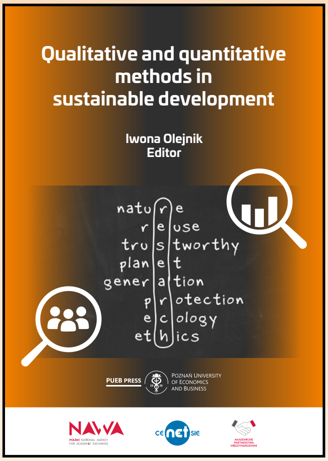

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4.

STRUCTURAL EQUATION MODELLING IN SUSTAINABLE DEVELOPMENT RESEARCH

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Abstract: This chapter is dedicated to the structural equation modelling methods applied to solve sustainable development research problems. A structural equation model is an abstraction of reality, and the researcher's job is to build a model that approximates that reality as closely as possible. This task can be difficult if we do not have a clear understanding of what the reality of the studied phenomena is. Sometimes there is a sound theory behind the studied phenomena, and we can use variables that other researchers have already pointed out as valid indicators. In other situations, we have to start with a set of variables and test many hypothetical relationships based only on theoretical work. In this chapter, we focus on providing researchers with the knowledge needed to specify, evaluate, and interpret structural equation models (SEMs) in any field of social sciences, but most and foremost—in research related to the concept of sustainable development.

Keywords: CB-SEM, PLS-SEM, structural equation modelling, sustainable development.

4.1. What is Structural Equation Modelling (SEM)?

Structural equation models represent an a-priori formulated and theoretically and / or logically justified complex relationships between variables in a linear system of equations. These models serve to estimate the effects (as coefficients) between the considered variables, as well as the measurement errors. SEMs are advanced statistical procedures for testing measurement models, predictive, and causal hypotheses. These multivariate statistical tools are very useful to conduct basic or applied research in the behavioural and social sciences (Bagozzi & Yi, 2012, p. 8). The SEM analytical framework represents a generalization of both multiple regression and factor analysis and subsumes most linear modelling methods as special cases. SEM makes it easier to specify and test models that include latent variables, multiple indicators, measurement errors, and complex structural relationships such as reciprocal causation (Heck & Thomas, 2015, p. 13). The emergence and development of SEMs trace back to three different scientific fields: (1) path analysis, originally developed in genetics and later in sociology (2) simultaneous-equation models, as developed in economics, and (3) factor analysis from psychology (Rosseel, 2012, p. 2). The three traditions were ultimately merged and popularized at the application level in the early 1970s by Karl Jöreskog (1970). In recent decades, a number of software applications, such as commercial programs LISREL (Jöreskog, Olsson, & Wallentin, 2016), Amos (Arbuckle, 2019), EQS, (Bentler, 2006), Mplus (Muthén & Muthén, 2017), STATA, (StataCorp, 2017) XLSTAT, JMP, SAS PROC CALIS, as well as non-commercial open source packages `lavaan`, `sem`, `semPLS` and `OpenMx` in R environment, or the Python package `semopy`, have been developed, which further contributed to, and initiated a methodological revolution in the field of consumer research[1].

4.1.1. SEM in a nutshell: basic concepts

Many questions in the field of social sciences are concerned with investigating causal dependencies between certain variables. If causalities are checked and proved with a data set, this is generally referred to as a *causal* analysis (Backhaus, Erichson, & Weiber, 2015, p. 67). In the context of causal analysis, it is particularly important that the researcher makes intensive logical considerations about the relationships between the variables before using the statistical method. Based on a theoretically justified hypothesis system, SEM is used to check whether the theoretically established relationships match the empirically obtained data. SEM therefore has

[1] A comprehensive overview of modern SEM software packages is provided by Westland (2019, pp. 26, 44–45).

a confirmatory nature and belongs to the statistical methods for testing hypotheses. SEM is able to consider interactions between variables and can include both directly *observable* (manifest) and *non-directly observable* (latent) variables in the analysis. If all variables are manifest, path analysis is used, whereas analyses with latent variables are mostly referred to in the literature as causal analyses (Weiber & Mühlhaus, 2014, p. 36). The special feature of SEM in the context of causal analysis can be seen in the fact that it can be used to check interactions between latent variables.

Let us start from the hypothesis that consumer attitude towards a brand determine the consumer buying behaviour. If we note the attitude with letter ξ, and the buying behaviour with letter η, then the causal dependence underlying this hypothesis could be presented visually as:

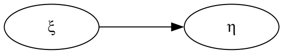


Figure 4.1. Structural model with two latent variables

Figure 4.1 graphically depicts the relationship between two unobservable (latent) variables, which are usually represented by ellipses and lowercase Greek letters. Assuming that the two variables are linearly related to each other, the hypothesis could be expressed mathematically as follows:

$$\eta = \gamma_0 + \gamma_1 \cdot \xi$$

Latent variables are referred to as hypothetical constructs, characterized by an abstract content. It is not possible to decide immediately whether the intended structural models are present in the reality or not. According to Bagozzi and Phillips, a hypothetical (theoretical) construct is an abstract entity which represents the 'true', unobservable state or nature of a phenomena. They achieve their meaning through formal connections to empirical concepts (Bagozzi & Phillips, 1982, p. 465).

In the context of SEM methodology, we can distinguish two types of latent variables: *exogenous* and *endogenous*. Exogenous latent variables are synonymous with independent variables because they "cause" fluctuations in the values of other latent variables in the model. They are considered to be influenced by directly observable variables that are external to the model. These variables serve as *indicators* of the underlying construct they represent. Endogenous latent variables are synonymous with dependent variables as they are influenced by the exogenous variables in the model, either directly or indirectly. Fluctuation in the values of endogenous variables is said to be explained by the model because all latent variables that influence them are included in the model specification (Byrne, 2016, p. 5). Endogenous latent variables are also considered to be influenced by other directly observable *indicator* variables. In Figure 4.1 consumers' attitude toward the brand is an exogenous latent variable and buying behaviour is an endogenous latent variable. Since we cannot directly measure the two latent variables in the model, it is necessary to operationalize them, i.e., to define an appropriate set of indicators that we need to measure for each construct. These indicators must depict the empirical representation of the unobservable, latent variables. SEM helps us verify a theoretically based hypothesis system that the relationships you have hypothesized among the latent variables and between the latent variables and the manifest indicators are indeed consistent with the empirical data at hand (Diamantopoulos & Siguaw, 2000, p. 4).

Structural equation models consist of two parts: a structural model and a measurement model. The **structural model** describes the relationships between the latent variables. Using our example, the structural model would explain whether there is a significant relationship between consumer attitudes towards the brand (exogenous latent variable ξ) and expected buying behaviour (endogenous latent variable η). The **measurement model** describes the set of manifest indicators that correspond to each latent variable. Let us assume that "Attitudes toward a brand" is described by three indicator variables: X_1 "This brand is eco-friendly", X_2 "This brand has a name you can trust", and X_3 "This is a high quality brand", while „Buying behaviour" is operationalized by two observable indicator variables: Y_1 "Number of items purchased" and Y_2 "Frequency of purchase". Based on these assumptions, the full structural equation mode can be represented as in Figure 4.2**.** Schematic representations of models are termed path diagrams because they provide a visual portrayal of relations that are assumed to hold among the variables under study. Essentially, a path diagram depicting a particular SEM model is actually the graphical equivalent of its mathematical representation whereby a set of equations relates dependent variables to their explanatory variables (Byrne, 2016, p. 10).

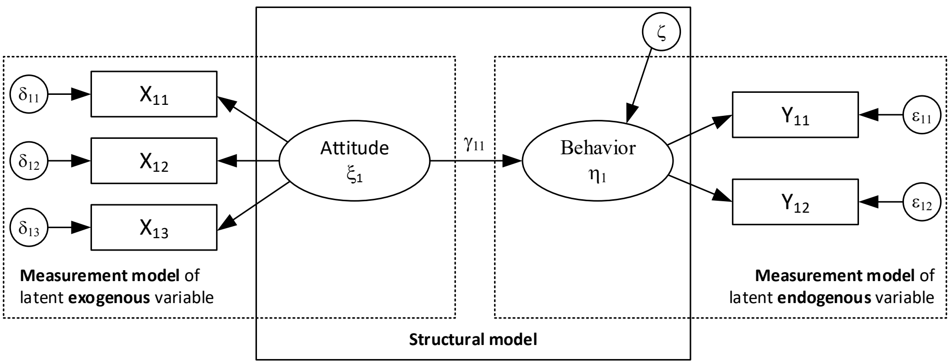


Figure 4.2. An example of full structural equation model

This model is termed "full" (or "complete") because it comprises both a measurement model and a structural model: the measurement model is depicting the links between the latent variables and their observed measures, and the structural model is depicting the links among the latent variables. A full model that specifies the direction of cause from one direction only is termed a recursive model; one that allows for reciprocal or feedback effects is termed a non-recursive model (Byrne, 2016, p. 7).

The notation of variables in Figure 4.2 has become largely unified in the literature.

Table 4.1 gives an overview of used abbreviations and their meanings. Statistical evaluation results in the so-called "path coefficients" that express the dependencies between variables in model. Typically, path coefficients are denoted with lowercase Greek letters, e.g.: β_{ij}, γ_{ij}, φ_{ij}, and ψ_{ij}.

Table 4.1. Variables in a complete structural equation model

Abbreviation	Meaning
η	Latent endogenous variable, which is explained in the model
ξ	Latent exogenous variable, which is not explained in the model
Y	Observable (measurable) indicator variable for a latent endogenous variable η
X	Observable (measurable) indicator variable for a latent exogenous variable ξ
ε	Disturbance (measurement error) for an indicator variable Y
δ	Disturbance (measurement error) for an indicator variable X
ζ	Disturbance for a latent endogenous variable η

Source: (Weiber & Mühlhaus, 2014, p. 39).

It is important to distinguish between two basic types of *measurement* models—**reflective and formative models** (Edwards & Bagozzi, 2000, pp. 161–164). An indicator is reflective if it is caused by the construct expression and therefore the causal relationship goes from the construct to the indicator as depicted in Figure 4.3a, where each of the X_1 Xiindicator variables is influenced by the construct ξ_1. This model might be appropriate when a researcher wants to test a theoretical explanation of a latent construct. It is obvious that both measurement models in Figure 4.2 are reflective. The reflective measurement model in Figure 4.3a can be represented by a set of regression equations as follows (Diamantopoulos, 1999, p. 446):

$$X_1 = \lambda_1 + \xi \cdot \delta_1 \qquad X_2 = \lambda_2 + \xi \cdot \delta_2 \qquad X_3 = \lambda_3 + \xi \cdot \delta_3$$

where: λ_1 is the expected effect of ξ on X_1, and δ_1 is the measurement error for the i^{th} indicator ($i = 1, 2, 3$).

Reflective measurement is consistent with the confirmatory factor analysis (CFA) model as the variance in each indicator is as a linear function of the underlying latent variable. It is appropriate to use CFA when we have some knowledge of the underlying latent variable structure. Based on theoretical knowledge, empirical research, or both, the researcher postulates relations between the observed measures and the underlying factors a priori and then tests this hypothesized structure. CFA focuses solely on how the observed variables are linked to their underlying latent factors. More specifically, it is concerned with the extent to which the observed variables are generated by the underlying latent constructs and thus the strength of the regression paths from the factors to the observed variables (i.e., the factor loadings λ_i) is of primary interest. Although relations between latent factors are also of interest, any regression structure among them is not considered in the factor analytic model (Byrne, 2016, p. 7).

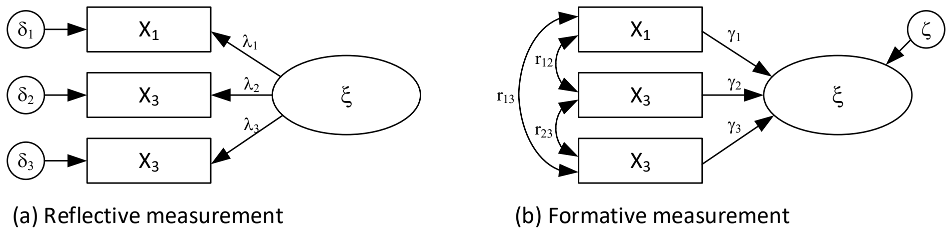


Figure 4.3. Reflective and formative measurement models

Source: (Diamantopoulos, 1999, p. 446).

However, in social-oriented studies we want to identify, e.g., what most important variables that ultimately influence the latent constructs are (e.g., attitudes toward a brand). In this case, we have a formative measurement model (see Figure 4.3b), because the indicators are assumed to be the cause for a latent variable to manifest. The causal relationship is going from the indicators to the constructs. In other words, under a formative perspective, a concept is assumed to be defined by, or to be a function of its measurements. The formal specification of the formative measurement model in Figure 4.3b is as follows (Diamantopoulos, 1999, p. 447):

$$\xi = y_1 X_1 + y_2 X_2 + y_3 X_3 + \zeta$$

where y_1 is the expected effect of X_1 on ξ and ζ is a disturbance term, with $cov(X_1, \zeta) = 0$ and $E(\zeta) = 0$.

In both formative and reflective measurement models, the measurement equation(s) follow a regression approach. The basic equation of a formative measurement model can be formulated as follows (Weiber & Mühlhaus, 2014, p. 257):

$$\boldsymbol{X_T} = X_0 + (X_S + X_R)$$

where $\boldsymbol{X_T}$ is the true construct value (not observable), X_0 is observed value (empirically measurable), X_S is systematic error, and X_R is random error.

In contrast, the following formulated relationship applies to the basic equation of reflective measurement models:

$$X_0 = \boldsymbol{X_T} + (X_S + X_R)$$

The decisive difference between the two measurement approaches is that in the reflective approach the measurement variable X_0 is the dependent variable and the construct is the independent variable. With the formative approach, this is exactly the opposite. One full structural equation model can contain only reflective, only formative or both reflective and formative indicators in its measurement models. It is obvious that in the reflective specification, the explanatory variable is latent, and the dependent variables are visible. In contrast, in the formative specification, the explanatory variables are manifest and the dependent variable is latent. This key difference between the two types of measurement models implies the use of different approaches to the statistical evaluation of parameters of SEMs (Jarvis, MacKenzie, & Podsakoff, 2003).

4.1.2. The model estimation

The relationships between latent and manifest variables cannot be exactly determined since the latent variables do not 'exist' in the same way as indicator variables do. It is even more difficult to determine causalities between two latent variables since both constructs can only be determined indirectly by their indicators. Measurement errors (also called residuals or disturbance) complicate the determination of the relationships. This is why all relationships between variables in SEMs can only be statistically estimated. There are two different approaches that can be used to estimate structural equation models: covariance-based structural equation modelling (CB-SEM) and variance-based partial least squares (PLS) path modelling, also referred to as PLS-SEM. Most notably, the first one estimates all model parameters by minimizing a global optimization criterion, whereas partial least squares path modelling does not involve such a global optimization procedure.[2] This seemingly small methodological difference leads to important practical implications (Hwang & Takane, 2014, p. xi). According to Hair, Ringle, and Sarstedt (2012, p. 312) „CB-SEM is a confirmatory approach that focuses on the model's theoretically established relationships and aims at minimizing the difference between the model implied covariance matrix and the sample covariance matrix. In contrast, PLS-SEM is a prediction-oriented variance-based approach that focuses on endogenous target

[2] In recent years another novel approach for structural equation modelling has also gained popularity. This approach, named *generalized structured component analysis*, was developed by Hwang and Takane (2004, 2014). and remains out of scope of this chapter.

constructs in the model and aims at maximizing their explained variance." There are some rules of thumbs that can be applied when deciding whether to use CB-SEM or PLS-SEM (Hair, Hult, Ringle, & Sarstedt, 2017, p. 18).

In general, if the purpose of the study is to verify and confirm some hypothetical theoretical concept (respectively theoretically defined psychological construction), the appropriate method is CB-SEM. However, if the aim of the study is to predict or develop an already known theory (containing some latent constructs in its description), the appropriate method is PLS-SEM. Statistically, PLS-SEM is similar to multiple regression analysis. The main goal of this approach is to maximize the explained part of the dispersion in the dependent (endogenous) constructs. PLS-SEM is less pretentious about the sample size and the requirement for normal statistical distribution of indicator variables. In other words, data requirements are less restrictive and, in general, should be applied in exploratory rather than confirmatory studies (Hair, Ringle, & Sarstedt, 2011, p. 140).

4.1.2.1. Model estimation using CB-SEM approach

Covariance-based approach, proposed by Jöreskog is the most often used approach to estimate and assess structural equation models (1973, 1970). The aim is to study the structure of the observed variables resulting from the variance-covariance matrix. In this way, it is possible to consider relationships between latent variables measured by manifest variables.

Since the variance-covariance matrix includes relationships between the variables, we can estimate the strength and direction of the links between variables in the model. However, there are some important assumption and features in CB-SEM. The latent variables are not defined by linear combination of manifest variables. They are true latent variables. Furthermore, the vector of error variables of measurement models is assumed to be pairwise uncorrelated and uncorrelated with all the latent variables (see Figure 4.2). This assumption turns CB-SEM approach into a "hard" model, in contrast to the "soft" PLS-SEM model (Schneeweiss, 1991, p. 152).

