Comparing Two Structural Equation Methods: An Investigation
Using The Consumer Involvement Profile (CIP)

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ABSTRACT

Research on involvement has been prolific over a thirty year period in marketing. Numerous definitions and measures for involvement have been constructed. This article focuses on replicating the Laurent and Kapferer’s Consumer Involvement Profile (CIP) [(Laurent and Kapferer, 1985)]. Analyses are undertaken with particular focus on using two structural equation methods, namely Covariance Based Structural Equation Modeling (CBSEM) and Partial Least Squares (PLS). The results are then discussed and the relative merits of both solutions are highlighted. It is concluded that for the data under study that PLS is considered a better technique to implement. PLS requires less stringent data distributional assumptions (Hulland, 1999), with the ability to handle more complex models (containing more variables) (Chin and Newsted, 1999) and overcomes common problems encountered with LISREL estimates such as estimator non-convergence and Heywood cases [negative unique variance estimates (Rindskopf, 1984)]. This study contributes to a growing literature on PLS being used as an alternative analysis option to LISREL when researchers’ experience some of the problems mentioned above (Fornell and Bookstein, 1982; Tenenhaus, Vinzi, Chatelin, and Lauro, 2005). The author argues that both tools are useful in the social researchers toolbox.

Keywords: involvement, CIP, Partial Least Squares, PLS, Structural Equation Modeling, LISREL

Introduction

This paper is written with the goal of analysing the CIP with two structural equation methods (CBSEM or PLS). This is to act as a basis for demonstration of the similarities and differences in the techniques and when each could be used. Firstly, the involvement literature is briefly reviewed. Secondly, the CBSEM and PLS modeling techniques are outlined. Thirdly, data is analysed using both methods. Finally, a discussion of the merits of both methods is conducted with reference to the data available for analysis.

The author acknowledges that the choice of methodology should be based on understanding each methods’ respective philosophical underpinning in keeping with the level of theoretical development in a discipline. Often a statistical method may need to be sensitive to the data collected being mindful of scaling and associated data problems that often can exist (multicollinearity, non-independence, missing data, nonnormality, etc).
Literature Review

Involvement is often viewed as a “property of the relationship between a person and a product category, rather than a specific possession (Ball and Tasaki, 1992:159).” It is generally accepted that the level of involvement is associated with the level of perceived personal relevance or importance of a specific product category to the customer (Zaichkowsky, 1985). Involvement has both intrinsic (enduring) and extrinsic (situational) elements (Richins and Bloch, 1986). Enduring involvement pertains to the accumulation of knowledge in long term memory compared with situational involvement which is much more temporal and influenced by the purchase situation (Richins and Bloch, 1986). The CIP (see figure 1) encompasses some aspects of both enduring involvement and situational involvement. The CIP consists of five first order factors/facets which are subsequently summed to form involvement profiles. The final CIP was developed to be a multidimensional measure of involvement. This was in keeping with previous studies that conceptualised involvement as being multidimensional in nature (Arora, 1982). The final five multi-faceted constructs are believed to represent antecedents of involvement (Day, Royne, Stafford, and Camacho, 1995; Zaichkowsky, 1994).

FIGURE 1: CONSUMER INVOLVEMENT PROFILE

The original CIP (Laurent and Kapferer, 1985) was a collection of 19 items (4 facets, not five
facets as shown in figure 1). Initial investigations using three samples with data collected via in-home interviewing and analysed using reliability and exploratory factor analysis found that the perceived risk/importance facet and probability of mispurchase were not distinct facets.

Discriminant validity was adequately demonstrated with low between construct intercorrelations. This was deemed satisfactory. The interest facet was not investigated in the initial 1985 study and was added after further research. The four facets in the Laurent and Kapferer (1985) article for the 14 product categories under investigation were presented as averages indexed to 100.

