

(Consistent) PLS-SEM vs. CB-SEM in Mobile Shopping

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Abstract

This paper seeks to examine and compare the regular and consistent PLS-SEM and CB-SEM by employing the augmented TAM, which stands as a proportionately complicated model. The present paper presents the pros and cons of each method and guides researchers and academics concerning which particular method is the most appropriate to employ in their studies. The findings of this paper are twofold: (1) performing CB-SEM and consistent PLS-SEM for reflectively structured models would have more robust outputs and would be more appropriate and beneficial in lieu of executing regular PLS-SEM; (2) consistent PLS-SEM has softer provisions since it does not necessitate a two-step analysis, high sampling sizes and normal distribution requirements, thus performing consistent PLS-SEM appears more viable and practical for researchers.

Keywords: CB-SEM, PLS-SEM, consistent PLS, research methodology, mobile marketing, mobile shopping

Mobil Alışveriş Düzleminde Consistent PLS-SEM ve CB-SEM Yöntemlerinin Karşılaştırılması

Öz

Araştırma, nispeten karmaşık bir model olan artırılmış Teknoloji Kabul Modelini kullanarak geleneksel ve tutarlı PLS-SEM ile CB-SEM yöntemlerini incelemeyi ve karşılaştırmayı amaçlamaktadır. Araştırmada, her yöntemin avantajları ve dezavantajları ortaya konmakta böylelikle araştırmacılara ve uzmanlara çalışmalarında hangi yöntemin kullanımının uygun olduğu konusunda rehberlik etmektedir. Çalışmanın bulguları ikiye ayrılmaktadır. İlk olarak çalışma, reflektif olarak yapılandırılmış modellerde geleneksel PLS-SEM yöntemini tercih etmek yerine CB-SEM veya consistent PLS-SEM yöntemlerini kullanmanın daha sağlam sonuçlar sağladığına işaret etmektedir. İkincisi ise CB-SEM yönteminin aksine consistent PLS-SEM yönteminin, iki aşamalı analiz, yüksek örneklem



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hacmi ve normal dağılım şartları gibi katı koşullar gerektirmemesi araştırmacılar için daha elverişli bir yöntem olduğunu göstermektedir.

Anahtar Kelimeler: CB-SEM, PLS-SEM, consistant PLS-SEM, araştırma metodolojisi, mobil pazarlama, mobil alışveriş

Introduction

Structural equation modeling (SEM) is a superior version of general linear modeling according to multiple regression analysis because of concurrently analyzing multilevel dependence relationships that "a dependent variable becomes an independent variable in subsequent relationships within the same analysis" (Shook et al. 2004, p.397). It also examines whether the hypothetical model is compatible with the collected data concerning the reflection a particular theory (Lei & Wu, 2007). Integrating factor analysis and linear regression models simultaneously, SEM gives researchers a possibility to examine relationships among theory-based latent variables and those of the items by predicting directly observable variables (Hair et al. 2014). It has two major statistical tools: covariance-based SEM (CB-SEM) and variance-based SEM (PLS-SEM).

CB-SEM separates the variance of each variable into two components. First is the common variance that is calculated from the variance combined with other items in a construct, and second is unique variance that includes both specific and error variance (Bollen, 1989; Rigdon, 1998).

The covariances of an array of variables are computed by CB-SEM, and each solution originates from covariances of those variables (common variance). Thus, CB-SEM employs a common factor model procedure in the prediction of the measurement models, which refers to the variance of a collection of items that can be correctly elucidated by the presence of a latent variable and individual random error (Spearman, 1927; Thurstone, 1947). CB-SEM employs a maximum likelihood (ML) prediction technique, and it intends "reproducing the covariance matrix [i.e., minimizing the difference between the observed and estimated covariance matrix], without focusing on explained variance" (Hair et al., 2011, p.139). The common factor prediction method rests on an approximation philosophy of reflective measurement. While doing so, CB-SEM requires strict restrictions concerning the multivariate normality of data and sample sizes, frequently driving to biased test statistics, which results in inadmissible solutions, and model identification problems (Hair et al. 2011; Willaby et al. 2015).

Partial Least Squares (PLS) path modeling method, VB-SEM, on the other hand, does not divide variances of observable variables into two. This method aims to reveal the overall variance of the constructs rather than demonstrating correlations among items (Reinartz et al. 2009). Therefore, PLS-SEM (VB-SEM) takes into consideration the total variance of the observed indicators in lieu of the correlations between indicators of the latent variables. The underlying idea is that variables can be connected linearly to shape composite variables that are inclusive illustrations of latent variables, and these linear amalgamations are accurate representations of the investigated structures (Sarstedt et al. 2016). PLS-SEM employs a regression-based ordinary least squares (OLS) prediction procedure to explain the variance of the latent variable "by minimizing the error terms [and maximizing] the R^2 values of the (target) endogenous constructs" (Hair et al., 2014, p.14). Therefore, PLS follows a composite model process, which rests on the approximation philosophy of formative measurement. Additionally, PLS path modeling can also cope with reflective measurement models. However, what makes PLS path modeling distinct is that it is appropriate for predictive and theory-testing research

(Henseler et al. 2009; 2014). Furthermore, it can also estimate complicated models that have a significant number of latent and manifest variables, and it has less rigorous premises in the distribution of variables and error terms (Henseler et al. 2009). However, Wold (1982) noted that regular PLS predictions specifically for path coefficients and loadings are just consistent within a high-volume sample size. To put it another way, as Gefen et al. (2011, p. vi) put forward, "parameter estimates for paths between observed variables and latent variable proxies are biased upward in PLS (away from zero), while parameter estimates for paths between proxies are attenuated." This situation is termed as PLS-SEM bias. A process that ignores random measurement errors may have serious consequences related to model results (Rigdon, 1994). Therefore, lack of consistency might exhibit substantial unfavorable consequences for research findings.

