlations are at an absolute value level of 0.01 or less.

The SEPATH module of STATISTICA 7.1 (StatSoft, 2005) generates data (300 cases) for manifest variables in compliance with the given inner model relationships and the correlations of manifest variables. Table 3 shows PLS path modeling outcomes of the SmartPLS software application (Ringle et al., 2005) which principally represent a replication of the results in Albers and Hildebrandt's (2006) study.

The objective of applying CTA-PLS is to evaluate whether the theoretical assumptions for PLS model estimations are consistent with the data. Specifically, the results from CTA-PLS assist in assessing the measurement model of latent variables with respect to the experimental data. According to a-priori assumptions and the correlation pattern, the latent exogenous variables (A, B, and C) have a formative measurement model whereas those of the latent endogenous variables (E1 and E2) are reflective in this numerical example.

An implementation of CTA-PLS within the SmartPLS software provides the basis for computing relevant statistics. Table 4 presents the results of CTA-PLS computations (5000 bootstrap subsamples) using the simulated data. Testing the mode of the measurement models at a given $\alpha=0.1$ level requires adjustments of the single model-implied non-redundant tetrad bootstrap (two-tailed) confidence intervals for multiple testing issues. At least for one of these tetrads in each of the measurement models of the latent exogenous variables, the Bonferroni-adjusted confidence interval does not include the parameter value of the null hypothesis ($H_0$: $\tau=0$). The CTA-PLS evaluation rejects $H_0$ for these tetrads and, thus, cannot

Table 3
PLS path modeling results for experimental data

| Manifest variables | Mode of outer models | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Reflective (loadings) | | | | | Formative (weights) | | | Reflective (loadings) | |
| | A | B | C | E1 | E2 | A | B | C | E1 | E2 |
| A1 | 0.50 | | | | | 0.08 | | | | |
| A2 | 0.45 | | | | | 0.15 | | | | |
| A3 | 0.52 | | | | | 0.11 | | | | |
| A4 | 0.71 | | | | | 0.67 | | | | |
| A5 | 0.61 | | | | | 0.67 | | | | |
| B1 | | 0.47 | | | | | 0.57 | | | |
| B2 | | 0.63 | | | | | 0.46 | | | |
| B3 | | 0.68 | | | | | 0.63 | | | |
| B4 | | 0.09 | | | | | 0.09 | | | |
| B5 | | 0.08 | | | | | 0.05 | | | |
| C1 | | | 0.55 | | | | | 0.44 | | |
| C2 | | | 0.71 | | | | | 0.25 | | |
| C3 | | | 0.81 | | | | | 0.21 | | |
| C4 | | | 0.79 | | | | | 0.20 | | |
| C5 | | | 0.51 | | | | | 0.44 | | |
| E11 | | | | 0.97 | | | | | 0.97 | |
| E12 | | | | 0.94 | | | | | 0.94 | |
| E13 | | | | 0.96 | | | | | 0.96 | |
| E21 | | | | | 0.95 | | | | | 0.95 |
| E22 | | | | | 0.94 | | | | | 0.94 |
| E23 | | | | | 0.96 | | | | | 0.96 |

| Latent variable | Inner model weights | |
|---|---|---|
| A→E1 | 0.80 | 0.85 |
| B→E1 | 0.18 | 0.17 |
| B→E2 | 0.44 | 0.43 |
| C→E2 | 0.57 | 0.58 |
| E1→E2 | 0.47 | 0.46 |