Further studies (Kapferer and Laurent, 1985; Kapferer and Laurent, 1986) refined the CIP by including the interest construct. This new structure was examined for validity and reliability with a sample of 1,568 including some 20 product categories. Nomological validity was supported by investigation of relationships with several dependent measures such as: level of extensive decision making, brand commitment, and reading articles (Bearden, Netemeyer, and Mobley, 1993). Subsequent studies have transformed the original Likert scale format into semantic differential formats (Jain and Srinivasan, 1990). However, the 5-point Likert version of scale is implemented in this study. The final CIP is a collection of 16 items that measure five first order constructs (see appendix 1).

A Critique of Two Approaches For Investigating Structural Relations

The use of structural equation modeling (SEM) has become increasingly popular with marketing researchers (Arnett, Laverie and Meiers, 2003; Bagozzi, 1978; Bove and Johnson, 2002; Coote, 1998; Coote, 2000; Grace and O'Cass, 2002). There has been a trend from the late 1980s towards greater use of confirmatory structural equation methods in involvement research (O'Cass, 1998). These methods allow for researchers to examine the "degree of correspondence between
measurements and concepts and at the same time takes this relationship into account in the test of substantive hypotheses (Bagozzi and Phillips, 1982: 46).” A key advantage of using SEM techniques is that it allows researchers to study the effects of measurement error (Hayduk, 1996; Schumacker and Lomax, 1996). There are two methods of investigating SEM’s’s (Vandenbosch, 1996). The first is Covariance Based Structural Equation Modeling (CBSEM) (Joreskog, 1971; Joreskog and Sorbom, 1996) or the LISREL model, and the other is PLS (Wold, 1973; Wold, 1974)\(^3\). Falk and Miller (1992) label each of the areas hard versus soft modeling. “The mathematics underlying the PLS system are rigorous, but the mathematical model is soft in the sense that it makes no measurement, distributional, or sample size assumptions (Falk and Miller, 1992: 3).”

PLS is similar to ordinary least squares regression, but being a components-based structural equations modeling technique (Lohmoller, 1989; Chin, Marcholin, and Newsted, 1996) it obtains estimates by simultaneously modeling the structural paths and measurement paths. CBSEM, on the other hand, aims to compare the differences between an algorithm estimated matrix with the observed sample covariance matrix from the data collected. It is the difference between the estimated and observed data matrices that indicates whether the implied model fits the data in question (Bollen, 1989).

**Overcoming Common Problems Experienced with CBSEM.**

PLS is often used instead of CBSEM techniques for many reasons. One benefit of PLS is that if correlations between the predictor variables are high (multicollinearity) implementing it can

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\(^2\) It is assumed that CBSEM methods, its estimators/principles are familiar to most readers. See (Bollen, 1989; Byrne, 2001; Hoyle, 1995; Kelloway, 1995; Kline, 1998) for a complete review.

\(^3\) Professor Herman Wold was Chair of the Department of Statistics at Uppsala University and he was Karl Joreskog’s PhD supervisor in the late 1960’s (Cudeck, 2001).
provide a solution (Fornell and Bookstein, 1982). Fornell and Bookstein (1982) firstly utilise CBSEM methods and, after coming to improper solutions (negative error variances and standardised loadings greater than 1), they choose to finish their analysis with PLS where the method is more data sensitive and subsequently converges to a solution. With a PLS solution they then highlight their structural model results concerning exit-voice theory. More recently, whilst studying mobile phone data for the European Customer Satisfaction Index (ECSI) Tenenhaus et al. (2005) analyse a reduced form of the full ECSI model (with less constructs included) to compare LISREL and PLS estimates due to LISREL non-convergence of the full ECSI model. It appears that LISREL may have limitations when researchers are investigating complex models with sample size constraints (Chin and Newsted, 1999). PLS is considered capable of explaining complex models (Chin, 1998; Fornell and Bookstein, 1982) and practically always converges (Wold, 1981). PLS is robust against deviations from the normal distribution (Cassel, Hackl, and Westlund, 1999). PLS also overcomes the factor indeterminancy problem of CBSEM (Fornell and Bookstein, 1982), can deal with smaller sample sizes (Wittingslow and Markham, 1999), is better able to cope with formative measures (Anderson and Gerbing, 1988), and does not rest on the assumption of observation independence (Falk and Miller, 1992).