While PLS-SEM bias has been a known issue for over three decades, studies on the bias issue have been gaining momentum only recently (Dijkstra & Henseler, 2015a; Sarstedt, et al. 2016; Hair et al. 2017; Cheah et al. 2018; Yıldız, 2021). The proponents of PLS-SEM and CB-SEM have gotten into high-tension discussions on reciprocity, even making comments, such as "there is no use for PLS whatsoever" (Antonakis et al. 2010, p. 1103) or "researchers should discontinue the use of PLS" (Rönkkö et al., 2016, p. 24). These controversial views have resulted in uncertainty among researchers. To deal with PLS-SEM bias problem, Dijkstra and Henseler (2015a, 2015b) offered consistent Partial Least Squares (PLSc) as a significant improvement. The consistent PLS-SEM calculates path coefficients, correlations between structures, and factor loadings in a consistent technique. With the introduction of PLSc, there was even more confusion among many researchers. Academics were puzzled whether to employ PLS or PLSc on the same data. According to Sarstedt et al. (2016), the actual bias occurs when academics are unaware of the background of the data (common or composite population). Thus, Sarstedt et al. (2016) proposed that future research should perform a comparison among CB-SEM, regular and consistent PLS-SEM on the data where both models are suitable for the population. Hitherto research has not evaluated the performance of three methods in the mobile shopping context. To fill the gap in the literature, this paper seeks to evaluate CB-SEM and regular and consistent PLS-SEM in mobile shopping setting by analyzing the augmented TAM (Taylor & Todd, 1995), which is relatively complicated and rests on a reflective measurement model. Consequently, this paper seeks to help researchers and academics to pick up the most convenient and practical method among the three different structural equation modeling approaches.

Literature Review and Hypotheses

This paper tries to assess three structural path modeling approaches through augmented TAM in the mobile shopping context. The model consists of basic assumptions of Theory of Reasoned Action (Ajzen & Fishbein, 1980), TAM (Davis, 1989; Davis et al. 1989), as well as Theory of Planned Behavior (Ajzen, 1991). Even though TAM does not include the effects of social pressure and control factors on behavior, these conceptual structures are the essential determinants of the behavior in Theory of Planned Behavior (TPB). In effect, Theory of Reasoned Action (TRA) is the foundational theory for both TAM and TPB.

The augmented TAM, in the same fashion with TAM, considers that the behavior of people is shaped by behavioral intentions and consequently, behavioral intentions of individuals depend on individuals' attitudes towards the use of a new system, its "perceived ease of use" as well as its "perceived usefulness." (Davis et al. 1989). The augmented TAM also has more predictive capacity since it is a far-reaching model to

include the conceptual structures of "social norm" and "perceived behavioral control." According to Taylor and Todd (1995), these concepts are widely used in social sciences.

The basic assumptions of TAM have been analyzed in the mobile shopping context (Agrebi & Jallais, 2015; Marriott et al., 2017; Saprikis et al., 2018; Chen & Tsai, 2019), but this research takes into account the augmented TAM and proposes the following hypotheses:

H1: *The perceived usefulness of mobile shopping apps has a significant connection with attitudes toward adoption behavior.*

H2: *The perceived usefulness of mobile shopping apps has a significant connection with behavioral intention.*

H3: *The perceived ease of use of mobile shopping apps has a significant connection with attitudes toward adoption behavior.*

H4: *The perceived ease of use of mobile shopping apps has a significant connection with behavioral intention.*

As it has been mentioned above, augmented TAM has been partly built on TRA and TPB. The second factor of an intended desire to do a given behavior, according to these theories, is the person's impression of social influence, which is characterized as the subjective norm (Ajzen, 1991). The connection between subjective norm and behavioral intention, suggested by TPB, has been discussed in different mobile shopping context (Yang, 2013; Marriott et al., 2017). In light of what has been said above, the following hypothesis has been offered.

H5: *The subjective norm has a significant connection with behavioral intention in shopping through mobile apps.*

A second time, as it has been mentioned above, augmented TAM shares the connection between perceived behavioral control and behavioral intention as in the case of TPB. TPB is predicated on the idea that attitude, subjective norm, and perceived behavioral control influence behavioral intention, and that behavioral intention and perceived behavioral control then cause behavior (Ajzen, 1991). Behavioral control has been found as a fundamental component in the adoption of new technology research (Taylor & Todd, 1995). While performing a task or goal by utilizing mobile services, users or consumers want to ensure that they have control over these services, and they also want to ascertain the functionality and performance of these mobile services. The users, who do not feel control over these services, may switch to alternative outlets, such as traditional retail stores. Taking these discussions into account, perceived behavioral control has also been analyzed in the mobile shopping context (Yang, 2012; Yang, 2013).

