TECHNICAL NOTE: Mediation analysis, categorical moderation analysis, and higher-order constructs modeling in Partial Least Squares Structural Equation Modeling (PLS-SEM): A B2B Example using SmartPLS

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Partial Least Squares Structural Equation Modeling (PLS-SEM) has gained acceptance as the 2nd generation multivariate statistical procedure for marketing research in recent years. Although there is a growing amount of literature utilizing this statistical procedure, researchers may still find reporting PLS-SEM results and designing advanced models difficult. This technical note is written to address such knowledge gap through a demonstration of a business-to-business (B2B) marketing example using SmartPLS. Advanced techniques such as mediation analysis, categorical moderation analysis, and higher-order constructs modeling are demonstrated in this paper.

Keywords: Partial Least Squares, PLS-SEM, SmartPLS, B2B Marketing, Mediation, Categorical Moderation, Higher-order Constructs

Introduction

Marketing researchers sometimes handle research projects that have small sample size and non-normal distributed data. For example, the project scope may involve soliciting feedbacks from female CEOs in multinational corporations where the number of participants is generally small. Garver and Mentzer (1999), and Hoelter (1983) proposed a critical sample size of 200 hence sample size of less than 200 is generally considered to be small. This issue of small sample size is particularly common in business-to-business (B2B) marketing research in which the participants are organizations such as manufacturers, wholesalers, retailers and government agencies. Traditional covariance-based structural equation modeling tools such as LISREL and AMOS may not be ideal for these research projects due to their strict data assumptions (Wong, 2010). Partial Least Squares Structural Equation Modeling (PLS-SEM) has emerged in recent years as a silver bullet to tackle this kind of data set because it can operate efficiently with small sample sizes (Reinartz, Haenlein, and Henseler, 2009) and avoid many of the restrictive data assumptions (Marcoulides & Saunders, 2006; Henseler, Ringle & Sinkovics, 2009; Wong, 2011).

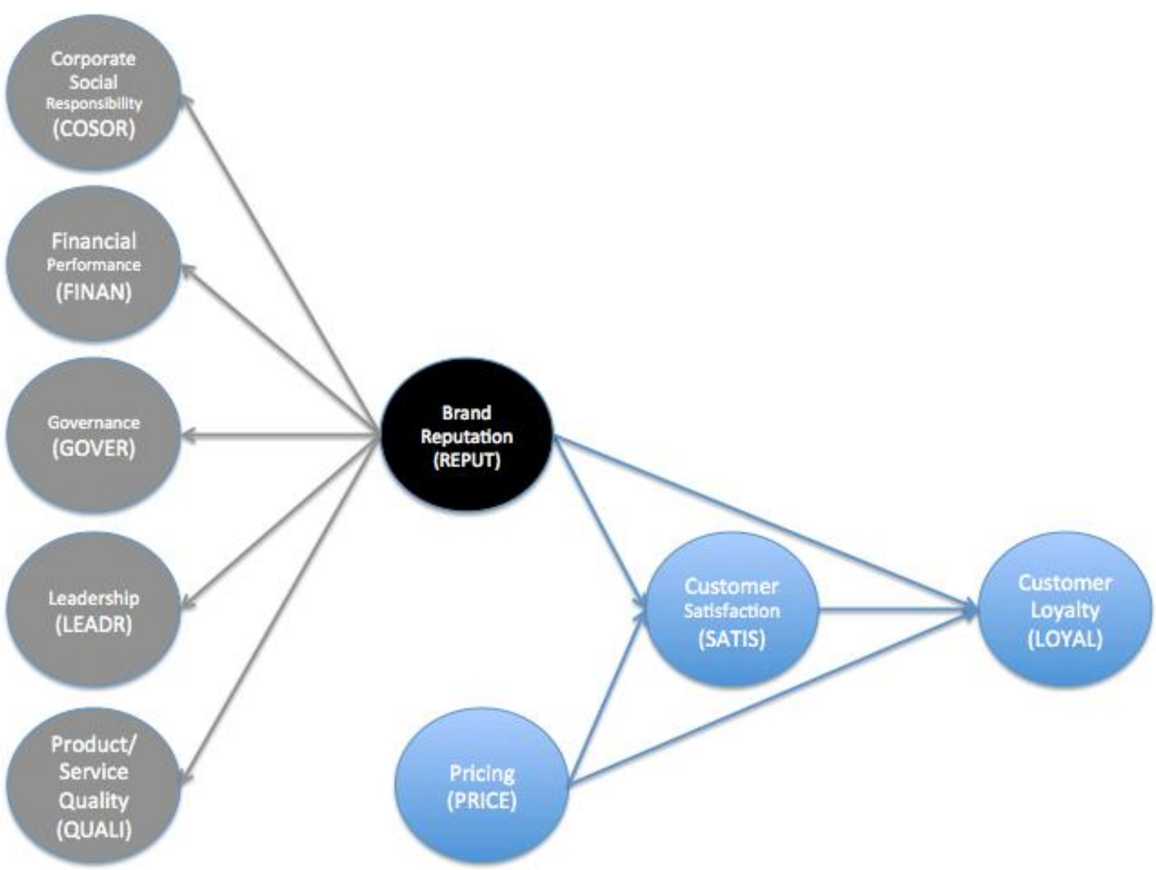
Despite the fact that PLS-SEM has been available since the mid-1960s (Wold 1973, 1985), it has only gained the attention of the academic and research community in the last decade when software tools such as PLS-Graph (www.plsgraph.com), WarpPLS (www.scriptwarp.com/warppls) and SmartPLS (www.smartpls.com) became available on the market (Wong, 2013). Since it is a relatively new approach to modeling, researchers who are new to PLS-SEM may find the analytical and reporting aspects challenging, especially in the areas of mediation analysis, categorical moderation analysis, and higher-order constructs modeling. This paper helps researchers to master these skill sets by demonstrating the mentioned analyses through a fictitious B2B research example in the photocopier industry. PLS-SEM model estimation will be performed in SmartPLS 2.0M3 software (Ringle, Wende, & Will, 2005), whereas data preparation will be performed in Microsoft Excel and IBM SPSS.

Conceptual Framework and Research Hypotheses

Background

In this research example, a researcher named Susan is the marketing vice president of a photocopier manufacturer. The company's business customers include organizations in both non-profit and for-profit sectors. Susan is interested in learning more about the driving forces behind customer loyalty, particularly factors such as brand reputation, pricing, and customer satisfaction. Susan has previously attended an EMBA course on brand reputation, and she recalled the five underlying indicators that contribute to a company's brand reputation; they are corporate social responsibility, financial performance, governance, leadership, and product/service quality. Susan is interested in carrying out a structural equation modeling exercise because her goal is to understand the relationships among these factors. Based on this information, Susan developed the conceptual framework for her research project (see Figure 1).

Figure 1: Conceptual Framework



Questionnaire Design and Data Collection

A questionnaire is designed around each latent construct of interest. Susan's business customers are asked to provide feedback in major areas that reflect the latent constructs in the model. Using a measurement scale from 0 to 10 (totally disagree to fully agree), business customers are asked to evaluate each statement (i.e., the indicator variable) such as "This company offers good after-sales service." in the questionnaire. Since brand reputation is a higher-order construct, it is evaluated by asking questions surrounding the five underlying factors. The statements to be evaluated are:

Table 1: Questionnaire Statements

Factor	Statement
Quality (QUALI)	[This company] offers reliable, high-quality photocopier.
	[This company] offers good after-sales service.
Corporate Social Responsibility (COSOR)	[This company] sponsors community events and programs.
	[This company] maintains production processes that minimize the impact to the environment.
Financial Performance (FINAN)	[This company] is a high-performance company, it delivers strong financial results.
	[This company] delivers above-market-average share price performance.
	[This company] has a comfortable cash position.
Governance (GOVER)	[This company] behaves ethically and is open and transparent in its business dealings.
	[This company] has good internal control.
	[This company] maintains full compliance in its financial disclosures and reports.
Leadership (LEADR)	[This company] has a strong, visible leader.
	[This company] is managed effectively.
	The senior management is well known for its good relationship with its employees.
Pricing (PRICE)	The price is reasonable.
	The total cost of ownership is reasonable.
Customer Loyalty (LOYAL)	I would recommend [this company] to other business partners.
	If I had to select again, I would choose [this company] as my photocopier supplier.
	I will remain a customer of [this company] in the future.
Customer Satisfaction (SATIS)	Overall, I am satisfied with the product and service provided by [this company].

A total of 200 questionnaires are received from Susan's business customers; 106 of them are non-profit organizations (including government agencies) whereas the rest are for-profit companies. Luckily, the collected questionnaires contain no missing data.

Hypotheses Development

Once the conceptual framework is finalized, the next step is hypotheses development. The first hypothesis is developed to explore the relationship between brand reputation and loyalty:

H_1: Brand reputation (REPUT) significantly influences customer loyalty (LOYAL)

The second hypothesis is developed to examine the relationship between brand reputation and customer satisfaction:

H_2: Brand reputation (REPUT) significantly influences customer satisfaction (SATIS)

The third and fourth hypotheses are created to explore the relationship between pricing and customer loyalty, and those between pricing and customer satisfaction, respectively:

H_3: Pricing (PRICE) significantly influences customer loyalty (LOYAL)

H_4: Pricing (PRICE) significantly influences customer satisfaction (SATIS)

The fifth hypothesis is created to test the linkage between customer satisfaction and customer loyalty:

H_5: Customer satisfaction (SATIS) significantly influences customer loyalty (LOYAL)

The Mediating Role of Customer Satisfaction

Customer satisfaction is an endogenous variable in the model. Other latent constructs such as brand reputation and pricing are hypothesized to influence customer satisfaction, which in turn affects customer loyalty. The potential mediating effect of customer satisfaction on other constructs are of interest in Susan's research and hence the sixth and seventh hypothesis are developed as the followings:

H_6: Customer satisfaction (SATIS) significantly mediates the relationship between brand reputation (REPUT) and customer loyalty (LOYAL)

H_7: Customer satisfaction (SATIS) significantly mediates the relationship between pricing (PRICE) and customer loyalty (LOYAL)

The categorical moderating role of business type

Susan is also interested in understanding if her findings in this PLS-SEM research can be applied to both non-profit and for-profit organizations. To confirm such insights, the last hypothesis of this research is developed to test the categorical moderating effect of business type (i.e., non-profit vs. for-profit) in the model:

H_8: There is significant categorical moderating effect of business type on the relationship among model constructs.