Methodology

The data was collected by a national mail self-completion questionnaire using Marketing Pro (a national white pages directory with addresses) as the sample frame. Marketing Pro is a CD ROM

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4 It must be noted that author’s of such articles evidencing non-convergence problems do not outline the specific causes for non-convergence. This may be due to the numerous possible causes of such problems including: “(1) sampling fluctuations, (2) model misspecification to the extent that no factor analysis model will fit the data, and (3) “indefiniteness” (underidentification) of the model, (4) empirical underidentification (Rindskopf 1984) and (5) outliers/ influential cases. [as modified from (Chen, Bollen, Paxton, Curran, and Kirby, 2001:470)].”

5 Marketers often carry out attitudinal studies and run the same item battery sometimes many times for the same individual. Data is often then stacked for analysis. Eg. Each respondent rates five brands on the same scale (Aaker, 1995). This violates the independence of case assumption in CBSEM.
directory which consolidates 7 million residential listings, Australia wide. The sample was drawn using a random procedure. The product categories were selected after four pretests were completed involving expert opinion, two studies of undergraduate student product class mentions, and by analysing awareness and equity scores from the Australia Scan national survey (Callaghan and Wilson, 1998). The final categories chosen also considered such issues as: the product class having national distribution, product class familiarity, and whether the final product classes selected would provide a mix of different involvement levels. The product classes to be studied included: Cola Soft Drinks, Film, Airlines, Credit Cards, Credit Cards, Luxury Cars, and Athletics Shoes. Some may argue that selection of well-known product classes predisposes the results to be of a positive nature. However, it is expected that people will exhibit different product class involvement levels for different categories. If respondents have a good knowledge and experience of the products, they would be able to provide reliable and valid responses to the questionnaire items. The study received 645 usable questionnaires. The final response rate was 25.8%. The model was analysed using LISREL 8.54 (Joreskog and Sorbom, 2003) and PLS Graph 3.0 (Chin and Fry, 2004).

**Results**

Firstly, descriptive statistics were examined in SPSS 12 and PRELIS. These preliminary analyses revealed that the data had no sizable missing data problems or outliers (Hair, Anderson, Tatham, and Black, 1995). However, all variables were significantly non-normal. There was a positive skew and leptokurtic distribution to the data (Byrne and Campbell, 1999). One of the key assumptions of maximum likelihood in CBSEM is that the variables in the model need to be multivariate normal (Cortina, Chen, and Dunlap, 2001). Some authors suggest that maximum likelihood estimation is relatively robust against violations of normality (Boomsma, 1983;
Gerbing and Anderson, 1985) whilst others believe asymptotic distribution-free (ADF, WLS) (Browne, 1984) estimation should be implemented. Using ADF estimation is much more computationally intensive requiring larger sample sizes. In this case, the sample size is large enough under conventional rules (Steenkamp and van Trijp, 1991; Holmes-Smith and Rowe, 1994). The LISREL analyses were run using both ML and ADF estimators. The polychoric correlation matrix (ML and ADF) with asymptotic covariance matrix (ADF only) was used as the data input, as is typical when using these estimators (Rigdon and Ferguson Jr., 1991). The model was run as a Single 2nd order factor model (five uncorrelated 1st order factors converging into one 2nd order involvement factor) and also as a Saturated model (five correlated 1st order factors).

Successful convergence and inspection of satisfactory goodness of fit statistics would confirm the factorial structure of the CIP. These two models were run with both estimators (ML and ADF). An inspection of all of the results revealed the presence of negative unique error variances (Heywood Cases) in all solutions. Despite all other fit statistics being in acceptable ranges (Hoyle, 1995) the four solutions could not be utilised further without purification. These results are not surprising as CBSEM models are often affected by many factors such as: Heywood cases, an inability to converge to a solution, parameters that are outside reasonable limits, large standard errors of parameter estimates, and large correlations among parameter estimates (Rindskopf, 1984). The offending items producing negative error estimates were (RIS3) and (INT3). Rindskopf (1984: 118) states that, “negative error variance estimates are often the result of an attempt to compensate for large factor loadings.” The result revealed this trend with some loadings in the 0.90 range. Negative unique variance estimates are frequently encountered (Joreskog, 1967) in CBSEM. "It is well-known …, one third of the data yield one or more

