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Comparison of Covariance-Based and Partial Least Square Structural Equation Modeling Methods under Non-Normal Distribution and Small Sample Size Limitations

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ABSTRACT

This study contains a repetition of the data analysis part of a research conducted on building the trust of generation Y customers in B2C websites. In this base study, since the samples size was a limitation of the study, analyses were conducted again by using CB-SEM and PLS-SEM methods separately and the results were compared in small sample size and non-normal distribution. Consistent results were obtained in all of tests of the hypotheses. Finding of this study highlighted the differences between CB-SEM and PLS-SEM and also compared the results obtained different estimation methods of ML, ADF and GLS under non-normal distribution and small sample size limitations.

Keywords: CB-SEM, PLS-SEM, Trust, Small Sample Size, Non-Normal Distribution

JEL-Clasification:

Normal Olmayan Dağılım ve Küçük Örneklem Büyüklüğü Kıstları Altında Kovaryans Tabanlı ve Kısmi En Küçük Kareler Yapısal Eşitlik Modellemesi Yöntemlerinin Karşılaştırılması

ÖZET

Bu çalışma, B2C web sitelerinde Y nesline mensup müşterilerin güvenini oluşturmaya yönelik bir araştırmanın veri analizi bölümünün tekrarını içermektedir. Bu temel çalışmada, örneklem büyüklüğü çalışmanın bir kısıtı olduğundan, CB-SEM ve PLS-SEM yöntemleri kullanılarak ayrı ayrı analizler yapılmış ve sonuçlar küçük örneklem büyüklüğünde ve normal olmayan dağılım altında karşılaştırılmıştır. Tüm hipotez testlerinde uyumlu sonuçlar elde edilmiştir. Bu çalışma bulgularında CB-SEM ve PLS-SEM arasındaki farklara değinilmiş ve ML, ADF ve GLS gibi farklı tahmin yöntemleri ile elde edilen sonuçlar karşılaştırılmıştır.

Anahtar Kelimeler: CB-SEM, PLS-SEM, Güven, Küçük Örneklem Hacmi, Normal Olmayan Dağılım

1. Introduction

In this study, the research titled as "Trust Building Model of Customers on B2C Websites: A Research on Generation Y Customers" was repeated by using a partial least square structural equation modeling (PLS-SEM) method (Civelek & Ertemel, 2018). The sample size limitation is the most important reason for repeating this work. In the sample, also distribution is non-normal because small sample size mostly leads to non-normal distribution. A comparison was made between the results found in both methods.

Recently, structural equation modeling method is increasingly used in scientific studies in the field of social sciences. The reason behind the spread of this statistical technique is that the direct and indirect relationships among the variables can be measured in a single model (Meydan & Şen, 2011). Another reason for the widespread adoption of this method is the taking of the measurement errors in to consideration. In this way, measurement errors can be minimized (Civelek, 2018). For complex models, the reason behind preferring structural equation modeling method instead of traditional regression analysis is that indirect effects among variables can be explained. Because in traditional regression analysis, only direct effects can be detected. In the method of structural equation modeling (SEM), direct and indirect effects are detected together. In the method of structural equation modeling, measurement model and structural model can be tested together. It is, therefore, superior to multiple regression (Civelek, Essentials of Structural Equation Modeling, 2018). There is one dependent variable in the multiple regression. However, there may be more than one dependent variable in the structural model in SEM, and a variable can be both a dependent variable and an independent variable in the same time. In SEM analyzes, more than one regression model can be analyzed at the same time, and indirect and direct effects can be measured at the same time. The indirect effect arises from the intervention of a variable that assumes the mediator role between two variables. The sum of the direct effect and the indirect effect of a variable on another variable is called the total effect (Raykov & Marcoulides, 2006).

There may be some cases where the assumptions of the estimation methods used in the structural equation modeling method are not met by the existing data set. In the small sample size case, there are methods that can be used if it is necessary to be satisfied with the existing data. The most used and preferred one of these methods for small sample size is partial least square structural equation modeling (PLS-SEM) method.