PLS-SEM Design Considerations

Sample size:

In Susan's research project, there are 200 participants (N=106 non-profit organizations; N=94 for-profit organizations). This sample size satisfies both the guidelines as suggested by Hair, Hult, Ringle, & Sarstedt (2013) that at least 59 observations are needed to achieve a statistical power of 80% for detecting R-square values of at least 0.25 (that is, 10 x 3 structural paths = 30 business customers), and the "10 times rule" (Thompson, Barclay, & Higgins, 1995). The "10 times rule" suggests that sample size should at least equal to "10 times the maximum number of structural paths pointing at a latent variable anywhere in the PLS path model".

Multiple-item vs. Single-item Indicators

This research originally includes a total of 19 indicator variables. Since the sample size is larger than 50, the indicating variables are designed to make use of multiple-item instead of single-item to measure the latent construct (Diamantopoulos, Sarstedt, Fuchs, Kaiser, & Wilczynski, 2012). Other than customer satisfaction (SATIS) which is a single-item construct, all others are each measured by 2 to 3 indicators (i.e., questionnaire questions).

Formative vs. Reflective Hierarchical Components Model

According to Lohmöller (1989), PLS-SEM can be designed as a hierarchical components model (HCM) that includes the observable lower-order components (LOCs) and unobservable higher-order components (HOCs) to reduce model complexity and make it more theoretical parsimony. The use of hierarchical component model can also reduce bias due to collinearity issues and eliminate potential discriminant validity problems (see Hair et al. 2013, p.229).

In Susan's photocopier research, it is designed as a reflective-reflective hierarchical component model (rr-HCM). The use of hierarchical component model can also reduce bias due to collinearity issues and eliminate potential discriminant validity problems - see Hair et al. (2013, p.229). Specifically, the HOC brand reputation holds a reflective relationship with its LOCs (quality, corporate social responsibility, financial performance, governance, and leadership) that are measured by reflective indicators that hang well together. This model design is in line with prior research regarding reputation for company (Hair et al., 2013, p235).

Data Preparation for SmartPLS

Prior to running PLS model estimation in SmartPLS, Susan has to manually type the questionnaire data into Microsoft Excel with the names of those indicators (e.g., loyal_1, loyal_2, loyal_3) being placed in the first row of an Excel spreadsheet. Each row represents an individual questionnaire response, with number from 0 to 10. Since there are 200 responses, there should be 201 rows in the spreadsheet (see Figure 2). The file has to be saved in the specific "CSV (Comma Delimited)" format in Excel because SmartPLS cannot import .xls or .xlsx files directly. To do this, go to the "File" menu in Excel, and choose "CSV (Comma Delimited)" as the file format type to save. See Wong (2013) for step-by-step instructions.

Figure 2: Data Entry in Microsoft Excel

	A	B	C	D	E	F	G	H	I	J	K
1	loyal_1	loyal_2	loyal_3	satis_1	price_1	price_2	quali_1	quali_2	brand_1	brand_2	brand_3
2	7	7	3	6	1	7	7	7	4	1	6
3	4	1	1	3	2	4	3	7	3	1	7
4	7	7	3	4	5	5	3	7	5	2	6
5	5	4	3	6	4	6	6	4	6	4	7
6	5	5	5	7	7	6	5	7	6	3	6
7	7	4	6	7	3	6	4	7	6	1	4
8	5	6	4	5	2	4	4	6	4	2	4
9	6	5	4	6	4	6	3	6	3	4	7
10	5	5	2	5	3	6	6	5	5	3	4
11	6	7	1	5	7	6	5	7	7	6	5
12	1	1	4	5	6	1	1	6	3	1	4
13	4	1	1	4	4	4	4	4	4	4	4
14	7	3	1	5	1	5	3	7	7	1	6
15	2	1	7	3	7	2	6	3	4	3	6
16	4	4	7	7	7	7	6	6	6	1	7
17	4	6	5	6	6	5	4	3	5	4	6
18	5	5	1	5	7	4	4	7	7	1	7
19	6	4	4	5	5	5	5	6	5	3	4
20	5	4	3	4	5	5	3	4	3	3	2
21	2	2	3	6	7	7	2	7	7	1	6
22	4	6	4	6	7	7	7	7	7	1	7
23	4	5	3	2	4	6	6	6	4	3	5

photocopier

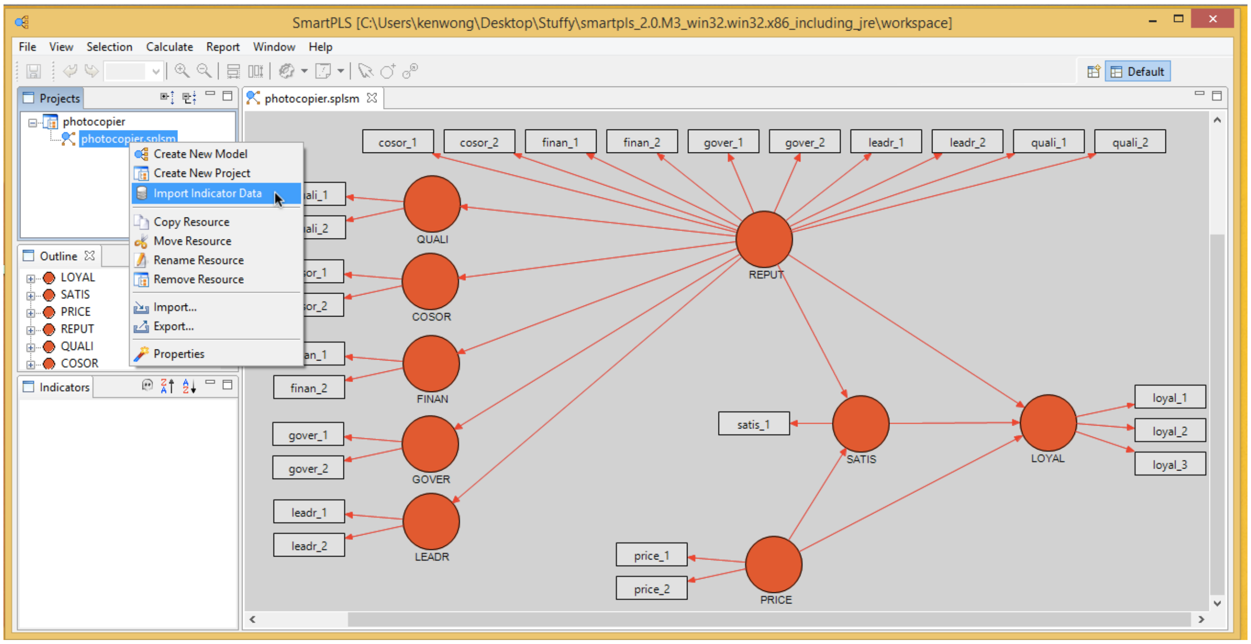
Data Analysis and Results

PLS Path Model Estimation

Susan designs the PLS model in SmartPLS based on the conceptual framework mentioned earlier. The HOC, brand reputation, is drawn using the "repeated indicators approach" Indicators from lower-order components (e.g., COSOR, FINAN, GOVER, LEADR and QUALI) are deployed again for the corresponding higher-order component (e.g., REPUT). Once the model is drawn, the indicator data can be imported into the SmartPLS software, this can be done by right clicking on the "photocopier.splsm" file in the "Projects" window, and then select "Import Indicator Data" (See Figure 3).

The PLS-SEM algorithm is run by using "Calculate → PLS Algorithm" and successfully converged within the guideline suggested by Hair et al., (2013). The PLS-SEM algorithm should converge in iteration lower than the maximum number of iterations (e.g. 300) as set in the algorithm parameter settings; in this PLS Path model estimation, the algorithm successfully converged after Iteration 8 (see Report→Default Report→PLS→Calculation Results→Stop Criterion Changes). Before Susan can properly assess the path coefficients in the structural model, she must first examine the indicator reliability, internal consistency reliability, discriminant validity, and convergent validity of the reflective measurement model to ensure they are satisfactory (Wong, 2013).