Table 4
CTA-PLS results for experimental data

| Model-implied non-redundant vanishing tetrad | Residual value | Bootstrap $t$-value | CI [a] | $\rho_c$ | Max. VIF | Percentage of absolute correlation values below 0.1 |
|---|---|---|---|---|---|---|
| $\tau_{A,1234}$ | 0.07 | 1.51 | [0.17; −0.03] | 0.70 | 3.05 | 0.00 |
| $\tau_{A,1243}$ | 0.07 | 1.91 | [0.15; −0.01] | | | |
| $\tau_{A,1235}$ | 0.12 | 2.37 | [0.24; 0.01] | | | |
| $\tau_{A,1352}$ | −0.06 | −1.48 | [0.04; −0.17] | | | |
| $\tau_{A,1345}$ | 0.06 | 1.04 | [0.19; −0.07] | | | |
| $\tau_{B,1234}$ | 0.01 | 0.35 | [0.06; −0.04] | 0.40 | 1.51 | 0.00 |
| $\tau_{B,1243}$ | 0.01 | 0.70 | [0.06; −0.03] | | | |
| $\tau_{B,1235}$ | 0.00 | 0.23 | [0.03; −0.02] | | | |
| $\tau_{B,1352}$ | −0.01 | −0.75 | [0.02; −0.04] | | | |
| $\tau_{B,1345}$ | −0.04 | −2.59 | [−0.01; −0.08] | | | |
| $\tau_{C,1234}$ | −0.07 | −1.97 | [0.01; −0.15] | 0.81 | 1.59 | 0.00 |
| $\tau_{C,1243}$ | −0.15 | −3.42 | [−0.05; −0.25] | | | |
| $\tau_{C,1235}$ | −0.02 | −1.11 | [0.03; −0.07] | | | |
| $\tau_{C,1352}$ | −0.06 | −1.71 | [0.02; −0.15] | | | |
| $\tau_{C,1345}$ | −0.06 | −2.01 | [0.01; −0.12] | | | |
| $\tau_{E1,1234}$ | −0.01 | −0.42 | [0.02; −0.03] | 0.97 | 6.32 | 0.00 |
| $\tau_{E1,1243}$ | −0.02 | −0.75 | [0.03; −0.07] | | | |
| $\tau_{E2,1234}$ | 0.02 | 0.78 | [0.08; −0.04] | 0.96 | 5.59 | 0.00 |
| $\tau_{E2,1243}$ | −0.01 | −0.40 | [0.02; −0.04] | | | |

[a] Adjustment of the 90% bias corrected bootstrap (two-tailed) confidence interval (CI) limits uses the Bonferroni method to account for multiple testing issues.

substantiate the reflective measurement of latent variables A, B, and C. This result provides support for the formative mode which complies with the design of the experiment. A sensitivity check that consists of ten additional CTA-PLS analyses with alternative orders of variables in the correlation matrices for each measurement model confirms the previous finding. Furthermore, the maximum variance inflation factor (VIF) in the measurement models does not reach a critical value which is an important issue to avoid multicollinearity problems when selecting the formative mode. However, the composite reliability $\rho_c$, one of the key evaluation criteria for the reflective mode in PLS path modeling (Chin, 1998), is above the critical value of 0.7 for the latent constructs A and C and, thus, affirms a reliable reflective measurement. This finding provides further evidence for the usefulness of CTA-PLS as an additional evaluation procedure for PLS path modeling results to uncover potential measurement model misspecifications.

Each latent variable E1 and E2 has three indicators in a reflective measurement model. In both cases, CTA-PLS analyses the mode of the measurement model by using one manifest variable from the measurement model of the other latent variable. According to the results of this evaluation (Table 4), drawing on 5000 bootstrap subsamples and a subsequent sensitivity analysis, the $H_0$ parameter value is within the bias-corrected and Bonferroni-adjusted bootstrap confidence intervals for all model-implied non-redundant vanishing tetrads (acceptance of $H_0$). The CTA-PLS evaluation provides support for reflective measurement models of latent variables E1 and E2. This finding matches the design of the experimental data. The level of single outer loading, the composite reliability $\rho_c$, and VIF further support the conclusion from the CTA-PLS assessment.

In applying CTA-PLS to simulated data with an underlying experimental design, CTA-PLS reliably identifies the operationalizations of measurement models for latent exogenous variables. The results substantiate the appropriateness of CTA-PLS for evaluating whether or not empirical data support a formative indicator specification against a reflective indicator specification in PLS path modeling. In conclusion, CTA-PLS represents a complementary procedure for the catalogue of criteria for evaluating the mode of measurement models in PLS path modeling.