The most common parameter estimation algorithm for CB-SEM is the maximum likelihood method (ML). It is robust and consistent, and provides extensive and good quality measurements, which is why it is used most frequently. The disadvantage of this method is the assumed multivariate normal distribution of the data. It is problematic in this context that data normally distributed in marketing are rarely found (Jahn, 2007, p. 12). Another normal theory estimator is generalized least squares (GLS). When the assumption of multivariate normality is met, ML and GLS estimates are asymptotically equal. However, ML estimation has been shown to outperform GLS estimation under model misspecification conditions (Olsson, Foss, Troye, & Howell, 2000; Pituch & Stevens, 2016, p. 649).

The quality of estimation is an important topic of the covariance analysis. Different criteria and goodness-of-fit measures are applied for this purpose. Some of the more important ones will be discussed later. In addition to assessing the proposed model, it is also possible to predefine and compare different variants of the model.

4.1.2.2. Model estimation using PLS-SEM approach

Partial least square methods (sometimes referred to as component-based SEM or simply PLS-SEM) is an alternative statistical approach for casual modelling with latent variables. This method was first proposed by Wold (1975), but later Lohmöller (1989) contributed to the significant expansion and upgrading of algorithm for latent variable path modelling with partial least squares. PLS-SEM estimates model structures by combining principal components analysis with ordinary least squares regression and is typically viewed as an alternative that overcomes the very restrictive assumption of CB-SEM (Hair, Risher, Sarstedt, & Ringle, 2019, p. 4). It aims to maximize explained variance of dependent latent variables in SEM (i.e., maximizes the values). PLS optimizes locally, i.e., it maximizes the prediction of each dependent variable. It is therefore forecast-oriented (Jahn, 2007, pp. 14–15). In recent years, there has been a growing interest in the use of PLS-SEM in the field of empirical marketing and management studies (Hair, Hult et al., 2017, p. xiv). The increased recent interest is primarily due to the attention given to formative indicators in the construction of latent variables. An essential advantage of using this approach is that PLS makes no distribution assumptions due to the nature of the least squares estimate. This means that models can be estimated using PLS without the data having to be multivariate normal distributed. For example, if there is a large skewness of the sample, this does not affect the parameter estimation in PLS. Another key characteristics and advantages of PLS-SEM is that this method has no identification issue with small sample size and works fine with metric data, quasi-metric (ordinal) scaled data, and binary coded variables (for comparison, CB-SEM works only with metric data). This approach also easily incorporates reflective and formative measurement models (Tenenhaus, Vinzi, Chatelin, & Lauro, 2005, p. 165). At the same time, however, it has some limitations concerning model evaluation. The most important of them is that there is no established global goodness-of-fit criterion for model adequacy.[3]

[3] For more details see (Hair, Hult, et al., 2017, pp. 19–20).

4.1.2.3. Choosing the right approach

There are several fundamental differences between CB-SEM and PLS-SEM approaches (Scholderer & Balderjahn, 2005). The first one lies in the understanding of latent variables that underlie the respective approaches. Latent variables in the first approach follow the tradition of psychometric theory, i.e., that is, they satisfy the conditions of local stochastic independence. If there are one or more latent variables that cause the relationships between the observed variables, these relationships should disappear if the latent variables are kept constant. However, the latent variables in PLS-SEM do not have such properties. They follow the econometric theory tradition, which defines latent variables as unobserved, but does not exclude deterministic functions of the observed variables from the class of latent variables. The second fundamental difference between CB-SEM and PLS-SEM lies in the assumptions about the sample distribution of the variables. CB-SEM approach requires a multivariate normal distribution of the observed and latent variables, which in many cases is a serious limitation when working with empirical data. PLS-SEM, on the other hand, makes no assumptions regarding the distribution of the model variables, but precisely because of this, it cannot offer the inferential statistical possibilities of CB-SEM. Furthermore, it can be seen that the advantages of PLS arise precisely from the weak points of the maximum likelihood estimation. On the other hand, CB-SEM have some strengths over PLS-SEM. These mainly relate to the quality measures, but also the efficiency, consistency and robustness of the estimation results. The central weak point of PLS-SEM is that there are no criteria for assessing the overall model; there is still no convincing goodness-of-fit index for the joint assessment of the measurement and structural model in the PLS approach (Hulland, 1999, p. 202). Some authors recommended the application of PLS-SEM for sample size of $n < 100$ and less than four indicators per latent variable or if there are uncertain model hypotheses. Otherwise, they strongly recommend the use of CB-SEM approach due to the higher performance and application potential (Scholderer & Balderjahn, 2005). According to other views, they should not be seen as competitive alternatives, but rather as complementary approaches (Jöreskog & Wold, 1982, p. 270). Several years ago, Sarstedt and others published detailed results of simulation studies and derived on their basis valuable recommendations for choosing the appropriate approach for SEM assessment, in cases of reflective and formative models (Sarstedt, Hair, Ringle, Thiele, & Gudergan, 2016, p. 4007).

In conclusion it can be summarized that CB-SEM and PLS-SEM estimates of the same models can only be compared to a limited extent. A CB-PLS model always contains a number of additional restrictions compared to PLS, even if the path diagrams appear identical at first glance. However, we strongly suggest you have a look at Hair and others “rules of thumb” for selecting CB-SEM or

PLS-SEM (Hair, Ringle, & Sarstedt, 2011, p. 144), according to which CB-SEM and PLS-SEM results should be similar, but if CB-SEM requirements cannot be met (e.g., model specification, identification, nonconvergence, data distributional assumptions), use PLS-SEM as a good approximation of CB-SEM results. In general, PLS-SEM is the best approach, if you need to use latent variable scores in subsequent analyses. CM-PLS is recommended when the goal is theory/conformation, or comparison of alternative theories. PLS-SEM would also be recommended when we conduct exploratory research and if there are formative measurement models.

4.1.3. Identification issues and model adequacy

Not every theoretically justified structural equation model with latent variables is susceptible to statistical identification using the CB-SEM approach.[4] The problem with "identifiability" stems from the fact that in order to unambiguously solve a system of linear equations (through which each SEM is described mathematically), it is necessary that the number of equations contained in it be greater than the number of estimating model parameters. The number of equations always corresponds to the number of elements of the correlation matrix of the theoretical model. The number of elements of this correlation matrix is determined by the number of indicator variables that are subject to empirical observation.[5] The difference between the number of equations and the number of unknown parameters to be evaluated represents the degree of freedom of the model. A necessary condition for the identification of any SEM is that the degree of freedom of the model is greater than, or equal to zero (Backhaus et al., 2015, p. 86). Formally, if we denote the number of endogenous variables in a model by p, respectively the number of exogenous variables by q and the number of parameters to be evaluated by t, to achieve identifiability (i.e., to be able to statistically evaluate the parameters of SEM), the following condition must be valid:

$$t \leq \frac{1}{2}(p+q)\cdot(p+q+1)$$

However, the fulfilment of the above condition is not sufficient to conclusively prove the identifiability of the SEM. An additional criterion for checking the possibility for statistical estimation of the model parameters is the absence of a linear relationship between the equations that describe it. If there are linear interactions,

[4] PLS-SEM is not constrained by identification issues, even if the model becomes complex—a situation that typically restricts CB-SEM use (Hair, Sarstedt, Ringle, & Gudergan, 2017, p. 34).

[5] The number of elements (i.e., the correlation coefficients) of the correlation matrix is always equal to $n(n + 1)/2$, where n is the number of indicator variables included in the model.

the initial empirically observed correlation matrix must be positively defined (i.e., to be invertible). A necessary condition for this is that the number of estimated parameters of the model is greater than the number of indicator variables (Backhaus et al., 2015, p. 87). If the model is identifiable, the CB-SEM approach can be applied to evaluate its parameters. As the alternative PLS-SEM approach is not limited by the problem of identifiability, it can also be applied in cases of non-fulfilment of the described conditions for identifiability.

However, regardless of the approach used, the interpretation of the SEM should always begin by examining the logical validity of the sign and the magnitude of the estimated parameters. Typically, the dependencies between variables whose standardized estimates have an absolute value above 0.2 and ideally above 0.3 are usually interpreted and considered meaningful. In the presence of reflective indicators, it is recommended that the factor weights are above 0.6–0.7, ensuring that at least 50 % of the information in the indicator variable is explained by the relevant latent variable (Chin, 1998a, p. xiii). When working with formative indicators and the PLS-SEM approach, the estimated parameters no longer have the meaning of factor loadings, but their interpretation as the "strength" of the relationship is the same.

Of course, each parameter of an estimated SEM could also be evaluated in terms of its statistical significance. The basic rule here is that at a significance level below 0.05, the parameter is considered significant and can be interpreted. However, the interpretation of the statistical significance of coefficients estimated by PLS is problematic, as it is presumed that there is no explicit requirement for PLS to have a normal statistical distribution of the data of the indicator variables. In such a scenario, it is necessary to use bootstrap resampling to simulate a sufficiently large number of replicates (usually over 1,000) and to calculate the level of statistical significance p-value for each parameter of the model.

After this preliminary examination of the individual assessments of the parameters of the model, it is possible to proceed to an in-depth analysis of its quality using indices of goodness-of-fit.

So, what exactly are the indices of model fit? When we run a structural equation modelling, we are building or proposing a model that is based on some conceptualization, some past work by other researchers, which is called a review of literature. So, based on all this work, you conceptualize a model in which different variables are related to each other. Some variables may act like causes and other variables may act like effects. Then we also have the error term in covariances. Now, how do we know that your model is a good model, or it is an acceptable model? We assume that if the role played by all variables in our model is more or less the same as the actual role played by these variables in real life, we say that we are approximating to the reality. Our model captures the actual reality in a sufficient way. These indices of model fit tell us, to what extent our model is a good model and to what extent the model fits the sample behaviour. Perhaps, we are not only restricted to the sample behaviour but many indices which also tell us, what the chances of this model being replicated are, in the entire population. So, the indices of model fit are very important and very useful and without using indices of model fit, we cannot be very sure about whether our model is a good fitting model or not.

Different indices (assessment criteria) for the "quality" of the model as a whole are used. The quality of the assessed model can be assessed by two different perspectives—in terms of its reliability and its validity. Statistical reliability in this case means the absence of random errors in the evaluated model, i.e., in repeated empirical observations with other random samples, the estimates of the model will remain stable, i.e., their interpretation should not change. Where the measurement is reliable, it allows a summary relating to a wide variety of circumstances to be derived from one particular use of the model. One of the forms of reliability proof is to carry out repeated tests on the same respondents twice or more. The aim is to ensure that respondents' responses do not vary significantly over time, so that measurement leads to stable results. The second, more commonly used form to demonstrate reliability is the calculation of an internal consistency criterion between the indicator variables associated with a particular latent structure. The rationale for internal consistency is that individual indicators must measure the same construct and therefore correlate strongly with the latent variable being explained. The most popular and widely-used measure of internal consistency are the alpha coefficient (better known as Cronbach's alpha) and the omega coefficient, also known as composite reliability, whose values are recommended to exceed the threshold of 0.7 (Bacon, Sauer, & Young, 1995, p. 400).

Statistical validity means the circumstance in which the differences in the observed estimates reflect only the actual differences of the studied characteristic, which is the object of measurement (i.e., the model to really measure and reflect what needs to be measured and reflected). Validity therefore means conceptual correctness of measurement. In other words, SEM is considered reliable when it does not contain systematic errors and is respectively defined as valid when it does not contain random errors.

Reliability is a necessary but not a sufficient condition for validity (Peter, 1979, p. 6). The validity of any SEM could be considered content, convergent, discriminant and nomological (Homburg & Giering, 1996, S. 7). Content validity is determined by the degree to which the variables in a given measurement model belong to the semantic area of the studied construct, and the constructed elements fully reflect all content aspects of the construct. Convergent validity is explained by the extent to which there are strong associative (correlation) relationships between the indicator variables describing a latent variable in SEM. Discriminant validity means that the associative relationships between indicator variables attributed to different latent variables should generally be weaker than those that measure the same latent variable. Ensuring nomological validity requires that the construction of a construct be integrated and empirically justified in a higher-level theoretical framework. To ensure content and nomological validity, careful selection and arrangement of the indicator variables is needed, as well as precise definition and interpretation of working hypotheses in the model.

However, proving convergent and discriminatory validity in SEM can be performed using two types of statistical criteria—local and global goodness-of-fit evaluation statistics.

4.1.3.1. Local criteria for model evaluation

When evaluating the reliability and validity of reflective measuring models with local goodness-of-fit statistical criteria, the aim is to check the adequacy of the measuring models. Here, on the one hand, the indicators are evaluated, and on the other hand—their relationship with the latent variables.

It is usually started by assessing the structural reliability by examining the factor loadings, the values of which must exceed 0.707 to make sure that more than half of the variance in the indicator variables is related to the latent construct.

The omega index is then checked for composite reliability, the values of which must be above 0.7 (Fornell & Larcker, 1981, p. 45). It is also possible to use the AVE indicator (AVE = average variance extracted). Fornel and Larcker claim, that „if AVE is less than 0,5, the variance due to measurement error is larger than the variance captured by the construct, and the validity of the individual indicators, as well as the construct, is questionable" (Fornell & Larcker, 1981, p. 46). The construct reliability and the average variance are suitable as test variables for the convergence validity of the indicators assigned to a factor. In order to complete the reliability and validity considerations, the discriminant validity is assessed using the Fornell / Larcker criterion (Fornell & Larcker, 1981, p. 46). It says that the average variance of a factor must be greater than any squared correlation between it and another construct. In addition, the coefficient of determination R^2, describing the share of the variance of an endogenous construct explained by the relationships in the model could always be calculated. Here the recommended minimum threshold is around 0,3 (Drengner, Gaus, & Jahn, 2008, p. 143). In summary, the evaluation of reflective measurement models using local statistical criteria should be in line with the following recommended scheme in Table 4.2.

Table 4.2. Recommended thresholds for assessment of reflective measurement models with local fit evaluation criteria

Construct / Indicators	Convergent validity			Discriminant validity	
	factor loadings	composite reliability	AVE[a]	Fornell / Larcker	R^2
(Requirement)	(≥0.707)	(≥0.7)	(≥0.5)	(AVE > Corr²)[b]	(>0.3)
Construct 1		…	…	… > …	…
Indicator 1–1	…				
Indicator 1–2	…				
Construct 2		…	…	… > …	…
Indicator 2–1	…				
Indicator 2–2	…				

[a] AVE = average variance extracted
[b] Corr² = highest squared correlation between the model constructs

Source: Based on (Drengner et al., 2008, p. 143).

When working with formative measurement models there is no need to assess internal composite reliability as well as convergent (and therefore discriminant) validity. For this reason, only the estimates of the path coefficients should be statistically significant (Jahn, 2007, S. 23). Since the evaluation of formative measurement models uses multiple regression, one of the main requirements is the absence of multicollinearity between the independent variables. Essentially, if estimated factor loadings, composite reliability, AVE, and Fornell / Larcker criterion meet the requirements for reflective measurement models (see Table 4.2), a reliable and valid measurement could be assumed. Afterwards it is possible to check the structural model. If the assumption that the model withstands the empirical examination is supported, then the hypotheses can be checked. The investigation of whether the data collected contradicts the relationships expressed by the model or not is conducted with the help of the global quality measures. These measures are called by different authors by different names, including "fit indices" (Marsh, Balla, & Hau, 1996, p. 315), "goodness-of-fit indices" (Jöreskog et al., 2016, p. 500) or simply "fit Statistics" (Bollen & Long, 1992, pp. 1–9).

4.1.3.2. Global criteria for model evaluation

Due to the different logic and statistical nature of CB-SEM and PLS-SEM assessment, different fit indices are applied to assess the adequacy of the defined models. As arguments for the 'best' global fit criterion cannot be argued, the following will outline some of the most commonly used ones.

CB-SEM evaluation

Two types of fit indices are used as global criteria for assessing the adequacy of CB-SEM—***absolute*** and ***incremental***. *Absolute* fit indices assess how well an a priori model reproduces the sample data. In order to test this agreement statistically, a chi-square test can be performed. The perfect representation of reality through the model mean that the null hypothesis is likely to be rejected as soon as the number of samples is large enough. In order to neutralize the sample size effect on the test result, it is also recommended to compute a relative chi-square (χ^2/df). A ratio of approximately 3 or less is considered 'beginning to be reasonable' (Arbuckle, 2019, p. 641). Furthermore, the probability p is calculated that the rejection of the null hypothesis would represent a wrong decision. Some authors recommend rejecting the model if p is less than 0,1 (Weiber & Mühlhaus, 2014, p. 204).

The Goodness of Fit Index (**GFI**) and the Adjusted Goodness of Fit Index (**AGFI**), which considers the degrees of freedom, are also commonly used. The possible range of GFI values is 0 to 1, with higher values indicating better fit (Hair, Black, Babin, & Anderson, 2019, p. 637). These indicators should be used with caution as they are sensitive to sample size as well as the size of the model (Anderson & Gerbing, 1984, p. 172).