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6 Minimum required sample size for use of ADF estimation \[1.5q(q+1)\] if \(q>12\), where \(q\) is the number of items. So if \(q=16\), \(1.5 \times 16 \times 17 = 408\) required sample size.
nonpositive estimates of the unique variances (Lee 1980: 313)” as modified from (Dillon, Mulani, and Kumar 1987:127). To help rectify these problems, the strategies of Dillon et al. (1987) were followed such as constraining the error variances to zero, a small positive value, and model reparameterisation through item deletion. All strategies did not solve the problem satisfactorily (often resulting in non convergence). Other fixes such as using ordinary least-squares or a generalised least-squares estimators were also implemented with the same results. Model respecification was attempted via merging factors together into a single involvement construct and a four-factor representation, however, it was not deemed prudent to proceed as this altered the conceptual representation of the original validated representation. It was believed that nonnormality could be the source of these improper solutions. Data transformations (log, square) of the original scale was not enacted as it could create interpretation difficulties.

Following the approach undertaken by other scholars (Fornell and Bookstein, 1982; Tenenhaus and al., 2005) PLS analysis was undertaken due to its ability to deal with nonnormal data. A hierarchical 2nd order repeated indicators model (Lohmoller, 1989:131) was estimated. In the repeated indicators approach, the item measures are used twice. The items are used once to represent the first-order constructs (product risk, symbolic value, etc.), and then again for measuring the second-order construct. The results of the PLS analysis are now discussed. All item loadings ranged between 0.599 and 0.917. Convergent validity is further supported by Average Variance Extracted (AVE) for all constructs exceeding 0.5 meaning that the amount of variance captured by the construct (through its items) is more than the amount of variance due to measurement error (Fornell and Larcker, 1981). The critical ratios from 500 bootstrap samples are all acceptable (>1.96, p<.05). All construct composite reliabilities (Werts, Linn, and Joreskog, 1974) were high ranging between 0.802 and 0.927. Discriminant validity was satisfied with all
correlations between composite constructs being lower than their respective reliability estimates (Gaski and Nevin, 1985). The structural coefficients were then investigated. All structural coefficients were significant except for Probability of Mispurchase. Further model modifications could consider this path/and construct being deleted from the final model. All other standardised beta coefficients linked to CIP are high (Product Risk/Importance $\beta=0.5177$; Symbolic Value $\beta=0.6130$; Hedonic Value $\beta=0.8416$; Enduring Interest $\beta=0.8308$). The average $R^2$ is 0.3448 indicating that CIP has significant strength in explaining variations in first order constructs. These results are quite positive and show the flexibility of using PLS to overcome CBSEM estimation difficulties. It should be noted that a weakness of PLS is that it has a tendency to underestimate structural parameter estimates. PLS performs better with more indicants per construct. “This implies caution against putting too much emphasis on PLS loadings when there are few indicators (Chin, Marcolin, and Newsted, 2003: 205).” However, the above stated problems have been negated somewhat due to the use of an adequate number of indicators representing both the 1st order constructs and the use of repeated indicators in the 2nd order CIP construct. A caveat of the presented results is that they provide evidence that the paths could exist (not definitive statistical tests of causal structure). However, the modeling approach is consistent with most structural equation modeling and especially suitable to the philosophy of “soft modeling” and its ability to process non-normal data (Falk and Miller, 1992).