## 5. CTA-PLS application using empirical data

This illustration draws on the European customers satisfaction index (ECSI) which national studies for different product and service categories employ to assess customer satisfaction via similar PLS path models (e.g., Hackl and Westlund, 2000). The ECSI represents an adaptation of the Swedish customer satisfaction barometer (Fornell, 1992) and is compatible with the American customer satisfaction index (ACSI; Fornell et al., 1996). Tenenhaus et al. (2005) present the ECSI path model, which focuses on the mobile phone industry, and provide the empirical data for this CTA-PLS application. The inner path model includes seven latent variables. All outer models use a reflective indicator specification. Fig. 2 shows the path model and SmartPLS computational estimates.

The inner ECSI path model draws on existing theory (Fornell et al., 1996) and empirical substantiation. Notwithstanding those findings, this conception has been subject to continuous discussions and alterations (e.g., Johnson et al., 2001). Little debate concerns the mode of measurement models. While the

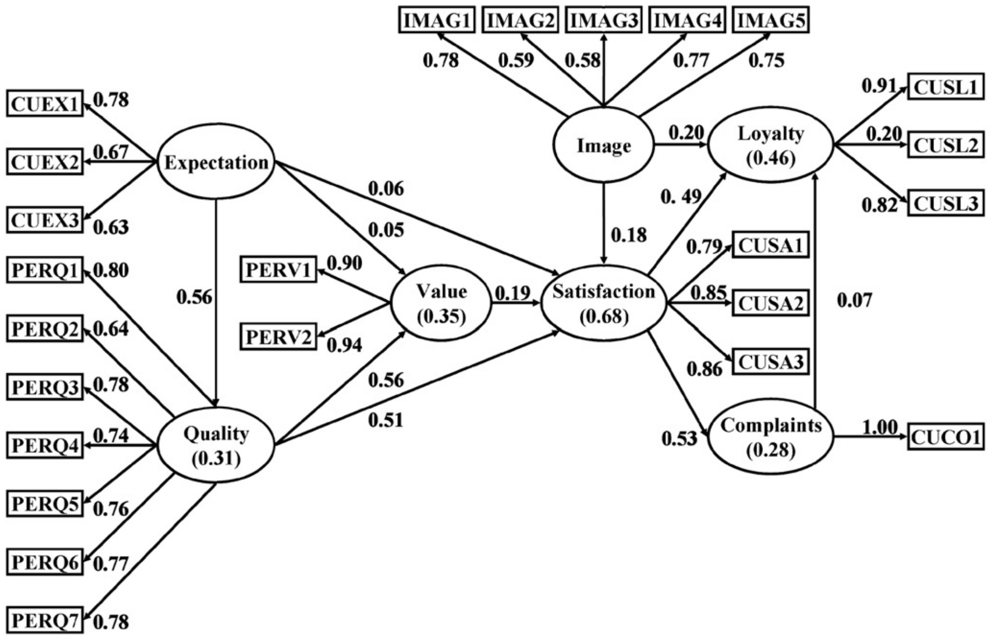


Fig. 2. ECSI example for mobile phone users.

reflective outer mode might be a reasonable operationalization in the initial ECSI model applications, their suitability is not unmistakable when one tests a potentially varied path model or applies altered manifest variables in similar or unrelated contexts. ECSI studies across divergent industries apply reflective measurement models (e.g., Eskildsen et al., 2004; Grønholdt et al., 2000) without addressing their appropriateness. This lack of consistency with regard to path model variation, manifest variable adaptation, and the research contexts suggests that ECSI studies require more reasoning with respect to the choice of reflective indicators to avoid measurement model misspecification (Jarvis et al., 2003). An evaluation of the outer relationships using CTA-PLS can assist in examining the theoretical assumptions with respect to the empirical data.

