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CB-SEM vs PLS-SEM comparison in estimating the predictors of investment intention

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Abstract. This paper compares different structural equation modeling approaches in estimating the predictors of investment intention. Covariance-based structural equation modeling (CB-SEM) and partial least squares structural equation modeling (PLS-SEM) techniques were compared in the estimation of the model according to the theory of planned behavior (TPB). Additionally, the consistent PLS algorithm (PLSc) was taken into consideration in the methods comparison. To determine which factors affect stock investment intention, a TPB model with attitude towards behavior, perceived behavioral control, and subjective norm as independent variables was estimated using three different approaches. The factors in the model were measured using survey indicators and the final sample included 200 Croatian residents. The results mostly show matching conclusions about the investment intention predictors, with a small difference observed in the PLS-SEM method. It can also be concluded that the factor loadings are higher according to PLS-SEM, as well as the indicators of convergent validity and reliability. On the other hand, CB-SEM shows stronger structural paths than PLS-SEM, and PLSc results are closer to those of CB-SEM. While CB-SEM shows better model fit, PLS-SEM shows high predictive power. This research further provides explanations of the differences and guidelines on when to use which approach.

Keywords: CB-SEM, investment intention, PLS-SEM, structural equation modeling

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1. Introduction

Structural equation modeling (SEM) is a second-generation multivariate technique aimed at explaining the relationships between multiple variables simultaneously. A specific characteristic of SEM is its ability to incorporate latent variables into the model. Such variables are not directly measurable, but can be indirectly measured with a set of items (indicators) or measured variables [4, 6, 11]. Since latent variables most commonly represent some psychological constructs, their corresponding items are in most cases measured through survey questionnaires.

This specific approach to SEM deals with model estimation based on the differences between the observed and the estimated covariance matrix. Therefore, the "classic" SEM approach is also known as covariance-based SEM (CB-SEM) and it represents a confirmatory method [6, 11, 12]. In order to conduct an analysis using CB-SEM, it is necessary to have an established theoretical background which researchers want to test on their own data. The results of CB-SEM show whether a theory can be confirmed or rejected across different samples [4, 6, 12].

In contrast, the emergence of partial least squares structural equation modeling (PLS-SEM) shows a causal-predictive orientation and a variance-based approach. Thus, the main goal of

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PLS-SEM is prediction, obtained by maximizing the explained variance in the dependent variable, making it suitable for theory development and exploratory research [11, 12, 13]. Another method, consistent PLS (PLSc), is a variation of the original PLS and it offers a correction for attenuation to PLS path coefficients. This method usually yields results very similar to those of CB-SEM [6, 12].

The aim of this research is to compare all three methods using the same model with the same dataset. In this way, it is possible to make clearer explanations of the differences and to set some guidelines for choosing the appropriate SEM method. The paper begins with an introduction, followed by a more detailed explanation of each SEM approach. The research context and the model are presented in Section 2. Section 3 describes the data collection and the used methodology, while Section 4 presents the empirical results and a comparison of the studied methods. The conclusion is provided in Section 5.

2. A review of SEM characteristics and research context

2.1. SEM characteristics

According to [11], SEM is a "multivariate technique combining aspects of factor analysis and multiple regression that enables the researcher to simultaneously examine a series of interrelated dependence relationships among the measured variables and latent constructs (variates), as well as between several latent constructs". Some of the main advantages of SEM can be inferred from this definition. Namely, simultaneous estimation of multiple relationships provides a more accurate depiction of the tested theory and accounts for measurement error in the process. However, one of the greatest strengths of SEM lies in its ability to incorporate latent variables into the model, since they cannot be directly measured but are often used in behavioral and social research. Instead, these variables are represented by a set of indicators obtained through data collection, commonly through primary data [6, 11, 12, 22, 24, 27, 32]. SEM can be divided into two different approaches: CB-SEM and PLS-SEM.

CB-SEM is a confirmatory method based on the differences between the observed and estimated covariance matrices. This allows for testing of the model fit, i.e. the extent to which the theoretically proposed model is confirmed by empirical data [4, 6, 11, 22]. The modeling can be conducted in one or two steps. Two-step modeling refers to the process where confirmatory factor analysis (CFA) is used in the first step to obtain model fit and construct validity measures for the measurement model. Only after achieving an acceptable fit, the structural model is tested for path significance. In contrast, one-step modeling tests the overall model fit without separating measurement and structural models [6, 11]. However, in both cases, model fit is obtained, as well as the assessment of construct validity. A valid result from one-step modeling implies that two-step modeling would also yield satisfactory results.