Root Mean Square Residual (**RMR**), which corresponds to the standard error in the regression analysis, can also be used as a measure of the covariance that is not explained on average in a model. There is also a standardized variant of this index (**SRMR**), that is useful for comparing fit across models. Lower RMR and SRMR values represent better fit and higher values represent worse fits. Hair et al. claim that an SRMR over 0,1 suggests a problem with the fit (Hair, Black et al., 2019, p. 638).

Browne and Cudeck (Browne & Cudeck, 1992, pp. 238–239) recommend another absolute index for global assessing the adequacy of CB-SEM—Root Mean Squared Error of Approximation (**RMSEA**). According to them, a value of RMSEA of about 0,05 or less would indicate a "close" fit of the model. A value greater than 0,1 indicates an unacceptable approximation. In addition, some software programs (such as AMOS) also calculate the probability value for testing the null hypothesis that the population RMSEA is no greater than 0,05 (Arbuckle, 2019, p. 645).

Incremental indices differ from absolute ones in the fact that they are resulted from the comparison of the estimated model with a null model that is more restricted than the target model because its variables must not correlate with each other. The most commonly used incremental index is Normed Fit Index (**NFI**). It ranges between 0 and 1, and a model with perfect fit would produce an NFI of 1. An alternative is Tucker Lewis Index (**TLI**), that is conceptually similar, but considers model complexity to some extent. Other popular indices are Comparative Fit Index (**CFI**) and Relative Non-centrality Index (**RNI**). Like the other incremental fit indices, higher values represent better fit, and the possible values generally range between 0 and 1 (Hair, Black et al., 2019, p. 638).

In general, the simultaneous use of the mentioned indices is recommended for the reliable assessment of CB-SEM, and the cut-off values given in

Table 4.3 can be used as a guide.

Table 4.3. Cut-off values for fit indices for global evaluation CB-SEM

RMSEA	RMR	SMRM	CFI/RNI/NFI/ TLI	χ^2/df	AGFI
< 0,08	< 0.05 (but not > 0.1)	< 0.05	> 0.90	< 3	> 0.90

Source: (Jahn, 2007, p. 27).

The fit indices discussed are also suitable for comparing different variants of a CB-SEM model. However, these alternative models should be similar in their complexity to ensure comparability.

PLS-SEM evaluation

The PLS approach has no reasonable global criterion for assessing the model quality, so that it cannot be assessed comprehensively. Some quasi-global quality measures applicable to PLS-SEM estimates are somewhat similar to those of a linear regression. For example, to assess the explanatory power of a PLS model, the coefficient of determination R^2 can be used for each latent endogenous variable. The interpretation is identical to that of tradition regression—describe proportion of the variance explained. According to Wynne Chin, values for R^2 of 0,19 are interpreted as "weak", of 0,33 as "moderate", and of 0.66 as "substantial" (Chin, 1998b, p. 323).

Suitable criterion is the so-called "effect size" f^2. Specifically, the effect size f^2 checks whether a particular exogenous latent variable has substantive impact on an endogenous variable by using or omitting independent variables in the structural equation, respectively. High values indicate that the exclusion of the corresponding exogenous variables causes a significant drop in R^2, which in turn means a high relevance in explaining the endogenous variables. Effect size of 0,02, can be viewed as small, 0.15 as medium, and 0,35 as large effect at the structural level (Chin, 1998b, p. 317).

An important criterion for assessing global predictive relevance of PLS models is Stone-Geisser Q_n^2 criterion (Chin, 1998b, p. 317). The Stone-Geisser Q_n^2 criterion evaluates the predictive relevance, i.e., how well the dependent (endogenous) is described on their independent (exogenous) variables in the structural model. If the value of this criterion is above zero, the model is predictive significant. A value of zero means that the model does not predict the original data better than an average estimate. Values less than zero speak against the quality prediction of the model structure. It should be noted that this measure can only be used sensibly for reflective measurement models (Herrmann, Huber, & Kressmann, 2006, p. 58; Weiber & Mühlhaus, 2014, p. 329).

Finally, the robustness of the results of a PLS-SEM estimate can be assessed using the bootstrapping method, in which different samples are used to estimate the PLS model (Chin, 1998b, p. 320). If the parameter estimators vary widely across the different samples, this speaks against the robustness of the estimation results. Usually, the first two moments of the distribution of the individual estimators, the mean value and the standard deviation over the samples are primarily considered.

However, in order to check the quality or "appropriateness" of a PLS solution, it is recommended to consider all available individual criteria for assessing the measurement models and the structural model in a kind of "synopsis".

Table 4.4 shows the criteria discussed above and their recommended cut-off levels.

If individual measurement models have deficits, it makes sense to perform modifications in order to achieve statistically significant results in all elements of the causal model, at least for partial structures or exploratory modifications (Ringle, 2004, p. 23).

Table 4.4. Recommended values for global evaluation criteria of PLS-SEM

Coefficient of determination (R^2)	Effect size (f^2)	Stone-Geisser criterion (Q^2_η)	Path coefficients (after bootstrapping)
~ 0.66 (substantial)	~ 0.35 (large)	> 0	> 0.2
~ 0.33 (moderate)	~ 0.15 (medium)		
~ 0.19 (weak)	~ 0.02 (small)		

Source: Based on (Chin 1998b, pp. 317–323; Ringle, 2004, p. 22; Jahn, 2007, p. 28).

If the local and global evaluation result is an acceptable mode (i.e., reliable and valid), the hypotheses can be tested. If the relationship between two constructs is significantly different from zero and runs in the positive direction (positive or negative relationship), the hypothesis expressed by them can be confirmed or rejected. Furthermore, the consideration of total effects helps to better understand the interdependencies in a complex model. A total effect is the total influence of one variable on another across all conceivable relationships with other constructs (Jahn, 2007, S. 30).

4.2. Comparing the performance of SEM approaches with simulated data

Following the research framework for evaluating customer satisfaction and loyalty proposed by Tenenhaus and others (2005) and Fornel, Johnson, Anderson, Cha, and Bryant (1996), we simulated data from a hypothetical survey (n = 799)[6]. The data consisted of 22 items (indicators) of corporate image, customer expectations, per-

[6] Similar models with artificially simulated other data are publicly available and found in Addinsoft (2020) and Ringle, Wende and Becker (2015).

ceived product and services quality, perceived value of product, customer satisfaction, customer loyalty and complaints. The proposed structural model for the associations among the hypothetical reflective constructs is illustrated in Figure 4.4. Obviously, the model contains six exogenous (ξ_j) and one endogenous (η) latent variables.

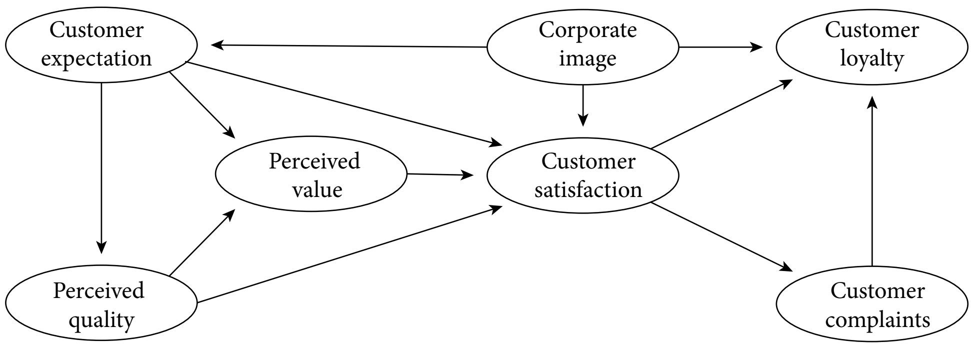


Figure 4.4. A structural model of customer satisfaction index

Source: (Tenenhaus et al., 2005, p. 161).

For clarity, on the path diagram, individual items for each factor are omitted. However, the observable indicators and variable names of latent factors are shown in Table 4.5 (Tenenhaus et al., 2005, p. 162; O'Loughlin & Coenders, 2004, p. 1236).

Table 4.5. Conceivable names of latent variables and their indicators

Latent variables (LV) {name / description}	Manifest variables (MV) name		Description (Likert-type statements) {All the items are scaled from 1 to 7. Scale 1 expresses a very negative, while scale 7 a very positive opinion}
CUEX (ξ_1) Customer expectation of the overall quality	Cuex1	(x_1)	Expectations for the overall quality of product
	Cuex2	(x_2)	Expectations for product to meet your personal need
	Cuex3	(x_3)	Expectation that things could go wrong at your product
PERQ (ξ_2) Perceived quality	Perq1	(x_4)	Please rate the overall quality of the product
	Perq2	(x_5)	Please rate the technical product features
	Perq3	(x_6)	Please rate the customer service and personal advice offered
	Perq4	(x_7)	Please rate the reliability and accuracy of the product
	Perq5	(x_8)	Please rate the clarity of information provided
PERV (ξ_3) Perceived value	Perv1	(x_9)	Please rate the quality of the product given the prices you pay
	Perv2	(x_{10})	Please rate the prices of product given the quality
IMAG (ξ_4) Corporate image	Imag1	(x_{11})	The product provider is a reliable and trustworthy company
	Imag2	(x_{12})	The product provider is a customer-centric company
	Imag3	(x_{13})	The product provider is innovative and forward looking
	Imag4	(x_{14})	The product provider has a social contribution for the society

CUSA (ξ_5) Customer satisfaction	Cusa1	(x_{15})	Overall, how satisfied are you with the product?
	Cusa2	(x_{16})	How close is this product to your ideal product?
	Cusa3	(x_{17})	Considering your expectations, to what extent has the product fallen short of, or exceeded your expectations?
CUSCO (ξ_6) Customer complaints	Cusco1	(x_{18})	How many times have you complained (either formally or informally) to sales or support personnel?
	Cusco2	(x_{19})	To what extent do you think that your product provider will / would care about your complaint?
CUSL (η_1) Customer loyalty	Cusl1	(y_1)	If you needed to choose a new product how likely it is that you would choose the same provider again?
	Cusl2	(y_2)	Let us now suppose that other providers decide to lower their prices, but your provider stays at the same level as today. At which level of difference (in %) would you choose another provider? [requires transformation into a seven-point scale]
	Cusl3	(y_3)	If a friend or colleague asked you for advice, how likely is it that you would recommend your product provider?

Source: Own work.

Based on the structural model presented in Figure 4.4, it is possible to formulate several hypotheses:

H1: *Customer expectation and perceived quality have positive impact on perceived value.*

H2: *Corporate image, customer expectation, perceived quality and perceived value have positive effects on customer satisfaction.*

H3: *Customer satisfaction has negative effect on customer complains*

H4: *Customer satisfaction and corporate image have positive effects on customer loyalty*

H5: *Customer complaints have negative effects on customer loyalty.*

If we collect customer survey data, we wish to ascertain whether our proposed model of hypothetic influence is an adequate model for the data. Since our task is related to explore performance and implementation issues of the two approaches considered for SEM, we created simulated data set[7] using the factor loadings similar to those reported by Tenenhaus and others (2005, p. 180), Liu, Ren, and Liu (2013, p. 780) and Askariazad and Babakhani (2015).

Following a five-step Bolen's procedure (Bollen & Long, 1992, p. 123), namely (a) model specification, (b) identification, (c) estimation, (d) testing fit, and (e) re-specification, we first try to identify the model already defined on the basis of past research by Tenenhaus and others (2005, p. 161) and illustrated in Figure 4.4. We use a covariance-based SEM and try to fit the model with three popular software packages—a free open source package 'lavaan' (Rosseel, 2012), IBM SPSS Amos (Arbuckle, 2019), as well as alternatively with the very robust procedure for SEM, developed by

[7] The data set is available for download here https://bit.ly/3mxzo8W.

STATA (StataCorp, 2017). We do this to find out whether the choice of software tool would affect the reliability of the results. Later, we will try to evaluate the instrumental validity of outputs, comparing the results obtained vie CB-SEM and PLS-SEM.

In order for a model to be identifiable, we need to compare the number of data points to the number of parameters to be estimated. Since the input data set is the variance/covariance matrix, the number of data points is equal to the number of elements of this matrix. Our simulated data set has 799 observations and 22 variables (corresponding to the manifest variables in Table 4.5). Therefore, the number of data point is $\{22 \cdot (22 + 1) / 2 = 253\}$. Because the number of parameters $\{0{,}5 \cdot (1 + 6) \cdot (1+ 6 + 1) = 28\}$ to be estimated is less than the number of data points, the model is "over identified", and the analysis can proceed (Byrne, 2016, p. 41).

4.2.1. CB-SEM approach

The subsequent estimation of the parameters of the model within the CB approach is possible with different numerical methods. In this case, we use the maximum likelihood (ML) function, to minimize the difference between the sample covariance and those predicted by the theoretical model. The method was chosen because we assumed and generated simulations data set with multivariate normal statistical distribution.[8]

4.2.1.1. Fit a model to data using 'lavaan' package in R/RStudio

To assess the model represented in Figure 4, its specification is needed first. After loading `lavaan` package in R/RStudio (Rosseel, 2012), each latent factor is described by its name on the left, followed by the 'is manifested by' symbol "=~" with the latent variables that it influences and its observed manifest variables. In our case, we call the model "ECSI" and use the following program code to build it:

```
ECSI <–“
 # Measurement model
 CUEX    =~ Cuex1 + Cuex2 + Cuex3
 PERQ    =~ Perq1 + Perq2 + Perq3 + Perq4 + Perq5
 PERV    =~ Perv1 + Perv2
 IMAG    =~ Imag1 + Imag2 + Imag3 + Imag4
 CUSA    =~ Cusa1 + Cusa2 + Cusa3
 CUSCO   =~ Cusco1 + Cusco2
 CUSL    =~ Cusl1 + Cusl2 + Cusl3
 # Structural model (defining latent variables)
 CUEX    ~ IMAG
```

[8] The data quality checks here are omitted, but it is plausible to inspect those with some descriptive statistics and tests for normality.

```
  PERQ    ~ CUEX
  PERV    ~ CUEX + PERQ
  CUSA    ~ CUEX + PERV + PERQ + IMAG
  CUSCO   ~ CUSA
  CUSL    ~ CUSA + CUSCO + IMAG "
```

To fit the model, we use the `sem()` command with the following syntax:

```
ECSI.fit <-sem(ECSI, data=ECSISimData, std.lv=TRUE)
```

We add an argument `std.lv=TRUE` to standardize the latent variables, which help us to compare relative influence strength. Below there is a part of the abbreviated output.

```
> summary(ECSI.fit, standardized=TRUE, fit.measures=TRUE )
lavaan 0.6-6 ended normally after 32 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of free parameters                         56

  Number of observations                           799

 Model Test User Model:

  Test statistic                               230.917
  Degrees of freedom                               197
  P-value (Chi-square)                           0.049

… …

 User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.992
  Tucker-Lewis Index (TLI)                       0.990

… …

 Root Mean Square Error of Approximation:

  RMSEA 0.015
  90 Percent confidence interval-lower           0.001
  90 Percent confidence interval-upper           0.022
  P-value RMSEA <= 0.05                          1.000

 Standardized Root Mean Square Residual:

  SRMR                                           0.025
```

We begin with the interpretation of chi-square test statistic, which in our case is equal to 230.917. It measures the difference between the sample covariance (correlation) matrix and the fitted covariance (correlation) matrix. According to Jöreskog and others (2016, p. 499), chi-square should be used as goodness-of-fit measure rather than a statistical test. To be used as a test statistic, all observed variables must have a multivariate normal distribution. A small chi-square corresponds to good fit and a large chi-square to bad fit. Chi-square tends to be large in large samples, because it is calculated as N times the minimum value of the fit function, where N is the sample size (number of observations). If chi-square test statistic is not significant ($p > 0.05$), we accepted null hypothesis, i.e., H0: There is no significant difference between sample covariance matrix and population covariance matrix. Hence the default model is almost on the verge of acceptable.

Because chi-square test statistics is very often significant in samples of large size, suggesting rejection of the proposed model, the relative chi-square could also be calculated by dividing the chi-squared test statistic by degrees of freedom of the model (Wheaton, Muthen, Alwin, & Summers, 1977, p. 99). Accepted range of values are between 1 and 3 (Carmines & McIver, 1983, p. 64). However, some researchers have recommended relative χ^2/df value between 2 to 5 indicating a reasonable fit (Marsh & Hocevar, 1985, p. 567). In our case, the value of relative chi-square is 1.17 (= 230.917/197), which indicates an acceptable fit between the hypothetical model and the sample data.

Next in the output we see the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI). Both incremental indices have values higher than 0.95, which indicate a strong model fit. This conclusion is also confirmed by the low residuals (RMSEA = 0.015 and SRMR = 0.025, where 0 means perfect fit).