In the ECSI model on the mobile phone industry (Fig. 2), Complaints represents a single indicator construct. The outer relationship has a value of 1.00 regardless of whether the measurement model uses the formative or reflective mode. Thus, the CTA-PLS analysis does not include the latent variable Complaints. Moreover, each measurement model of the latent variables Expectation, Loyalty, Satisfaction, and Value includes less than four manifest variables. Thus, carrying out the CTA-PLS procedure requires adding manifest variables from measurement models of other latent variables and reducing the number of model-implied vanishing tetrads (Table 1). For example, with respect to the inclusion of manifest variables CUSA1 and CUSA2 in the measurement model of latent variable Value, the evaluation only uses a single model-implied vanishing tetrad.

Table 5 presents the results from the CTA-PLS computations (5000 bootstrap subsamples). For at least one model-implied non-redundant vanishing tetrad in each of the measurement models with one exception, the parameter value of $H_0$: $\tau=0$ is not in the bias-corrected 90% (two-tailed) Bonferroni-adjusted confidence interval. In these cases, CTA-PLS rejects $H_0$ and, thus, does not give evidence for the reflective measurement model specification. A sensitivity analysis confirms this finding. The only exception is the evaluation of the latent variable Loyalty. Correlations of 0.05, 0.10, and 0.54 among the three manifest variables are at least in one case too close to zero to reasonably apply CTA-PLS. The correlation pattern supports the assumption that the manifest variables are independent determinants which form the latent construct.

In contrast, an evaluation of the outer measurement results in this example using Chin's (1998) catalogue of criteria for PLS path modeling would support the reflective models. The composite reliability $\rho_c$, for example, is above the level of 0.7 for all latent variables. However, regarding the individual item reliability, the standardized loadings should be above 0.7. Only one indicator, CUSL2, in the measurement model of Loyalty does not fulfill these requirements. This manifest variable has an outer loading of 0.20 and is a candidate for omission in a scale purification process. However, before omitting manifest variables, one can carry out CTA-PLS analysis to reject or maintain the reflective measurement operationalization. As variance inflation is not at a critical level in any of the measurement models, the analysis entails an alteration of the initial assumptions in that the manifest variables represent formative cause indicators. Fig. 3 presents the revised path model and PLS estimates.

Two findings are evident with regard to the analysis. First, the inner path model estimates do not change significantly when all measurement models have a formative instead of a reflective mode. Second, contrary to a-priori assumption, the manifest variables appear to be cause indicators at distinctive levels in formative measurement models. This provides a foundation on which to analyze the particular relevance of each indicator to explain the latent variable. Most importantly, the peculiarities of