Structural equation modeling is also called covariance-based structural equation modeling (CB-SEM) because it is based on the covariance matrix. But PLS-SEM is a variance-based analysis method. For this reason, it is also called as the variance-based structural equation modeling. The PLS-SEM method is an advantageous method when the assumptions of least squares are neglected. This is a second generation multivariate analysis method that allows measurement and structural models to be analyzed together. Therefore it is an alternative to CB-SEM. PLS-SEM is an explanatory analysis method but CB-SEM is confirmatory method (Hair, Hult, Ringle, & Sarstedt, 2017). According to some sources in the literature, covariance-based structural equation modeling is a more powerful and reliable method. For this reason, the partial least squares method is generally preferred in cases where the following conditions are found: Insufficient sample size, non-normal distribution, the number of indicators connected to the latent variable is less than three, there is multicollinearity, there is missing value and the number of observations is less than the number of explanatory variables. In the cases that these conditions are found PLS-SEM is a much superior method to CB-SEM because it reduces the unexplained variance to a minimum level. As the model becomes more complicated no larger sampling is required in PLS-SEM by contrast with CB-SEM. There is a 10-fold rule in the literature about the sample sensitivity of the PLS-SEM method. According to this rule, in the measurement models, 10 times sample size is required for the number of indicators used to measure the constructs. In structural models also there is a requirement to have 10 times sample size for the paths (Barclay, Higgins, & Thompson, 1995).

Besides, PLS-SEM is a non-parametric method since it does not have any distributional assumption (Hair, Hult, Ringle, & Sarstedt, 2017). It is also an explanatory approach, which is why it is preferred in exploratory research. In other words, when the theory is under developed and relations need to be explained, it can be said that researchers prefer to use PLS-SEM (Rigdon, 2012). In the literature, there are some sources that demonstrate the advantages of the PLS-SEM method (Henseler, Dijkstra, Sarstedt, Ringle, Diamantopoulos, & Straub, 2014). Despite some drawbacks, PLS-SEM has become an increasingly used method in scientific studies (Hair, Hult, Ringle, & Sarstedt, 2017). In the CB-SEM method, many of the fit indices are influenced by sample size. In some papers, minimum sample size for CB-SEM analysis is recommended as 150 (Bentler & Chou, 1987). The minimum sample size that must be used in the CB-SEM is recommended as at least 10 times the number of parameters that can be estimated in the model (Jayaram, Kannan, & Tan, 2004). In some papers in the literature, it is also stated that the sample size for CB-SEM should be within the range of 200-500 (Çelik & Yılmaz, 2013).

The most important assumption of the maximum likelihood estimation method is the multivariate normal distribution. This assumption is often violated because ordinal and discrete scales are generally used in social sciences. Also, when the sample size is low, the normal distribution condition is usually not fulfilled. Violation of the assumption of multivariate normal distribution of observed variables cause high χ^2/DF value and significant test outcome. In case of violation of this assumption, it is recommended to use different estimation methods such as weighted least squares (WLS) instead of the maximum likelihood. This method can be used if the data is continuous but does not meet the normal distribution. Other prediction methods that can be preferred in non-normal distribution are ADF (asymptotically distribution free), MLM (Robust Maximum Likelihood) and GLS (generalized least squares) (Tabachnick & Fidell, 2001). In CB-SEM, as the complexity level of the model increases, the number of observations must also be increased. It is also necessary to increase the number of data in case of the distribution is non-normal (Kline, 2011).

2. Background

2.1. Word of Mouth

Word of mouth (WoM) is defined as an interpersonal communication regarding a brand between a receiver and a communicator. The receiver perceives this communication as non-commercial (Arndt, 1967). WoM communication is implicitly more trustworthy and in WoM none of the participants are marketing sources (Bone, 1995). Further, in order for the communication to be considered as WoM, the medium should also be perceived as independent of the brand. With the advent of the digital revolution, an electronic extension of WoM, eWoM has evolved. eWoM is defined as any positive or negative statement made by consumers about a brand which is made available to a multitude of people via the Internet (Hennig-Thurau et. al, 2004). Existing literature measure WoM with different dimensions. One important dimension is the WoM content that focuses on what's being said about the brand (Higie et al, 1987). Higie et al (1987), Bone (1992) have studied this WoM dimension. Another dimension is WoM intensity, which can be identified as the scope of WoM and studied extensively by Godez et all (2004), Harrison-Walker (2001).

2.2 Brand Awareness

Brand awareness can be defined as "the ability of a potential buyer to recognize or recall that a brand is a member of a certain product category (Aaker, 1991). Brand recognition takes place when consumers are exposed to brand-oriented messages. Brand awareness provides added value to a brand which creates familiarity, and hence commitment from consumers (Aaker, 1991). Brand recall can be defined as the consumers' ability to retrieve brand-related information from their memory.

