

Chapter 17

Dealing with Nonlinearity in Importance-Performance Map Analysis (IPMA): An Integrative Framework in a PLS-SEM Context

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Abstract Importance-performance map analysis (IPMA) combines PLS-SEM estimates, indicating the importance of an exogenous construct's influence on another endogenous construct of interest, with an additional dimension comprising the exogenous construct's performance in a two-dimensional map. From a practical point of view, IPMA contributes to more rigorous management decision-making. The basic principles of IPMA are well understood, yet the inter-construct relationships are typically modeled as being linear. An abundance of empirical literature indicates that this may lead to erroneous conclusions. In an IPMA context, this can lead to false conclusions regarding an exogenous construct's importance. Although several approaches exist to account for nonlinear inter-construct relationships, these approaches are characterized by drawbacks impeding their applications in practice. Overall, this serves as a backdrop for the current chapter which aims to contribute to (PLS-SEM) IPMA theory in the following ways. First, we provide an integrative framework to guide IPMAs using PLS-SEM. Second and synergistically with the first contribution, we introduce a so-called log-log model that allows to capture the most common functional forms (i.e., both linear and nonlinear) without the need to make a priori assumptions about the correct functional form specification. Third, a comprehensive empirical application is provided that illustrates our proposed IPMA framework as well as the proposed log-log model to more adequately capture the nature of the PLS-SEM relationships ultimately defining the IPMA's importance dimension.

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17.1 Introduction

The central tenet of the satisfaction-profit chain (SPC) is that effectively managing drivers of customer satisfaction is the road to enhanced business performance (Anderson and Mittal 2000; Kamakura et al. 2002). From a decision-making point of view, and building on the relationships put forward in the SPC, importance-performance map analysis (IPMA) can be considered an effective tool in satisfaction and thus business performance and management (cf. Matzler et al. 2004). The fact that managers are increasingly held financially accountable for their decisions further underscores the relevance of IPMA (Seggie et al. 2007).

In a nutshell and in general terms, IPMA contrasts the impact of key exogenous constructs or indicators (both are also referred to as drivers or input constructs or variables) in shaping a certain endogenous target construct with the average value, representing performance of the driver construct or indicator (Ringle and Sarstedt 2016). Combining the importance and performance measures of the drivers in a two-dimensional map then allows managers to identify key drivers of the target construct, to formulate improvement priorities, to find areas of possible overkill, and to pinpoint areas of “acceptable” disadvantages (see also Matzler et al. 2004).

IPMA per se is not restricted to a partial least squares structural equation modeling (PLS-SEM) context. However, IPMA in combination with PLS-SEM offers several key advantages, such as PLS-SEM’s ability to model a comprehensive nomological web of interrelations among constructs and its ability to include latent constructs. In line with these advantages, the focus in this chapter will be on IPMA in a PLS-SEM context.

Although several IPMA applications in a PLS-SEM context have emerged in the literature in recent years (e.g., Hock et al. 2010; Völckner et al. 2010; Rigdon et al. 2011), a common characteristic of these applications is that they all assume linear relationships. Inspection of the literature reveals that linear relationships are not necessarily appropriate in modeling business phenomena. Examples include Narasimhan and Kim (2002) in operations research, Langfred (2004) and Sciascia and Mazzola (2008) in management, Titah and Barki (2009) in management information systems, Lu and Beamish (2004) in strategy, and Seiders et al. (2005) in marketing.

Also regarding customer satisfaction management, which is the substantive domain central to this chapter, the possibility of nonlinearity needs to be taken into account when modeling the nomological web of relationships put forward in the SPC (Mittal et al. 1998; Dong et al. 2011; Anderson and Mittal 2000). In terms of IPMA, failing to take into account possible nonlinearities might lead to erroneous strategic decision-making regarding the management of customer satisfaction drivers.

Ignoring the customer satisfaction management background for the moment, the two general objectives of this chapter are twofold: first, to provide an integrative framework on how to conduct an IPMA that is both managerially relevant and theoretically valid and, second, to compare and contrast different analytical approaches

to account for nonlinear structural model effects that determine importance scores in the IPMA. Given the added value of PLS-SEM in conducting an IPMA, the proposed IPMA framework and the approaches to deal with nonlinear relationships are, without loss of generalizability, discussed in a PLS-SEM context.