Overall model fit is primarily evaluated with the chi-square (χ^2) test, the sole inferential statistic which compares the statistical difference between the observed and estimated covariance matrices. A good fit implies that the differences are statistically insignificant, making chi-square a measure of badness of fit [6, 11, 15]. However, chi-square has its limitations in the fact that it assumes multivariate normality of the data, so large deviations from this assumption could result in a significant result even if the model is correctly specified. Additionally, chi-square is sensitive to sample size, tending to increase with it, consequently leading to a significant result [11, 15, 16]. Due to these limitations, other model fit measures are recommended for reporting in CB-SEM analysis. One of these measures is the normed chi-square (χ^2/df), where a ratio between 2 and 5 is considered acceptable [6, 15, 16]. Other measures include the root mean square error of approximation (RMSEA) and standardized root mean residual (SRMR), which require lower values in order to establish good model fit (RMSEA$<$0.08 or $<$0.10; SRMR$<$0.05). Additionally, goodness-of-fit measures, such as comparative fit index

(CFI), Tucker Lewis index (TLI), goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI), normed fit index (NFI) compare the model fit against a null or independent model. Therefore, higher values, usually above 0.90 are required for a good model fit [6, 11, 15, 16].

PLS-SEM is a causal-predictive approach aimed at maximizing the explained variance in dependent latent constructs, hence it is also known as a variance-based approach to SEM. In addition, it also evaluates data quality obtained through measurement model analysis [6, 12, 26]. In PLS-SEM, the assumption of multivariate normality of data is not required to estimate the model, distinguishing it as a non-parametric approach to SEM. While CB-SEM requires large samples, PLS-SEM can effectively handle both larger and smaller samples. One of its advantages is also the ability to handle single-item constructs, which is problematic for CB-SEM because of model identification issues. Furthermore, PLS-SEM offers greater statistical power, making it suitable for theory development in exploratory research [4, 10, 11, 12, 22, 26]. In social sciences, most of the measurement is reflective (the construct causes the indicators), but sometimes formative measurement can occur (the indicators cause the construct). While the indicators in the reflective measurement are interchangeable, it is not the case in the formative measurement [12]. In case of formative models, PLS-SEM should be used rather than CB-SEM. The treatment of latent constructs should also be considered, since the constructs can be viewed as common factors or composites. The common factor approach is widely used in CB-SEM and it is based solely on common variance in the data, while the composite approach, which includes common, specific, and error variance, is used in PLS-SEM [10, 12, 22]. Common factor assumes causal indicators, which should fully measure a certain concept along with an error term. Composite indicators are considered an approximation of a concept, which is a more realistic view in social sciences. According to [10], due to random error in composite models and factor indeterminacy in common factor models, both approaches yield only approximations of theoretical concepts. In other words, "common factor proxies cannot be assumed to carry greater significance than composite proxies in regard to the existence or nature of conceptual variables" [10].

Both CB-SEM and PLS-SEM require the analysis of the measurement and structural models (in PLS-SEM: the outer and inner model). The first part of the analysis verifies the validity and reliability of the constructs, while the second part deals with the assessment of structural paths and their significance. In contrast to CB-SEM, which is a parametric approach that yields statistical significance as a test result, PLS-SEM, as a non-parametric method, relies on the bootstrapping procedure in order to obtain significance [10, 11, 12, 22]. As previously mentioned, CB-SEM is focused on model fit and theory testing, whereas PLS-SEM is prediction oriented. Therefore, even though some model fit measures can be obtained for PLS-SEM, the main focus lies in analyzing the in-sample and out-of-sample predictive power of the model. In-sample predictive power is assessed with the coefficient of determination (R^2). PLS predict procedure is recommended for assessing the model's out-of-sample predictive power [29]. Lately, the cross-validated predictive ability test (CVPAT) has also been developed and recommended as a prediction-oriented tool [28].

In an attempt to provide a factor-based approach within PLS-SEM, the consistent PLS-SEM approach (PLSc) was proposed. It uses Nunnally and Bernstein's equation as a correction factor to the traditional PLS algorithm, obtaining consistent construct correlations and indicator loadings if the common factor model holds true [6, 7, 9, 12]. PLSc has been shown to yield results very similar to those of CB-SEM, while retaining the advantages of PLS-SEM, but its statistical power is somewhat lower [7, 9, 12, 34].

Considering all of the above, it is clear that CB-SEM and PLS-SEM should be viewed as complementary rather than competitive. The choice of method should be based on the research goal (purely confirmatory or causal-predictive), the measurement philosophy, the sample size, and data characteristics.

2.2. Research context

The focus of the paper is to compare different SEM approaches for model estimation. The model used in the research is the model of the theory of planned behavior (TPB) in the context of stock market investment intention, as an illustrative example. Therefore, the model only serves as an example in the methodological comparison. The concept and essence of the model are briefly described to give context to the reader. TPB assumes that different motivational factors, such as attitude towards behavior, subjective norm, and perceived behavioral control, significantly influence a certain behavioral intention [2, 3, 20, 23, 33]. Intention is the central factor in TPB, capturing these motivational factors and indicating the level of effort people are willing to put into performing a certain behavior [2]. In this paper, the intention is specifically oriented towards stock market investments.