2.3. Brand Trust

In e-commerce context, the brand trust is defined as a set of beliefs of consumer regarding defined characteristics and possible future behavior of the e-commerce site. Brand trust affects customer attitudes towards web site (Lee et.al, 2005) and intention to purchasing (Quelch and Klein, 1996).

3. Research Model and Hypotheses

The theoretical model is shown in Figure 1. This model aims to clarify the relationships among word of mouth, brand awareness and brand trust.

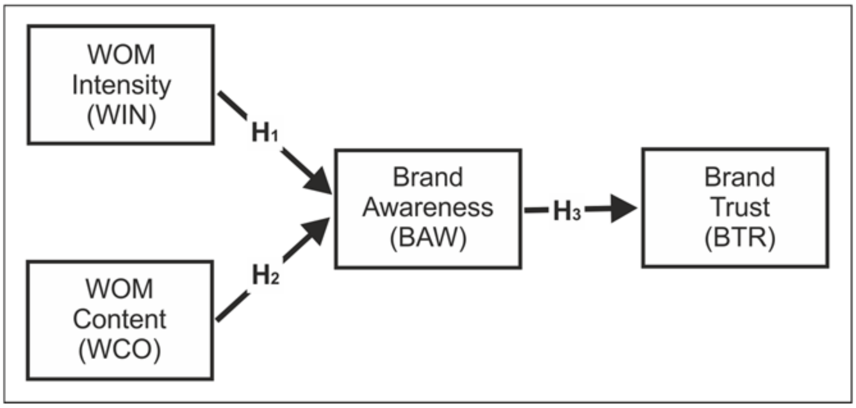


Figure 1. Theoretical Model

According to Hoyer (1990) and MacDonald et all (2000) WoM affects brand awareness. Hoyer (1990) and MacDonald and Sharp (2000) pointed out the role of WoM on brand awareness in consumer buying behavior. According to some research in literature (Smith and Wheeler, 2002, Macdonald and Sharp, 2000), brand awareness has a relationship with trust. Prior studies show that a brand with high brand awareness leads to higher brand trust and stimulate purchase behavior and that if consumers are more familiar with a brand, they would be more likely to trust (Smith & Wheeler, 2002). Thus, in the light of the existing literature, following hypotheses were put forward:

H_1: WOM Intensity (WIN) has a positive effect on Brand Awareness (BAW).

H_2: WOM Content (WOC) has a positive effect on Brand Awareness (BAW).

H_3: Brand Awareness (BAW) has a positive effect on Brand Trust (BTR).

4. Research Method

When the sample size is low, the data usually does not distribute normally. Firstly, therefore, Kolmogorov-Smirnov and Shapiro-Wilk tests were conducted to assess the normal distribution (Sarstedt & Mooi, 2014). In case of the data is continuous but does not meet the normal distribution, in CB-SEM there are different estimation methods instead of the maximum likelihood (ML) such as asymptotically distribution free (ADF) and generalized least squares (GLS) (Tabachnick & Fidell, 2001). Therefore, before comparing CB-SEM and PLS-SEM, a comparison was conducted among different estimation methods in CB-SEM. Finally results of CB-SEM and PLS-SEM were compared.

5. Measures and Sampling

The scales adopted by Han et al. from prior studies were used to measure brand awareness and brand trust (Han, Nguyen, & Lee, 2015). To measure the eWOM, the scale developed by Goyette et al. was used (Goyette, Ricard, Bergeron, & Marticotte, 2010). 5-point Likert scale ranging from strongly disagree to strongly agree was used. More than 400 distributed, 305 valid questionnaires were gathered from prominent cities throughout Turkey. 171 of the respondents are male and 134 are female. The most important limitation of this research is the sample size. Although preferred sample size is more than 400, due to practical constraints, only 305 valid sample size has been reached. Nevertheless, validity and reliability of the scale has been determined.To assess convergent validity, confirmatory factor analysis was performed. CFA results indicated that the model has good fit: $\chi 2$/DF =1.266, CFI=0.974, IFI=0.975, RMSEA= 0.047. In order to assess discriminant validity, the square roots of average variance extracted values were compared with correlation values of the constructs. In Table 3, the diagonals demonstrate the square root of AVE value of each variable. And as shown in Table 3, the square roots of average variance extracted values are beyond the correlation values in the same column (Byrne, 2010). Reliability of each construct individually calculated. Composite reliability and Cronbach α values are beyond the threshold level (i.e. 0.7) (Fornell & Larcker, 1981). Average variance extracted values, composite reliabilities, , Cronbach α values and Pearson correlation coefficients of the constructs are shown in Table 3.