Table 5
CTA-PLS results for ECSI data

| Model-implied non-redundant vanishing tetrad | Residual value | Bootstrap $t$-value | CI [a] | $\rho_c$ | Max. VIF | Percentage of absolute correlation values below 0.1 |
|---|---|---|---|---|---|---|
| $\tau_{\text{Expectation},1234}$ | 0.22 | 0.69 | [0.84; −0.40] | 0.73 | 1.16 | 0.00 |
| $\tau_{\text{Expectation},1243}$ | 0.55 | 2.06 | [1.08; 0.04] | | | |
| $\tau_{\text{Image},1234}$ | 0.93 | 2.1 | [1.97; −0.09] | 0.82 | 1.51 | 0.00 |
| $\tau_{\text{Image},1243}$ | 1.15 | 2.52 | [2.24; 0.12] | | | |
| $\tau_{\text{Image},1235}$ | 0.51 | 1.54 | [1.29; −0.25] | | | |
| $\tau_{\text{Image},1352}$ | 0.20 | 0.54 | [1.10; −0.66] | | | |
| $\tau_{\text{Image},1345}$ | −0.39 | −1.16 | [0.40; −1.18] | | | |
| $\tau_{\text{Loyalty},1234}$ | 0.01 | 0.02 | [0.87; −1.35] | 0.71 | 1.43 | 0.17 |
| $\tau_{\text{Loyalty},1243}$ | −0.22 | −0.29 | [1.46; −1.47] | | | |
| $\tau_{\text{Quality},1234}$ | 0.17 | 0.56 | [1.01; −0.65] | 0.91 | 2.11 | 0.00 |
| $\tau_{\text{Quality},1243}$ | 0.65 | 2.15 | [1.47; −0.17] | | | |
| $\tau_{\text{Quality},1235}$ | 0.65 | 2.15 | [1.48; −0.15] | | | |
| $\tau_{\text{Quality},1352}$ | 0.14 | 0.56 | [0.80; −0.54] | | | |
| $\tau_{\text{Quality},1237}$ | 1.14 | 2.74 | [2.26; 0.02] | | | |
| $\tau_{\text{Quality},1245}$ | 0.49 | 1.90 | [1.18; −0.19] | | | |
| $\tau_{\text{Quality},1247}$ | 0.22 | 0.89 | [0.88; −0.44] | | | |
| $\tau_{\text{Quality},1257}$ | 0.44 | 1.71 | [1.14; −0.25] | | | |
| $\tau_{\text{Quality},1672}$ | −0.35 | −0.99 | [0.62; −1.28] | | | |
| $\tau_{\text{Quality},1346}$ | 0.43 | 0.93 | [1.69; −0.82] | | | |
| $\tau_{\text{Quality},1374}$ | −0.44 | −1.72 | [0.24; −1.13] | | | |
| $\tau_{\text{Quality},1356}$ | 0.02 | 0.10 | [0.53; −0.50] | | | |
| $\tau_{\text{Quality},1465}$ | −0.29 | −0.99 | [0.47; −1.08] | | | |
| $\tau_{\text{Quality},1467}$ | 0.05 | 0.29 | [0.55; −0.45] | | | |
| $\tau_{\text{Satisfaction},1234}$ | 0.78 | 2.22 | [1.51; 0.12] | 0.78 | 1.76 | 0.00 |
| $\tau_{\text{Satisfaction},1243}$ | 0.84 | 1.97 | [1.69; 0.02] | | | |
| $\tau_{\text{Value},1243}$ | 1.87 | 3.37 | [2.80; 0.97] | 0.92 | 1.96 | 0.00 |

[a] Adjustment of the 90% bias corrected bootstrap (two-tailed) confidence interval (CI) limits uses the Bonferroni method to account for multiple testing issues.

the CTA-PLS analysis of the empirical data can assist in developing persuasive explanations in situations where theoretical indicator specifications do not fit the observations. The ECSI data provide a suitable basis for analyzing whether the operationalization of manifest variables in the outer models is subject to misspecification or not. The criteria that Jarvis et al. (2003) suggest to determine whether a measurement model should have formative or reflective indicators are useful for this purpose. A persuasive example is the latent variable Quality that employs the following manifest variables (Tenenhaus et al., 2005, p. 162): a) "Overall perceived quality", (b) "Technical quality of the network", (c) "Customer service and personal advice offered", (d) "Quality of the services you use", (e) "Range of services and products offered", (f) "Reliability and accuracy of the products and services provided", (g) "Clarity and transparency of information provided". Consistent with an examination of decision rules for determining whether a construct is formative or reflective (Jarvis et al., 2003), these manifest variables are rather independent with defining characteristics that form the latent construct. Consequently, contrary to a-priori assumptions, the measurement model should use a formative indicator specification.

The application of CTA-PLS to this set of empirical data and path model demonstrates how the method can contribute to evaluating whether empirical data support a formative indicator specification against a reflective indicator specification in PLS path modeling. Contrary to the initial assumptions, based on the CTA-PLS results, the procedure suggests making an alteration to the measurement models from the reflective to the formative mode. In the example of the latent variable Quality, applying qualitative decision rules (Jarvis et al., 2003) to examine the underpinnings of the specifications provides ex post support for formative measurement models from a theoretical point of view.