Figure 3: Importing Indicator Data



Indicator Reliability

Since reliability is a condition for validity, indicator reliability is first checked to ensure the associated indicators have much in common that is captured by the latent construct. After examining the outer loadings for all latent variables[1], the 2 indicators that form COSOR are removed because their outer loadings are smaller than the 0.4 threshold level (Hair et al., 2013). Meanwhile, 3 indicators (Finan_2, Gover_2, and Leadr_1) are found to have loadings between 0.4 to 0.7. A loading relevance test is therefore performed for these 3 indicators to see if they should be retained in the model. In a loading relevance test, problematic indicators should be deleted only if their removal from the PLS model leads to an increase of AVE and composite reliability of their constructs over the 0.5 thresholds. These figures can be obtained from the software by viewing "Report→Default report→PLS→Quality Criteria→Overview". As the elimination of these 3 indicators would result in an increase of Average Variance Extracted (AVE) and composite reliability of their respective latent construct, they are removed from the PLS model. The remaining indicators are retained because their outer loadings are all 0.7 or higher. An indicator's outer loading should be 0.708 or above since that number squared (0.7082) equals 0.50, meaning the latent variable should be able to explain at least 50% of each indicator's variance. The PLS algorithm is re-run. The resulting path model estimation is presented in Figure 4 and the outer loadings of various constructs are shown in Table 2:

[1] For brand reputation, the outer loadings for higher-order construct (REPUT) instead of lower-order construct (i.e., QUALI, COSOR, GOVER…etc.) are examined (see Hair et al, 2013, p235).

Figure 4: PLS Path Model Estimation

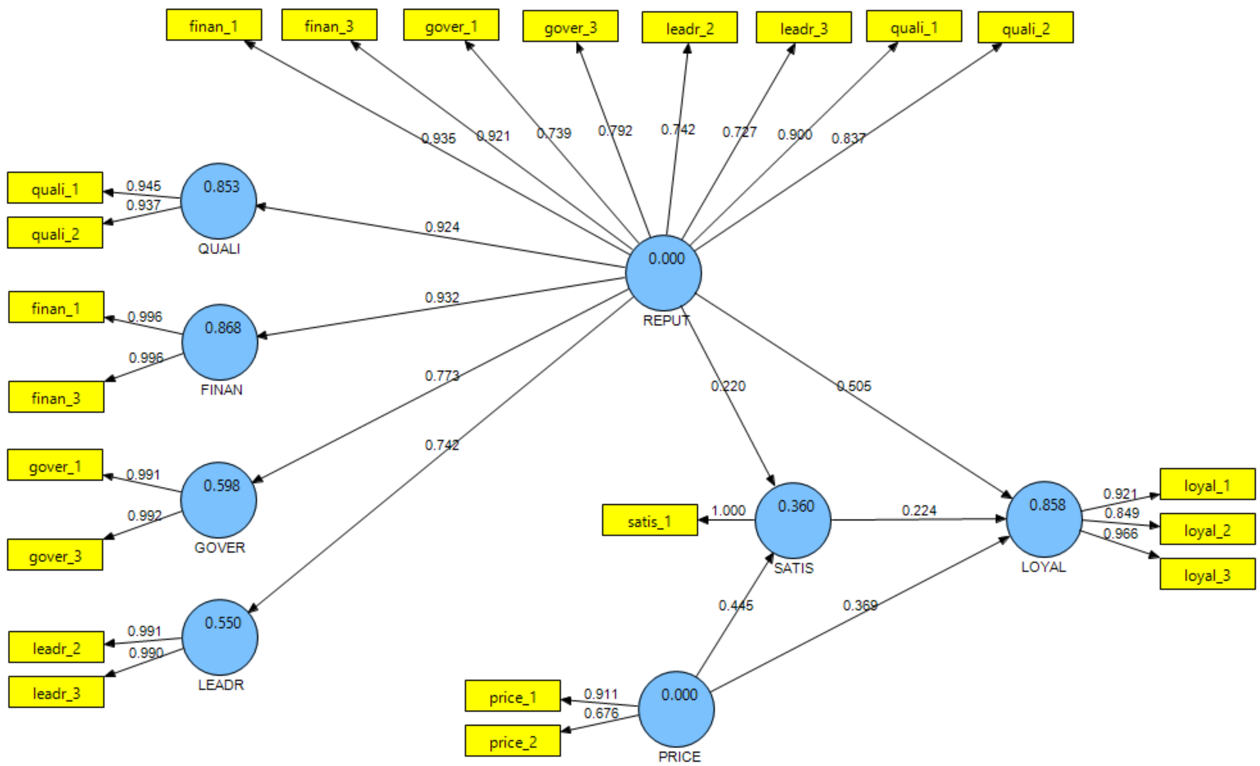


Table 2: Outer Loadings

Constructs (Latent Variables)		Outer loadings
	Brand Reputation (REPUT)	
Quality (QUALI)		
Quali_1	[This company] offers reliable, high-quality photocopier	0.900
Quali_2	[This company] offers good after-sales service	0.837
Financial Performance (FINAN)		
Finan_1	[This company] is a high-performance company, it delivers strong financial results	0.935
Finan_3	[This company] has a comfortable cash position	0.921
Governance (GOVER)		
Gover_1	[This company] behaves ethically and is open and transparent in its business dealings	0.739
Gover_3	[This company] maintains full compliance in its financial disclosures and reports	0.792
Leadership (LEADR)		
Leadr_2	[This company] is managed effectively	0.742
Leadr_3	The senior management is well known for its good relationship with its employees	0.727
	Pricing (PRICE)	
Price_1	The price is reasonable	0.911
Price_2	The total cost of ownership reasonable	0.676

	Customer Loyalty (LOYAL)	
Loyal_1	I would recommend [this company] to other business partners	0.921
Loyal_2	If I had to select again, I would choose [this company] as my photocopier supplier	0.849
Loyal_3	I will remain a customer of [this company] in the future	0.966
	Customer Satisfaction (SATIS)	
Satis_1	Overall, I am satisfied with the product and service provided by [this company]	1

Internal Consistency Reliability

In PLS-SEM, composite reliability rather than Cronbach's alpha is used to evaluate the measurement model's internal consistency reliability. The internal consistency reliability is traditionally checked using Cronbach's alpha. However, it is not suitable for PLS-SEM because it is sensitive to the number of items in the scale, and this measure is also found to generate severe underestimation when applied to PLS path models (see Werts, Linn, & Joreskog, 1974).

In Susan's research, the composite reliability[2] for the constructs REPUT, PRICE and LOYAL are shown to be 0.9454, 0.7791, and 0.9378 respectively, indicating high levels of internal consistency reliability (Nunnally & Bernstein, 1994). Prior research suggests that a threshold level of 0.60 or higher is required to demonstrate a satisfactory composite reliability in exploratory research (Bagozzi and Yi, 1988) but not exceeding the 0.95 level (Hair et al., 2013). Please note that the value of SATIS is 1.00 but it does not imply perfection in composite reliability because it is a single-item variable.

Convergent validity

Convergent validity refers to the model's ability to explain the indicator's variance. The AVE can provide evidence for convergent validity (Fornell and Larcker, 1981). Bagozzi and Yi (1988) suggest an AVE threshold level of 0.5 as evidence of convergent validity. Two of our constructs exceeded this level and the rest are not too far away from this level. Since all of these constructs met discriminant validity and other reliability tests, they are kept in the model to maintain content validity. The AVE for the latent construct LOYAL, PRICE, and REPUT are 0.8343, 0.6432, and 0.6859 respectively, well above the required minimum level of 0.50 (Bagozzi and Yi, 1988). Therefore, the measures of the three reflective constructs can be said to have high levels of convergent validity.

Discriminant Validity

The Fornell-Larcker criterion (1981) is a common and conservative approach to assess discriminant validity and it can be applied in PLS-SEM. Another method is cross-loading examination, in which the indicator's loading to its latent construct should be higher than that of other constructs. See "Reports→Default Report→PLS→Quality Criteria→Cross Loadings". To

[2] If there is a HOC, only consider the composite reliability of the HOC (e.g., REPUT) and not its LOC (e.g., QUALI, FINAN, GOVER and LEADR).

establish the discriminant validity[3], the square root of average variance extracted (AVE) of each latent variable should be larger than the latent variable correlations (LVC). Table 3 clearly shows that discriminant validity is met for this research because the square root of AVE for REPUT, PRICE, SATIS and LOYAL are much larger than the corresponding LVC. To find LVC values, go to “Reports→Default report→PLS→Quality criteria→Latent variable correlation”.

Table 3: Fornell-Larcker Criterion

	Latent Variable Correlations (LVC)				**Discriminant Validity met?** (Square root of AVE>LVC?)
	LOYAL	PRICE	REPUT	SATIS	
LOYAL	***0.9134***				Yes
PRICE	0.7883	***0.8020***			Yes
REPUT	0.8245	0.5769	***0.8282***		Yes
SATIS	0.6760	0.5722	0.4772	Single-item	Yes

Note: The square root of AVE values is shown on the diagonal and printed in italics; non-diagonal elements are the latent variable correlations (LVC).