Briefly, attitude towards behavior can be defined as the extent to which a person considers a behavior pleasant or unpleasant [2, 3, 20]. Therefore, a favorable and positive attitude leads to a higher intention to perform a certain behavior [2, 20, 33]. When considering stock market investment intention, this assumption was found to be true in previous research [3, 19, 20, 23]. Therefore, the first research hypothesis is proposed:

H1. Attitude towards behavior significantly affects investment intention.

Subjective norm represents the perceived social pressure whether to perform a behavior or not. People will often behave in a certain way if they are under a higher social pressure. In other words, if they perceive that people who are close to them and who influence them in daily life think that they should perform a certain action, they might do it under pressure, even if they do not want to [2, 3, 20]. Most people are often concerned about the opinions of others, thus subjective norm might often be the most influential factor affecting behavioral intention. It was previously found that subjective norm positively affects individual's stock investment intention, showing the importance of social pressure in forming a higher intention towards a certain behavior [3, 19]. However, it was also found that among younger generations (Y and Z), subjective norm was not an important predictor of investment intention or it even had a negative impact [20, 23]. Clearly, younger people have less role models who might encourage them for investing, or they are generally less prone to be under social pressure, since they are less affected by the opinions of others. Nevertheless, social influence still remains one of the most important factors in predicting certain behavior, leading to the formulation of the second research hypothesis:

H2. Subjective norm significantly affects investment intention.

Lastly, perceived behavioral control refers to the perception of ease or difficulty in performing a specific behavior. It reflects past experiences and expected obstacles [2, 20, 23]. It is expected that people with higher perceived behavioral control will consequently have higher intentions towards performing a behavior. This relationship has been confirmed in most of the previous research, showing that people with stronger control show higher stock investment intentions [3, 19, 20]. According to these findings, the third hypothesis is proposed:

H3. Perceived behavioral control significantly affects investment intention.

The research model investigates how attitude towards behavior, subjective norm, and perceived behavioral control affect investment intention in Croatia. There is no similar research in Croatia and other emerging markets, which have not yet been studied much in the context of behavioral finance. Croatians generally exhibit low engagement in stock market activities, they possess lower financial literacy and prefer to invest in real estate [31]. However, as TPB proposes general factors in prediction of a certain behavior, it is hypothesized that the same general pattern should be applicable to any sample, including Croatian.

3. Data and methodology

3.1. Research instrument and data collection

Data were collected via a survey questionnaire, distributed to the general Croatian population online from May to July 2023. The first part of the survey consists of questions regarding the socio-demographic traits of the respondents, while the second part is related to the factors of the theory of planned behavior. Namely, the questions were represented as statements measuring the attitude towards behavior (ATT), perceived behavioral control (PBC), subjective norm (SN), and investment intention (INT) on a 5-point Likert scale (1=strongly disagree, 5=strongly agree). The statements from the survey were based on the research of [23] and they represent the items for further structural modeling. The items are shown in Table 1.

	Attitude towards behavior (ATT)
ATT1	I think that investing in the stock market can enhance the financial knowledge of individuals.
ATT2	I think that stock investment is meaningful.
ATT3	I think that stock investment is a good idea.
	Perceived behavioral control (PBC)
PBC1	I have enough time for stock investment.
PBC2	I have enough money for stock investment.
	Subjective norm (SN)
SN1	I will participate in stock investment if my spouse thinks it is useful.
SN2	I will participate in stock investment if my family approves it.
SN3	I will participate in stock investment if my colleagues do.
SN4	I will participate in stock investment if I have proven friend success on it.
	Investment intention (INT)
INT1	I intend to engage in stock investment in the near future.
INT2	I will recommend others to invest in the stock market.
INT3	I will continue to invest in the stock market.

Table 1: *Items in the model.*

3.2. Data

As previously mentioned, this research focuses on the Croatian general population. Data were collected online via e-mail, social networks, etc. Since there is no “one-size-fits-all” formula for sample size in SEM, there are only general guidelines. According to [11], the minimum sample size for models with seven or fewer constructs and modest communalities with values around 0.5 is 150 cases. The research model has four constructs, and the communalities range from 0.49 to 0.814. However, the sample should be increased in case of deviations from multivariate normality, as is the case in this research. A priori sample size was determined with Daniel Soper’s formula [30], which takes into account the number of indicators and constructs in the model, the anticipated effect size, and the desired probability and statistical power levels. With 4 constructs and 12 indicators, a medium anticipated effect size (0.3), a 5% probability level, and an 80% desired statistical power level, the recommended minimum sample size was 200. The calculator was used in order to get the suggested sample size as accurately as possible. Simpler models require smaller samples, and a median sample size, often generally recommended as a minimum, is 200 cases [11, 18]. The “10 times rule” can also be considered as a rough guideline for PLS-SEM, stating that the sample should be 10 times the number of arrows pointing at a construct, which is three in this research, implying a sample of 30 cases is needed [11]. These rules of thumb are being abandoned in favor of methods that take statistical power into account. Thus, according to [12]’s sample size recommendation in PLS-SEM, for a statistical power of 80%, with a maximum number of three independent latent variables, as in this model, a sample size of only 37 cases would be needed to achieve a statistical power of 80% for detecting R^2

values of at least 0.25, with a 5% probability of error. The final sample consists of 200 Croatian residents, which is far beyond the proposed limit.