H6: *The perceived behavioral control of mobile shopping apps has a significant connection with behavioral intention.*

H7: *The perceived behavioral control of mobile shopping apps has a significant connection with behavior*

Furthermore, according to augmented TAM, behaviors of individuals are influenced by "behavioral intentions," and "perceived behavioral control." Also, components of "behavioral intentions" include "attitudes," "social norms," and "perceived behavioral control." In addition, "attitudes towards the usage behavior" are determined by "perceived usefulness" and "perceived ease of use." These assumptions have been tested in the mobile shopping domain (Tak & Panwar, 2017; Zhu et al., 2017), and the following hypotheses have been proposed:

H8: *The attitude concerning mobile shopping apps has a meaningful connection with behavioral intention.*

H9: The behavioral intention has a meaningful connection with the acceptance of mobile shopping apps.

Research and Methodology

In this section, first, the authors will begin by providing a background pertaining to the research context. Ensuingly, an explanation will be provided concerning the research model. Mobile shopping is a common way to browse, compare, and buy products and services online whenever and wherever customers want to use a mobile device (Groß, 2014). By using mobile network services, such as 4.5G and LTE, the number of mobile broadband subscribers, who have been accessing internet services via mobile devices, reached 63 million in the second quarter of 2020 in Turkey (ICTA - Quarterly Market Report, 2020). Considering the market volume of 80 billion TRY, the e-trade market report also revealed that the mobile share of e-commerce turnover has increased to approximately 60 percent (Deloitte, 2019).

The augmented TAM, which sets the basis to compare three methods (CB-SEM, regular and consistent PLS-SEM), includes 7 structures, 22 indicators, and 9 relationships (Figure 1). The augmented TAM, first of all, considers that the behavior (BEH) is affected by behavioral intention (BI) and perceived behavioral control (PBC). Secondly, the behavioral intention is affected by attitudes (ATT), subjective norm (SN), perceived behavioral control (PBC) as well as perceived usefulness (PU), and perceived ease of use (PEOU). Last of all, attitude (ATT) is shaped by perceived usefulness (PU) and perceived ease of use (PEOU). The research employs adapted and established scales from previous examinations that predict variables on a five-point Likert scale.

The empirical data was accumulated through face-to-face surveys from 430 Turkish consumers who shop via mobile apps in the metropolitan city of Istanbul in December of 2019. Nevertheless, only 400 of these surveys have been accepted in the investigation. The descriptive data in this study reveals that the age of participants range from 18 to 55, of whom 43 % are female, and 57 % are male. All of the attendees stated that they earn more than the minimum wage on a monthly basis.

This research employed the "ten-times-rule" criteria to adjust for the PLS-SEM bias and CB-SEM requirements and population already exceeds the so-called threshold (Barclay et al. 1995).

In this section, the augmented TAM and hypotheses shall be analyzed by using SmartPLS 3 (regular and consisted PLS) and AMOS 24, then the results of each analysis shall be presented respectively. Based on these analyses, CB-SEM and VB-SEM methods shall be compared; then the theoretical model shall be evaluated, which is derived from the outputs of three different methods. Finally, drawing on these results, the pros and cons of these methods shall be discussed on the basis of the research model.

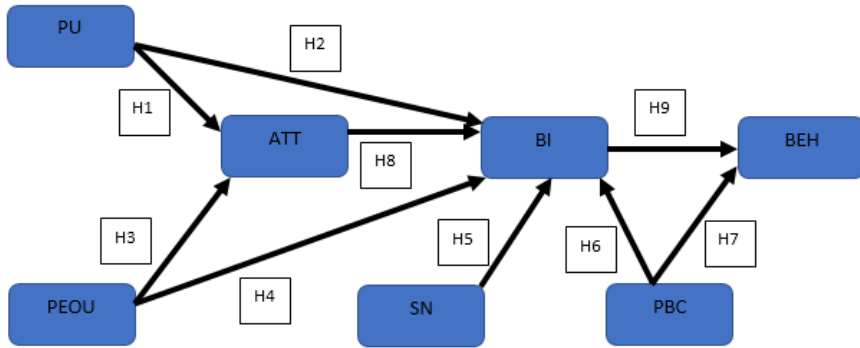


Figure 1. The Augmented TAM

Results of the SEM Analyses

Before performing the analyses, the authors verified whether the data is normally distributed to meet the assumptions of SEM. In effect, the normal distribution is considered a requirement only for CB-SEM. According to Kline (2016), the normal distribution requirement for data is considered acceptable if values are in the range of ± 3 . The data from this study has ascertained normal distribution requirements in agreement with Kline (2016).

CB-SEM Results

Confirmatory Factor Analysis (CFA) has been executed via AMOS 24 to verify the conceptual structures and measurement models for the research model. Initially, the authors examined the augmented TAM in terms of consistency, validity, and reliability. As it has been mentioned in the research and methodology section above, the augmented TAM consists of 7 structures, 22 indicators, and 9 relationships. Before proceeding, the indicators, which have the factor loadings (PEOU4, PU3, PU4, PBC2) below 0.6 in CFA process, have been removed since goodness of fit indexes are not considered acceptable. Subsequently, CFA has been reperformed with a new model, which consists of 7 structures and 18 indicators with the following results: $X^2 = 400.280$, $DF=113$, $X^2/DF=3.542$, $p=0.000$, $CFI=0.952$, $GFI=0.924$, $RMSEA=0.068$. Built on the new results, goodness of fit indexes for the measurement models stand within the recommended ranges (Hair et al. 2010). Table 1 presents convergent validity and reliability values.