In relation to the work by Ringle and Sarstedt (2016) on IPMA as an extension of basic PLS-SEM, addressing the abovementioned research objectives yields the following contributions to theory and practice. First, our framework extends the work by Ringle and Sarstedt (2016) by paying attention to key decisions that need to be made in the pre-analytical stages of IPMA. That is, in order to arrive at an IPMA that is truly relevant both practically and theoretically, it is critical to keep in mind that IPMA is more than just a data analytical tool. Rather, IPMA involves making several interrelated decisions that start already at the research design phase, such as measurement model specification and questionnaire design. Second, although the current research focuses on nonlinearities in the SPC, the different methods to account for nonlinearity in structural model relationships discussed are generally applicable. As such, this study responds to the recent surge of interest in modeling nonlinear effects in PLS-SEM (see also Henseler et al. 2012). Third, in terms of IPMA, being able to adequately capture the functional form of structural relationships leads to an increased likelihood of improved strategic decision-making.

The remainder of this chapter is structured as follows. The subsequent two sections, Sects. 17.2 and 17.3, serve as a preparatory basis for the actual contributions as outlined above. Section 17.2 explains the basic principles of IPMA. In Sect. 17.3, the SPC is discussed as well as the need for taking into account nonlinearities in the SPC. Section 17.4 introduces the integrative IPMA framework and discusses the various stages involved. Again, without loss of generalizability, the framework discusses IPMA in combination with PLS-SEM. In Sect. 17.4, attention is particularly devoted to the modeling of nonlinear relationships in PLS-SEM. Section 17.5 describes the application of the proposed IPMA framework using real-life data. Sections 17.6 and 17.7 conclude this chapter.

17.2 IPMA: The Basics

17.2.1 *What Is IPMA?*

IPMA, originally introduced by Martilla and James (1977), yields insight into which drivers must be prioritized to achieve superior levels of a target construct of interest (e.g., satisfaction). In general, data derived from (satisfaction) surveys are used to construct a two-dimensional map, where performance is depicted along the horizontal axis (i.e., x-axis) and importance on the vertical axis (i.e., y-axis). As is shown in Fig. 17.1, for both axes, a cutoff value is specified to split each axis in a low and a high segment, dividing the matrix into the following four quadrants.

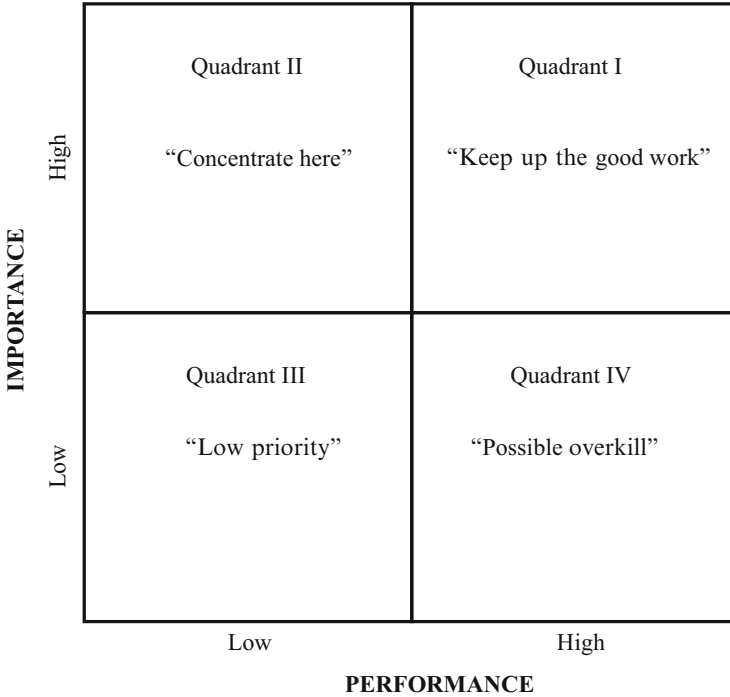


Fig. 17.1 Basic PLS-SEM IPMA chart

Drivers in quadrant I, named “Keep up the good work,” are characterized by both a high importance level and a high performance level. These drivers represent opportunities for gaining or sustaining a superior level of the target construct. The drivers in quadrant II, named “Concentrate here,” are key elements for improvement, as these drivers are considered important by respondents, while the perceived level of performance leaves things to be desired. The two quadrants at the bottom of the matrix are characterized by a low importance level. Hence, assuming equal costs, improvement initiatives concerning drivers located here can be expected to provide the lowest return on investment. Quadrant III, referred to as “Low priority,” combines low importance with low performance. Drivers in this quadrant do not merit special attention or additional effort. Finally, quadrant IV, named “Possible overkill,” represents drivers on which the respondents perceive a high level of performance but do not consider them very important. Similar to quadrant III, these drivers do not represent feasible alternatives for improving target construct performance. Rather, to avoid the risk of possible overkill, resources committed to these drivers would be better employed elsewhere.