6. Comparison of the Analyses Results

In order to assess the normality, Kolmogorov-Smirnov and Shapiro-Wilk tests were applied. The results of these tests are shown in Table 1. As shown in the Table, all of the constructs do not fit normal distribution assumption. Shapiro-Wilk test is more reliable in the small sample size (Durmuş, Yurtkoru, & Çinko, 2013).

Table 1. Normality Test Results

	Kolmogorov-Smirnov		Shapiro-Wilk	
	Statistic	Sig.	Statistic	Sig.
WIN	0.149	,000	,960	,001
WCO	0.235	,000	,834	,000
BAW	0.199	,000	,858	,000
BTR	0.153	,000	,937	,000

Kolmogorov-Smirnov and Shapiro-Wilk tests only indicate that the normal distribution hypothesis rejected. Although PLS-SEM does not require the data to be normally distributed extremely non-normal data is problematic in the assessment of the significances of the parameters. In extremely non-normal distribution, bootstrap method provides limited guidance (Hair, Hult, Ringle, & Sarstedt, 2017). Therefore skewness and kurtosis measures were additionally examined. In Table 2, skewness and kurtosis values of the constructs are shown. As shown in the Table, distributions of WCO and BAW constructs are too peaked. This means that WCO and BAW are more problematic comparing other constructs.

Table 2. Skewness and Kurtosis Test Results

	Skewness		Kurtosis	
	Statistic	Std. Error	Statistic	Std. Error
WIN	-0.424	0.221	-0,079	0.438
WCO	-1.522	0.221	4.745	0.438
BAW	-1.254	0.221	4.413	0.438
BTR	0.677	0.221	0.690	0.438

In Table 3, values of Pearson correlation coefficients are shown. As shown in the Table, all of correlation values are statistically significant.

Table 3. Correlations, AVE and Reliability of the Constructs

Variables	1	2	3	4
1.WIN	(.70)			
2.WCO	.223*	(.74)		
3.BAW	.185*	.105*	(.77)	
4.BTR	.269*	.205*	.105*	(.82)
Composite reliability	.79	.78	.81	.86
Average variance ext.	.49	.55	.59	.67
Cronbach α	.77	.77	.81	.86

*p < 0.05

Note: Diagonals show the square root of AVEs.

In Table 4, the results obtained by different estimation methods of maximum likelihood (ML), asymptotically distribution free (ADF) and generalized least squares (GLS) are shown.

Table 4. ADF and GLS Estimation Results Comparison in CB-SEM

Relations	ML	ADF	GLS
WIN → BAW	0.313*	0.342*	0.381*
WOC → BAW	0.311*	0.644*	0.299*
BAW → BTR	0.355*	0.188*	0.411*