Constructs and variables	Loadings PLS/PLSc/AMOS	AVE PLS/PLSc/AMOS	CR PLS/PLSc/AMOS	P _A PLS/PLSc
PEOU1	0.743/ 0.575 /0.660	0.594/ 0.554 /0.552	0.878/ 0.830 /0.830	0.851/ 0.843
PEOU2	0.841/ 0.828 /0.833			
PEOU3	0.826/ 0.793 /0.756			
PEOU4	0.625/deleted/deleted			
PEOU5	0.798/ 0.755 /0.713			
PU1	0.806/ 0.856 /0.790	0.580/ 0.607 /0.594	0.846/ 0.753 /0.745	0.770/ 0.768
PU2	0.801/ 0.693 /0.751			
PU3	0.683/deleted/deleted			
PU4	0.751/deleted/deleted			
ATT1	0.932/ 0.904 /0.912	0.722/ 0.633 /0.639	0.884/ 0.830 /0.833	0.881/ 0.882
ATT2	0.937/ 0.910 /0.919			
ATT3	0.648/ 0.504 /0.492			
SN1	0.945/ 0.906 /0.873	0.886/ 0.774 /0.773	0.940/ 0.872 /0.872	0.874/ 0.874
SN2	0.938/ 0.853 /0.885			
PBC1	0.879/ 0.838 /0.780	0.633/ 0.534 /0.515	0.837/ 0.690 /0.678	0.750/ 0.721
PBC2	0.743/deleted/deleted			
PBC3	0.758/ 0.604 /0.649			
BI1	0.894/ 0.879 /0.890	0.840/ 0.760 /0.659	0.940/ 0.905 /0.927	0.905/ 0.905
BI2	0.950/ 0.868 /0.895			
BI3	0.905/ 0.868 /0.914			
B1	0.869/ 0.713 /0.725	0.751/ 0.501 /0.505	0.858/ 0.668 /0.668	0.668/ 0.668
B2	0.863/ 0.703 /0.692			

Table 1. Measurement Model Results

In the structural model evaluation, except for an indicator (ATT3) of the attitude construct, all indicators have the factor loading of 0.6 and above. As presented in Table 1, since the AVE of attitude (ATT) exceeds the threshold value of 0.5 and CR value of 0.8, the indicator has not been removed from the study. As a general rule concerning reliability coefficients, scores above 0.7 are assessed as acceptable for the initial stages of research, while scores above 0.8 or 0.9 are attained as convincing (Nunnally & Bernstein, 1994). According to Henseler et al. (2009), all scores less than 0.6 are unacceptable in terms of reliability. In the present study, CR scores ranged from 0.668 to 0.872, thus representing reliability for all structures. Other than CR, AVE scores, ranging from 0.502 to 0.809, have confirmed convergent validity.

Since PLS-SEM requires assessing discriminant validity by analyzing heterotrait-monotrait ratio (HTMT) correlations, the same technique has also been employed during the CB-SEM analysis for confirmation (Gaskin, 2016). Henseler et al. (2015) recommend that a threshold value of HTMT exceeding 0.90 denotes a lack of discriminant validity, which means the structural model involves very similar constructs. The present study includes acceptable discriminant validity levels for all structures in the augmented TAM (Table 2).

The next phase in CB-SEM is to examine the structural model. Table 3 displays beta coefficients, and R² of endogenous structures. The outcomes of the structural model exhibit an acceptable model fit (X² = 515.482; DF = 118; X²/DF = 4.368; p = 0.000, CFI = 0.933; GFI = 0.903; RMSEA = 0.078). The coefficient of determination (R²) can range from 0 to 1. As a rule, R² scores of 0.67, 0.33, and 0.19 are labeled as substantial, moderate, and weak in PLS (Chin, 1998). The path coefficients are all significant at the p (0.05) level, except for PEOU => BI (H4); SN=>BI (H5); PBC=>BI (H6) (Table 3).

PLS/PLSc/AMOS	ATT	B	BI	PBC	PEOU	PU
B	0.809/0.809 / 0.809					
BI	0.868/0.868 / 0.868	0.739/0.73 9 /0.739				
PBC	0.667/0.686 / 0.686	0.884/0.85 9 /0.859	0.650/0.68 6 /0.686			
PEOU	0.560/0.559 / 0.559	0.792/0.78 7 /0.787	0.580/0.58 9 /0.589	0.812/0.79 4 /0.794		
PU	0.608/0.544 / 0.544	0.851/0.69 7 /0.697	0.637/0.59 6 /0.596	0.757/0.696 / 0.696	0.822/0.72 0 /0.720	
SN	0.405/0.405 / 0.405	0.565/0.56 5 /0.565	0.287/0.28 7 /0.287	0.326/0.28 5 /0.285	0.271/0.26 2 /0.262	0.330/0.27 2 /0.272

Table 2. Discriminant Validity (HTMT) Scores

In the present study, R² of “behavior” is 81%. “Perceived behavioral control” (0.806) has the greatest impact on “behavior,” accompanied by “behavioral intention” (0.229). R² of “behavioral intention” is 69%. “Attitude” (0.684) has the greatest impact on “behavioral intention,” accompanied by “perceived usefulness” (0.157), “perceived ease of use” (0.061), “subjective norm” (0.022), and “perceived behavioral control” (0.010). R² of “attitude” is 43%. “Perceived ease of use” (0.453) has the greatest impact on “attitude,” accompanied by “perceived usefulness” (0.243). Table 3 (italic values) summarizes the hypotheses tests, beta coefficients, p values, and R² values based on the CB-SEM.