When looking at gender, most of the respondents are female (61.5%) compared to male (38.5%). Most of the respondents are 18-25 years old (24.5%), followed by those aged 36-45 and 46-55 with the same share of 22.5%. 13.5% of people are 26-35, and 12.5% are 56-65 years old. Only 4.5% of the respondents are 66 or older. The age structure is obviously related to the sample structure according to work experience, since most of the respondents have less than 5 years of work experience (30%). The second largest group represents people with more than 20 years of work experience (23.5%). 21.5% of the respondents have 5-10 years of work experience, while 11.5% of the respondents have worked 11-15 years, and 13.5% of them have worked for 16-20 years. The main income source for the respondents is their monthly salary (71.5%), pension is the source for 5.5% of the people, social care for 1%, and the rest of the respondents (22%) have stated that they have other main income source. Most of the people are highly educated, since only 28% have not finished any level of college education, and the remaining 72% have obtained at least bachelor's degree or a higher level of education.

3.3. Methodology

Data analysis was conducted with SmartPLS 4 software [25], which was initially developed for PLS-SEM estimation, but currently has the ability to estimate both PLS-SEM and CB-SEM models. Before modeling, the multivariate normality of the data was examined with Mardia's multivariate skewness and kurtosis tests, which showed that the data deviate from this assumption ($p<0.001$) [21]. Since the items were measured on a Likert scale, this is not a surprising result. Modeling with maximum likelihood (ML) estimation was continued despite this result, which goes against the requirements of CB-SEM. Estimation with the weighted least squares mean and variance adjusted (WLSMV) estimator for ordinal data was done as an additional control, and it was found that the results do not significantly differ compared to the ML estimator. Moreover, the research model is quite simple and the sample size is sufficiently large, thus contributing to more reliable estimates [18]. This also implies that the estimates are robust to data non-normality and that the model is well specified, since it relies on TPB. Namely, TPB is a widely established theory which can be used for confirmatory purposes, so the default ML estimation is used to compare the different approaches, because it is most common and it represents the essence of CB-SEM most precisely. Additionally, as [5] proposed in his comparison of PLS-SEM with CB-SEM's different estimators, the CB-SEM results among different estimators were not contradictory.

In the first step, a CFA model was estimated as a prerequisite for further structural modeling, as suggested by [11]. After establishing a good model fit, CFA was followed by structural model analysis with the CB-SEM approach. The first SEM analysis refers to the measurement model. Model fit measures were examined, followed by the standard analysis of convergent validity using average variance extracted (AVE) and reliability using Cronbach's alpha and composite reliability [6, 11]. Two methods were used to assess the discriminant validity: Fornell and Larcker criterion and heterotrait-monotrait (HTMT) ratio of correlations. According to the Fornell and Larcker criterion, the correlations between the constructs are compared with the square root of the AVE of each construct. It is assumed that a construct should be better at explaining its own indicators' variance rather than the indicators of other constructs [1, 8, 11, 14]. However, this approach has some flaws, because it tends to overstate discriminant validity problems, especially if indicator loadings vary strongly [1, 8]. Thus, recent research has shown that heterotrait-monotrait (HTMT) ratio of correlations is a better choice for discriminant validity testing. HTMT measures "the ratio of the between-trait correlations to the within-trait correlations" [12], i.e. it compares the correlations of the indicators measuring different constructs to the correlations of indicators measuring the same construct. Therefore, lower

HTMT values are preferable. The threshold is 0.85 or a more flexible value of 0.90. HTMT inference can also be calculated to further demonstrate discriminant validity [12, 14]. This measurement model analysis in the PLS-SEM approach is called the outer model analysis, but it includes the same steps as in CB-SEM for reflective models [12]. Therefore, the results for validity and reliability testing are first presented for all three techniques, according to the aforementioned guidelines.

Afterwards, the structural model (or in PLS-SEM: the inner model) is assessed. According to [11] and [12], this part of the analysis explores the strength, direction and significance of the structural paths. CB-SEM gives p-values as a standard output of the test, while for PLS-SEM, the bootstrapping procedure is used to obtain the significance of the paths [10, 11, 12, 22]. Lastly, only for the PLS-SEM approach, predictive measures were also analyzed with the coefficient of determination (R^2) and the PLSpredict procedure [12, 29].