Note: Regression coefficients are standardized

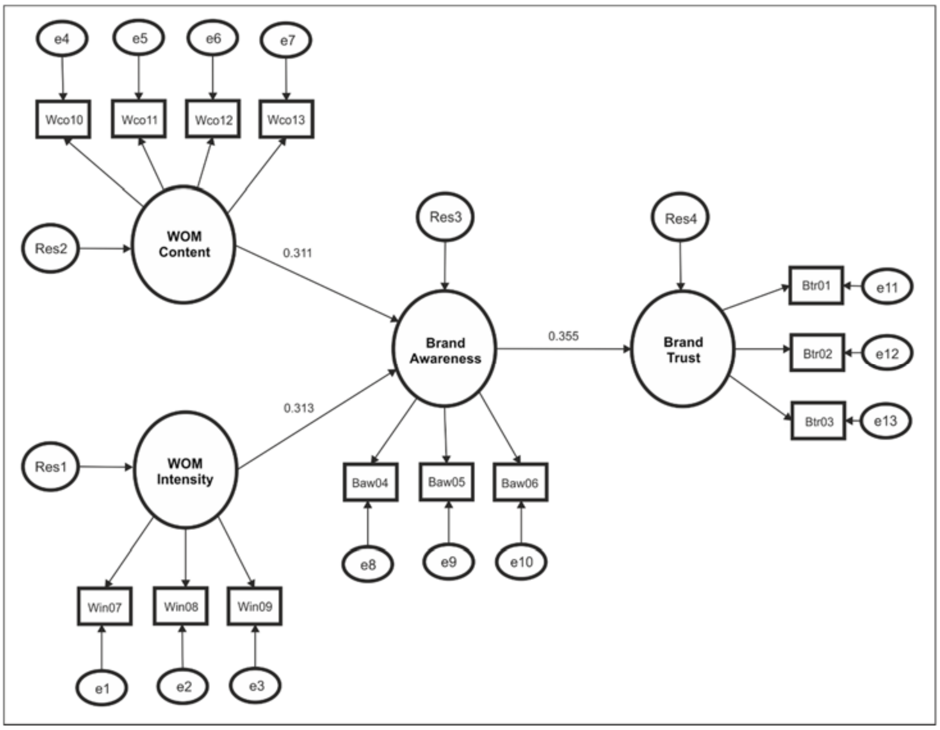
*p<0.05

In Table 5, size and significance of path coefficients estimate values calculated in CB-SEM and PLS-SEM methods are compared with each other. PLS-SEM depends upon bootstrap procedure to test the significance of the estimates because it is a nonparametric statistical method. In the significance level of 5%, p values smaller than 0.05 are considered as significant. When comparing the results obtained by two different methods, all of the hypotheses test results are found consistent.

Table 5. CB-SEM and PLS-SEM Hypotheses Results Comparison

Relations		Estimates		Significance		Comparison	Results
		CB-SEM	PLS-SEM	CB-SEM	PLS-SEM		
WIN→BAW	H_1	0.313	0.251	0.019	0.029	Consistent	Supported
WCO→BAW	H_2	0.311	0.272	0.014	0.013	Consistent	Supported
BAW→BTR	H_3	0.355	0.261	0.000	0.006	Consistent	Supported

Note: Regression coefficients are standardized



Note: $\chi 2$/DF = 1.677, CFI = 0.933, IFI = 0.935, RMSEA= 0.075

Figure 1. CB-SEM Results in ML

In Figure 1, CB-SEM structural model is shown. This model was analyzed by using maximum likelihood estimation method. In order to evaluate the structural model, the absolute and relative goodness of fit indices were used. The absolute goodness of fit indices are the root mean square error of approximation (RMSEA) and the χ^2 goodness of fit statistic.

Table 6. CB-SEM Structural Model Fit Indices

Fit Indices	ML	ADF	GLS
$\chi 2$/DF	1.677	1.401	1.174
CFI	0.933	0.916	0.902
IFI	0.935	0.921	0.915
RMSEA	0.075	0.058	0.038

The relative goodness of fit indices are the comparative fit index (CFI) and the incremental fit index (IFI). As shown in Table 6, structural model fit indices adequately indicate satisfactory model fits for each method. RMSEA value is highly sensitive to the sample size and in GLS method reach more satisfactory result comparing other methods.

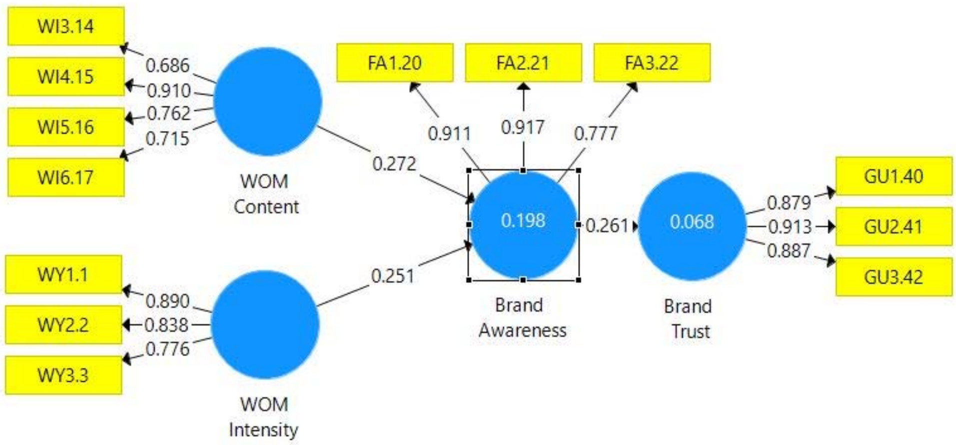


Figure 2. PLS-SEM Results

In CB-SEM, evaluation of the model relies on goodness of fit measures which are based on the fit between empirical and theoretical covariance matrix. But in PLS-SEM, the most used evaluation measures are R^2 (explained variance), f^2 (effect size) and Q^2 (predictive relevance)