Hypothesis PLS/PLSc/AMOS	Standard beta	p-value	Decision	R ²
PU => ATT	0.307/ 0.280 / <i>0.243</i>	0.000/ 0.003 / <i>0.002</i>	+ / + / +	0.29/0.35/ <i>0.43</i>
PEOU => ATT	0.278/ 0.361 / <i>0.453</i>	0.000/ 0.000 / <i>0.000</i>	+ / + / +	
ATT => BI	0.615/ 0.712 / <i>0.684</i>	0.000/ 0.000 / <i>0.000</i>	+ / + / +	0.62/0.75/ <i>0.69</i>
PU => BI	0.144/ 0.145 / <i>0.157</i>	0.011/ 0.090 / <i>0.010</i>	+ / - / +	
PEOU => BI	0.072/ 0.039 / <i>0.061</i>	0.077/ 0.650 / <i>0.600</i>	- / - / -	
SN => BI	0.026/ 0.057 / <i>0.022</i>	0.386/ 0.109 / <i>0.526</i>	- / - / -	
PBC => BI	0.084/ 0.086 / <i>0.010</i>	0.064/ 0.474 / <i>0.938</i>	- / - / -	
PBC=>B	0.435/ 0.642 / <i>0.806</i>	0.000/ 0.000 / <i>0.000</i>	+ / + / +	
BI=>B	0.341/ 0.304 / <i>0.229</i>	0.000/ 0.003 / <i>0.000</i>	+ / + / +	0.46/0.77/ <i>0.81</i>

Table 3. Structural Model Results

Lastly, 6 of the 9 hypotheses are supported (p:0.05). As mentioned above, three hypotheses (H4, H5, H6) are rejected. In light of the findings above, while behavioral intention and behavior have a substantial level of R², “attitude” has a moderate level of R².

PLS-SEM Results

The augmented TAM, which consists of 7 structures, 22 indicators, and 9 relationships, has been analyzed with SmartPLS 3 both in regular and consisted PLS (Ringle et al. 2015). PLS can predict and evaluate both measurement and structural models simultaneously (Duarte & Raposo, 2010). The validity and reliability scores must be examined while evaluating the reflective measurement model (Hair et al. 2014). The outer loadings range from 0.4 to 0.7 should be evaluated for elimination from the scale if the CR and AVE scores increase as a result of their removal (Hair et al. 2014). The majority of the outer indicator loadings, which are presented in Table 1, are above the threshold

for regular PLS and PLSc. With regards to regular PLS results, loadings (PEOU4, PU3) between 0.4 and 0.7 have not been extracted from the study, considering acceptable CR and AVE scores. Conversely, based on PLSc results, four indicators (PEOU4, PU3, PU4, PBC2) have been removed from the study, while the others (PEOU1, PU2, ATT3, PBC3) have not been excluded, taking the above-mentioned criteria into account. All scores less than 0.6 demonstrate a lack of reliability. All latent variables except PBC (0.690 for PLSc) and BEH (0.668 for PLSc) have CR values of above 0.7, as indicated in Table 1. Besides, rho coefficients (ρ_A), which are an element of PLSc, are fulfilled for all measurement models. The results verify reliability of all constructs.

Pertaining to validity in the analysis, since AVE values, as indicated in Table 1, are higher than the threshold of 0.5 for both regular PLS and PLSc, the convergent validity of the structural measurements is also fulfilled. The discriminant validity analysis contains investigation of the heterotrait-monotrait ratio of correlations (HTMT), as mentioned earlier. Since HTMT values of the augmented TAM does not exceed the above-mentioned threshold, the discriminant validity criterion is also fulfilled. (Table 2).

The final sub-stage of PLS-SEM is the evaluation of the structural model. The collinearity diagnostic is an initial process for the assessment of the structural model, which requires an assessment of variance inflation factor (VIF) scores. If there is a VIF score greater than 3.3 at the factor level, this is an indication of both the collinearity problem and the common method bias problem (Kock, 2015 Gaskin, 2017). Since all VIF scores stand above the threshold in the model, there exists no collinearity and bias problem. After computing path coefficients in the structural model, the following stage in PLS-SEM is bootstrapping analysis, which is used to test hypotheses, which ensures the significance of the path coefficients. It is recommended to have 5,000 bootstrap samples as a rule of thumb. Table 3 presents hypotheses test results, path coefficients, significance values, and R^2 scores. Both regular and consistent PLS have the same results with the exception of the path from the "perceived usefulness" to "behavioral intention"; thus, H2 is rejected in PLSc. The path coefficients are all significant at the p (0.05) level, except for the paths for PEOU \Rightarrow BI (H4); SN \Rightarrow BI (H5); PBC \Rightarrow BI (H6); therefore, H4, H5, and H6 are rejected in both methods (Table 3).