The resulting structural coefficients for the proposed model can be plotted using `semPlot` package (Epskamp et al., 2019) with the following code:

```
semPaths(ECSI.fit , what="est", fade=FALSE , residuals=FALSE, rotation = 2,
 structural=FALSE , nCharNodes =6, edge.label.cex =0.6,
 sizeMan = 5, sizeLat = 6)
```

Now we could draw a few conclusions. Because the model shows good fit to the data, we are able to interpret the results. We can use the coefficient estimates to answer questions about the association of the latent factors with the outcomes of interest. However, before proceeding, it is necessary to check whether the coefficient estimates are statistically significant. The function summary(ECSI.fit) also displays this result (only the essential part of the result is shown below).

```
… …
                 Estimate    Std.Err    z-value    P(>|z|)
 CUEX ~
```

```
  IMAG               0.488      0.064      7.635     0.000
  PERQ ~
  CUEX               0.547      0.059      9.261     0.000
  PERV ~
  CUEX               0.647      0.102      6.363     0.000
  PERQ              -0.008      0.072     -0.108     0.914
  CUSA ~
  CUEX               0.028      0.092      0.306     0.759
  PERV               0.273      0.074      3.696     0.000
  PERQ               0.485      0.063      7.714     0.000
  IMAG               0.073      0.066      1.111     0.267
  CUSCO ~
  CUSA              -0.618      0.063     -9.803     0.000
  CUSL ~
  CUSA               0.676      0.078      8.641     0.000
  CUSCO             -0.177      0.069     -2.550     0.011
  IMAG               0.156      0.063      2.481     0.013
… …
```

It is obvious that `perceived quality` (PERQ) does not have a statistically significant effect on `perceived value` (PERV). The same conclusion can be drawn for the latent variables `customer expectation of the overall quality` (CUEX) and `corporate image` (IMAG) and their effect on `customer satisfaction` (CUSA). All other coefficient estimates (not shown) are statistically significant and can be interpreted.

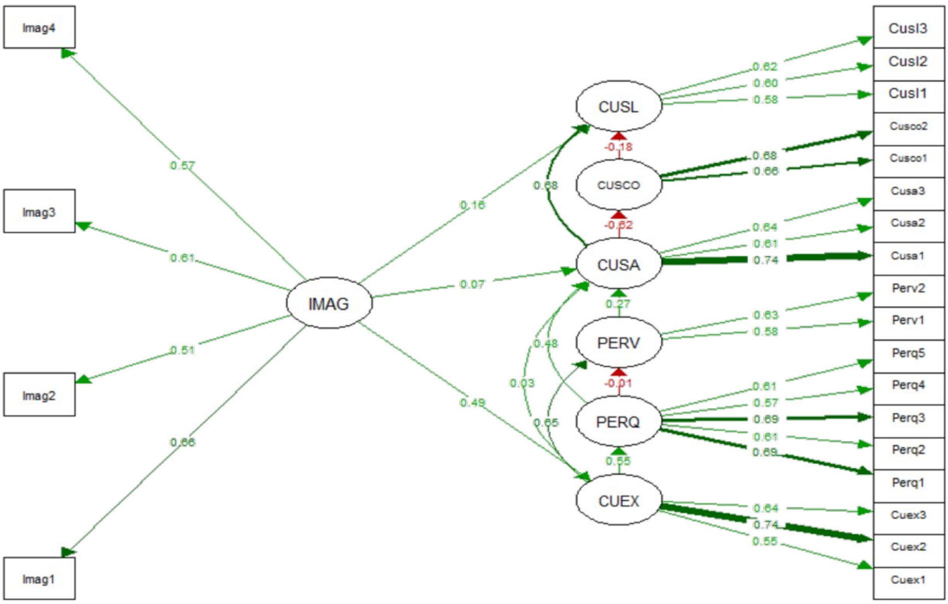


Figure 4.5. Path diagram with coefficient estimates for the ECSI model using `lavaan`

Source: Own work.

However, it should be noted that a good fit in CB-SEM is not enough for reliable interpretation and valid conclusions. It is recommended to compare the proposed model to one or more plausible alternative models, in order to prove that our proposal is superior to other reasonable models (Chapman & Feit, 2019, p. 283). The specification of an alternative model depends on the research objectives and / or the theory it is based on. When defining it, one can also start from the so-called "weak" and / or statistically insignificant relationships observed in the assessment of the baseline model. It is also possible to make a comparison with an already existing model from the literature, the result of past research.

In the present example, we could "clear" the basic model of "weak" relationships, such as the dependence of `Customer satisfaction` on` Corporate image` and `Customer expectation`, as well as the dependence of `Perceived value` on `Perceived quality`. This alternative model ECSIalt can be described as follows:

```
# Specification of ECSCalt model----
ECSIalt <-"
 # Measurement model
 CUEX     =~ Cuex1   + Cuex2    + Cuex3
 PERQ     =~ Perq1   + Perq2    + Perq3   + Perq4   + Perq5
 PERV     =~ Perv1   + Perv2
 IMAG     =~ Imag1   + Imag2    + Imag3   + Imag4
 CUSA     =~ Cusa1   + Cusa2    + Cusa3
 CUSCO    =~ Cusco1  + Cusco2
 CUSL     =~ Cusl1   + Cusl2    + Cusl3
 # Structural mode
 CUEX    ~ IMAG
 PERQ    ~ CUEX
 PERV    ~ CUEX
 CUSA    ~ PERV + PERQ
 CUSCO   ~ CUSA
 CUSL    ~ CUSA + CUSCO + IMAG "
```

After fitting and plotting (Figure 4.6) the alternative model to the initial data, it is necessary to compare the obtained results with those of the basic model. Using the function `compareFit()` (available after installing and loading the `semTools` package) we can directly compare the performance of the two models:

```
# Fit the ECSIalt model with CB-SEM
ECSIalt.fit <-sem(ECSIalt, data=ECSISimData, std.lv=TRUE)

# Creating a path diagram of ECSIalt
semPaths(ECSIalt.fit , what="est", fade=FALSE , residuals=FALSE, rota-
tion = 2,
      structural=FALSE , nCharNodes =6, edge.label.cex =0.6,
      sizeMan = 5, sizeLat = 6)
```

```
# Compare the proposed model with the alternative model&
> summary(compareFit(ECSI.fit , ECSIalt.fit , nested=TRUE))

################### Nested Model Comparison #####################
Chi-Squared Difference Test

              Df    AIC     BIC    Chisq   diff Df diff Pr(>Chisq)
ECSI.fit     197  51358   51620   230.92
ECSIalt.fit  200  51354   51602   232.94         2.027      3     0.5668

####################### Model Fit Indices ######################
 chisq df pvalue cfi tli aic bic rmsea srmr
ECSI.fit   230.917† 197 .049  .992  .990  51357.820  51620.089  .015
.025†
ECSIalt.fit 232.944 200 .055 .992† .991† 51353.847† 51602.066† .014†
.026

################## Differences in Fit Indices ##################
                    df   cfi  tli    aic     bic rmsea    srmr
ECSIalt.fit-ECSI.fit   3     0     0 -3.973 -18.023     0   0.001
```

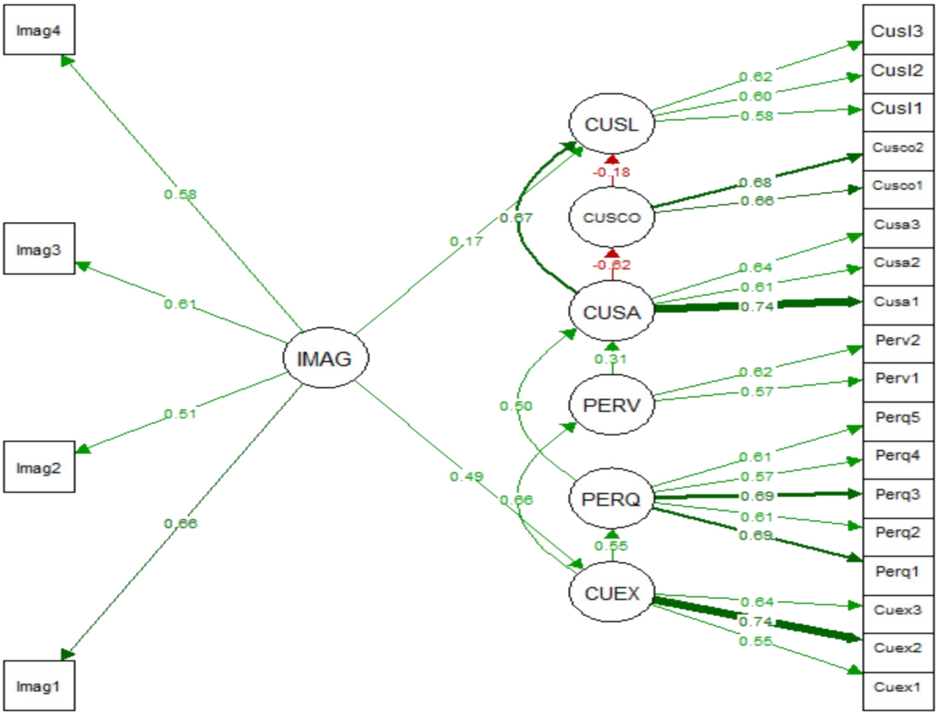


Figure 4.6. Path diagram with coefficient estimates for the ECSIalt model using `lavaan`

Source: Own work.

From these results it can be concluded that the alternative model is slightly better than the basic model. This can be seen from the direct comparison of test statistics, incremental indices and information criteria AIC and BIC (lower is better). However, this superiority is not statistically significant because chi-square difference between the two models (2.027) is not statistically significant ($p = 0.5668$). In these circumstances, it is reasonable to interpret the alternative model.

4.2.1.2. Fit a model to data using IBM SPSS AMOS

Probably one of the most popular software programs for evaluating CB-SEM is IBM SPSS AMOS. AMOS is distributed commercially, and its use is associated with significant costs. A trial version could be obtained from https://ibm.co/35VjjEe and a free downloadable user guide is also available. In this part we will demonstrate briefly how to use this package to evaluate the proposed linear structure model depicted in Figure 4.4. We use the same data set as in the previous demonstration.

With the AMOS program it is very easy to build a model using simple graphical tools. This is undoubtedly an advantage, especially when the researcher is feeling uncomfortable with programming, and is very useful when one is taking first steps in SEM. Typical graphic elements of path diagrams are used to draw the model: rectangles for observed variables; ellipses for unobserved variables; single-headed arrows for causal relationships; double-headed arrows for covariance; circle for error terms. A data file has to be selected, then AMOS will perform all necessary computations for evaluating the model and display an output with the results. However, other approaches to specify the desired model are also available in AMOS, but they involve describing it with equation statements. Choosing "AMOS graphic" option when starting the program will let the researcher draw the theoretical model graphically and there will be no need to express the relationships with manually written equation statements. We will not describe in detail how to build the model using the graphic interface of AMOS as it is well described in the user manual provided by the developer. Instead, we will focus on the evaluation results and compare it with the ones obtained with `lavaan` package.

When the model is specified and the data file is selected, the calculation of the estimates can be easily done with one click. AMOS will provide us with both graphical and textual view on the results. The graphical output shows the estimates next to each arrow on the model path diagram, and fit indexes are displayed under the path diagram (see Figure 4.7). This way of reviewing the results is comprehensive and allows the researcher to take a quick glance at the estimates and the evaluation criteria.

It is evident from the fitness indexes under the path diagram that the model fits the data. The χ^2 test and its degrees of freedom and p-value indicate that (since we can reject the null hypothesis) our predicted model matches the data. Alternatively, we can rely on the relative $\chi^2 = 1.171$, which also confirms the good model fit. Amos provides the benchmark values of all reported fitness indexes in brackets, so it is easier to compare each measure to its threshold. In this case GFI, CFI, and RMSEA all indicate that the model fits the data. However, detailed results are presented in the textual output. It includes several sections which are shown in the upper left corner in Figure 4.8.

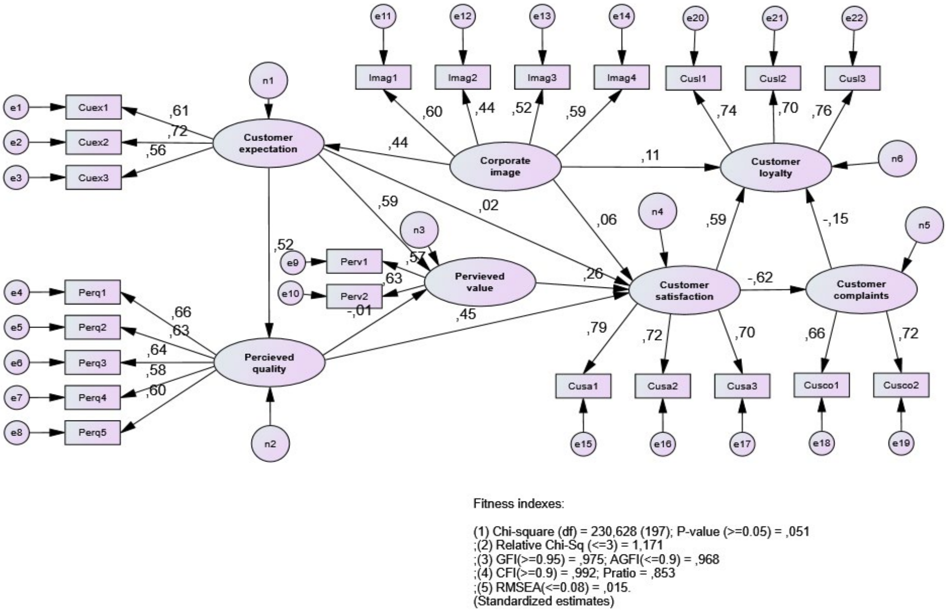
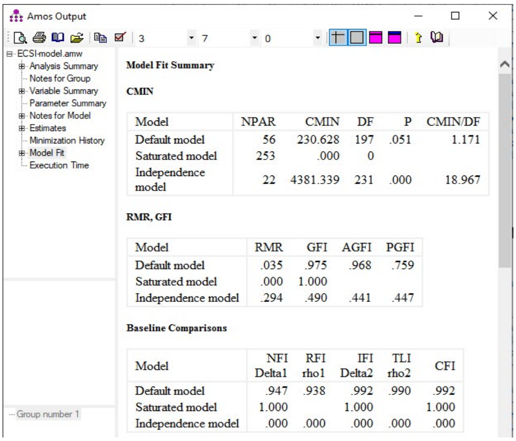


Figure 4.7. Path diagram with coefficient estimates for the ECSI model using IBM SPSS Amos

Source: Own work.



Amos Output

ECSI-model.amw
Analysis Summary
Notes for Group
Variable Summary
Parameter Summary
Notes for Model
Estimates
Minimization History
Model Fit
Execution Time

Group number 1

Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	56	230.628	197	.051	1.171
Saturated model	253	.000	0		
Independence model	22	4381.339	231	.000	18.967

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	.035	.975	.968	.759
Saturated model	.000	1.000		
Independence model	.294	.490	.441	.447

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.947	.938	.992	.990	.992
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Figure 4.8. Textual output from ECSI model evaluation with Amos

Source: Own work.

Since the χ^2 test is sensitive to the sample size we cannot rely solely on this test to make a conclusion about the model fit. We need to look at the goodness-of-fit statistics, reported in `Model fit` section, and decide whether it is correctly specified and thus—fits the data well. Amos reports plenty of goodness-of-fit measures and sometimes they may lead to different conclusions. It is important to choose to rely on those measures that are shown to be appropriate in situations similar to the one at hand in terms of sample size, applied estimation procedure, model complexity, and the presence/absence of multivariate normality and variable independence (Byrne, 2016, p. 101). In this example, we will use the same criteria that were reported in the `lavaan` package output and explained in part "1.3.2. Global criteria for model evaluation" of this chapter. In the output we can see that both CFI and TLI have values higher than 0.95 (CFI = 0.992 and TLI = 0.990), which indicates a good model fit. This conclusion is also confirmed by the low residuals: RMSEA = 0.015 and SRMR = 0.026, where 0 means perfect fit. We can proceed the assessment by observing the model estimates.

Selecting the 'Estimates' section will show all parameters estimates and their *p*-values (Table 4.6). These estimates are almost identical with those we obtained with the `lavaan` package. The relationships between CUSA and both CUEX and IMAG, and between PERV and PERQ are not significant, and we should remove them from the initial model and re-evaluate an alternative model, as we did with `lavaan` package. However, all regression weights of each measurement model are statistically significant and there is no need to remove any indicator variables.