Evaluation of the Structural Model in PLS-SEM: Collinearity Assessment

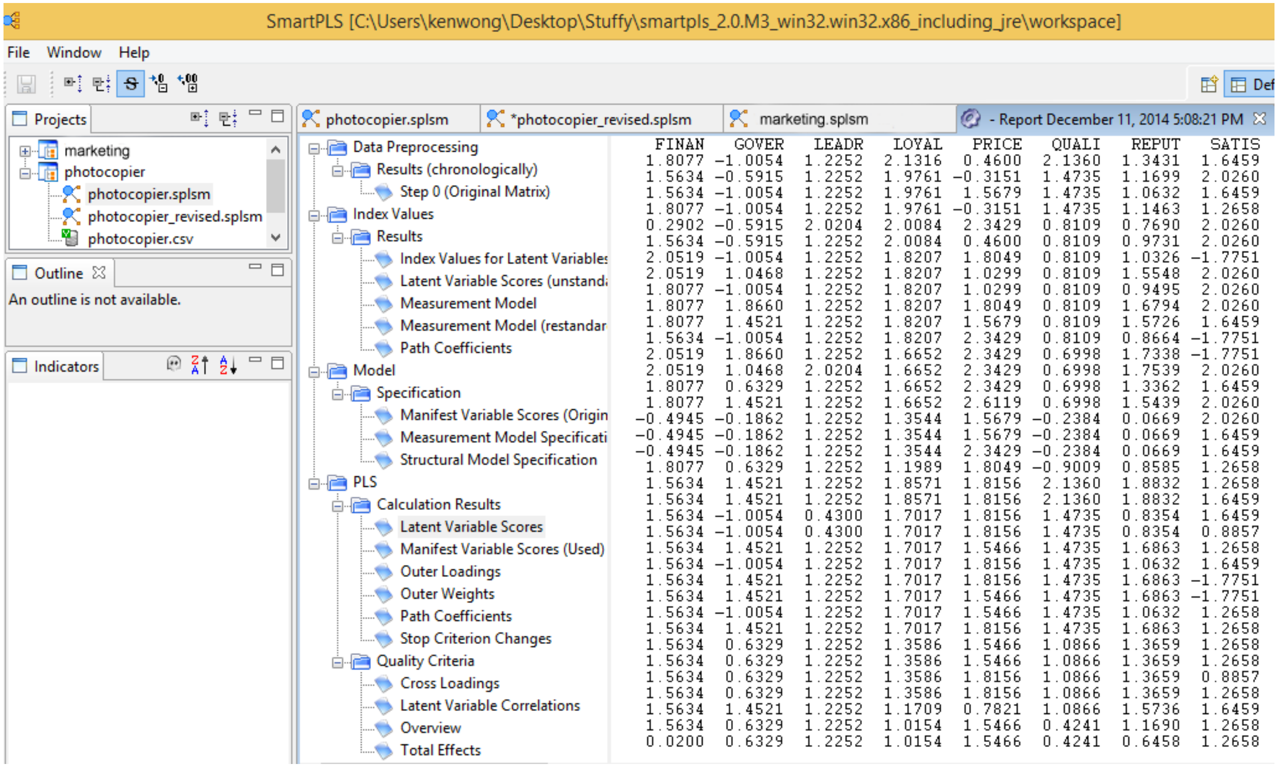
In addition to checking the measurement model, the structural model has to be properly evaluated before drawing any conclusion. Collinearity is a potential issue in the structural model and that variance inflation factor (VIF) value of 5 or above typically indicates such problem (Hair et al., 2011). Since SmartPLS does not generate the VIF value, another piece of statistical software such as IBM SPSS has to be utilized. This procedure involves a few easy steps. First, generate the latent variables scores in SmartPLS. Go to “Report→PLS→calculation results→ Latent Variable Scores” (See Figure 5).

Then, copy the data into Microsoft Excel, save it in “CSV (Comma Delimited)” format and then open it in IBM SPSS (see Figure 6).

In Susan’s PLS model, both LOYAL and SATIS act as dependent variables because they have arrows (paths) pointing towards them. As such, we need to run two different sets of linear regression to obtain their corresponding VIF values. For the first run of linear regression (in SPSS, go to “Analyse→Regression→Linear”), LOYAL is the dependent variable whereas REPUT, PRICE, and SATIS serve as “Independent” variables (see Figure 7). In the Linear Regression window, click the “Statistics…” button and then put a check mark next to “Collinearity diagnostics” (see Figure 8) to obtain the VIF value (see Table 4).

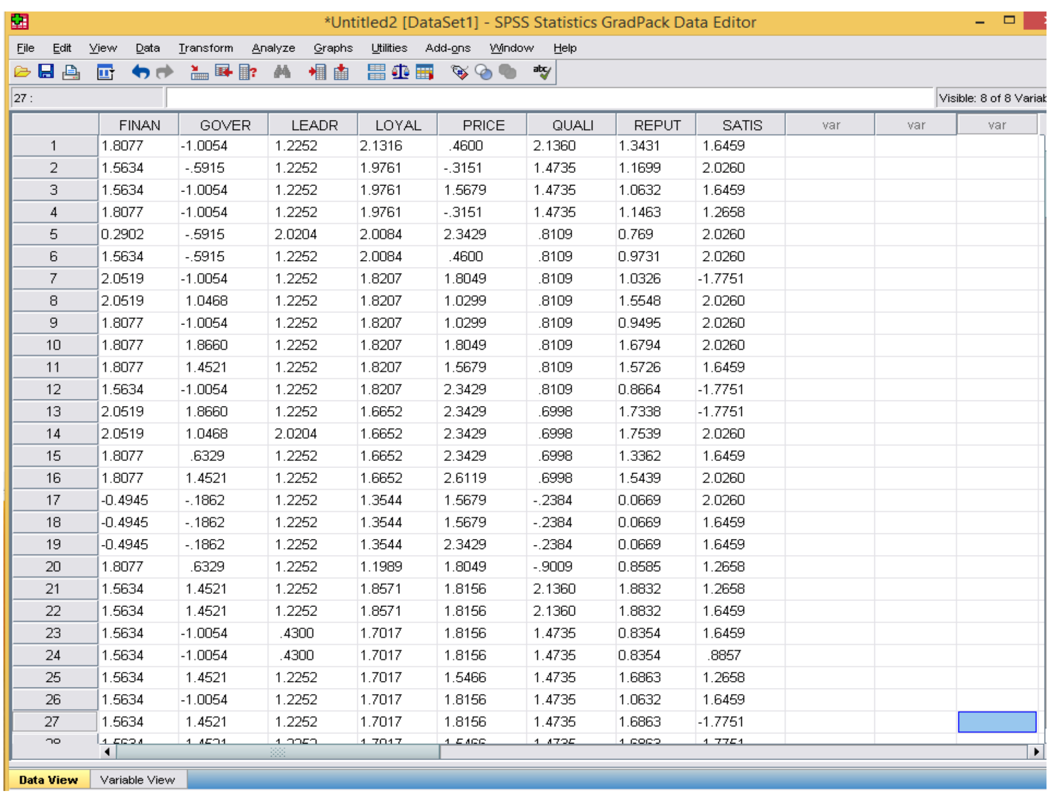
[3] If there is a HOC, only consider the discriminant validity of the HOC (e.g., REPUT) and not its LOC (e.g., QUALI, FINAN, GOVER and LEADR).

Figure 5: Latent Variables Scores



FINAN	GOVER	LEADR	LOYAL	PRICE	QUALI	REPUT	SATIS
1.8077	−1.0054	1.2252	2.1316	0.4600	2.1360	1.3431	1.6459
1.5634	−0.5915	1.2252	1.9761	−0.3151	1.4735	1.1699	2.0260
1.5634	−1.0054	1.2252	1.9761	1.5679	1.4735	1.0632	1.6459
1.8077	−1.0054	1.2252	1.9761	−0.3151	1.4735	1.1463	1.2658
0.2902	−0.5915	2.0204	2.0084	2.3429	0.8109	0.7690	2.0260
1.5634	−0.5915	1.2252	2.0084	0.4600	0.8109	0.9731	2.0260
2.0519	−1.0054	1.2252	1.8207	1.8049	0.8109	1.0326	−1.7751
2.0519	1.0468	1.2252	1.8207	1.0299	0.8109	1.5548	2.0260
1.8077	−1.0054	1.2252	1.8207	1.0299	0.8109	0.9495	2.0260
1.8077	1.8660	1.2252	1.8207	1.8049	0.8109	1.6794	2.0260
1.8077	1.4521	1.2252	1.8207	1.5679	0.8109	1.5726	1.6459
1.5634	−1.0054	1.2252	1.8207	2.3429	0.8109	0.8664	−1.7751
2.0519	1.8660	1.2252	1.6652	2.3429	0.6998	1.7338	−1.7751
2.0519	1.0468	2.0204	1.6652	2.3429	0.6998	1.7539	2.0260
1.8077	0.6329	1.2252	1.6652	2.3429	0.6998	1.3362	1.6459
1.8077	1.4521	1.2252	1.6652	2.6119	0.6998	1.5439	2.0260
−0.4945	−0.1862	1.2252	1.3544	1.5679	−0.2384	0.0669	2.0260
−0.4945	−0.1862	1.2252	1.3544	1.5679	−0.2384	0.0669	1.6459
−0.4945	−0.1862	1.2252	1.3544	2.3429	−0.2384	0.0669	1.6459
1.8077	0.6329	1.2252	1.1989	1.8049	−0.9009	0.8585	1.2658
1.5634	1.4521	1.2252	1.8571	1.8156	2.1360	1.8832	1.2658
1.5634	1.4521	1.2252	1.8571	1.8156	2.1360	1.8832	1.6459
1.5634	−1.0054	0.4300	1.7017	1.8156	1.4735	0.8354	1.6459
1.5634	−1.0054	0.4300	1.7017	1.8156	1.4735	0.8354	0.8857
1.5634	1.4521	1.2252	1.7017	1.5466	1.4735	1.6863	1.2658
1.5634	−1.0054	1.2252	1.7017	1.8156	1.4735	1.0632	1.6459
1.5634	1.4521	1.2252	1.7017	1.8156	1.4735	1.6863	−1.7751
1.5634	1.4521	1.2252	1.7017	1.5466	1.4735	1.6863	−1.7751
1.5634	−1.0054	1.2252	1.7017	1.5466	1.4735	1.0632	1.2658
1.5634	1.4521	1.2252	1.7017	1.8156	1.4735	1.6863	1.2658
1.5634	0.6329	1.2252	1.3586	1.5466	1.0866	1.3659	1.2658
1.5634	0.6329	1.2252	1.3586	1.5466	1.0866	1.3659	1.2658
1.5634	0.6329	1.2252	1.3586	1.8156	1.0866	1.3659	0.8857
1.5634	0.6329	1.2252	1.3586	1.8156	1.0866	1.3659	1.2658
1.5634	1.4521	1.2252	1.1709	0.7821	1.0866	1.5736	1.6459
1.5634	0.6329	1.2252	1.0154	1.5466	0.4241	1.1690	1.2658
0.0200	0.6329	1.2252	1.0154	1.5466	0.4241	0.6458	1.2658