4. Empirical results and discussion

4.1. Validity and reliability analysis

The first step of the analysis prior to CB-SEM is CFA. Before conducting this analysis, indicator multicollinearity was assessed with variance inflation factor (VIF) values. All values are below the threshold of 5, indicating that there is no multicollinearity problem (Table 2). It obtained satisfactory model fit, except for the significant chi-square result, most likely caused by data non-normality and the sample size (χ^2=129.937, p<0.001; χ^2/df=2.707; RMSEA=0.092; SRMR=0.043; GFI=0.904; NFI=0.918; TLI=0.926; CFI=0.946). The second step is to estimate the structural model, which was first done for the CB-SEM approach. The results show that the model fit measures are exactly the same as for the CFA, i.e. a significant chi-square, but satisfactory values for all other measures (χ^2=129.937, p<0.001; χ^2/df= 2.707; RMSEA=0.092; SRMR=0.043; GFI=0.904; NFI=0.918; TLI=0.926; CFI=0.946). PLS-SEM and PLSc were also estimated. Even though their main focus is not on model fit, and these measures in the context of PLS-SEM are still evolving and should be taken with caution, SRMR and NFI are available in the output for comparison with CB-SEM. PLS-SEM model fit was not satisfactory (SRMR=0.066, NFI=0.805), while it was good for PLSc (SRMR= 0.048, NFI= 0.907). PLSc results are close to those of CB-SEM. Measurement (outer) model evaluation was done through validity and reliability analysis. The results for all techniques can be seen in Table 2.

	CB-SEM			PLS-SEM			Consistent PLS-SEM				
	Loading	AVE	Composite reliability	Loading	AVE	Composite reliability	Loading	AVE	Composite reliability	Cronbach's alpha	VIF
Attitude toward behavior (ATT)											
ATT1	0.692	0.632	0.839	0.811	0.749	0.899	0.713	0.628	0.835	0.832	1.632
ATT2	0.851			0.893			0.828				2.253
ATT3	0.833			0.889			0.831				2.206
Perceived behavioral control (PBC)											
PBC1	0.812	0.633	0.775	0.912	0.816	0.899	0.830	0.635	0.776	0.775	1.668
PBC2	0.779			0.895			0.762				1.668
Subjective norm (SN)											
SN1	0.585	0.524	0.817	0.702	0.636	0.874	0.598	0.523	0.812	0.809	1.476
SN2	0.701			0.785			0.659				1.723
SN3	0.814			0.844			0.768				2.138
SN4	0.773			0.850			0.843				2.060
Investment intention (INT)											
INT1	0.918	0.769	0.909	0.941	0.842	0.941	0.885	0.764	0.906	0.906	3.860
INT2	0.864			0.910			0.887				2.849
INT3	0.847			0.902			0.849				2.769

Table 2: *Convergent validity and reliability for the constructs.*

Indicator loadings are substantially high (>0.7) for all constructs, with a few exceptions for CB-SEM and PLSc. However, these small deviations did not affect validity. Namely, all AVE values exceed the cutoff value of 0.5, showing that each construct explains more than 50% of the variance in its indicators, thus confirming the convergent validity of the constructs across all techniques [11, 12]. Cronbach's alpha and composite reliability were both above the threshold of 0.7, demonstrating the reliability of the constructs. These results further confirm that using only two indicators to represent the construct PBC is valid. Even though SEM often requires at least three indicators per construct, there is no magic number of indicators per construct. More indicators make the model more complex, and sometimes it is better to leave some items out if they are highly redundant [18]. From an empirical point of view, these two indicators measuring PBC represent the construct very well according to all aforementioned measures of validity and reliability. Furthermore, the model has no identification issues despite this lower number of indicators for PBC, since it also includes other variables. Namely, as [17] suggest, the model should include at least two correlated latent constructs and two indicators per construct, which correlate with an indicator of another construct, but the indicators' errors should be uncorrelated [11, 17, 18]. This is true for the research model, implying that there is a sufficient number of indicators per construct [17]. From a theoretical point of view, PBC can be understood as the perceived ease or difficulty in performing a certain behavior [2]. Thus, in the context of stock investment intention, time and money can be considered as crucial factors, since time availability and sufficient financial resources are essential for stock investment engagement. These factors inevitably influence investor's confidence and ability to invest, which accurately reflects PBC. Additionally, the goal was to keep the model parsimonious for easier estimation, and to compare the performance of different SEM approaches under non-perfect conditions.

Discriminant validity was tested with both Fornell and Larcker criterion and the HTMT ratio. The results based on Fornell and Larcker criterion for all models separately are shown in Table 3, while HTMT is the same across all methods and is shown in Table 4. When observing discriminant validity through the Fornell and Larcker approach, it can be seen that there is a potential problem with ATT and INT, and SN is highly correlated with all other constructs in the CB-SEM model and PLSc. The values are very similar. In contrast, in PLS-SEM, all of the AVE square root values are higher than the correlations with other constructs, fully supporting discriminant validity [1, 8, 12]. The reason for this can be found in the fact that this descriptive approach to discriminant validity tends to overstate the problem, even more when there are higher variations of the indicator loadings. This is exactly the case in CB-SEM and PLSc models, where there are higher variations of the loading values for ATT and SN, while in the PLS-SEM the variations of the loadings are not so high. In order to overcome this issue, discriminant validity was also assessed with the HTMT ratio, showing that all values are below the threshold of 0.9, confirming discriminant validity. Since the highest correlation was found between ATT and INT, HTMT bootstrap 95% confidence intervals were calculated for additional verification. Discriminant validity was additionally supported, since the confidence interval does not span the value of 1 (0.822-0.957) [12, 14].