Table 4.6. Regression weights of the initial ECSI model

			Estimate	S.E.	C.R.	P
CUEX	<---	IMAG	0.473	0.069	6.865	***
PERQ	<---	CUEX	0.519	0.062	8.416	***
PERV	<---	CUEX	0.638	0.093	6.850	***
PERV	<---	PERQ	−0.008	0.075	–.108	**0.914**
CUSA	<---	PERV	0.276	0.079	3.510	***
CUSA	<---	CUEX	0.028	0.092	.306	**0.760**
CUSA	<---	PERQ	0.508	0.068	7.523	***
CUSA	<---	IMAG	0.071	0.064	1.109	**0.267**
CUSCO	<---	CUSA	−0.662	0.059	−11.261	***
CUSL	<---	CUSA	0.615	0.067	9.227	***
CUSL	<---	CUSCO	−0.150	0.059	−2.543	0.011
CUSL	<---	IMAG	0.137	0.056	2.459	0.014
Cuex3	<---	CUEX	1.000			
Cuex2	<---	CUEX	1.154	.095	12.090	***
Cuex1	<---	CUEX	.859	.075	11.418	***

			Estimate	S.E.	C.R.	P
Perq5	<---	PERQ	1.000			
Perq4	<---	PERQ	0.944	0.077	12.305	***
Perq3	<---	PERQ	1.142	0.087	13.172	***
Perq2	<---	PERQ	1.011	0.078	13.016	***
Perq1	<---	PERQ	1.130	0.084	13.476	***
Perv2	<---	PERV	1.000			
Perv1	<---	PERV	0.918	0.115	8.014	***
Imag1	<---	IMAG	1.000			
Imag2	<---	IMAG	0.779	0.092	8.505	***
Imag3	<---	IMAG	0.928	0.099	9.400	***
Imag4	<---	IMAG	0.870	0.088	9.913	***
Cusa3	<---	CUSA	1.000			
Cusa2	<---	CUSA	0.955	0.054	17.537	***
Cusa1	<---	CUSA	1.159	0.062	18.619	***
Cusl1	<---	CUSL	1.000			
Cusl2	<---	CUSL	1.033	0.060	17.119	***
Cusl3	<---	CUSL	1.076	0.059	18.099	***
Cusco2	<---	CUSCO	1.000			
Cusco1	<---	CUSCO	0.970	0.087	11.107	***

Source: Own work.

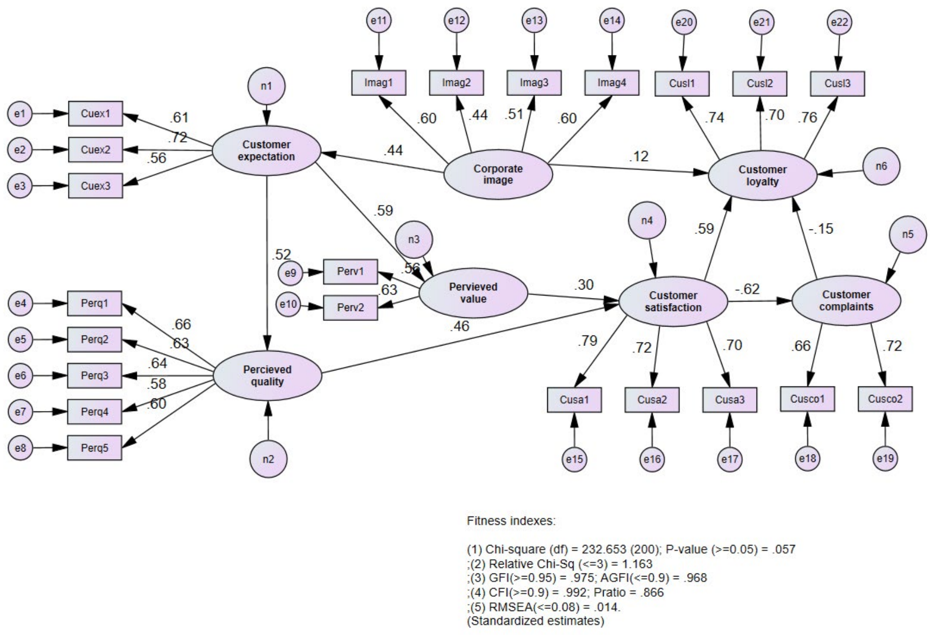


Figure 4.9. Path diagram with coefficient estimates for the ECSIalt model using IBM SPSS Amos

Source: Own work.

The evaluated alternative model is almost indistinguishable from that obtained with the `lavaan` package and we can make the same conclusions about the adequacy of its fit to the data.

4.2.1.3. Comparing and interpreting the results

Comparing the values of the model fit measures that resulted from using the two different software solutions confirms the good model fit (see Table 4.7). The obtained parameter estimates for the ESCIalt model are all statistically significant. Once again, no indicator variables need to be removed from the measurement model, as all regression weights are also significant.

Table 4.7. Fit indices of the ECSIalt model obtained from `lavaan` and IBM SPSS Amos

	Model fit indexes	
	`lavaan`	IBM SPSS Amos
χ^2 (df)	232.944 (200)	232.653 (200)
χ^2/ ratio	1.165	1.163
	0.992	0.992
	0.991	0.991
	0.014	0.014
	0.026	0.026*

* Amos does not produce this statistic as one of its regular fit indices. It can be calculated by selecting `Plugins—> Standardized RMR` from the drop-down menus, then clicking on the `Calculate Estimates` button again.

Source: Own work.

We can also compare the standardized parameter estimates of the structural model, which are presented in Table 4.8. Amos reports these values in the `Estimates` section of the output. In order to obtain standardized estimates with `lavaan`, you can use `parameterEstimates()` function and add `standardized=TRUE` as an argument:

```
# Obtaining the standardized parameter estimates for ECSIalt model
Stand.par <-parameterEstimates(ECSIalt.fit, standardized = TRUE)
```

The standardized estimates are located in the column "std.all" in the output. It is obvious that the two software solutions produce identical estimates.

Table 4.8. Standardized estimates of the ECSIalt model obtained from `lavaan` and IBM SPSS Amos

	Standardized Weights	
	`lavaan`	*IBM SPSS Amos*
CUEX <--—IMAG	0.442	0.442
PERQ <--—CUEX	0.522	0.522
PERV <--—CUEX	0.590	0.590
CUSA <--—PERV	0.297	0.463
CUSA <--—PERQ	0.463	0.297
CUSCO <--—CUSA	–0.619	–0.619
CUSL <--—CUSA	0.590	0.590
CUSL <--—CUSCO	–0.155	–0.155
CUSL <--—IMAG	0.115	0.115

Source: Own work.

We would use the coefficient estimates in the alternative model to answer substantive questions about the associations of the latent factors with the outcomes of interest and to prove defined five hypotheses. In the general case, all statistically significant path coefficients whose estimates are greater than 0.5 can be interpreted as strong impact, between 0.3 and 0.5 as moderate, and below 0.3 as weak impact. The sign in front of the respective coefficient on the other hand shows the direction of this influence (positive or negative). The summary of the predefined hypotheses in this example is presented in Table 4.9.

Table 4.9. Summarized results of the defined hypotheses testing

Hypothesis		Fulfilment of hypothesis
H1:	Customer expectation and perceived quality have positive impact on perceived value	partially supported due to lack of statistical significance of PERQ
H2:	Corporate image, customer expectation, perceived quality and perceived value have positive effects on customer satisfaction	partially supported due to lack of statistical significance of CUEX and IMAG
H3:	Customer satisfaction has negative effect on customer complains	supported
H4:	Customer satisfaction and corporate image have positive effects on customer loyalty	supported
H5:	Customer complaints have negative effects on customer loyalty	supported

Source: Own work.

4.2.2. PLS-SEM approach

In the previous section, we considered the possibility for estimating a linear structural model based on a covariance-based approach. We note that in this approach the aim is to consider as much of the total covariance in the data as possible, among all observed and latent variables. CB-SEM requires relatively strict assumptions about data sets, such as continuous and multivariate normally distributed data, normally distributed residuals, relatively large sample size, generally three or more indicators per latent construct, reliability of indicators (Hair, Hult et al., 2017, p. 3). Although CB-SEM is a powerful analytical tool that test a model rigorously and allows for model comparison (Chapman & Feit, 2019, p. 285), all of these requirements at the same time are relatively rare in empirical marketing research. Therefore, in practical cases where the structural model is complex (many constructs and many indicators), the sample size is small, and the research goal is to predict key target constructs or identify key "driver" constructs, the use of the PLS-SEM approach is recommended (Hair, Risher et al., 2019).

However, we would like to emphasize once again that PLS-SEM approach in general does not outperform CB-SEM, as it does not allow to assess a global "goodness of fit" that is comparable across models. We recommend its use in cases where CB-SEM fails when estimating the model.

In the next section we will demonstrate three alternative software solutions for linear structural modelling based on PLS-SEM approach.[9] To ensure comparability, we will use the same data set and try to evaluate the same model presented in Figure 4.4.

4.2.2.1. Fit a model to data using `semPLS` package in R/RStudio

The R package `semPLS` is probably the most popular free open-source software for estimating complex structural equation models (Monecke & Leisch, 2012; Monecke, 2015; Ravand & Baghaei, 2016). After the package has been installed in R/RStudio, the following program code can be used to fit the presented ECSI model to the same data set ECSISimData. What is special about compiling the program code is that, unlike the procedure in the `lavaan` package, here the specification of the complete model requires two separate steps. The first step consists in defining the measurement model, which describes the relationships between the latent variables and their observable indicator variables.

The second step specifies the structural model that describes the relationships between the latent variables.

[9] There are many other open-source and commercial software statistical package for fitting PLS-SEM. Venturini and Mehmetoglu (2019, pp. 3–4) give a concise overview of the most popular of them.

Referring to the model in Figure 4.4, the measurement model could be defined as follows:

```
# Step ONE: Defining a measurement model
ECSIPLSmm <—matrix(c(
 “CUEX”, “Cuex1”,
 “CUEX”, “Cuex2”,
 “CUEX”, “Cuex3”,
 “PERQ”, “Perq1”,
 “PERQ”, “Perq2”,
 “PERQ”, “Perq3”,
 “PERQ”, “Perq4”,
 “PERQ”, “Perq5”,
 “PERV”, “Perv1”,
 “PERV”, “Perv2”,
 “IMAG”, “Imag1”,
 “IMAG”, “Imag2”,
 “IMAG”, “Imag3”,
 “IMAG”, “Imag4”,
 “CUSA”, “Cusa1”,
 “CUSA”, “Cusa2”,
 “CUSA”, “Cusa3”,
 “CUSCO”,”Cusco1”,
 “CUSCO”,”Cusco2”,
 “CUSL”, “Cusl1”,
 “CUSL”, “Cusl2”,
 “CUSL”, “Cusl3” ), ncol=2, byrow=TRUE)
```

The definition of the structural model from Figure 4.4 is performed in a similar matrix format:

```
# Step TWO: Defining a structural model
ECSIPLSsm <—matrix(c(
 “CUEX”, “PERQ”,
 “CUEX”, “PERV”,
 “CUEX”, “CUSA”,
 “PERQ”, “PERV”,
 “PERQ”, “CUSA”,
 “PERV”, “CUSA”,
 “CUSA”, “CUSL”,
 “CUSA”, “CUSCO”,
 “CUSCO”,”CUSL”,
 “IMAG”, “CUEX”,
 “IMAG”, “CUSA”,
 “IMAG”, “CUSL” ), ncol=2, byrow=TRUE)
```

To fit the PLS model to the simulated 799-respondent data set, we use `plsm(data, strucmod, measuremod)` command line from semPLS package, based on matrices that previously were defined on step one and step two. Next, using `sempls(model, data)` command line we can estimate model parameters:

```
# Defining the whole model and fit it to data
library(semPLS)

ECSIPLS.mod <-plsm(data=ECSISimData , strucmod=ECSIPLSsm , measuremod
=ECSIPLSmm)
ECSIPLS.fit <-sempls(model=ECSIPLS.mod , data=ECSISimData)
```

The evaluation results are contained in the `ECSIPLS.fit` object. To estimate the factor structure (so-called factor loadings) of the measurement model, it is necessary to use the command plsLoadings (MODEL):

```
> plsLoadings(ECSIPLS.fit)
  IMAG CUEX PERQ PERV CUSA CUSCO CUSL
Imag1 0.71      .      .      .       .      .       .
Imag2 0.59      .      .      .       .      .       .
Imag3 0.70      .      .      .       .      .       .
Imag4 0.72      .      .      .       .      .       .
Cuex1    .   0.76      .      .       .      .       .
Cuex2    .   0.83      .      .       .      .       .
Cuex3    .   0.72      .      .       .      .       .
Perq1    .      .   0.75      .       .      .       .
Perq2    .      .   0.71      .       .      .       .
Perq3    .      .   0.72      .       .      .       .
Perq4    .      .   0.68      .       .      .       .
Perq5    .      .   0.70      .       .      .       .
Perv1    .      .      .   0.78       .      .       .
Perv2    .      .      .   0.86       .      .       .
Cusa1    .      .      .      .    0.86      .       .
Cusa2    .      .      .      .    0.83      .       .
Cusa3    .      .      .      .    0.81      .       .
Cusco1   .      .      .      .       .   0.85       .
Cusco2   .      .      .      .       .   0.87       .
Cusl1    .      .      .      .       .      .    0.83
Cusl2    .      .      .      .       .      .    0.81
Cusl3    .      .      .      .       .      .    0.85
```

In this example, all latent variables have strong loadings with its manifest indicator variables. If a latent variable has a factor loading below 0.3 for any indicator (which in this case is not present), or below 0.5 for all of its indicators—then the reliability of the measures will be debatable and further investigation and / or re-specification of the model structure is needed (Chapman & Feit, 2019, p. 288).

To obtain the values of the coefficients of the relationships between the latent variables (i.e., the structural model) it is necessary to use the command `pathCoeff(MODEL)`. The results are presented below:

```
> pathCoeff(ECSIPLS.fit)
       IMAG    CUEX    PERQ    PERV     CUSA  CUSCO    CUSL
IMAG      .   0.287       .       .    0.062      .   0.096
CUEX      .       .   0.370   0.334    0.114      .       .
PERQ      .       .       .   0.065    0.354      .       .
PERV      .       .       .       .    0.157      .       .
CUSA      .       .       .       .        . -0.443   0.475
CUSCO     .       .       .       .        .      .  -0.161
CUSL      .       .       .       .        .      .       .
```

We see that 'Customer complaints' has a negative influence on 'Customer loyalty', and 'Customer satisfaction' has also negative influence on 'Customer complaints', which corresponds to the expectations (face validity).

In order to visualize the results of the evaluation through the familiar path diagram, it is necessary to take several additional technical steps, using the free available third-party software component Graphviz.[10] Using the program command `pathDiagram(MODEL, FILE, full-TRUE, …)` we can create a plot with the structural coefficients and loadings as an output as *.dot file. Once Graphiz software is installed, we can process this file as input and produces the corresponding image as a PDF or PNG file. For this purpose, first it is necessary to execute the following program line:

```
# Creating object for path diagram for Graphviz
pathDiagram(ECSIPLS.fit , file = "ECSIPLSfull", full = TRUE , digits = 2,
 edge.labels = "values", output.type = "graphics", graphics.fmt = "pdf")
```

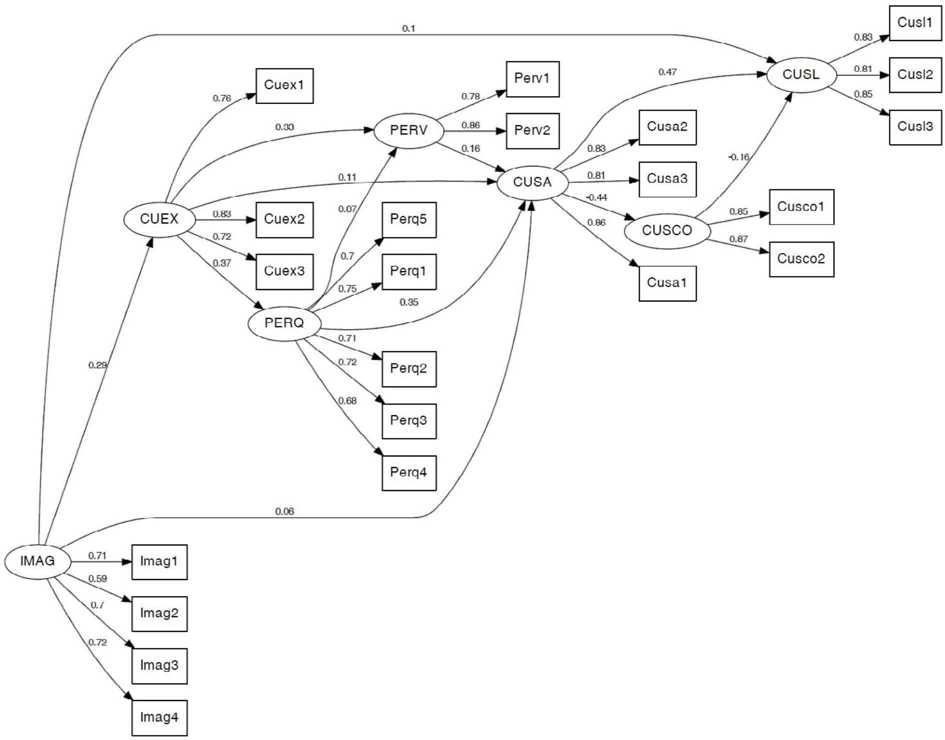
Because PLS models do not assess global model fit, according to Chapman and Feit (2019, p. 289), „(…) there is not a general way to compare CB-SEM and PLS-SEM results apart from interpreting the models and their implications, so it is not advisable to compare the coefficients directly".