Figure 6: Data in SPSS



	FINAN	GOVER	LEADR	LOYAL	PRICE	QUALI	REPUT	SATIS	var	var	var
1	1.8077	-1.0054	1.2252	2.1316	.4600	2.1360	1.3431	1.6459			
2	1.5634	-.5915	1.2252	1.9761	-.3151	1.4735	1.1699	2.0260			
3	1.5634	-1.0054	1.2252	1.9761	1.5679	1.4735	1.0632	1.6459			
4	1.8077	-1.0054	1.2252	1.9761	-.3151	1.4735	1.1463	1.2658			
5	0.2902	-.5915	2.0204	2.0084	2.3429	.8109	0.769	2.0260			
6	1.5634	-.5915	1.2252	2.0084	.4600	.8109	0.9731	2.0260			
7	2.0519	-1.0054	1.2252	1.8207	1.8049	.8109	1.0326	-1.7751			
8	2.0519	1.0468	1.2252	1.8207	1.0299	.8109	1.5548	2.0260			
9	1.8077	-1.0054	1.2252	1.8207	1.0299	.8109	0.9495	2.0260			
10	1.8077	1.8660	1.2252	1.8207	1.8049	.8109	1.6794	2.0260			
11	1.8077	1.4521	1.2252	1.8207	1.5679	.8109	1.5726	1.6459			
12	1.5634	-1.0054	1.2252	1.8207	2.3429	.8109	0.8664	-1.7751			
13	2.0519	1.8660	1.2252	1.6652	2.3429	.6998	1.7338	-1.7751			
14	2.0519	1.0468	2.0204	1.6652	2.3429	.6998	1.7539	2.0260			
15	1.8077	.6329	1.2252	1.6652	2.3429	.6998	1.3362	1.6459			
16	1.8077	1.4521	1.2252	1.6652	2.6119	.6998	1.5439	2.0260			
17	-0.4945	-.1862	1.2252	1.3544	1.5679	-.2384	0.0669	2.0260			
18	-0.4945	-.1862	1.2252	1.3544	1.5679	-.2384	0.0669	1.6459			
19	-0.4945	-.1862	1.2252	1.3544	2.3429	-.2384	0.0669	1.6459			
20	1.8077	.6329	1.2252	1.1989	1.8049	-.9009	0.8585	1.2658			
21	1.5634	1.4521	1.2252	1.8571	1.8156	2.1360	1.8832	1.2658			
22	1.5634	1.4521	1.2252	1.8571	1.8156	2.1360	1.8832	1.6459			
23	1.5634	-1.0054	.4300	1.7017	1.8156	1.4735	0.8354	1.6459			
24	1.5634	-1.0054	.4300	1.7017	1.8156	1.4735	0.8354	.8857			
25	1.5634	1.4521	1.2252	1.7017	1.5466	1.4735	1.6863	1.2658			
26	1.5634	-1.0054	1.2252	1.7017	1.8156	1.4735	1.0632	1.6459			
27	1.5634	1.4521	1.2252	1.7017	1.8156	1.4735	1.6863	-1.7751			

Figure 7: Linear Regression

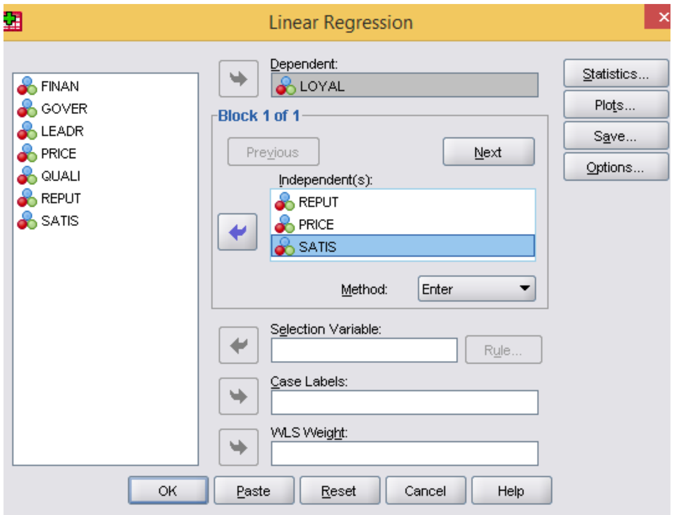


Figure 8: Linear Regression: Statistics

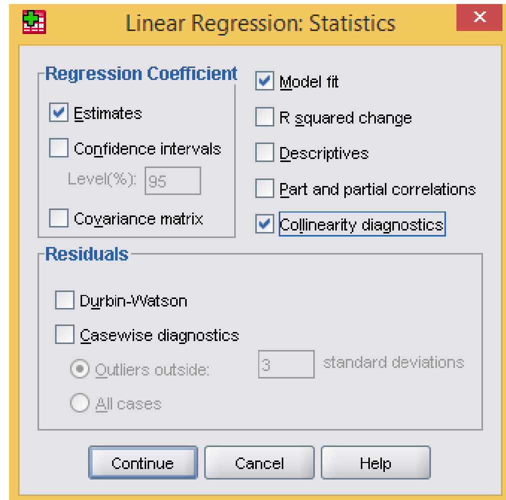


Table 4: Coefficients Table (First Set)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-3.319E-6	.027		.000	1.000		
	REPUT	.505	.034	.505	14.972	.000	.635	1.575
	PRICE	.369	.036	.369	10.210	.000	.553	1.808
	SATIS	.224	.034	.224	6.669	.000	.640	1.562

a. Dependent Variable: LOYAL

For the second set of linear regression, configure SATIS as dependent variable and REPUT and PRICE as independent variables. The VIF values are shown in Table 5.

Table 5: Coefficients Table (Second Set)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-1.254E-5	.057		.000	1.000		
	REPUT	.220	.070	.220	3.158	.002	.667	1.499
	PRICE	.445	.070	.445	6.378	.000	.667	1.499

a. Dependent Variable: SATIS

The collinearity assessment results are summarized in Table 6. It can be seen that all VIF values are lower than five, suggesting that there is no indicative of collinearity between each set of predictor variables.

Table 6: Collinearity Assessment

First Set			Second Set		
Constructs	VIF	Collinearity Problem? (VIF>5?)	Constructs	VIF	Collinearity Problem? (VIF>5?)
REPUT	1.575	No	REPUT	1.499	No
PRICE	1.808	No	PRICE	1.499	No
SATIS	1.562	No			

Dependent variable: LOYAL *Dependent variable: SATIS*

Coefficient of Determination (R^2)

A major part of structural model evaluation is the assessment of coefficient of determination (R^2). In Susan's research, LOYAL is the main construct of interest. From the PLS Path model estimation diagram (see Figure 4), the overall R^2 is found to be a strong one. Threshold value of 0.25, 0.5 and 0.7 are often used to describe a weak, moderate, and strong coefficient of determination (Hair at el., 2013). In our case, it suggests that the three constructs REPUT, PRICE, and SATIS can jointly explain 85.8% of the variance of the endogenous construct LOYAL. The R^2 value is 0.858; it is shown inside the blue circle of the LOYAL construct in the PLS diagram (see Figure 4). The same model estimation also reveals the R^2 for other latent construct; REPUT and PRICE are found to jointly explain 36.0% of SATIS's variances in this PLS-SEM model.

Path Coefficient

In SmartPLS, the relationships between constructs can be determined by examining their path coefficients and related t statistics via the bootstrapping procedure. Go to "Calculate → bootstrapping" in SmartPLS. Select "200" as cases because there are 200 business customers in this research. From Table 7, it can be seen that all of the structural model relationships are significant, confirming our various hypotheses about the construct relationships. The t Value is obtained in SmartPLS whereas the corresponding p Value is calculated in Microsoft Excel using the TDIST (x,degree of freedom, tails) command, such as TDIST(12.0146,199,2) for the REPUT →LOYAL path. The PLS structural model results enable us to conclude that REPUT has the strongest effect on LOYAL (0.505), followed by PRICE (0.369) and SATIS (0.224).

The PLS model estimation (see Figure 4) also reveals that the high-order construct, REPUT, has strong relationships with its low-order constructs, QUALI (0.924), FINAN (0.932), GOVER (0.773) and LEADR (0.742). This means that the lower-order constructs, QUALI, FINAN, GOVER, and LEADR, are highly correlated for the higher-order construct REPUT to explain more than 50% of each LOC's variance.