In Figure 2, path analysis results in PLS-SEM are shown. Coefficient indicates the direct relations. In Table 7, comparison of R^2 values of the dependent latent variables are shown. In PLS-SEM, the most used measure to assess the path models is the coefficient determination (R^2). R^2 value indicates the predictive power of the model and refers to combined effects of exogenous latent variables on an endogenous latent variable and represents the amount of variance explained (Hair, Hult, Ringle, & Sarstedt, 2017). There is rule of thumb for acceptable value of R^2 that differs according to the discipline. In consumer behavior area 0.20 R^2 value can be considered as high. For this study, the values in Table 7 can be considered as acceptable (Hair, Ringle, & Sarstedt, PLS-SEM: Indeed a silver bullet, 2011).

Table 7. Comparison of R^2 Values of the Dependent Variables

Variables	PLS-SEM	CB-SEM
BAW	0.198	0.302
BTR	0.068	0.126

Effect size f^2 is a measure of the impact of a construct on another. It is calculated by omitting the construct from the model. Effect size f^2 represents the change in R^2 when a construct omitted from the model. To assess f^2, following values of 0.02, 0.15 and 0.35 are used. These values represent respectively, small, medium and large effects (Cohen, 1988). In Table 8, effect size values are shown.

Table 8. Effect Size(f^2) Values

Relations	f^2
WIN → BAW	0.063
WCO → BAW	0.074
BAW → BTR	0.073

In PLS-SEM, another measure to assess the models is predictive relevance (Q2). This value is also called as Stone-Geisser's Q2 value (Geisser, 1974). Q2 values are calculated for dependent variables in the model and indicate predictive relevance of path model for a dependent variable specifically. To calculate Q2 values, blindfolding procedure is used. Blindfolding procedure depends upon omission of data points. Q2 values larger than 0 indicate that the model has predictive relevance for a certain dependent variable. Conversely, values of zero or below indicate lack of predictive relevance. In Table 9, Q2 values of each construct are shown.

Table 9. Q^2 Values of the Dependent Variables in PLS-SEM

BAW	0.129
BTR	0.047

7. Conclusion

Both statistical methods produced consistent and robust results. These results, therefore, provided a confirmation of the theoretical research model. All the hypotheses were supported by the tests conducted both CB-SEM and PLS-SEM. Although consistent results were obtained in both methods analysis conducted in CB-SEM resulted in significantly higher R^2 values than PLS-SEM. Squared multiple correlations for each endogenous construct in CB-SEM model are relatively high. But, in PLS-SEM model, R^2 values of BAW and BTR can be considered as moderate and weak respectively. Consequently, finding of this study highlighted the differences between CB-SEM and PLS-SEM and also compared the results obtained different estimation methods of ML, ADF and GLS under non-normal distribution and small sample size limitations. While PLS-SEM is the most preferred method to handle small sample sizes and non-normal data distribution, results obtained in CB-SEM are non-contradictory.

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REFERENCES

- Aaker D. (1991). *Managing Brand Equity: Capitalizing on the Value of a Brand Name*, the Free Press, New York, NY.
- Arndt, J. (1967). Word of mouth advertising: A review of the literature. Advertising Research Foundation.
- Barclay, D., Higgins, C., & Thompson, R. (1995). The partial least squares approach to causal modeling: Personal computer adoption and use as illustration. *Technology Studies, 2*, 285-309.
- Bentler, P. M., & Chou, C.-P. (1987). Practical Issues in Structural Modeling. *Sociological Methods Research, 16*(1), 78-117.
- Bone, P. F. (1995). Word of Mouth effects on short-term and long-term product judgments. *Journal of Business Research, 32(3), 213–223.*
- Bone, P. F. (1992). Determinants of Word-of-Mouth communication during product consumption. *Advances in Consumer Research, 19, 579–583*
- Byrne, B. M. (2010). *Structural Equation Modeling with AMOS.* New York: Routledge Taylor & Francis Group.

- Civelek, M. (2018). *Essentials of Structural Equation Modeling.* Lincoln: University of Nebraska Lincoln-Zea Books.

- Civelek, M. (2018). *Yapısal Eşitlik Modellemesi Metodolojisi.* İstanbul: Beta.