17.2.2 IPMA and PLS-SEM

In a PLS-SEM context, the basic idea of IPMA as described above and shown in Fig. 17.1 remains unaltered. Nevertheless, PLS-SEM has several key advantages over traditional IPMA, which typically relies on multiple regression analysis. First, in determining the importance scores, PLS-SEM is a valuable analytical tool as it is capable of integrally assessing a complex network of relationships connecting drivers to a target construct of interest. Second, it can incorporate latent constructs. This is particularly relevant as in many research contexts, key constructs can only be validly measured by a set of indicators. These key constructs may concern both drivers and target constructs in the IPMA.

Consistent with Ringle and Sarstedt (2016), it should be stressed that in a PLS-SEM context, the IPMA may be conducted at either the latent variable or indicator level. The IPMA principles are not influenced by whether the analysis is done at the latent variable or indicator level. However, analysis at the indicator level leads to improved actionability, as indicators describe elements that shape the corresponding construct.

17.2.3 Performance Scores

As can be seen in Fig. 17.1, the horizontal axis captures driver performance. There are several ways to express these performance scores, depending on whether the IPMA is done at the indicator or latent variable level.

For IPMA at the indicator level, the mean or median score of the indicator represents the relevant performance score. Alternatively, for IPMA at the latent variable level, the average latent variable score represents perceived performance. With regard to the latter, it needs to be stressed that, in order to be meaningful, the latent variable's indicator weights all need to be in the same direction (Tenenhaus et al. 2005; Ringle and Sarstedt 2016).

Furthermore, to enhance the interpretability of the results, the performance scores are usually rescaled on 0–100 scale. Equation (17.1) shows how the latent variable scores are rescaled using the procedure suggested by Fornell et al. (1996):

$$LV^{\text{rescaled}} = \left(\frac{\sum_{i=1}^j w_i \bar{x}_i - \sum_{i=1}^j w_i \min [x_i]}{\sum_{i=1}^j w_i \max [x_i] - \sum_{i=1}^j w_i \min [x_i]} \right) \times 100 \quad (17.1)$$

In Eq. (17.1), w_i is the indicator weights associated with indicator x_i , while $\max[x_i]$ and $\min[x_i]$ denote, respectively, the maximum and minimum possible values for indicator x_i . Again, all weights need to be in the same direction. Equation (17.1) is also applicable at the indicator level. In this case, the calculation needs to be done at the indicator level using a weight equal to 1. Note that this rescaling is done automatically by SmartPLS 3 (Ringle et al. 2015).

17.2.4 Importance Scores

As can be seen in Fig. 17.1, the vertical axis of the chart captures the drivers' importance scores. Analytically, the importance score reflects the total effect of a predictor construct (i.e., driver) on a particular target construct. In general terms, and assuming a recursive structural model, let parameter δ_{kl} ($k \neq l$) reflect the total effect of construct k on construct l . Thus, parameter δ_{kl} reflects the entire set of relationships in a structural model connecting latent construct k to latent construct l . Parameter δ_{kl} can be calculated from the empirical results describing the set of relationships connecting latent construct k to latent construct l , as shown below in Eq. (17.2):

$$\delta_{kl} = \sum_{P:(LV_k \rightarrow LV_l)} \left(\prod_{(LV_k, LV_l) \in P} \beta_{ij} \right) \quad (17.2)$$

In Eq. (17.2), and in the case of linear relationships, β_{ij} are the structural model coefficients belonging to the paths that connect latent construct k to latent construct l . In words, Eq. (17.2) states that the total effect of construct k on construct l can be computed by calculating the product of the structural model coefficients β_{ij} belonging to each of the separate direct relationships connecting construct k and construct l and subsequently summing these products' overall relevant paths connecting construct k and construct l . Or equivalently, as Nitzl et al. (2016) put it, the total effect is the sum of the relevant direct and indirect effects.

The idea expressed by Eq. (17.2) can be extended to include measurement model parameters as well, which is relevant for IPMAs conducted at the indicator level. In this case, the weight of indicator needs to be included in Eq. (17.2) as well. A graphical illustration of this can be found in Streukens and Leroi-Werelds (2016). Note that Ringle and Sarstedt (2016, p. 1869) indicate that this extension to the indicator level by including the indicator's weight in Eq. (17.2) can be done for both formative and reflective indicators.