R^2 of behavior for regular PLS is 46% in the research. "Perceived behavioral control" (0.435) has the greatest impact on "behavior", accompanied by "behavioral intention" (0.341). R^2 of "behavioral intention" is 62%. "Attitude" (0.615) has the greatest impact on "behavioral intention", accompanied by "perceived usefulness" (0.144), "perceived behavioral control" (0.084), "perceived ease of use" (0.072), and "subjective norm" (0.026). R^2 of "attitude" is 29%.

"Perceived usefulness" (0.307) has the greatest impact on "attitude," accompanied by "perceived ease of use" (0.278). On the other hand, R^2 of "behavior" in **PLSc** for the research model is 77%. "Perceived behavioral control" (0.642) has the greatest impact on "behavior," accompanied by "behavioral intention" (0.303). R^2 of "behavioral intention" is 75%. "Attitude" (0.712) has the greatest impact on "behavioral intention," accompanied by "perceived usefulness" (0.145), "perceived behavioral control" (0.086), "subjective norm" (0.057), and "perceived ease of use" (0.039). R^2 of "attitude" is 35%. "Perceived ease of use" (0.361) has the greatest impact on "attitude," accompanied by "perceived usefulness" (0.280). All R^2 values except "attitude" in regular PLS are at substantial level for both methods. R^2 value of attitude is at moderate level.

The next stage of the evaluation for structural model' predictive ability in PLS-SEM requires cross-validated redundancy (Q^2). Q^2 values greater than zero demonstrate that the accuracy of the path model predictions for the pertinent construct is satisfactory (Sarstedt et al. 2017). While the predictive relevance of "attitude" ($Q^2 = 0.157$) is medium, the relevance of "behavioral intention" ($Q^2 = 0.513$), and of "behavior" ($Q^2 = 0.353$) is large

in regular PLS. On the other hand, Q^2 values of "attitude," "behavioral intention," and "behavior" are 0.183, 0.492, and 0.311, respectively, in PLSc. Therefore, while the predictive relevance for "behavioral intention" and "behavior" is large, the relevance remains medium for "attitude" in PLSc (Hair et al. 2014).

Last but not least, even though PLS-SEM does not have a well-established goodness-of-fit measure (Sarstedt et al. 2017), an alternative way for goodness-of-fit measure is the use of standardized root mean square residual (SRMR), as suggested by Henseler et al. (2014). PLS-SEM carries two kinds of SRMR values, which are defined as saturated and estimated models. While the saturated model assesses the correlations among all constructs, the estimated one takes the model structure into consideration (SmartPLS, 2020). The SRMR values for saturated and estimated models are 0.065 and 0.089, respectively in regular PLS. Likewise, in PLSc, the SRMR values for saturated and estimated models are 0.042 and 0.077, respectively. In light of the findings above, all SRMR values except the estimated model in regular PLS, are below the thresholds of 0.08 for both methods (Hu and Bentler, 1999).

Comparative Discussion of the Results

In light of what has been presented so far, while the outcomes of CB-SEM, and PLS-SEM (both regular and consistent) exhibit minor differences in testing hypotheses, they show some considerable differences in the employment of method choice. Table 1 shows that regular PLS has relatively higher factor loadings than PLSc. As presumed by Gefen et al. (2011) and Sarstedt et al.'s. (2017) previous studies, this is a clear sign of PLS-SEM bias. In general terms, CB-SEM and consistent PLS-SEM produce closer factor loadings. Although regular PLS has not involved the removal of any indicator, the same indicators (PEOU4, PU3, PU4, PBC2) have been excluded from the study during the analysis for CB-SEM and consistent PLS-SEM. That being case, regular PLS-SEM, has provided greater validity and reliability values for the model constructs as consistent PLS-SEM and CB-SEM have lower levels of construct validity and reliability. In addition, consistent PLS-SEM and CB-SEM have generated relatively close values for construct validity and reliability.

In the present study, the authors analyzed the augmented TAM by employing three different methods and ascertained that the consumer adoption of mobile shopping is explained at a substantial level with the existing conceptual structures. As it could be seen in Table 3, both consistent PLS-SEM and CB-SEM exhibit greater R squares (81% for CB-SEM, 77% for PLS-SEM) compared to regular PLS-SEM (46%); thus, the former two methods are superior in explaining the total variance of adoption behavior. Therefore, the results of all three methods demonstrate that the acceptance of mobile shopping is explained by "behavioral intention," "perceived behavioral control," and antecedents of "behavioral intention" such as "attitude," "perceived ease of use," and "usefulness." This output is in alignment with the previous research in the literature (Yıldız, 2021). The analyses for all three methods demonstrate that "perceived behavioral control" has the strongest effect on "adoption behavior" (PLS:0.44; PLSc:0.64; CB-SEM:0.81). A meaningful connection between "perceived behavioral control" and "intention" is also supported by the previous research (Yang, 2013; Tak & Panwar, 2017; Zhu et al. 2017).