- Civelek, M., & Ertemel, A. (2018). Trust Building Model of Customers on B2C Websites: A Research on Generation Y Customers. *Journal of History Culture and Art Research, 7*(1), 332-340.

- Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences.* Mahwah: Lawrence Erlbaum.

- Çelik, H. E., & Yılmaz, V. (2013). *Lısrel 9.1 ile Yapısal Eşitlik Modellemesi.* Ankara: Anı Yayıncılık.

- Durmuş, B., Yurtkoru, E., & Çinko, M. (2013). *Sosyal Bilimlerde SPSS'le Veri Analizi.* İstanbul: Beta.

- Fornell, C. & Larcker, D. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, 18(1), 39-50.

- Geisser, S. (1974). A predictive approach to the random effects model. *Biometrika, 61*, 101-107.

- Godes, D. & Mayzlin, D. (2004). Se servir des conversations en ligne pour étudier le bouche-à-oreille. *Recherche et Applications en marketing*, 19(4), 89–111

- Goyette, I.; Ricard, L.; Bergeron, J. & Marticotte, F. (2010). e-WOM Scale: Word-of-Mouth Measurement Scale for e-Services Context. *Canadian Journal of Administrative Sciences*, 23(5), 5-23.

- Hair, J., Hult, G., Ringle, C., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling PLS-SEM.* Los Angeles: SAGE.

- Hair, J., Ringle, C., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice, 19*, 139-151.

- Han, S.; Nguyen, B. & Lee, T. (2015). Consumer-based chain restaurant brand equity, brand reputation, *International Journal of Hospitality Management*, 50(1), 84-93.

- Harrison-Walker, L. J. (2001). The measurement of Word-of-Mouth communication and an investigation of service quality and customer commitment as potential antecedents. *Journal of Service Research.*

- Henseler, J., Dijkstra, T., Sarstedt, M., Ringle, C., Diamantopoulos, A., & Straub, D. (2014). Common beliefs and reality about partial least squares: Comments on Rönkkö & Evermann (2013). *Organizational Research Methods, 17*, 182-209.

- Hennig-Thurau, T.; Gwinner, K. P.; Walsh, G. & Gremier, D. D. (2004). Electronic Word-of-Mouth via consumer opinion platforms: what motivates consumers to articulate themselves on the Internet? *Journal of Interactive Marketing*.

- Higie, R. A.; Feick, L. F. & Price, L. L. (1987). Types and amount of Word-of-Mouth communications about retailers. *Journal of Retailing*.

- Hoyer, W. D. (1990). The effects of brand awareness on choice for a common, repeat-purchase product ,*Journal of Consumer Research*, 17, 141-8. H

- Jayaram, J., Kannan, V., & Tan, K. (2004). Influence of initiators on supply chain value creation. *International Journal of Production Research, 42*(20), 4377-4399.

- Kline, R. (2011). *Principles and practice of structural equation modeling* (3nd Ed. b.). New York: Guilford.
- Lee, G. & H. Lin (2005). Customer Perceptions of E-service Quality in Online Shopping*, International Journal of Retail and Distribution Management, Vol. 33, 2:161-176.*
- Meydan, C. H., & Şen, H. (2011). *Yapısal Eşitlik Modellemesi AMOS Uygulamaları.* Ankara: Detay Yayıncılık.
- Macdonald, E. K. & Sharp, B. M. (2000). Brand awareness effects on consumer decision making for a common, repeat purchase product: a replication. *Journal of Business Research*, 48, 5-15.
- Quelch, J. A. & Klein, L. R. (1996), The Internet and International Marketing, *Sloan Management Review*, 37(3), Spring, 60–75.
- Raykov, T., & Marcoulides, G. (2006). *A First Course in Structural Equation Modeling.* Mahwah: Lawrence Erlbaum Associates.
- Rigdon, E. (2012). Rethinking partial least squares path modelling: In praise of simple methods. *Long Range Planning, 45*, 341-358.
- Sarstedt, M., & Mooi, E. (2014). *A Concise Guide to Market Research: The Process, data, and Methods Using IBM SPSS Statistics.* Berlin: Springer.
- Smith, S. & Wheeler, J. (2002). *Managing the customer experience: Turning customers into advocates.* London: Prentice Hall Financial Times and Pearson Education Ltd.
- Tabachnick, B., & Fidell, L. (2001). *Using multivariate statistics.* Boston: Ally and Bacon.