After fitting the model to the data, however, the question of its statistical evaluation remains open. Because by PLS-SEM there is no summary metric for global model assessment and comparison, there are three possible approaches to its validation. First, we can examine the model's coefficients for their face validity. *Face validity* is the extent to which a coefficient estimated corresponds to our subjective expectation (in size and sign). Second, we can calculate the overall coefficient of determination (R^2) for the model, which is a measure of overall variance explained

[10] Graphviz can be downloaded for free from: http://www.graphviz.org/download/

within each part of the model. Thirdly, one can think about applying a bootstrap method to examine coefficient stability (Hair, Sarsted et al., 2011, pp. 423–424; Chapman & Feit, 2019, p. 289).

Figure 4.10. Path diagram with PLS coefficient estimates for the ECSI model using `semPLS`



Source: Own work.

The calculation of the coefficient of determination R^2 for each of the latent variable is possible by the `rsquared()` function:

```
> rsquared(ECSIPLS.fit)
 R-squared
IMAG .
CUEX 0.082
PERQ 0.137
PERV 0.132
CUSA 0.244
CUSCO 0.196
CUSL 0.345
```

There is no general "rule of thumb" for interpreting this measure, but since the R^2 values range is between 0 and 1, the closer the empirical score of R^2 to 1, the better the model.

A more general approach to access coefficient stability is to use a bootstrapping procedure. We can perform it with `bootsempls()` command. A key point in performing the procedure is setting a sufficiently large value for resample sets of observation. In this case, we set 1000:

```
# Bootstrapping
set.seed (5250)
ECSIPLS.boot <-bootsempls(ECSIPLS.fit , nboot =1000, start="ones")
```

After 1000 resample through command summary() we get the following results:[11]

```
> summary(ECSIPLS.boot)
Call: bootsempls(object = ECSIPLS.fit, nboot = 1000, start = "ones")

Lower and upper limits are for the 95 percent perc confidence interval

          Estimate          Bias  Std. Error         Lower     Upper
lam_1_1     0.7125     -4.38e-03     0.03923      0.620324     0.779
lam_1_2     0.5876     -2.54e-03     0.05264      0.464342     0.677
lam_1_3     0.7003     -2.02e-03     0.04066      0.613629     0.771
lam_1_4     0.7246     -2.90e-03     0.03804      0.643485     0.789
lam_2_1     0.7570     -5.85e-04     0.02085      0.712676     0.793
lam_2_2     0.8300     -4.54e-04     0.01547      0.797551     0.857
lam_2_3     0.7235     -2.77e-04     0.02533      0.670878     0.768
lam_3_1     0.7504     -8.70e-04     0.01963      0.708437     0.786
lam_3_2     0.7102     -1.42e-03     0.02290      0.659964     0.753
lam_3_3     0.7207     -7.41e-04     0.02166      0.674986     0.761
lam_3_4     0.6786      4.17e-05     0.02510      0.629882     0.723
lam_3_5     0.6991     -5.56e-04     0.02452      0.645462     0.745
lam_4_1     0.7815     -3.36e-03     0.03328      0.701759     0.832
lam_4_2     0.8624      9.87e-04     0.02183      0.817765     0.906
lam_5_1     0.8602     -2.73e-04     0.00911      0.840928     0.876
lam_5_2     0.8269     -1.02e-03     0.01329      0.798288     0.851
lam_5_3     0.8122     -7.55e-04     0.01537      0.780249     0.840
lam_6_1     0.8481     -9.06e-04     0.01594      0.813603     0.876
lam_6_2     0.8690      5.01e-05     0.01334      0.841386     0.894
lam_7_1     0.8345     -7.65e-04     0.01297      0.806461     0.857
lam_7_2     0.8090     -5.58e-04     0.01502      0.776243     0.836
```

[11] Note that the use of bootstrapping procedure with relatively small samples (e.g., < 100) is sometimes problematic and the model could be unstable because bootstrap iterations failed to converge.

```
lam_7_3      0.8502      -3.05e-04      0.01032         0.829233      0.869
 beta_1_2    0.2870       2.70e-03      0.02939         0.229344      0.348
 beta_2_3    0.3697       3.80e-03      0.02903         0.313689      0.430
 beta_2_4    0.3337       5.64e-04      0.03285         0.265878      0.395
 beta_3_4    0.0654       3.65e-04      0.03545        -0.003022      0.133
 beta_1_5    0.0619       3.02e-03      0.03275         0.000189      0.130
 beta_2_5    0.1135      -1.47e-03      0.03321         0.047941      0.177
 beta_3_5    0.3544      -1.38e-03      0.03247         0.285964      0.417
 beta_4_5    0.1567       1.28e-03      0.03407         0.090795      0.225
 beta_5_6   -0.4433      -1.75e-03      0.03018        -0.505684     -0.385
 beta_1_7    0.0961       1.11e-03      0.02896         0.037563      0.155
 beta_5_7    0.4747      -1.63e-03      0.02759         0.418293      0.525
 beta_6_7   -0.1606      -1.35e-03      0.02969        -0.220249     -0.102
```

In the output above, the labels lam_x_x correspond to the factor loadings of the measurement model, while the labels beta_x_x correspond to the coefficients of the structural model. Problematic coefficients are those in which upper and lower bounds include 0, and for which we therefore do not have even directional confidence. We observe only two cases, at beta_3_4 and beta_6_7. They correspond to the influence of IMAG on CUSA, i.e., of ` Corporate image` on `Consumer satisfaction`, and PERQ on PERV, i.e., of `Perceived quality` on `Perceived value`. The interpretation should be that such an influence is unlike. The results of the simplified alternative CB-SEM models prompted us to a similar conclusion.

The results of the bootstrapping procedure can be visualized as a parallel plot. This plot can be created using the following program code:

```
parallelplot(ECSIPLS.boot , reflinesAt = 0, alpha =0.8,
 varnames=attr(ECSIPLS.boot$t, "path") [23:34],
 main="Path coefficients in 1000 PLS bootstrap iterations (N=799)")
```

The resulting plot is shown in Figure 4.11. We can see all bootstraps estimates of the coefficients of structural model and their spread between lower and upper limits for the 95% confidence interval. We should read this by looking at the spread of estimates along each of the horizontal grid lines representing one structural model coefficient. For example, the influence of `Perceived quality` on `Perceived value`, as well as `Corporate image` on `Customer satisfaction` are generally estimated to be positive, but several of the estimates hold the relationship to be slightly negative. Therefore, the interpretation of this coefficient could not be reliable, and we could not use them confidently. We made a similar conclusion after the application of CB-SEM in the previous subsection.

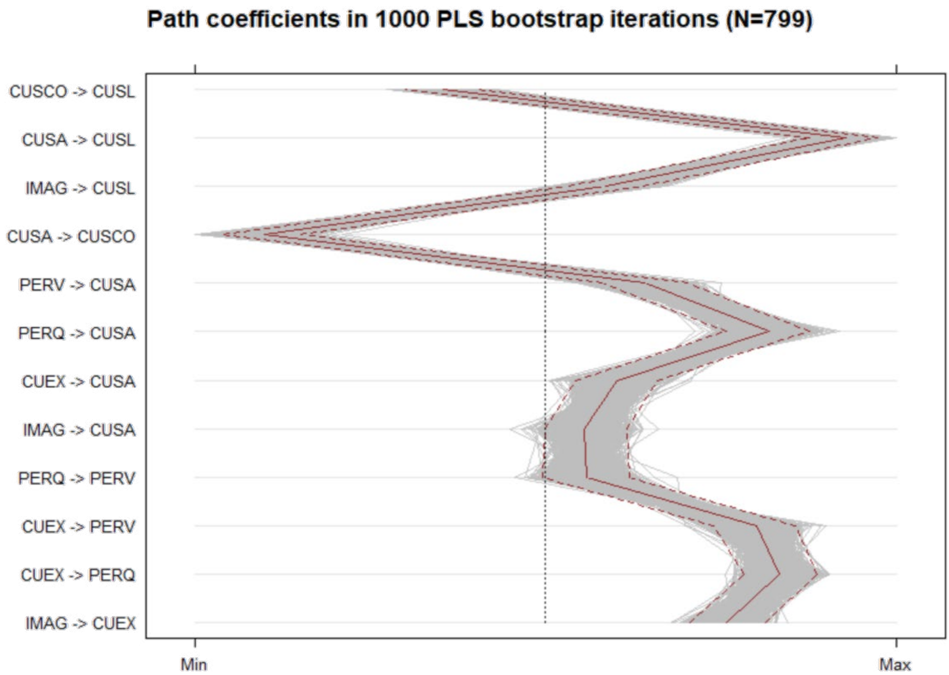


Figure 4.11. Bootstrapped coefficients for the PLS model. Each line plots the twelve estimated coefficients of the structural for one complete bootstrap iteration

Source: Own work.

4.2.2.2. Fit a model to data using SmartPLS

Currently, SmartPLS[12] is probably the most popular commercially available software to use the PLS-SEM method. It is more convenient than any other open-source or commercial software solution. The graphical interface is very easy and intuitive to work with and it allows us to focus on the research itself rather than to struggle with the software. In this sub-section, we will illustrate the use of SmartPLS to evaluate the theoretical model we already tested with `lavaan` package, IBM SPSS Amos, and `semPLS` package, using the same simulated dataset.

Drawing the conceptual model with the use of graphical tools is easy. You can use the guidelines in the official recourses available here. After a data file is imported, you can easily drag and drop indicator variables from a list to a particular construct in the model you have drawn. Once you have built the structural and measurement models, you can proceed to the model evaluation.

There are two types of PLS algorithms available in SmartPLS—a regular PLS algorithm and a consistent PLS algorithm (PLSc). The latter is appropriate when

[12] For a trial version, visit: www.smartpls.com.

some or all constructs have reflective measurement models because it performs a correction of these constructs' correlations. However, one can run both algorithms and compare the results. The model in Figure 4.12 shows the estimated ECSI model applying the regular PLS algorithm.

SmartPLS contains many options for evaluating and verifying analytical results. Detailed instructions, guidelines and recommendations for reporting the results of the PLS-SEM approach using this software can be found in Hair, Sarsted and others (2011, 2019). We will briefly comment on the model estimation procedure.

The results show the outer weights and/or loadings of each measurement model. If the path diagram at hand has a construct with formative measurement model, then we are interested at the outer weights for this construct. For reflective measurement models, we need to look at the outer loadings. The ECSI model has only reflective measurement models, thus the parameters for all indicator variables displayed in Figure 4.12 are the outer loadings.[13] There are few outer loadings that fall under the recommended threshold value of 0.7 (see Table 4.2). We can remove each indicator that loads poorly on the construct and check whether this improves the reliability and validity of the measurement model. Before we do this, we should assess the current measurement models.

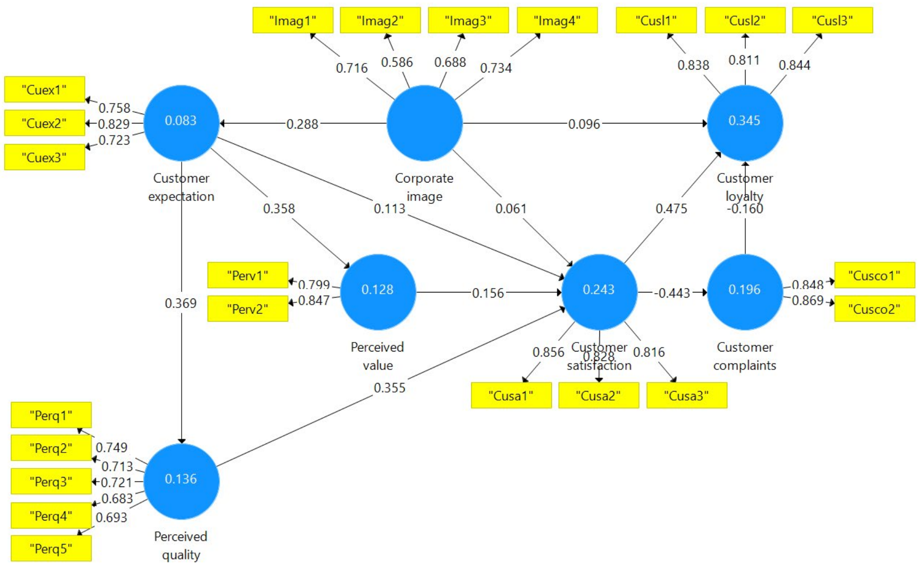


Figure 4.12. Path diagram with PLS coefficient estimates for the ECSI model using SmartPLS

Source: Own work.

[13] In SmartPLS you can choose to display the outer weights, loadings or both on the path diagram depending on the type of the measurement models you have.

There are several criteria reported in the results that can be used to evaluate the measurement models (see Table 4.10). Both Cronbach's alpha and rho (ρ) are used to assess the internal consistency of each construct. In our example, most of the latent variables have values of these two measures above 0.6, except for "Perceived value".

We can use the average variance extracted to assess the convergent validity of the constructs. In our example, all constructs have AVE > 0.5, except for IMAG. However, since this value is very close to the threshold, we will not delete any indictors at this point.

Table 4.10. Evaluation of reliability and validity of the measurement models

	Cronbach's alpha	rho_A	Composite reliability	Average variance extracted (AVE)
Perceived value	0.53	0.53	0.81	0.68
Perceived quality	0.76	0.76	0.84	0.51
Corporate image	0.62	0.63	0.78	0.47
Customer loyalty	0.78	0.78	0.87	0.69
Customer complaints	0.64	0.65	0.85	0.74
Customer satisfaction	0.78	0.79	0.87	0.69
Customer expectations	0.66	0.68	0.81	0.60

Source: Own work.

The discriminant validity of each measurement model can be judged by the Fornell / Larcker criterion. In Table 4.11 we can see the square root of AVE for each construct, which should be higher than the correlations with other constructs. In our example, this is true for all constructs, thus their measurement models have a good discriminant validity.

Table 4.11. Square root of AVEs and correlations between constructs (Fornell/ Larcker criterion)

	CUEX	CUSA	CUSCO	CUSL	IMAG	PERQ	PERV
Customer expectations	0.77						
Customer satisfaction	0.32	0.83					
Customer complaints	–0.15	–0.44	0.86				
Customer loyalty	0.25	0.56	–0.38	0.83			
Corporate image	0.29	0.17	–0.07	0.19	0.68		
Perceived quality	0.37	0.44	–0.24	0.26	0.16	0.71	
Perceived value	0.36	0.27	–0.14	0.22	0.11	0.19	0.82

Source: Own work.

The next step is to evaluate the relationships between latent variables and if they explain each construct to a satisfactory extent. Estimated R^2 values of the latent variables appear in the circles representing each construct (see Figure 4.12).

They are identical to those obtained using the `semPLS` package (see Figure 4.10). SmartPLS contains a powerful bootstrapping algorithm, with the help of which it is possible to estimate the statistical significance of each of the estimated coefficients of the model (see Table 4.12). From the table it is clear that only the influence of `Corporate image` on `Customer satisfaction` is not significant (*p* value > 0.05).

Table 4.12. Statistical significance of coefficients after bootstrapping

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T-Statistics (|O/STDEV|)	*p*-values
Corporate image—> Customer expectation	0.288	0.291	0.032	9.117	0.000
Corporate image—> Customer loyalty	0.096	0.095	0.030	3.171	0.002
Corporate image—> Customer satisfaction	0.061	0.065	0.033	1.830	**0.067**
Customer complaints—> Customer loyalty	–0.160	–0.160	0.031	5.243	0.000
Customer expectation—> Customer satisfaction	0.113	0.111	0.035	3.224	0.001
Customer expectation—> Perceived quality	0.369	0.371	0.031	11.864	0.000
Customer expectation—> Perceived value	0.358	0.359	0.030	12.018	0.000
Customer satisfaction—> Customer complaints	-0.443	-0.445	0.028	15.754	0.000
Customer satisfaction—> Customer loyalty	0.475	0.475	0.029	16.649	0.000
Perceived quality—> Customer satisfaction	0.355	0.356	0.032	11.069	0.000
Perceived value—> Customer satisfaction	0.156	0.157	0.035	4.474	0.000

Source: Own work.

4.3. Solving sustainability research problems with SEM

Sustainable development is a concept that recommends a set of ethical-oriented goals for nations who are aspiring to make economic growth widespread, to encourage social welfare, and to protect the environment from human-induced degradation (Sachs, 2015, p. 3). We can apply structural equation modelling in various sustainable development research areas when the problem at hand requires testing complex relationships between latent variables. In a recent meta-analysis of scientific articles related to sustainable development (in which some form of SEM was used), the authors conclude that 61% of all research teams used SmartPls, 26% used Amos, 8% used LISREL, and 5% used other software solutions when evaluating conceptual models (Mardani et al., 2017). Survey data was used for model evaluation and the respondents were either clients (end-users of products and services) or companies' representatives (usually senior or junior managers, but also other types of employees).

In this sub-section, we will focus on examples of research problems solved with the use of SEM. While this is just a summary of possible areas in SD where this type of analysis is appropriate for solving specific problems, applying SEM can answer many other research questions.