Conclusions

PLS has been shown to be a very successful technique at modeling satisfaction (Fornell 1992; Johnson and Fornell, 1991), complaint behaviour (Fornell and Wernerfelt, 1988), retailing studies (Lee, 2000; O’Cass and Fenech, 2003) and marketing in general (White, Varadarajan, and Dacin, 2003). Using PLS appears a promising and very flexible approach to model testing in providing...
solutions when LISREL fails to come to meaningful solutions. This has been demonstrated with
this data set. Fornell and Bookstein (1982: 444) believe that poor LISREL estimates “suggest
several possibilities: (1) the theory is wrong, (2) the data are inaccurate, (3) the sample size is too
small, or (4) covariance structure analysis is not appropriate for this analysis task.” Previous
replication studies would suggest that (1) is unlikely (Kapferer and Laurent 1985; Laurent and
Kapferer 1985). It is a possibility that the data is inaccurate (2) and technically it should be tested
on split half samples or with a validation sample. The sample size (3) analysed was deemed
adequate by conventional standards. It is believed that that CBSEM was not satisfactory in this
case due to data distribution problems.

The use of involvement constructs in marketing models are many, with it often being used as a
mediator between relationships (Mitchell, 1979) and more often as a moderator (Homburg and
Giering, 2001) of relationships. The involvement construct has recently been modeled as an
antecedent in business research on loyalty and satisfaction using LISREL (Bennett, Härtel, and
McColl-Kennedy, 2005). Political opinion leadership is examined as part of a broader PLS model
of which voter involvement (O'Cass, 2002) was a construct significantly influencing opinion
leadership, subjective knowledge, and information seeking (O'Cass and Pecotich, 2005).
Involvement constructs will continue to have a central role in many research studies.

There are two notable limitations with this research. This study only investigates six product
classes which may have had an effect on reproducing the initial factor structure observed by
Laurent and Kapferer (1996). Although the selection of product classes is quite diverse from a
mix of category types, researchers are urged to consider selecting a larger product class set in
future studies. Furthermore, this cross sectional study does not prove causal sequence. Only an
experimental design or a longitudinal study can assist. Malhotra (1996), in a meta-analytic study
on statistical methods implemented in major marketing journals, illustrated that the use of structural equation methods had increased dramatically. It is this author’s belief that both CBSEM and PLS modeling methods will increasingly be implemented in marketing studies well into the future. Researchers will need a working knowledge of both in their research toolbox.

APPENDIX 1: CONSUMER INVOLVEMENT PROFILE QUESTION ITEMS

Following is a list of statements about [Product Category]. We would like to know how involved or interested you are in [Product Category] in general. Please indicate how much you agree or disagree by using a “1” to “5” scale where “1” means you “Totally Disagree” and “5” means to “Totally Agree”. You may use any number between 1 and 5. (“X” ONE BOX ONLY FOR EACH STATEMENT)

<table>
<thead>
<tr>
<th>Item</th>
<th>Statement</th>
<th>Totally Disagree</th>
<th>Agree</th>
</tr>
</thead>
<tbody>
<tr>
<td>RIS1</td>
<td>1. When you choose a product category, it is not a big deal if you make a mistake.*</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>RIS2</td>
<td>2. It is really annoying to purchase a product category that is not suitable</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>RIS3</td>
<td>3. If, after I bought a product category, my choice proves to be poor, I would be really upset.</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>PMIS1</td>
<td>4. Whenever one buys a product category, one never really knows whether it is the one that should have been bought.</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>PMIS2</td>
<td>5. When I face a choice over a number of product category, I always feel a bit at a loss to make my choice.</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>PMIS3</td>
<td>6. Choosing a product category is rather complicated.</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>PMIS4</td>
<td>7. When one purchases a product category, one is never certain of one’s choice.</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>SYM1</td>
<td>8. I can tell a lot about a person by the product category he or she chooses.</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>SYM2</td>
<td>9. The product category I buy gives a glimpse of the type of man/woman I am.</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>SYM3</td>
<td>10. The product category you buy tells a little bit about you.</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>HEDV1</td>
<td>11. It gives me pleasure to purchase a product category.</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>HEDV2</td>
<td>12. Buying a product category is like buying a gift for myself.</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>HEDV3</td>
<td>13. Product category are somewhat of a pleasure to me.</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>INT1</td>
<td>14. I attach great importance to product category.</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>INT2</td>
<td>15. One can say product category interest me a lot.</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>INT3</td>
<td>16. Product category are a topic that leaves me totally indifferent.*</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

* Denotes reverse scored items.

Bibliography