	CB-SEM				PLS-SEM				Consistent PLS-SEM			
	ATT	INT	PBC	SN	ATT	INT	PBC	SN	ATT	INT	PBC	SN
ATT	0.795				0.865				0.793			
INT	0.871	0.877			0.776	0.918			0.890	0.874		
PBC	0.767	0.789	0.796		0.607	0.662	0.903		0.751	0.788	0.797	
SN	0.758	0.636	0.767	0.724	0.648	0.556	0.609	0.798	0.778	0.642	0.760	0.723

Table 3: *Discriminant validity according to Fornell-Larcker criterion.*

	ATT	INT	PBC	SN
ATT				
INT	0.892			
PBC	0.748	0.788		
SN	0.793	0.642	0.767	

Table 4: *Discriminant validity according to HTMT ratio.*

4.2. Structural model analysis

Structural model results based on each technique separately are shown in Table 5, and the path diagrams are seen in Figures 1-3. It can be concluded that, according to all models, ATT has a positive and significant effect on INT. This is expected, since a more positive attitude towards investing implies that a person will actually show a higher intention to invest. PBC also positively and significantly affects INT, regardless of the method used. This shows that people with a higher perception of control, in terms of time and money, will consequently have higher investment intentions. Lastly, SN has a negative effect on INT in all of the models. However, its strength is significantly lower for PLS-SEM, while it is highest in PLSc, though relatively close to the coefficient in CB-SEM. Since there is practically no effect (β=-0.025) in PLS-SEM, the path is not significant. In CB-SEM and PLSc, this path is significant at the 0.10 significance level. It implies that people under higher social pressure to invest will have lower investment intentions, which is an unexpected result. This can be explained by the fact that the sample consists mostly of younger people, who care less about social influence and they might find other people unreliable, thus choosing not to follow their advice.

In general, all path coefficients are lowest for PLS-SEM and highest for PLSc. Effect sizes are also presented in Table 5, to determine whether each exogenous construct has a substantive impact on the endogenous construct (INT). For CB-SEM and PLSc, the results are similar, with PLSc yielding somewhat higher values. ATT has the highest effect on INT in all observed models, and its effect is considered large. In CB-SEM, PBC has a medium effect size, and SN has a small effect size. These effects become strong for PBC, and medium for SN in the PLSc model. In contrast, PLS-SEM effect sizes are significantly lower. ATT shows a large effect on INT, PBC has a medium effect, and SN practically has no effect on INT in the PLS-SEM model.

According to the results from CB-SEM and PLSc, all research hypotheses can be accepted as true, i.e. all factors of TPB significantly affect investment intention. On the other hand, according to PLS-SEM results, only H1 and H3 can be accepted, while H2 should be rejected, since SN has no significant impact on INT.

Path	CB-SEM			PLS-SEM			Consistent PLS-SEM		
	Path coefficient	p-value	Effect size	Path coefficient	p-value	Effect size	Path coefficient	p-value	Effect size
ATT $\rightarrow$ INT	0.743	<0.001	1.043	0.604	<0.001	0.546	0.828	<0.001	1.572
PBC $\rightarrow$ INT	0.397	0.002	0.266	0.311	<0.001	0.157	0.397	0.014	0.387
SN $\rightarrow$ INT	-0.232	0.054	0.101	-0.025	0.705	0.001	-0.304	0.068	0.205