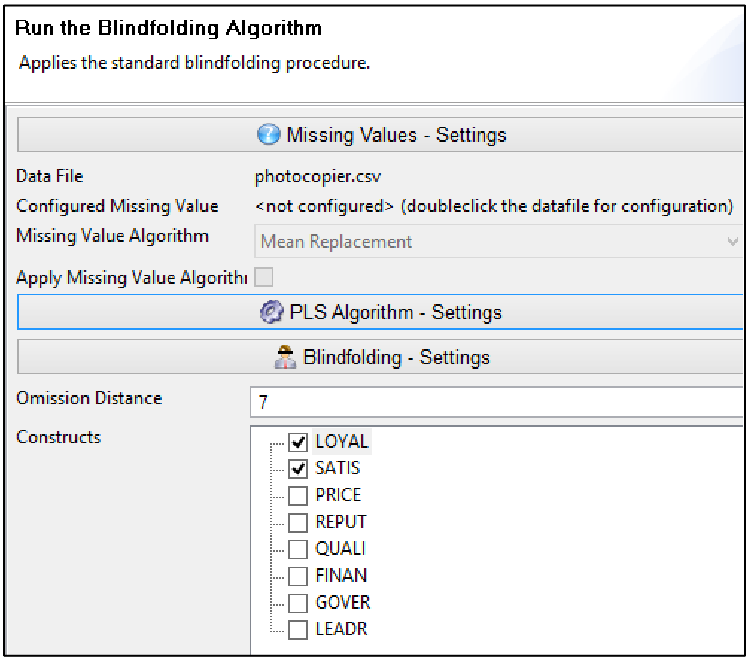
Table 7: Significance Testing Results of the Structural Model Path Coefficients

Hypothesis	Path:	Path Coefficients	*t* Values	*p* Values	Hypothesis
H_1	REPUT → LOYAL	0.505	12.0146	0.00	Accepted
H_2	REPUT → SATIS	0.220	2.8595	0.00	Accepted
H_3	PRICE → LOYAL	0.369	6.7934	0.00	Accepted
H_4	PRICE → SATIS	0.445	5.0263	0.00	Accepted
H_5	SATIS → LOYAL	0.224	4.0670	0.00	Accepted

Predictive relevance (Q^2)

An assessment of Stone-Geisser's predictive relevance (Q^2) is important because it checks if the data points of indicators in the reflective measurement model of endogenous construct can be predicted accurately. This can be achieved by making use of the blindfolding procedure in SmartPLS. LOYAL and SATIS are the two endogenous constructs in the model so they are selected for running the Blindfolding Algorithm (see Figure 9).

Figure 9: Blindfolding



The following table summarizes the results. It is observed that the proposed model has good predictive relevance for all of the endogenous variables. Chin (1998) suggests that a model demonstrates good predictive relevance when its Q^2 value is larger than zero (see Table 8).

Table 8: Results of Coefficient of Determination (R^2) and Predictive Relevance (Q^2)

Endogenous Latent Variable	R^2 Value	Q^2 Value
LOYAL	0.858	0.709
SATIS	0.360	0.356

Q^2 is the "1-SSE/SSO" value as shown in the "Construct Crossvalidated Redundancy" section in blindfolding.

The f^2 and q^2 Effect Sizes

The final step in structural model evaluation is to assess the effect of a specific exogenous construct on the endogenous construct if it is deleted from the model. This can be achieved by examining the f^2 and q^2 effect sizes, which can be derived from R^2 and Q^2 respectively. The f^2 effect size can be calculated manually by taking (R^2_{included} - R^2_{excluded}) / (1 - R^2_{included}). Similarly, the q^2 effect size can be calculated by taking (Q^2_{included} - Q^2_{excluded}) / (1 - Q^2_{included}). Following Cohan's (1988) guideline which states that f^2 values of 0.02, 0.15, and 0.35 are interpreted as small, medium, and large effect sizes, respectively, it can be said that in general, the exogenous variables have medium to large f^2 and q^2 effect sizes on the endogenous variables (see Table 9).

Table 9: Results of f^2 and q^2 Effect Sizes

	LOYAL			SATIS		
	Path Coefficient	**f^2 Effect Size**	**q^2 Effect Size**	**Path Coefficient**	**f^2 Effect Size**	**q^2 Effect Size**
REPUT	0.505	0.993	0.444	0.220	0.050	0.053
PRICE	0.369	0.486	0.215	0.445	0.208	0.209
SATIS	0.224	0.225	0.087	n/a	n/a	n/a

Note: Target constructs appear in the first row, whereas the predecessor constructs are in the first column.

Customer Satisfaction (SATIS) as a Mediator

The relationships among constructs in PLS-SEM can be complex and not always straightforward. To gain a better understanding of the role of SATIS in our model, its potential mediating effect on the linkage between REPUT and LOYAL (see Figure 10), and those between PRICE and LOYAL (see Figure 11) are examined in Susan's research. This is accomplished by following the Preacher and Hayes (2008) procedure, which is used instead of the traditional Sobel (1982) test because it does not have strict distributional assumptions (Hair et al, 2013).

Figure 10: Mediation Analysis (First Set: H_6)

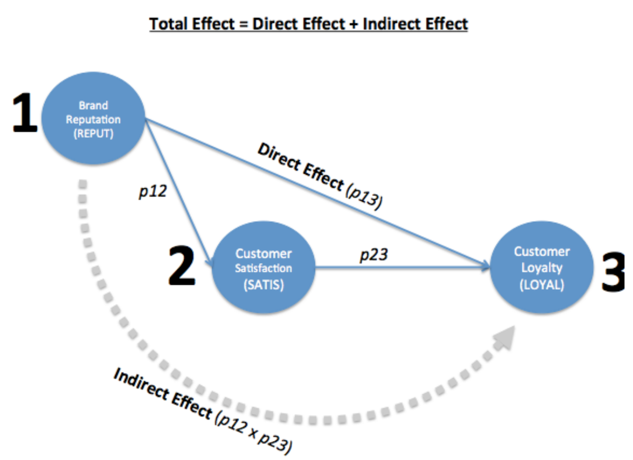
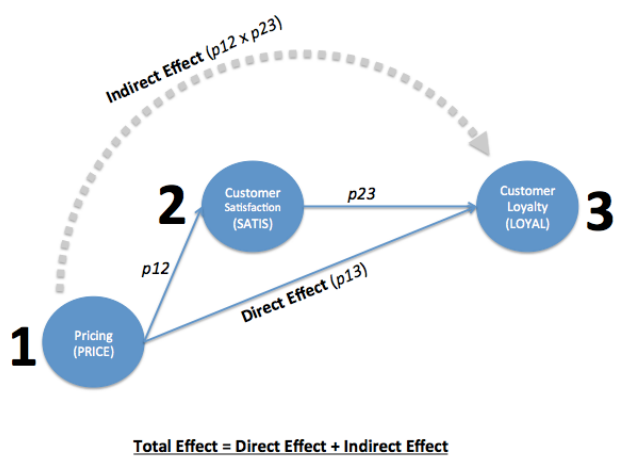


Figure 11: Mediation Analysis (Second Set: H_7)



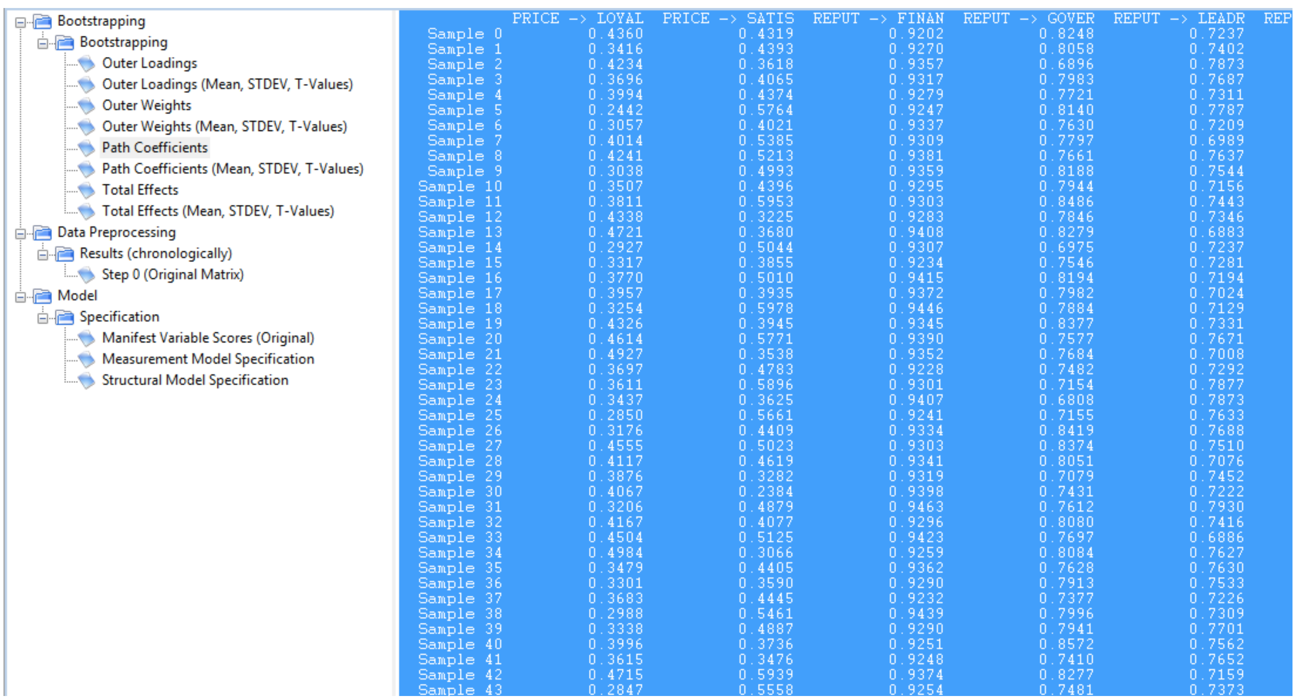
The Preacher and Hayes (2008) procedure involves the use of bootstrapping in a 2-step procedure:

(i) The significance of direct effect is first checked (if the significance of direct effect cannot be established, there is no mediating effect) using bootstrapping without the presence of the mediator SATIS in the model. Procedure-wise, go to the "Projects" window, right click on your splsm file, select "Copy resource" to create a revised PLS model in the new window where you can eliminate the SATIS construct. Then, perform a Bootstrapping with 200 cases. The result can be seen at "Report→Default Report→Bootstrapping→Bootstrapping→Path Coefficients (Mean, STDEV, *T*-Values)", and

(ii) The significance of indirect effect and associated *T*-Values are then checked using the path coefficients when the mediator SATIS is included in the model. SmartPLS does not calculate the indirect effect values automatically. As such, once the Bootstrapping procedure (with mediator) is completed, copy all 5000 path coefficients (see Default report→Bootstrapping→ Bootstrapping → Path Coefficients) to an Excel spreadsheet. Create a column in the spreadsheet as "indirect effect" which is the multiplication result of the 2 paths (p12 x p23). Finally, calculate the Standard Deviation of these 5000 path coefficients by using the Excel command "=STDEV(D4:D5003)" assuming it starts at cell D4. See Figure 12 and 13. The T-Value of indirect effect is calculated by dividing the indirect effect (i.e. p12 x p23) as observed in the PLS model estimation graph by the bootstrapping standard deviation. For example, for REPUT→LOYAL, t = 0.0493/0.0243 = 2.029. If the significance of indirect effect cannot be established, there is no mediating effect. Having a significant indirect effect is the basis to determine the mediator's magnitude.