Apart from "behavior," which has been mentioned above, all three methods also explain "behavioral intention" substantially in the research model (CB-SEM: 69%; regular PLS: 62%; PLSc: 75%). Likewise, "attitude" has the strongest effect on "behavioral intention" in all three methods (regular PLS:0.62; PLSc:0.71; AMOS:0.68). While "attitude" is the only construct that has a significant effect on "behavioral intention," "perceived ease of use", "subjective norm," and "perceived behavioral control" exhibit insignificant relationships with "behavioral intention." Taking all three methods into consideration,

contrary to previous research (Yang, 2013; Yıldız, 2021), the results for all hypotheses, except for "perceived usefulness," which has an insignificant relationship with behavioral intention, exhibit similar results for regular and consistent PLS-SEM as well as CB-SEM. In addition, as opposed to TPB's (Ajzen, 1991) assumptions and prior research in the mobile context, "perceived ease of use," "social norm," and "perceived behavioral control" do not have a meaningful impact on "behavioral intention" (Yang, 2013; Tak & Panwar, 2017; Saprikis et al. 2018).

Taking all the above-mentioned results into consideration, the implications can be enumerated as:

- The judgment of significant others (family, close friends, or reference groups) does not have any impact on shopping behavior in the mobile context.
- The perception of control on behavior has no effect on intention; however, it influences behavior.
- In alignment with previous research, perceived usefulness does not establish any meaningful relationship with behavioral intention.

Lastly, all three methods explain "attitude" at a substantial level (CB-SEM: 43%; regular PLS: 29%; PLSc: 35%). The authors have verified that "perceived usefulness" and "ease of use" have a meaningful effect on "attitude" in all three methods, similar to the basic assumptions of TAM (Davis, 1989). While "perceived ease of use" has the strongest effect on "attitude" in both PLSc (0.36) and CB-SEM (0.45), "perceived usefulness" (0.30) has the greatest impact on "attitude." These outputs also refer to similar consequences for CB-SEM and consistent PLS-SEM. Taking the strongest path coefficients on "attitude", "behavioral intention", and "behavior" into consideration, parameter estimates for paths among proxies are attenuated for regular PLS-SEM, as it could be seen in Table 3, consequently leading to an indication for PLS-SEM bias.

Conclusions and Limitations

Drawing on Sarstedt et al.'s (2016) suggestion, which stresses the future need for comparison of CB-SEM, regular and consistent PLS-SEM on the data where common and composite factor models fit in the population, the authors compare the performance of three methods in the mobile shopping context by assessing the augmented TAM, which is proportionately complicated and a reflectively structured model.

In summary, the results suggest that all three methods explain shopping behavior of consumers via mobile apps at a substantial level in the augmented TAM. Also, when hypotheses tests are taken into consideration, the model exhibits similar results with CB-SEM as well as with regular and consistent PLS-SEM, with the exception of H2. Even though regular PLS-SEM is based on a composite factor model, considering the results of the hypotheses, it did not exhibit a significant difference compared to those of CB-SEM and consistent PLS-SEM. Thus, this paper reveals that regular PLS-SEM does not entail Type I and Type II errors. It is possible to conclude that regular PLS-SEM does not appear to have a serious impact on hypothesis testing for this case.

Pertaining to PLS-SEM bias, outer loadings of regular PLS-SEM are greater than those of the other methods. In addition, path coefficients, which have the greatest effect on "attitude," "behavioral intention," and "behavior," are attenuated for regular PLS-SEM that may result in PLS-SEM bias.

In sum, consistent PLS-SEM and CB-SEM have remarkably similar outputs at the measurement model level, such as indicator loadings, validity, and reliability scores. Still, further, the variances of conceptual variables are explained almost on par with each other

in the model. In general, therefore, these results suggest that performing CB-SEM and consistent PLS-SEM for common factor models or reflectively structured ones would have more robust outputs and would be more appropriate and beneficial for researchers in lieu of executing regular PLS-SEM, which is inherently based on composite factor model analysis. Owing to the fact that consistent PLS-SEM has softer provisions since it does not necessitate a two-step analysis (confirmatory and structural analyses) as well as high sampling sizes and normal distribution requirements, performing consistent PLS-SEM appears more viable and practical for researchers.

Finally, concerning the limitations, while this study tested the augmented TAM, which is a reflectively structured model, it did not examine three methods from a composite factor model standpoint. Furthermore, since this study has been performed in the mobile shopping setting, it would be more appropriate to validate the finding of the present study in some other contexts.

Theoretical and Practical Implications

Keeping Sarstedt et al.'s (2016) suggestion in mind, the present study seeks to examine and compare the results of CB-SEM as well as regular and consistent PLS-SEM methods. This study aims to test the augmented TAM, which is a relatively complicated model (Taylor and Todd, 1995) by comparing aforementioned methods in the mobile shopping setting. Hitherto previous research has employed CB-SEM and regular PLS-SEM to a large extent. Furthermore, no research has attempted to make a comparison concerning the performance of all three methods (CB-SEM, regular and consistent PLS-SEM) in the mobile shopping setting.