Table 5: *Structural model coefficients.*

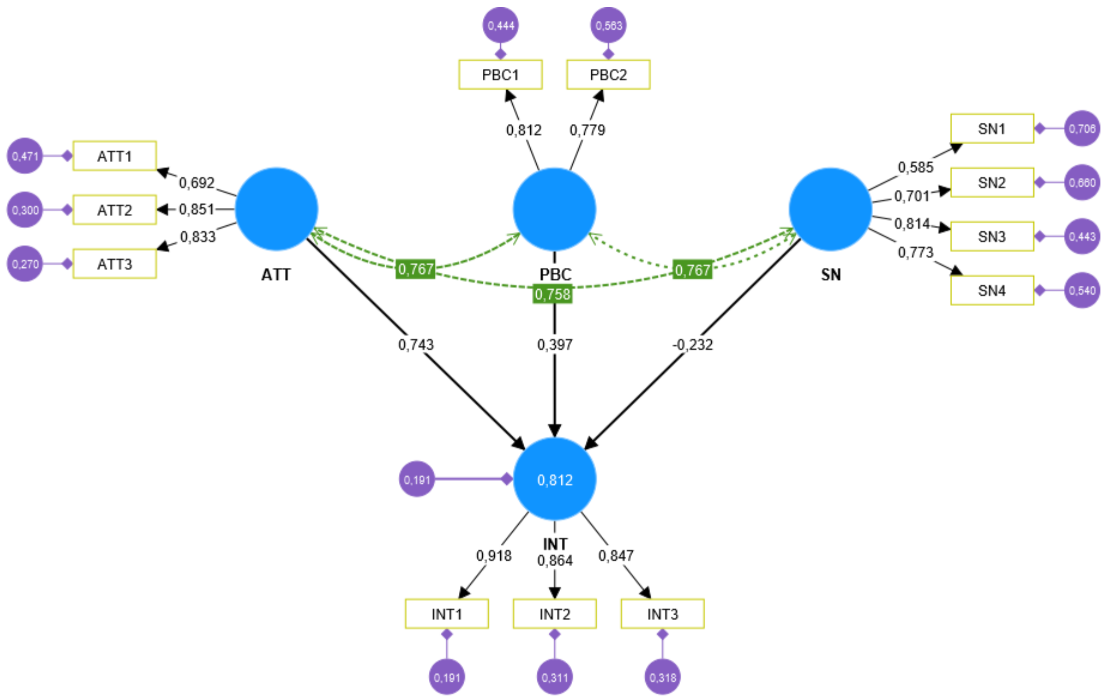

Figure 1: *Path diagram with standardized estimates (CB-SEM).*

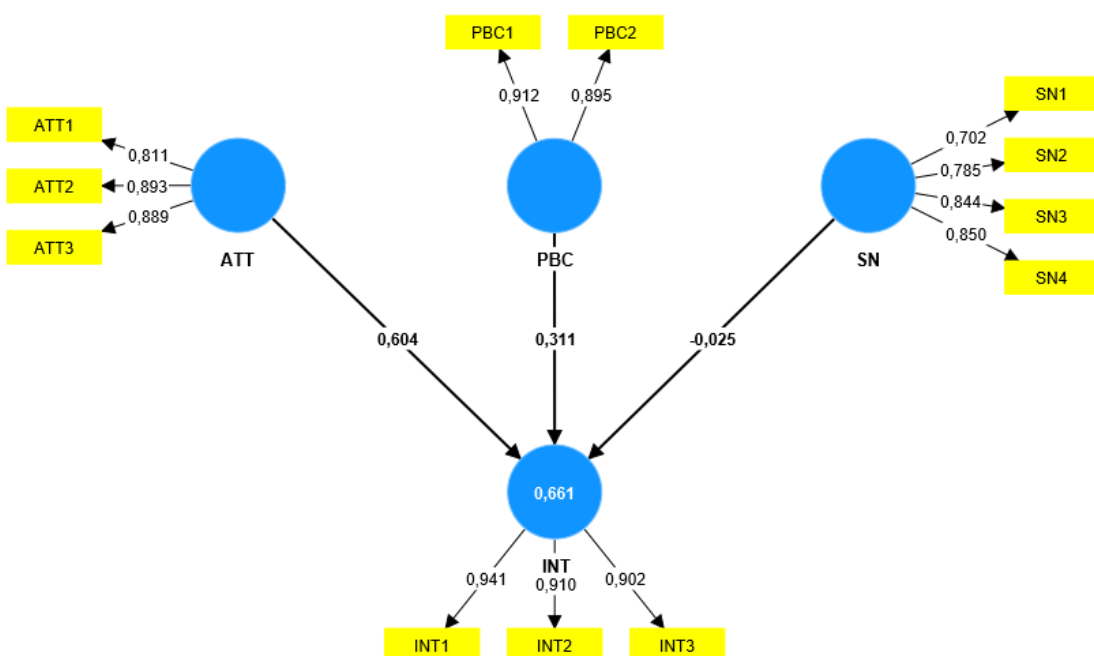

Figure 2: *Path diagram with standardized estimates (PLS-SEM).*

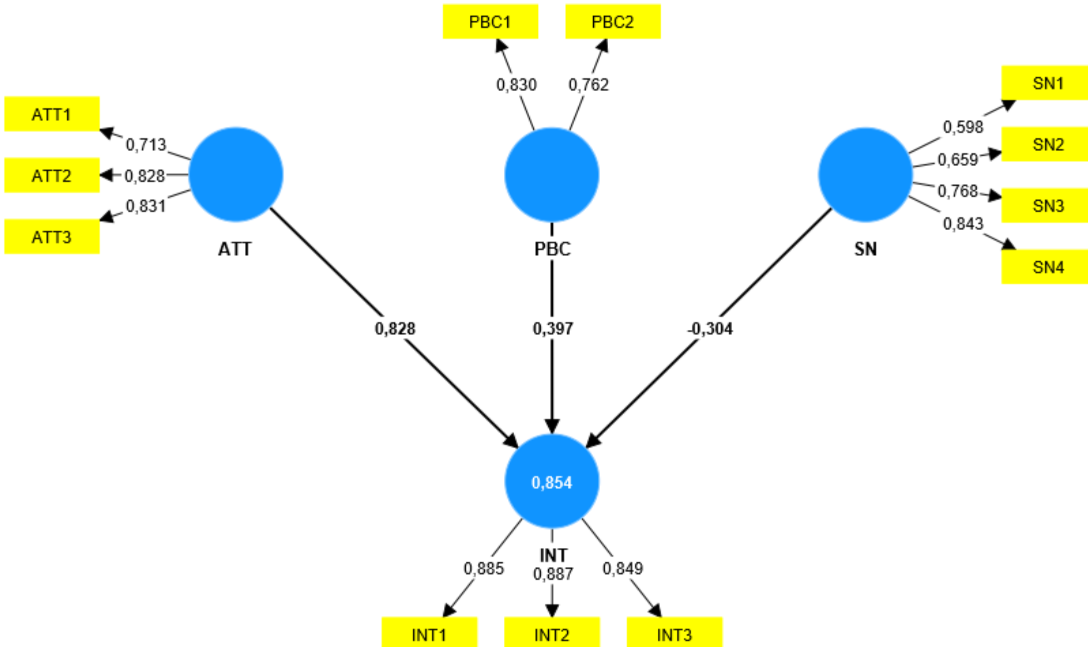

Figure 3: *Path diagram with standardized estimates (PLSc).*

All path diagrams show the R^2 for INT, which is very high for all models. PLS-SEM has the lowest value (0.661), while the values are higher and very similar for CB-SEM (0.812) and PLSc (0.854). This shows that the combination of all exogenous constructs in the models explains a very high proportion of the variance in INT. Thus, all models have high explanatory power.

	Q^2predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
INT1	0.555	0.738	0.539	0.760	0.560
INT2	0.562	0.738	0.538	0.751	0.547
INT3	0.511	0.744	0.558	0.746	0.565

Table 6: *PLSpredict results.*

PLS-SEM focuses on prediction, so out-of-sample predictive power was tested for this technique with the PLSpredict procedure. According to [29], in this procedure the focus should be on the indicators of the key endogenous construct. This model has only one endogenous construct (INT), so prediction errors of its indicators were analyzed. The results show that all root mean squared error (RMSE) and mean absolute error (MAE) values are lower in the PLS model compared to the LM model, confirming the high predictive power of the model [29]. This is further confirmed with CVPAT, since PLS predictions significantly outperformed the prediction benchmarks ($p<0.001$) [28].

5. Conclusion

This research focuses on comparing different SEM approaches (CB-SEM, PLS-SEM, and PLSc) on a model of the TPB in the context of investment intentions. It can be concluded that the evaluation of the measurement model does not differ significantly among different methods. Indicator loadings, validity, and reliability measures are somewhat higher when estimating a PLS-SEM model. CB-SEM and PLSc results are very similar. The same conclusion can be made for structural modeling, where CB-SEM and PLSc path coefficients are very close, while PLS-SEM structural paths are weaker. Measures of model fit are satisfactory for CB-SEM, confirming that the theoretical model holds true for the sample. PLSc output provides only a few measures, which are also almost the same as in CB-SEM. On the other hand, PLS-SEM's model fit measures are slightly worse, but this is not