4.3.1. Sustainable development as a concept and strategy

Whenever we want to study general perceptions of sustainability as a concept or as a strategy implied by firms or public entities, we can use SEM to test our theoretical models. The three facets of SD can be understood differently by different communities or organizations. For example, a researcher may want to know how residents of one area perceive local ecological initiatives, economic measures, and social inclusion practices and whether these constructs influence the perceptions of sustainable development of this area. A simple structural model of this type is depicted in Figure 4.13. Each construct in this model could represent the complex understanding of people for each aspect of sustainable development or could reflect people's perceptions of specific measures undertaken by the government to encourage sustainable development. Previous research is a good starting point when selecting appropriate indicator variables, as is a preliminary qualitative study.

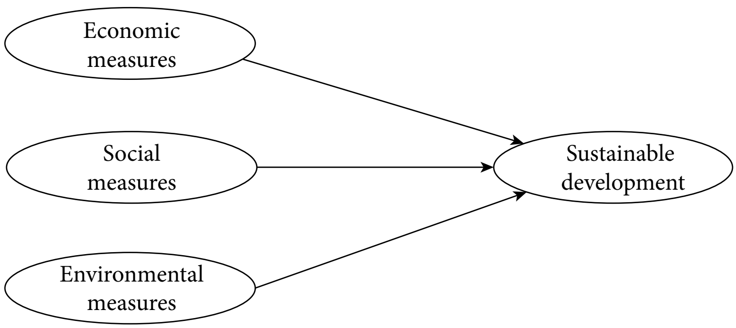


Figure 4.13. Structural model of the influence of economic, social and environmental measures undertaken by the government to the perception of sustainable development

Source: Own work.

4.3.2. Supply chain management

Practices related to supply chain management have a considerable environmental effect. Researchers in this field might be interested in studying the supplier's perspective on shifting to more sustainable transportation practices. The willingness to adopt a sustainable strategy can depend on many factors.

The theoretical model in Figure 4.14 shows the relationships between a company's environmental performance and different aspects of its purchasing behaviour (Large & Thomsen, 2011). Working with green suppliers and collaborating on environmental issues hypothetically influence 'Environmental performance improvement' and 'Purchasing performance'. The model was validated with survey data obtained from a sample of 109 purchasing and supply managers, using PLS-SEM methodology.

The relationships between latent variables in the structural model depicted in Figure 4.14 was initially considered positive. All measurement models are reflective, having Cronbach's alpha > 0.7 (cited in previous research), average variance extracted > 0.6, and composite reliability > 0.7. The latent variable "Strategic level of purchasing" had three items aimed at measuring the perceived actions that the purchase department took on a strategic level. The next construct—"Environmental commitment"—was also measured with three indicators: policy statement, value and understanding, all designed to measure the extent to which supply managers perceive environmental concerns are part of their company's policy, values and efforts to make employees also acknowledge the importance of environmental management. The construct "Purchasing's environmental capabilities" is measured with three indicators that captured the respondent's perceptions about the environmental goals of the purchase department and environmental training as well as activities performed by the purchasing personnel. The "Green supplier assessment" is measured through three items, i.e., reflecting the extent to which companies perform environmental assessment of potential suppliers, giving them feedback and performing environmental audits. "Green collaboration with suppliers" is supposed to reflect the respondents' perceptions of the extent to which their companies make joint efforts with the suppliers to reduce waste, help suppliers improve their performance and provide them with training. "Environmental performance improvement" is measured by six indicator variables—waste reduction, improved compliance with environmental laws, increased level of recycling, environmental protection, improved environmental reputation, and improved overall environmental performance. The last construct in the structural model is measured through five items: specifications, on time delivery, quantities, and internal satisfaction with the purchasing department.

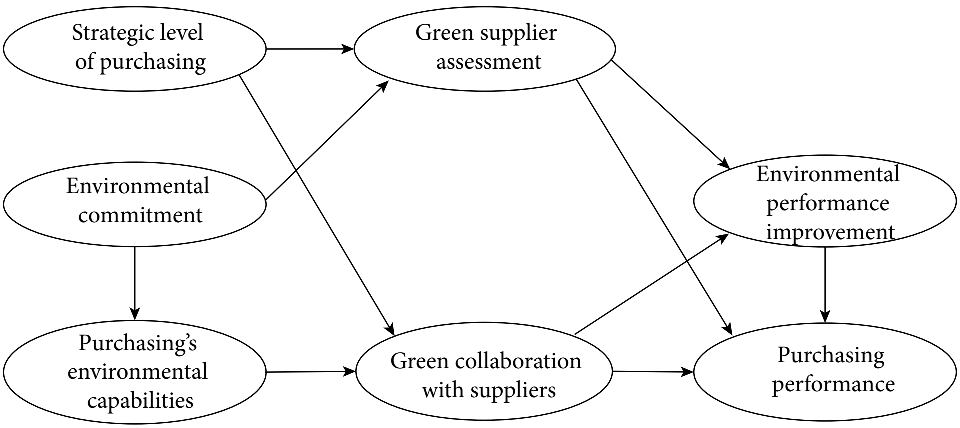


Figure 4.14. Structural model of environmental and purchase performance of firms buying from 'green' suppliers

Source: (Large & Thomsen, 2011).

All hypothetical relationships in the model in Figure 4.14 was confirmed, except the relationship between "Green collaboration with suppliers" and "Purchasing performance". The research contributed to the understanding of how green supplier assessment and collaboration with suppliers on environmental issues can positively influence firm's environmental performance. On the other hand, the improvement of environmental performance had a positive influence on the purchasing performance of companies.

4.3.3. Corporate social responsibility

A research dedicated to the link between corporate social responsibility (CSR) and environmental supplier development (ESD) has concluded that the latter influence positively the financial performance and competitive advantage of firms (Agan, Kuzey, Acar, & Açıkgoz, 2016).

The model in Figure 4.15 includes four latent variables: "Corporate social responsibility", "Environmental supplier development", "Financial performance", and "Competitive advantage". Four multi-item scales were used to measure these constructs, which included 45 different items. However, due to low factor loadings, some of the items were propped, which resulted in 35 items in the final measurement model. These indicators loaded on three factors (sub-dimensions) describing the CSR: "CSR to employees", "CSR to customers", "CSR to environment", "CSR to media", and "Partnership with NGOs". Items related to ESD were loaded on three factors, namely "Supplier evaluation", "Incentives", and "Direct involvement". Performance questions were loaded on two factors named 'Financial Performance' and 'Competitive Advantage'.

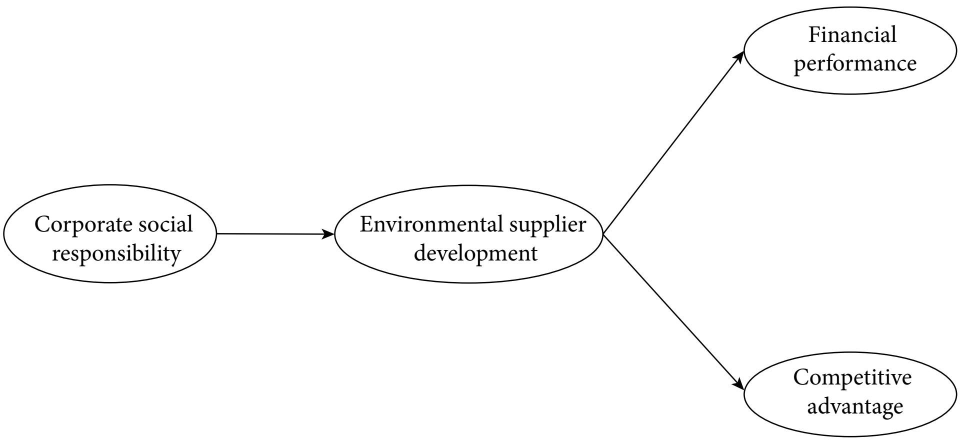


Figure 4.15. Structural model of the relationship between CSR, ESD and company performance

Source: (Agan et al., 2016).

All three relationships in the model in Figure 4.15 are hypothesized as being positive. This was confirmed by applying PLS-SEM. The data needed to evaluate the conceptual model was gathered through a survey and included 314 responses from mid- or high-level managers, directors or engineers in manufacturing firms. The research showed that CSR have a positive influence on ESD, although the latter is poorly explained solely by CSR and there are probably other relevant determinants. However, ESD also impacts positively the financial performance and competitive advantage of companies.

4.3.4. Innovations linked to sustainability

Green innovation can consist of either creating 'green' products or adopting 'green' processes. Green innovation comprises innovation in technologies for energy saving, pollution prevention, waste recycling, green product designing, and corporate environmental management.

The theoretical model in Figure 4.16 shows the hypothetical relationships between green supply chain management (GSCM) practices and technological innovation in manufacturing firms (Lee, Ooi, Yee-Loong, & Seow, 2014).

- Six indicators measure "Internal environmental management": commitment of GSCM from senior managers; support for GSCM from mid-level managers; cross-functional cooperation for environmental improvements; total quality environment management; environmental compliance and auditing programs; environmental management system exists.
- Three indicators measure "Eco-design": design of products for reduced consumption of material / energy; design of products for reuse, recycle, recovery of material, component parts; design of products to avoid or reduce use of hazardous of products and / or their manufacturing process.
- Three indicators measure "Investment recovery": investment recovery (sale) or excess inventories / materials; sale of scrap and used materials; sale of excess capital equipment.
- Four indicators measure "Green purchasing": cooperation with suppliers for environmental objectives; environmental audit for supplier's internal management; suppliers' ISO 14000 certification; second-tier supplier environmentally friendly practice evaluation.
- Three indicators measure "Cooperation with customers": cooperation with customer for eco-design; cooperation with customer for cleaner production; cooperation with customer for green packaging.
- "Technological innovation" is measured with nine indicators: "We are able to produce products with novelty features"; "We use the latest technology for new product development"; "The speed of new product development is fast enough / competitive"; "We have enough new products introduced to the market"; "We

have new products which are first-in-market (early market entrants)"; "We are technologically competitive"; "We use up-to-date/new technology in the process"; "We are fast in adopting process with the latest technological innovations"; "The process, techniques and technology change rapidly in our company."

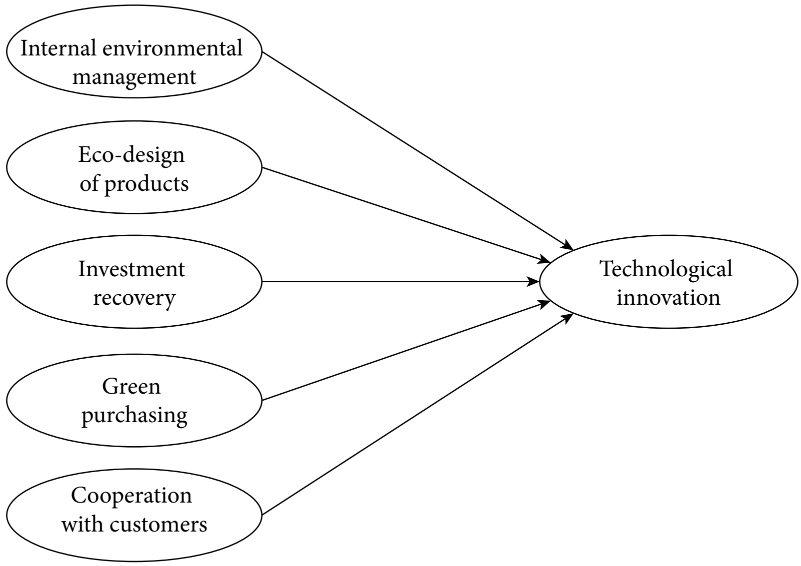


Figure 4.16. Structural model of the impact of green supply chain management practices on the technological innovation in firms

Source: (Lee et al., 2014).

The model was tested with survey data collected from environmental and operation managers in manufacturing companies of different sizes. The results showed that latent variables 'Internal environmental management', 'Eco-design of products' and 'Investment recovery' have a significant positive effect on technological innovation in firms.

4.3.5. Consumer behaviour and sustainable consumption

Human psychology is everything but simple. Most of the processes that make us think, feel or act in a certain way are not straightforward and easy to measure or interpret. It is quite the opposite: there can be many possible variables that have an effect on the way we perceive information and derive meaning from it, then form feelings and decide how to behave. Studying consumer behaviour almost always includes efforts to measure multi-dimensional psychological phenomena, such as consumer satisfaction, consumer loyalty, expectations and experience with the product, attitude and many others. In other words, the researcher is interested in analysing complex structures of latent nature, that are not a subject of direct observation and measurement. This is where SEM comes at hand, and by applying this type of analysis, we can answer some common questions regarding consumer behaviour linked to sustainability.

Globally, consumers are focusing their preferences on products and brands that are implementing different innovations to promote sustainability. Environmental awareness is increasing, and this makes consumers look for, and choose eco-friendly products, avoid waste, and reuse products and materials (Euromonitor International, 2020). Very often, the researcher or practitioner wants to know, e.g.:

– What factors contribute to the adoption of sustainability-related behaviours?
– Why do consumers choose to buy a brand positioned as sustainable?
– What factors contribute the most to the satisfaction with a sustainable product alternative?
– How do consumers perceive sustainable product attributes?
– Do perceptions of sustainable product attributes affect the product choice?
– What influences loyal behaviour towards sustainable companies and products?

The structural model in Figure 4.17 shows the hypothetical influence of different aspects of sustainable development on customer satisfaction, loyalty and willingness to pay (Xu & Gursoy, 2015). This model was tested in the field of hospitality supply chain management, with survey data obtained from 499 consumers who stayed in a hotel within the last 6 months. The data is reported to fit the measurement model well, with acceptable levels of reliability and discriminant validity for each construct.

The results show that all three dimensions of sustainable development adopted by hotels have a positive effect (direct or indirect) on consumer behaviour. The more hotels invest in sustainable practices, the more satisfied and loyal customers are, and the higher willingness to pay for the service they express.

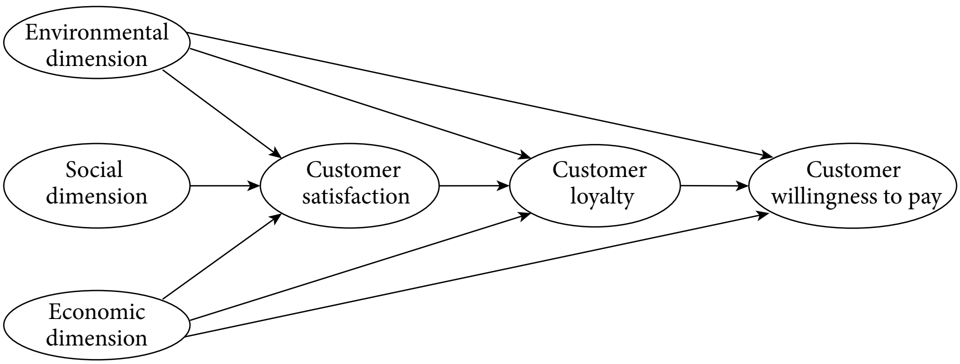


Figure 4.17. Structural model of the impact of SD dimensions on customer satisfaction, loyalty, and willingness to pay

Source: (Xu & Gursoy, 2015).

Another model explaining the link between product information, perceived value and specific buying decision process on consumer's willingness to buy 'green' products is given in Figure 4.18. This conceptual model was tested with survey data gathered in 27 member states of the EU, with a sample size $n = 26573$ (Couto, Tiago, Gil, Tiago, & Faria, 2016). The available product information, perceived value and considerations linked to the buying decision process hypothetically influence positively consumers' willingness to pay for a green product. Six indicators are used to measure the "Product information" construct: information on the shelf, information in advertisements, on the internet, in a leaflet at the shop, on a bar code that can be scanned by a smartphone, and on the label on the product. Participants are asked to rate each of these sources of information as more or less preferable when looking for environmental information about a product. The next construct, "Perceived value", is also measured with six indicators, aimed at capturing the different aspects of value related to environmentally friendly products: good value for money; as effective as other products; using them being the right thing to do; setting a good example with the purchase; making a difference to the environment; positive opinion of friends and family about using environmentally friendly products.

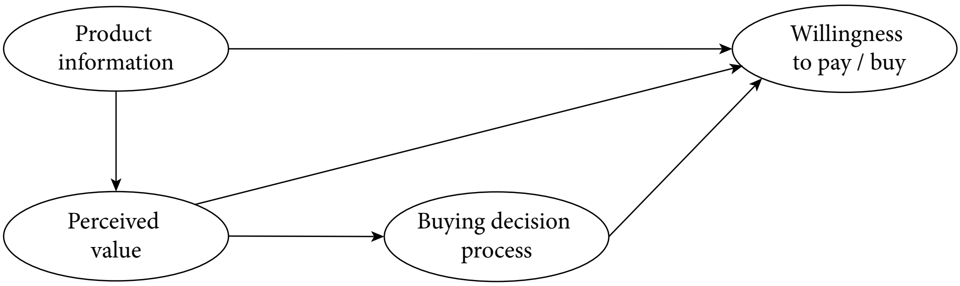


Figure 4.18. Structural model of willingness to pay / buy as a result of product information

Source: (Couto et al., 2016).