Considering the general inclination of researchers to employ the CB-SEM, the employment of PLS-SEM method is relatively limited. Bearing that in mind, the authors performed a literature search for the employment of regular and consistent PLS-SEM and searched both "mobile marketing" and "pls-sem" keywords simultaneously in assorted journal databases between the years 2015 and 2020. The search process had a result of 14 articles in Science Direct (Elsevier), 3 articles in Web of Science Core Collection, 21 articles in Emerald Insight, and 12 articles in Proquest ABI/INFORM Collection (in a total of 50 articles). The articles reviewed in the literature, by and large, are on mobile shopping (Jimenez et al. 2019; Tan & Ooic, 2018; Dakduk et al. 2020; Verkijika, 2018; Groß, 2016; Faqih, 2015; Mahapatra, 2017; Nel & Boshoff, 2019, 2020; Chen, 2018; Ghazali et al. 2018; Rezaei & Valaei, 2017; Thakur, 2018; Celik & Kocaman, 2017; Shukla et al. 2018; Liu et al, 2019; San-Martín et al. 2019); mobile application use and its adoption (Molinillo et al. 2019; Ameen et al. 2020; Schmitz et al. 2016; Tseng, 2020; Sung, 2020; Tan et al. 2017; Gong et al. 2018; Gupta et al. 2018; Hong et al. 2017; Kuo et al. 2019; Nakuze et al. 2019); mobile advertising (Tan et al. 2018; Lee et al. 2017; Bakare et al. 2017; Goh et al. 2020); mobile banking (Tran & Corner, 2016; Owusu Kwateng et al. 2019; Thaker et al. 2019; Singh & Srivastava, 2020); mobile payment (Gupta & Arora, 2019; Hariguna et al. 2020); mobile coupons (Souiden et al. 2019; Liu et al. 2015); mobile services (Rezaei et al. 2016, Smith, 2020; Alam et al. 2019); mobile marketing (Alzubi et al. 2018; Eneizan et al. 2019); mobile social media (Carlson et al. 2019) mobile instant messaging (Lee & Hsieh, 2019); and finally mobile location tagging (Hsieha & Lee 2020).

The authors scrutinized the above-mentioned articles and noted that most of the studies employed formative-based regular PLS-SEM with reflectively structural models, which leads to PLS-SEM bias. Most strikingly, none of these studies employed consistent PLS-SEM in mobile marketing. To resolve and clarify this issue, the authors put forth the pros and cons of each method and guide researchers and academics on which particular method is the most appropriate to employ in their studies. In essence, contrary to PLS-

SEM, which estimates parameters to maximize the variance explained for all endogenous structures in the model with a series of OLS regression, CB-SEM predicts model parameters with the aim of minimizing the inconsistency between the estimated and sample covariance matrices. For this reason, two methods have different approaches to SEM with distinct analyzing techniques. Cheah et al. (2018) posit that regular PLS-SEM should be preferred for estimating composite models with formative indicators. Contrastingly, CB-SEM should be preferred for predicting common factor models with reflective indicators. Thus, researchers should prefer to employ regular PLS in composite structured models, whereas they should opt for consistent PLS-SEM or CB-SEM method in reflectively structured measurement models. Considering strict prerequisites of CB-SEM, such as the performance of confirmatory analysis, normal distribution requirement, and high sample size, consistent PLS-SEM offers softer requirements to researchers and therefore should be preferred over CB-SEM as validated in our study. Nevertheless, researchers should bear in mind that bias is not just a PLS-SEM specific problem. On the occasions where researchers prefer to analyze composite factor models with formative indicators employing covariance-based analysis methods, such as AMOS and LISREL, they will again face biased results (Sarstedt et al. 2016). Keeping this in mind, researchers and academics should employ an analysis method only after determining measurement and structural models based on whether their research model rests on a common factor model with reflective indicators or a composite factor model with formative indicators.

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Özet

Araştırma, nispeten karmaşık bir model olan artırılmış Teknoloji Kabul Modelini kullanarak geleneksel ve tutarlı PLS-SEM ile CB-SEM yöntemlerini incelemeyi ve karşılaştırmayı amaçlamaktadır. CB-SEM yöntemi literatürde araştırmacılar tarafından geniş bir kullanım alanı bulmasına karşın araştırmalarda PLS-SEM metodunun tercih edilmesinde göreceli bir artış olduğu görülmektedir. CB-SEM yöntemi örtük değişkenlerin göstergelerinin birlikte paylaştığı kovaryanstan yola çıkarak bir çözüm üretmekte ve modelin uyumunu ön plana çıkarmaktadır. Diğer taraftan PLS-SEM yöntemi örtük değişkenlerin göstergelerinin ilgili faktör boyutunu biçimlendiren birer vekil değişken olarak kabul etmekte ve modelin yüksek bir açıklama gücüne sahip olmasını amaçlamaktadır. Literatür incelendiğinde CB-SEM taraftarı araştırmacılarla PLS-SEM taraftarı araştırmacılar arasında bir tartışma olduğu görülmektedir. Araştırma; regular ve consistent PLS-SEM ile CB-SEM yöntemlerinin avantajları ve dezavantajlarını ortaya konmakta böylelikle araştırmacılara ve uzmanlara çalışmalarında hangi yöntemin kullanımının uygun olduğu konusunda rehberlik etmektedir. Çalışmanın bulguları ikiye ayrılmaktadır. İlk olarak çalışma, reflektif olarak yapılandırılmış modellerde geleneksel PLS-SEM yöntemini tercih etmek yerine CB-SEM veya consistent PLS-SEM yöntemlerini kullanmanın daha sağlam sonuçlar sağladığına işaret etmektedir. İkincisi ise CB-SEM yönteminin aksine consistent PLS-SEM yönteminin, iki aşamalı analiz, yüksek örneklem hacmi ve normal dağılım şartları gibi katı koşullar gerektirmemesi araştırmacılar için daha elverişli bir yöntem olduğunu göstermektedir.