essential, since it is not a confirmatory technique. PLS-SEM should rather focus on the R^2 for the model's in-sample predictive power and other tests (PLSpredict, CVPAT) for out-of-sample predictive power. All of the tests show that the model has high predictive abilities and can be reliable for replication with new data. These findings are in line with previous research dealing with SEM estimator comparison [4, 6, 34] on other theoretical models.

Researchers and practitioners should note that the appropriate SEM approach should be chosen according to the research goal as the most important criterion. For purely confirmatory purposes, one should choose CB-SEM, and for predictive purposes, PLS-SEM should be chosen. PLSc should be used instead of CB-SEM if some of the assumptions (normality, sufficient sample size) are not met, but the goal is still confirmatory. Thus, PLS-SEM cannot be chosen over CB-SEM solely due to a small sample or a violation of data normality, although these could be some of the reasons for the preference of PLS-SEM. However, these are not the most important aspects of the method choice. PLS-SEM has recently gained more popularity because it is causal-predictive, and it is assumed that this is the case in most social research. Therefore, PLS-SEM should be chosen in theory development research. Nevertheless, CB-SEM should not be overlooked in cases of confirmatory analysis. It is not excluded to use both methods complementary and comparatively.

Although this paper shows the comparison of three different approaches to SEM, a very simple model was used, which can be considered a limitation. More complex models can be compared across these methods to draw further conclusions. Even though this model provided a proper solution despite the lower number of indicators for PBC construct, researchers are advised to always ensure a larger number of potential indicators in their research, since some of them can be left out in order to establish construct validity. Researchers are encouraged to use at least three indicators per construct whenever possible to avoid potential estimation issues. Future research can also be based on the comparison of these SEM approaches for a unique model under different conditions. For example, a model can be estimated for smaller and larger sample sizes to see if there are any deviations across the three different SEM approaches depending on the sample size.

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