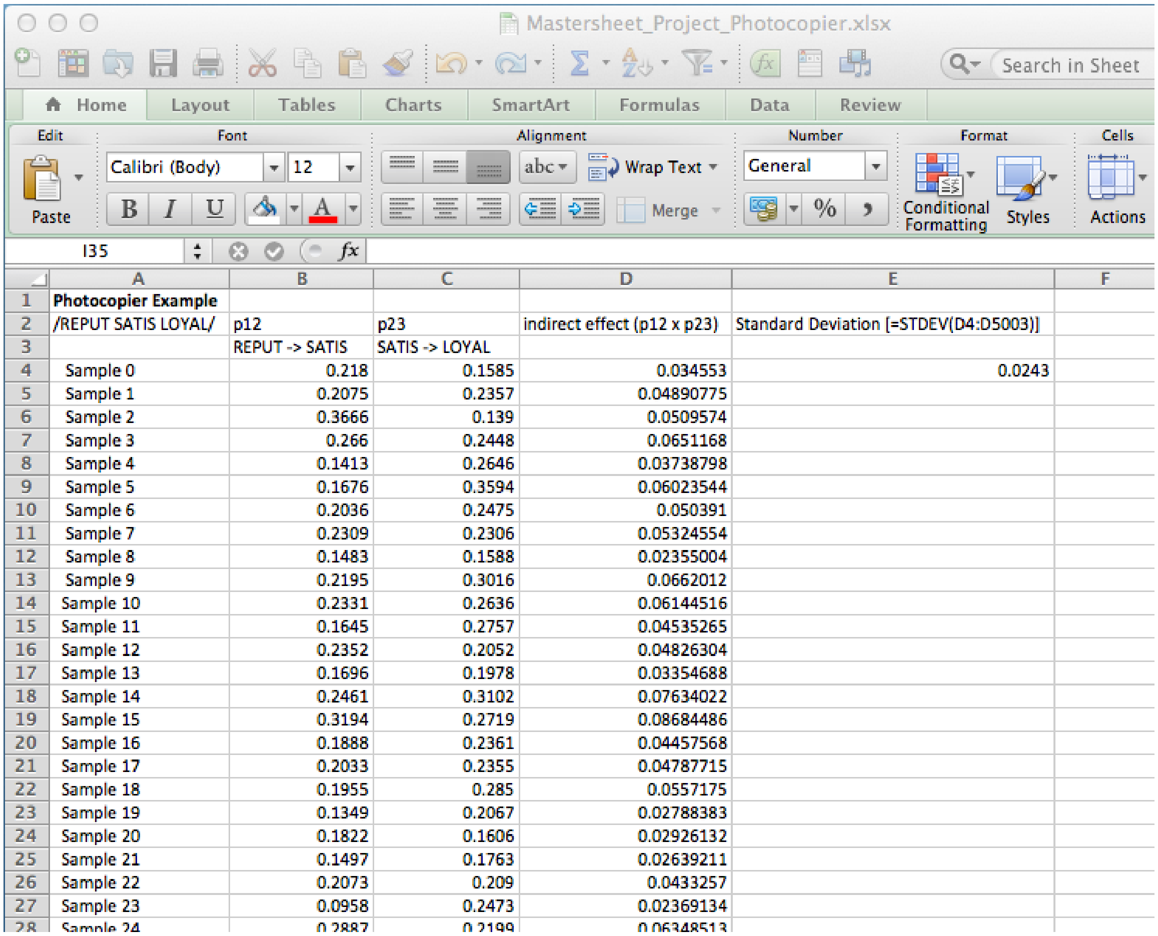
This 2-step procedure is performed twice; first for testing the hypothesis six (H_6) and then subsequently for hypothesis seven (H_7) (see Figure 12 and 13).

Figure 12: Path Coefficients from Bootstrapping



	PRICE -> LOYAL	PRICE -> SATIS	REPUT -> FINAN	REPUT -> GOVER	REPUT -> LEADR	REP
Sample 0	0.4360	0.4319	0.9202	0.8248	0.7237	
Sample 1	0.3416	0.4393	0.9270	0.8058	0.7402	
Sample 2	0.4234	0.3618	0.9357	0.6896	0.7873	
Sample 3	0.3696	0.4065	0.9317	0.7983	0.7687	
Sample 4	0.3994	0.4374	0.9279	0.7721	0.7311	
Sample 5	0.2442	0.5764	0.9247	0.8140	0.7787	
Sample 6	0.3057	0.4021	0.9337	0.7630	0.7209	
Sample 7	0.4014	0.5385	0.9309	0.7797	0.6989	
Sample 8	0.4241	0.5213	0.9381	0.7661	0.7637	
Sample 9	0.3038	0.4993	0.9359	0.8188	0.7544	
Sample 10	0.3507	0.4396	0.9295	0.7944	0.7156	
Sample 11	0.3811	0.5953	0.9303	0.8486	0.7443	
Sample 12	0.4338	0.3225	0.9283	0.7846	0.7346	
Sample 13	0.4721	0.3680	0.9408	0.8279	0.6883	
Sample 14	0.2927	0.5044	0.9307	0.6975	0.7237	
Sample 15	0.3317	0.3855	0.9234	0.7546	0.7281	
Sample 16	0.3770	0.5010	0.9415	0.8194	0.7194	
Sample 17	0.3957	0.3935	0.9372	0.7982	0.7024	
Sample 18	0.3254	0.5978	0.9446	0.7884	0.7129	
Sample 19	0.4326	0.3945	0.9345	0.8377	0.7331	
Sample 20	0.4614	0.5771	0.9390	0.7577	0.7671	
Sample 21	0.4927	0.3538	0.9352	0.7684	0.7008	
Sample 22	0.3697	0.4783	0.9228	0.7482	0.7292	
Sample 23	0.3611	0.5896	0.9301	0.7154	0.7877	
Sample 24	0.3437	0.3625	0.9407	0.6808	0.7873	
Sample 25	0.2850	0.5661	0.9241	0.7155	0.7633	
Sample 26	0.3176	0.4409	0.9334	0.8419	0.7688	
Sample 27	0.4555	0.5023	0.9303	0.8374	0.7510	
Sample 28	0.4117	0.4619	0.9341	0.8051	0.7076	
Sample 29	0.3876	0.3282	0.9319	0.7079	0.7452	
Sample 30	0.4067	0.2384	0.9398	0.7431	0.7222	
Sample 31	0.3206	0.4879	0.9463	0.7612	0.7930	
Sample 32	0.4167	0.4077	0.9296	0.8080	0.7416	
Sample 33	0.4504	0.5125	0.9423	0.7697	0.6886	
Sample 34	0.4984	0.3066	0.9259	0.8084	0.7627	
Sample 35	0.3479	0.4405	0.9362	0.7628	0.7630	
Sample 36	0.3301	0.3590	0.9290	0.7913	0.7533	
Sample 37	0.3683	0.4445	0.9232	0.7377	0.7226	
Sample 38	0.2988	0.5461	0.9439	0.7996	0.7309	
Sample 39	0.3338	0.4887	0.9290	0.7941	0.7701	
Sample 40	0.3996	0.3736	0.9251	0.8572	0.7562	
Sample 41	0.3615	0.3476	0.9248	0.7410	0.7652	
Sample 42	0.4715	0.5939	0.9374	0.8277	0.7159	
Sample 43	0.2847	0.5558	0.9254	0.7481	0.7373	

Figure 13: Calculating STDEV in Excel



	A	B	C	D	E	F
1	**Photocopier Example**					
2	/REPUT SATIS LOYAL/	p12	p23	indirect effect (p12 x p23)	Standard Deviation [=STDEV(D4:D5003)]	
3		REPUT -> SATIS	SATIS -> LOYAL			
4	Sample 0	0.218	0.1585	0.034553	0.0243	
5	Sample 1	0.2075	0.2357	0.04890775		
6	Sample 2	0.3666	0.139	0.0509574		
7	Sample 3	0.266	0.2448	0.0651168		
8	Sample 4	0.1413	0.2646	0.03738798		
9	Sample 5	0.1676	0.3594	0.06023544		
10	Sample 6	0.2036	0.2475	0.050391		
11	Sample 7	0.2309	0.2306	0.05324554		
12	Sample 8	0.1483	0.1588	0.02355004		
13	Sample 9	0.2195	0.3016	0.0662012		
14	Sample 10	0.2331	0.2636	0.06144516		
15	Sample 11	0.1645	0.2757	0.04535265		
16	Sample 12	0.2352	0.2052	0.04826304		
17	Sample 13	0.1696	0.1978	0.03354688		
18	Sample 14	0.2461	0.3102	0.07634022		
19	Sample 15	0.3194	0.2719	0.08684486		
20	Sample 16	0.1888	0.2361	0.04457568		
21	Sample 17	0.2033	0.2355	0.04787715		
22	Sample 18	0.1955	0.285	0.0557175		
23	Sample 19	0.1349	0.2067	0.02788383		
24	Sample 20	0.1822	0.1606	0.02926132		
25	Sample 21	0.1497	0.1763	0.02639211		
26	Sample 22	0.2073	0.209	0.0433257		
27	Sample 23	0.0958	0.2473	0.02369134		
28	Sample 24	0.2887	0.2199	0.06348513		