## 6. Conclusion

This paper proposes an evaluation of measurement models applying CTA, in compliance with PLS path modeling assumptions, and demonstrates the application of CTA-PLS employing experimental as well as empirical data. The integrative CTA-PLS assessment is consistent with multivariate generalizability theory and offers a basis for drawing inferences about the two contending perspectives as well as for balancing conceptual rigor and empirical evaluation of the mode of measurement models. This approach for measurement model assessment in PLS path modeling includes three components: (a) an initial theoretical a-priori specification of the measurement model, (b) the integrative CTA-PLS evaluation of measurement

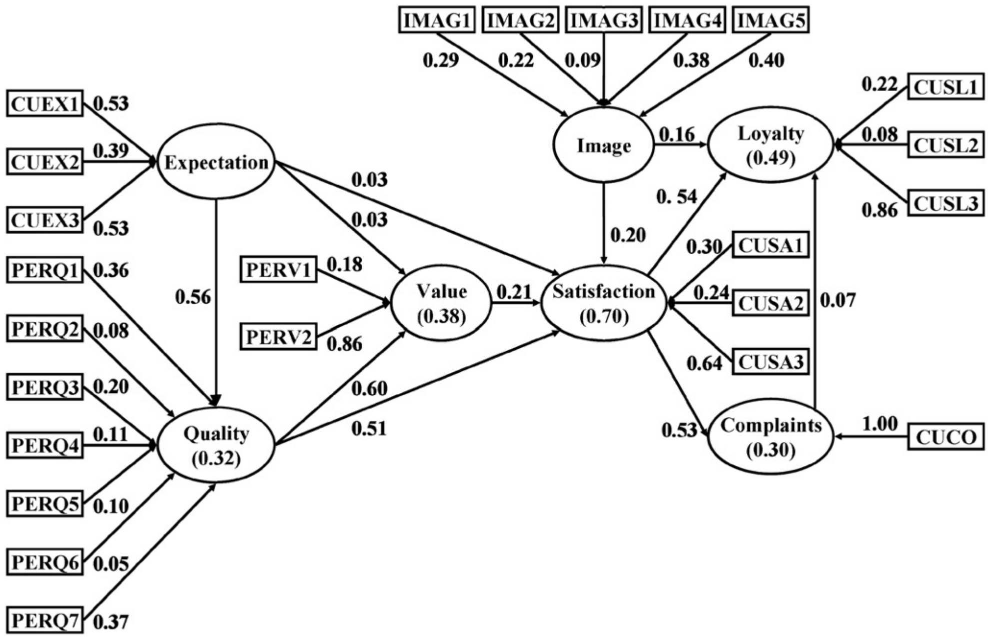


Fig. 3. Revised ECSI example for mobile phone users.

models applying CTA in a manner that is consistent with PLS path modeling assumptions, and (c) the straightforward application of the SmartPLS software that includes the CTA-PLS module.

Although CTA-PLS would typically follow an initial theoretical consideration to confirm or disconfirm the appropriateness of formative or reflective measurement models, the method might, however, also precede a posterior re-examination in a manner similar to the theoretical a-priori specification which may be undertaken to assess a possible misspecification of measurement models. A-priori theoretical specification and posterior re-examination along with empirical data are essential steps in understanding the structure of the measurement models. CTA-PLS can disconfirm the appropriateness of a reflective measurement model and, thus, can provide support for a formative indicator specification. But CTA-PLS does not include conclusive verification with respect to the completeness of the formative measurement model that covers the entire domain of the construct, meaning that the indicator variables should collectively represent all dimensions of the construct with no overlap. Notwithstanding, CTA-PLS represents a valuable approach to expand the statistical tests in PLS path modeling that, in particular, do not offer much support to evaluate the appropriateness of formative measurement models. The methodology allows substantiating the direction of outer relationships with respect to empirical data but switching the mode of measurement models (e.g., from a reflective one to a formative one) without further consideration, however, does not represent the concluding result of a CTA-PLS analysis, unless additional supporting theoretical or conceptual reasoning provides clarification.