"Buying decision process" is measured with four indicators, reflecting different dimensions used to evaluate products before making a purchase decision. These are: product's impact on the environment; price; quality; brand name. The last construct represents the consumers' willingness to pay more for a product if they consider it as environmentally friendly. There are five indicators for this construct, all representing an increasing extra payment rate for environmentally friendly products. Only two out of five research hypothesizes were supported after the analysis. Willingness to pay was positively influenced by product information, but not by perceived information and buying decision process. Perceived product value did influence positively the buying decision process.

The willingness to pay / (WTP) for renewable energy is in the focus of another research (Lin & Syrgabayeva, 2016). Four constructs are tested for their direct or indirect effects on the willingness to pay more for renewable energy. The single construct that hypothetically have a direct positive effect on WTP more for renewable energy is "Attitude toward renewable energy". The latter is positively influenced by "Environmental concern", "Environmental belief" and "Knowledge about renewable energy". All other hypothetical relationships between the constructs are also positive (see Figure 4.19).

Multiple items are used to reflect the constructs, all measured on a 5-point Likert scale. "Environmental concern" construct has three indicators representing the concern about pollution, air pollution, and water usage. "Knowledge about renewable energy" reflects on three indicators about knowledge and familiarity with renewable energy sources and with wind-generated energy. "Environmental belief" is measured with three indicators representing the extent to which respondents believe that the environment, reliability, and environmental safety are important when considering renewable energy. "Attitude toward renewable energy" reflects on three statements indicating the extent to which respondents like renewable energy more than traditional one, their preference to buy and to use renewable energy. Finally, "Willingness to pay more for renewable energy" reflects on three variables, measuring the intention to pay more for renewable energy.

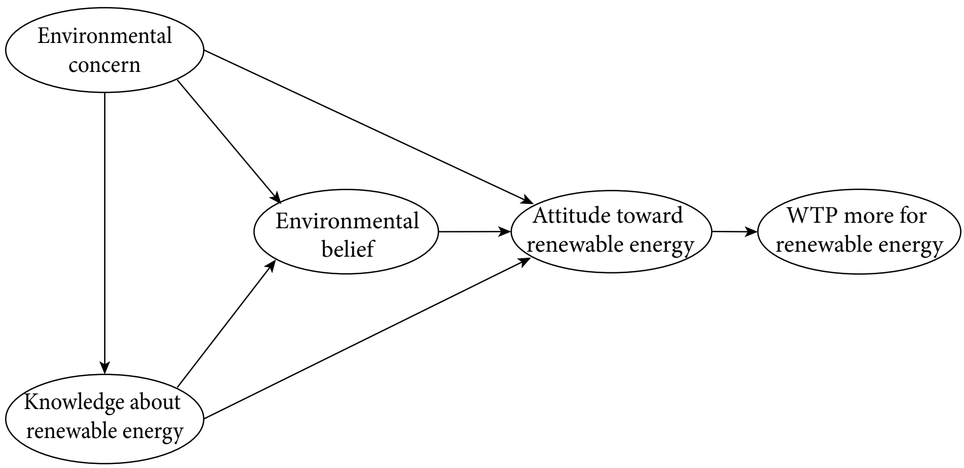


Figure 4.19. Structural model of the impact of the attitude toward renewable energy on the willingness to pay more.

Source: (Lin & Syrgabayeva, 2016).

PLS-SEM was used to assess the described conceptual model. The measurement model was found to be reliable, and all constructs had good convergent validity. The structural model was found to fit the data relatively well. Two of the hypothetical relationships were not statistically significant: the environmental concern did not have a direct impact on the knowledge about renewable energy, and the latter did not influence the attitude toward renewable energy. All other hypotheses used to build the conceptual model were supported. Consumers were found to have a better attitude toward renewable energy when they rated higher the importance of their environmental beliefs and when their concerns about the environment were also higher. A better attitude toward renewable energy also had a positive effect on the WTP more for renewable energy.

4.3.6. Human resource management

Promoting social welfare is one of the pillars of sustainable development. Public policies in this regard are aimed at ensuring healthy lives and well-being; providing access to quality education; ensuring gender equality; creating inclusive societies and institutions. In an effort to study each goal within the social aspect of sustainable development, researchers inevitably have to deal with complex phenomena of latent nature. As social constructs, most of these categories have many nuances and very often are interrelated, thus their studying require application of SEM methods.

Some social sustainability problems addressed in public policies are also relevant for private companies. Businesses that aim to be socially responsible are making efforts not only to minimize their environmental footprints but also to establish fair treatment of their employees and guarantee equality and inclusion. Sometimes these efforts are imposed by legal norms, and other times companies just want to stand out, emphasizing their fair working conditions and social care for employees. There is no doubt, however, that human resource management is a part of the sustainability strategies of companies.

Another noteworthy aspect of sustainability strategy, implemented by different human resource activities, is promoting sustainable behaviours to employees on every hierarchy level. This is also linked with the idea that even though companies are taking actions to become environmentally responsible, it is the motivation of employees that boosts the environmental performance of firms.

In the next example, human resource management practices are hypothesized to have an impact on the adoption of environmental practices by companies, which also have a direct effect on the operational performance (Jabbour, Jabbour, Govindan, Teixeira, & Freitas, 2013). Another latent variable in the theoretical model is the lean manufacturing that is hypothesized to influence the adoption of environmental practices (see Figure 4.20). The theoretical model was tested using survey data. The questionnaire included 28 items reflecting the latent variables and was distributed among automotive sector companies. The final sample included 75 respondents on managerial positions in production / operations areas.

- Indicator variables of 'Environmental management' construct include: clear policy of valorising environmental management; environmental training for all employees; 3Rs (reduction, reuse, and recycling); development of products with smaller environmental impact; development of production processes with smaller environmental impact; supplier selection based on environmental criteria; ISO 14001 or other environmental management system; voluntary promotion of information on environmental performance.
- Indicator variables of 'Human resource' construct include recruiting and selection; training; performance evaluation; rewards; benefits.
- Indicator variables of 'Operational performance' construct include: cost; time-to-market; new products; quality; flexibility; delivery.
- Indicator variables of 'Lean manufacturing' construct include: multifunctional involvement in the process; continuous improvement; 5S; total productive maintenance; Kanban; just-in-time; lot reduction; improvement circles; vendor development.

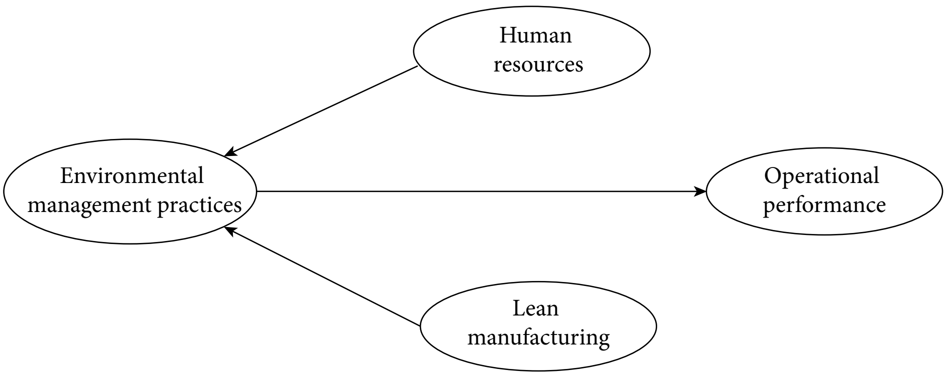


Figure 4.20. Structural model of environmental practices adoption impact on operational performance

Source: (Jabbour, Jabbour, Govindan, Teixeira, & Freitas, 2013).

The final measurement model included 25 indicator variables. The results showed that human resource and lean manufacturing practices positively influence the adoption of environmental practices, although this influence is weak to moderate. Environmental practices also positively influence operational performance.

*

Structural equation modelling methods are a powerful toolbox for researchers in any field to study complex phenomena of latent nature. A structural equation model relates observed manifest variables (indicators) to underlying constructs. It estimates the strength of the associations in a proposed model, as well as the degree to which the model fits the data.

There are two general SEM approaches—the covariance-based approach (CB-SEM) and the partial least squares approach (PLS-SEM). Both CB-SEM and PLS-SEM approaches represent an analysis at the aggregation level and suggest a set of statistical constraints. These two approaches should not be seen as an alternative to each other but rather as complementary.

CB-SEM is more restrictive in terms of statistical requirements, the fulfilment of which the researcher should start with it. PLS-SEM is less restrictive, but it has other shortcomings, such as its inability to use a global criterion to assess the structural model.

In addition to the statistical requirements, structural equation modelling methods also have requirements regarding the data to be analysed. This is why SEM should be applied if there is a reliable theory about the relationships between the variables, and as much information as possible is included in the analysis, whereby one can obtain this information from theoretical sources or previous exploratory analysis. Building a "good" model that is most likely to reflect the studied phenomena and can be validated with empirical data requires us to have solid theoretical knowledge of the studied phenomena.

Questions / tasks

1. What is the main idea of the SEM method?
2. What are the main differences between CB-SEM and PLS-SEM methodologies?
3. Can you name some of the advantages of PLS-SEM?
4. What is the difference between formative and reflective measurement models?
5. What kind of sustainable development research problems can be solved using SEM?
6. Is the PLS-SEM approach to model testing appropriate for the model depicted in Figure 4.14? Why?
7. What are the possible formulations of items used to measure the "Environmental commitment" construct, which was part of the structural model depicted in Figure 4.14?
8. What indicators can you suggest being used for the latent variables in Figure 4.17?
9. The structural model depicted in Figure 4.20 is based on three research hypotheses. Can you formulate them?

Task 1

Allnature Cream Cheese is a product made with natural ingredients. It is intended to satisfy the need of consumers for healthy alternative of processed cheese. The product can be directly consumed or used as an ingredient in various recipes. The marketing and sales department of the manufacturing company wanted to know what influences the buying decision of consumers and to use this knowledge in their strategy. They decided to gather qualitative data about the product attributes that influence the purchase intentions of potential buyers. Three parallel focus groups were organised with participants representing targeted consumer segments. The following product attributes were lined out as most important when deciding to buy cream cheese:

- **Health**
  Consumers are generally concerned about the health effects of the products they consume. They perceive cream cheese as healthier than the processed cheese, but they still pay attention to product ingredients when choosing a product. Consumers prefer products made from natural ingredients, although sometimes they do not trust the labels "eco", "green", or "bio".
- **Sustainability**
  While health benefits are a more personal reason why consumers choose to buy *Allnature Cream Cheese*, perceived sustainability of the production process is related to their concerns about environmental changes and nature preservation. Generally, consumers perceive favourably any company that adopt sustainability innovation processes, and this is expected to influence the perception of the company's products.
- **Price**
  Consumers expect prices of healthier product alternatives to be higher than those of conventional products. They are somehow ready to pay more for healthier products. However, the price level is still a concern when choosing a product.

These results were somehow satisfying for the marketing and sales team. The all-natural ingredients of the product and the ongoing transformation of production practices in an effort to apply a sustainability strategy are good premises for market success of the new product. The research team created a conceptual model of the potential influence of cream cheese product attributes to the purchase intentions of consumers (Figure 4.21). This influence is assumed to have both direct and indirect aspects. On the one hand, when consumers perceive the product as more healthy, sustainable and cheaper, their intentions to purchase it are expected to be higher. On the other hand, these perceived product attributes could influence the overall perception of the product as attractive, which in turn can affect consumers' purchase intentions. After a thorough discussion, the research team defined the following hypotheses for the next stage of the study:

H$_1$: The healthier the product is perceived by the consumer, the more attractive it is.
H$_2$: The healthier the product is perceived by the consumer, the stronger is the intention to buy.
H$_3$: The more sustainable the production process is, the more attractive the product is to consumers.
H$_4$: The more sustainable the production process is, the higher the probability that it will be purchased.
H$_5$: The more attractive the product is perceived by consumers, the more likely it is to be purchased.
H$_6$: The higher the price level of the product, the lower the probability that it will be purchased.

In the discussion on the above hypotheses, it was pointed out that there might be correlations between the latent variables “Health”, “Sustainability” and “Price”.

The next step in the study was to gather quantitative data to test the stated hypotheses. The team made a list of suitable indicator variables that should be included in the measurement models of each latent variables (see Table 4.13). It took 3 months to gather 1000 responses to an online-distributed survey. 262 cases were removed due to incomplete answers and the remaining 738 are available for downloading here: The respondents were asked: “How would you rate *Allnature Cream Cheese* on each of the following (…)”. A 6-point Likert scale, where 1 = ”low” and 6 = ”high”, was used to measure all indicator variables.

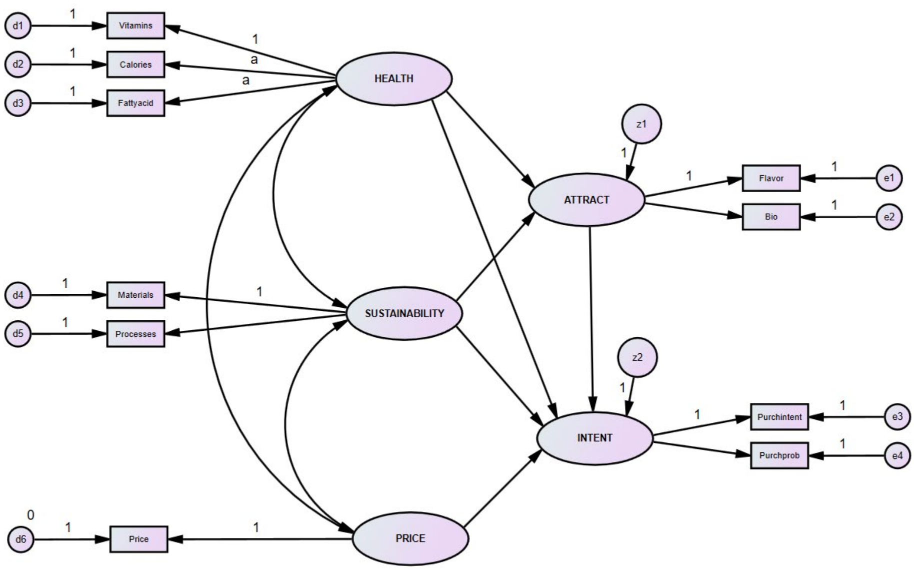


Figure 4.21. Path diagram of cream cheese purchase behaviour

Source: Own work.

The number of parameter estimates in this model is as follows:

- In the structural model there are:
  β_{21}; γ_{11}; γ_{12}; γ_{21}; γ_{22}; γ_{23}; ζ_{11}; ζ_{11} → 8 parameters.
- In measurement models of the endogenous latent variables, there are:
  λ_{21}; λ_{41}; ε_{21}; ε_{22}; ε_{33}; ε_{44} → 6 parameters.
- In measurement models of the exogeneous latent variables, there are:
  λ_{21} $(=\lambda_{31})$; λ_{52}; δ_{11}; δ_{22}; δ_{33}; δ_{44}; δ_{55} → 7 parameters.
- Correlations between the latent exogeneous variables and their variances will also be estimated:
  φ_{11}; φ_{21}; φ_{22}; φ_{31}; φ_{32}; φ_{33} → 6 parameters.

The overall number of parameters to be estimated is 27. We have four y – indicator variables and six x – indicator variables, which means that there are $\frac{1}{2}(4+6).(4+6+1)=55$ empirical correlations, variances and covariances. Hence, the degrees of freedom of the model are and this model is identifiable.

Table 4.13. Variables in the model

Latent variable	Indicator variable
Exogeneous variables (ξ)	
ξ_1 : HEALTH	x_1 : Vitamins
	x_2 : Calories
	x_3 : Fattyacids
ξ_2 : SUSTAINABILITY	x_4 : Materials
	x_5 : Processes
ξ_3 : PRICE	x_6 : Price
Endogenous variables (η)	
η_1 : ATTRACT	y_3 : Flavour
	y_3 : Bio
η_1 : INTENT	y_3 : Purchintent
	y_3 : Purchprob

Source: Own work.

Answer the following questions:

1. Which latent variables are part of the structural model?
2. Which variables are part of the measurement model of 'USAGE'?
3. Which latent variables are endogenous? Why?
4. Which latent variables are exogenous? Why?
5. Can you find any potential problems in the specification of the model in Figure 4.21

6. What approach to the model evaluation would you use and why?

Work individually on the following tasks:
1. Assess the measurement models using Cronbach's alpha.
2. Use an appropriate SEM approach to test the research hypothesis.
3. Apply another SEM approach and compare the results.

Some practical guidelines:
- Latent variable PRICE is explained by only one indicator variable. This is why we assume that the factor loading λ_{63} equals 1. This means that this parameter is fixed and will not be a subject of evaluation. The error term δ_{63} must also be fixed to 0. This is needed in order to apply CB-SEM approach to a model featuring latent variable with only one indicator.
- The latent variable HEALTH reflects equally indicator variables *calories* and *fattyacids*. This is why, in the model in Figure 4.21, λ_{21} equals λ_{31} (both arrows are marked with letter 'a').
- Note that the expected relationship between PRICE and INTENT is negative, while all other relationships between latent variables are expected to be positive. The data file in .csv format is available here: http://bit.ly/3kMpqQD

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