Magnitude of Mediation

Once the significance of the indirect effect is established, the strength of the mediator can be examined through the use of total effect and variance account for (VAF). Remember that Total effect = direct effect + indirect effect. In H_6, the total effect is 0.505 + 0.049 = 0.554. Meanwhile, VAF = indirect effect/total effect. Again in H_6, VAF = 0.049/0.554 = 0.089. Mediation analysis results are presented in Table 10. It can be said that only 8.9% of REPUT's effect on LOYAL can be explained via the SATIS mediator. Since the VAF is smaller than the 20% threshold level, SATIS is argued to have no mediating effect on the REPUT→LOYAL linkage. According to Hair et al. (2013), partial mediation is demonstrated when VAF exceeds the 0.2 threshold level and that full mediation is demonstrated when it exceeds 0.8. However, 21.3% of PRICE's effect on LOYAL can be explained via the SATIS mediator and the magnitude is considered to be partial. These findings lead us to reject hypothesis H_7 but accept hypothesis H_8 about SATIS's mediator role.

Table 10: Mediation analysis in PLS-SEM

Hypothesis	Procedure	Path:	Path Coef.	Indirect Effect	STDEV	Total Effect	VAF	*t* Values	Sig. Levels	*p* Values	Hypothesis
H6	Step 1: Direct effect (without mediator)	REPUT --> LOYAL	0.550	n/a				13.931	***	0.000	Rejected
	Step 2: Indirect Effect (with mediator)	REPUT --> LOYAL	0.505	n/a		0.554	0.089	2.029	**	0.050	
		REPUT --> SATIS	0.220	0.049	0.024						
		SATIS --> LOYAL	0.224								
H7	Step 1: Direct Effect (without mediator)	PRICE --> LOYAL	0.473	n/a				11.269	***	0.000	Accepted
	Step 2: Indirect Effect (with mediator)	PRICE --> LOYAL	0.369	n/a		0.469	0.213	2.645	***	0.010	
		PRICE --> SATIS	0.445	0.100	0.038						
		SATIS --> LOYAL	0.224								

Multi-group Analysis (PLS-MGA) – Business Type

Before starting this research project, Susan's colleagues in the sales department keep telling her that non-profit business customers often behave very differently from for-profit ones in their decision-making processes. Hence, a multi-group analysis (PLS-MGA) is conducted using the parametric approach as suggested by Keil et al., (2000), which involves a modified two-independent-sample t test to compare path coefficient across two groups of data. With the help of bootstrapping, the standard deviation of the path coefficient can be calculated. This way, Susan can explore if there is any categorical moderating effect of business type (i.e., non-profit = group 1; for-profit = group 2) on her research findings. This kind of concern is understandable because heterogeneity may exist to show significantly differences in model relationships. Becker, Rai, Ringle, & Völckner (2013) advise that researchers who failed to consider this potential issue may draw incorrect conclusions.

The main idea is to check if the variances of the PLS parameter estimates (i.e. path coefficients) differ significantly across the two groups. The standard errors of the PLS parameter estimates can be found using the bootstrapping procedure. The bootstrapping standard deviation is the same as the bootstrapping standard error in SmartPLS. To find the standard error (se(p(1)) of the parameter estimates in Group 1, run bootstrap with 106 cases; to find the standard error (se(p2)) of the parameter estimates in Group 2, run bootstrap with 95 cases. See "Report→Default Report→Bootstrapping→path coefficients (Mean, STDEV, *T*-Values)→standard errors". As revealed in Table 11, only 1 relationship (PRICE→LOYAL) differs significantly across the two groups. To reject the null hypothesis of equal path coefficients (i.e., to prove that the path coefficient is different across the 2 groups), the empirical *T*-Value must be larger than the critical value from a *T* distribution with $n^1 + n^2 - 2$ degrees of freedom. All other path coefficients do not differ significantly. The lack of heterogeneity leads us to reject the eighth hypothesis (H_8) about the categorical moderation role of business type in the model.

Table 11: Results of Multi-group Analysis (PLS-MGA)

Hypothesis		Group 1: Non-profit		Group 2: For-profit		Group 1 vs. Group 2				Hypothesis
		p1	se(p(1))	p2	se(p(2))	|p(1)-p(2)|	t Value	Significance Level	p Value	
H8	REPUT --> LOYAL	0.486	0.069	0.535	0.058	0.049	0.545	NS	0.587	Rejected
	SATIS --> LOYAL	0.241	0.084	0.195	0.085	0.046	0.386	NS	0.700	
	PRICE --> LOYAL	0.371	0.091	0.365	0.076	0.006	3.266	***	0.001	
	REPUT --> SATIS	0.147	0.108	0.307	0.108	0.160	1.050	NS	0.295	
	PRICE --> SATIS	0.470	0.131	0.416	0.122	0.054	0.300	NS	0.764	
	n	106		94						

Note: p(1) and p(2) are path coefficients of Group 1 and Group 2, respectively; se(p(1)) and se(p(2)) are the standard error of p(1) and p(2), respectively.
*p<0.10. **p<0.05. ***p<0.01 NS=not significant

Summary of Hypothesis Testing

All of the hypotheses except two are accepted in Susan's research, and their results are summarized in Table 12. REPUT is found to have significant impact to both LOYAL and SATIS (H_1 & H_2), whereas PRICE significantly influences these two endogenous variables as well (H_3 & H_4). It has also been found that SATIS maintains a significant linkage to LOYAL (H_5). Meanwhile, SATIS serves as a significant mediator to the relationship between PRICE and LOYAL (H_7). There is no significant categorical moderating effect of business type in the model so the last hypothesis (H_8) is rejected.

Table 12: Summary of Hypothesis Testing

Hypotheses		Accepted? (Yes/No)
H_1	Brand reputation (REPUT) significantly influences customer loyalty (LOYAL)	Yes
H_2	Brand reputation (REPUT) significantly influences customer satisfaction (SATIS)	Yes
H_3	Pricing (PRICE) significantly influences customer loyalty (LOYAL)	Yes
H_4	Pricing (PRICE) significantly influences customer satisfaction (SATIS)	Yes
H_5	Customer satisfaction (SATIS) significantly influences customer loyalty (LOYAL)	Yes
H_6	Customer satisfaction (SATIS) significantly mediates the relationship between brand reputation (REPUT) and customer loyalty (LOYAL)	No
H_7	Customer satisfaction (SATIS) significantly mediates the relationship between pricing (PRICE) and customer loyalty (LOYAL)	Yes
H_8	There is significant categorical moderating effect of business type on the relationship among model constructs	No

Managerial Implications for Susan

This research has provided Susan with several insights into her photocopier business, especially the factors that drives loyalty from her business customers. The following findings and managerial implications can be drawn:

1. Customer loyalty is influenced by several factors, including but not limit to brand reputation, product pricing, and customer satisfaction. Resources have to be allocated to look after these areas in general.

2. Out of these three factors, brand reputation is the most important one, followed by pricing and then customer satisfaction. That means the company should make brand reputation management a priority, in case sufficient resources are not available to manage these three areas at the same time.

3. Brand reputation is not a single-dimension factor. Instead, it is mostly affected by customers' perception of the company's product/service quality and financial performance, followed by its governance and leadership performance. Resources should be allocated in this sequence if they are limited. Contrary to common belief, this research does not find corporate social responsibility to have any significant relationship with brand reputation. As such, the company should first focus on the mentioned four areas of brand reputation before increasing the company's corporate social responsibility initiatives.

4. This research shows that customer satisfaction significantly mediates the strengths between pricing and loyalty. This means that if the customers are dissatisfied, they may not become loyal to the photocopier manufacturer even if the price is reasonable. As a result, account managers should not simply focus on getting the lowest pricing for their customers; it would be more important for them to understand their customers' needs, react to their concerns, and keep them satisfied.

5. No significant categorical moderating effect of business type is observed in this research, so the same conclusion can be drawn for both non-profit and for-profit organizations. In other words, Susan does not need to run separate programs to drive customer loyalty for each of these customer segments.

Conclusion

PLS-SEM is an emerging statistical procedure for structural modeling that marketing researchers can consider when conducting researches with limited number of participants. This technical note helps readers to understand how PLS-SEM can be applied in B2B research through the use of a fictitious example in the photocopier industry. Although PLS-SEM seems to be silver bullet for tackling data set with small sample size and non-normal data distribution, researchers must not ignore the proper model assessments prior to drawing a conclusion. There are many aspects of this statistical procedure such as reliability, validity, collinearity issues, predictive relevance, and effect sizes that have to be assessed, in addition to reporting the coefficient of determination and path coefficients as found in the PLS model. Finally, PLS-SEM can be configured to perform advanced modeling such as mediator and categorical moderation analysis. A higher-order construct is presented to illustrate how it can be incorporated in a reflective hierarchical components model.

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