CTA-PLS is similar in principle to the approach that Bollen and Ting (2000) propose for CTA-SEM and includes the following steps: (1) Form and compute all vanishing tetrads for the measurement model of a latent variable; (2) identify model-implied vanishing tetrads; (3) eliminate redundant model-implied vanishing tetrads; (4) perform a statistical significance test for each remaining vanishing tetrad; and (5) evaluate results by accounting for the relevant set of multitude tests. While comparable, the conceptualization of CTA-PLS in this paper differs from CTA-SEM in Step 2, in Step 4, and in Step 5. In Step 2, representing a minor variation, methodological assumptions noticeably reduce the range of possible model-implied vanishing tetrads in PLS path modeling. Step 4 involves a similar single tetrad significance assessment but contrary to the CTA-SEM procedure, CTA-PLS employs a bootstrapping routine to carry out an appropriate statistical test in the PLS methodological context. The bias corrected bootstrap (two-tailed) $1-\alpha$ confidence interval, which the Bonferroni method adjusts in order to account for multiple testing issues allows accepting or rejecting $H_0$ for every model-implied non-redundant vanishing tetrad at a given $\alpha$ level. The CTA-PLS approach is implemented as a new module in the software application SmartPLS (Ringle et al., 2005). Thereby, PLS path modeling offers a tetrad test for evaluating the mode of the measurement model, formative or reflective, as Bollen and Ting (2000) suggest.

The findings from both, the application of CTA-PLS to experimental data and to empirical data, demonstrate the usefulness of CTA within the context of PLS path modeling. To reiterate, imprudent minor or significant variations of path models, changes regarding the blocks of manifest variables and the direction of outer relationships without accounting for theoretical underpinnings as well as applications to alternative contexts can lead to an inappropriate utilization of measurement models and, consequently, require additional reasoning with respect to the choice of the reflective or formative mode to avoid measurement model misspecification. These issues become particularly relevant for explorative PLS path modeling analyses and those applications which lean on weak theoretical and conceptual grounds. Hence, the correct specifications of outer models in general, and formative ones in particular, are of great importance in PLS path modeling. The CTA-PLS approach provides a basis for assessing whether empirical data support a formative indicator specification against a reflective indicator specification. Consequently, this paper provides a contribution which can assist in avoiding measurement model misspecification and resultant issues that are critical for the interpretation of PLS path model estimations. This posterior re-examination following the CTA-PLS analysis, which "aims to test whether a prespecified model is consistent with a data set" (Rigdon, 2005, p. 1940), can build on Diamantopoulos and Winklhofer's (2001) approach to index construction, the criteria put forward by Jarvis et al. (2003), and Rossiter's (2002) C-OAR-SE procedure. Moreover, this research complements prior works regarding specification analysis and search for inner path model relationships in PLS (c.f. Marcoulides, 2003; Marcoulides and Drezner, 2003).

As a final point, future research may extend CTA-PLS beyond evaluating the mode of measurement models. An alternative simultaneous CTA test statistic (Bollen and Ting, 1998, 2000) allows evaluating the overall fit of model structures. Hence, the CTA test statistic could provide a method for testing the fit of a model that might also link PLS path modeling with CBSEM, even though the issue does not concern whether to use formative or reflective indicators. The simultaneous test statistic is consistent with and complements the CBSEM procedure and provides similar outcomes in comparison to the test statistic that results from CBSEM when applying the weighted least squares (WLS) method (Bollen and Ting, 1993). Besides discussing certain exceptions, Bollen and Ting (2000) use a numerical example to demonstrate that this consistency usually holds for the typical case of reflective measurement models. Unlike conventional CBSEM, PLS path modeling does not aim to test a model in the sense of evaluating discrepancies between empirical and model-implied covariance matrices. Eluding assumptions about data distributions or even sample size, PLS does not produce an overall test statistic like conventional SEM's $\chi^2$ (Rigdon, 2005). Future research can focus the issue of simultaneous tetrad testing within the PLS path modeling context. Advances in this area may provide a basis for using the overall CTA fit statistic as an extension to the limited number of criteria that are currently available for assessing PLS model fit. Thus, notwithstanding the usefulness of applying CTA within the PLS path modeling context to assist in assessing the formative or reflective mode of measurement models, further research into the relevance of the CTA test statistic within PLS could lead to developing a method for testing the fit of the path model.

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