Finally, the statistical significance of the importance scores can be assessed by means of bootstrap confidence intervals as outlined in detail by Streukens and Leroi-Werelds (2016).

17.2.5 Defining the Quadrants

Determining the cutoff values concerning what constitutes low performance/importance and high performance/importance is rather arbitrary. Multiple ways exist to specify these values. A commonly used way to specify these cutoff values is to use the mean (e.g., see Matzler et al. 2004) or median (e.g., see Berghman et al. 2013) value accompanying each of the axes.

17.3 The SPC and Nonlinear Relationships

17.3.1 Introduction of the SPC

As mentioned in the introduction, the IPMA and the SPC are a golden combination for many (marketing) managers. This stems from the fact that both the IMPA and the SPC are concerned with making effective resource allocation decisions in order to enhance business performance. To integrate the strengths of both models, the relationships put forward in the SPC (see also Fig. 17.2) can be estimated using PLS-SEM. Subsequently, the PLS-SEM estimation results can be used to calculate the importance scores (see also Eq. 17.2).

Starting at the back end of the chain, business profitability is positively influenced by customer loyalty, which reflects a customer's overall attachment to an offering, brand, or organization (Oliver 1999). In customer research, behavioral intentions are typically used as a proxy for customer loyalty. Customer satisfaction is the customers' cumulative evaluation that is based on all experiences with the company's offering over time (Anderson et al. 1994), and ample research supports the positive impact of this construct on customer loyalty (e.g., see Leroi-Werelds et al. 2014; Streukens et al. 2011). Consistent with Fishbein's (1967) multi-attribute model, customer satisfaction is a function of perceived attribute performance. Here, attributes are specific and measurable characteristics associated with a particular offering (see also Streukens et al. 2011). For example, in Gomez et al.'s (2004) study, attributes related to customer service, quality, and value for money were included as predictors of overall satisfaction with a supermarket.

Note that for the current study, the focus will be on the relationship between attribute performance and overall satisfaction and the relationship between overall satisfaction and loyalty. This is indicated in Fig. 17.2 by the dotted rectangle.

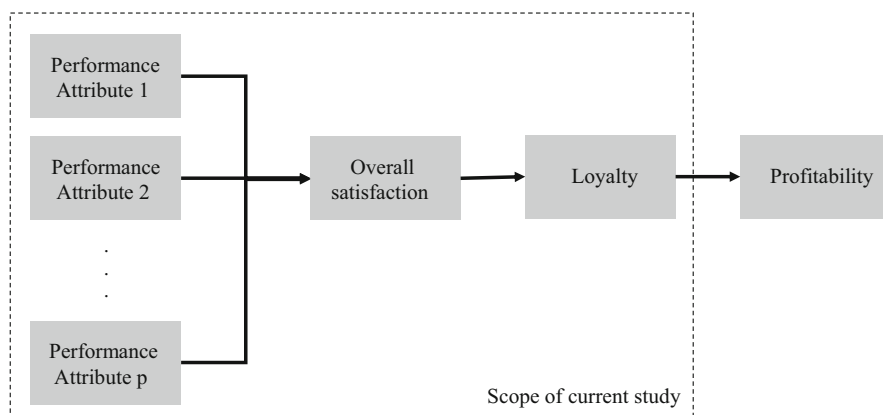


Fig. 17.2 The satisfaction-profit chain (adapted from Anderson and Mittal 2000)

17.3.2 *Nonlinear Relationships in the SPC*

Although the significance and direction of the relationships put forward in the SPC are well supported, an increasing amount of research suggests that the functional form of these relationships is not necessarily linear. Failing to account for possible nonlinearity in the links comprising the SPC may result in not finding support for expected linkages and/or incorrectly prioritize efforts to improve performance. Put differently, the danger of conducting PLS-SEM and the subsequent IPMA through a linear lens could be the misallocation of resources (see also Anderson and Mittal 2000).

In Sect. 17.3.2.1 the Kano-model (Kano et al. 1984) will be used to discuss the different (non)linear functional forms that may describe the attribute-overall satisfaction relationship. After that, Sect. 17.3.2.2 outlines five possible (non)linear functional forms regarding the relationship between overall satisfaction and loyalty.

17.3.2.1 Attribute Performance and Overall Satisfaction: Kano's Model

The Kano model distinguishes among three different types of attributes: *attractive* attributes (“delighters”), *must-be* attributes (“dissatisfiers”), and *one-dimensional* attributes (“satisfiers”). Figure 17.3 provides a graphical overview of Kano's model.

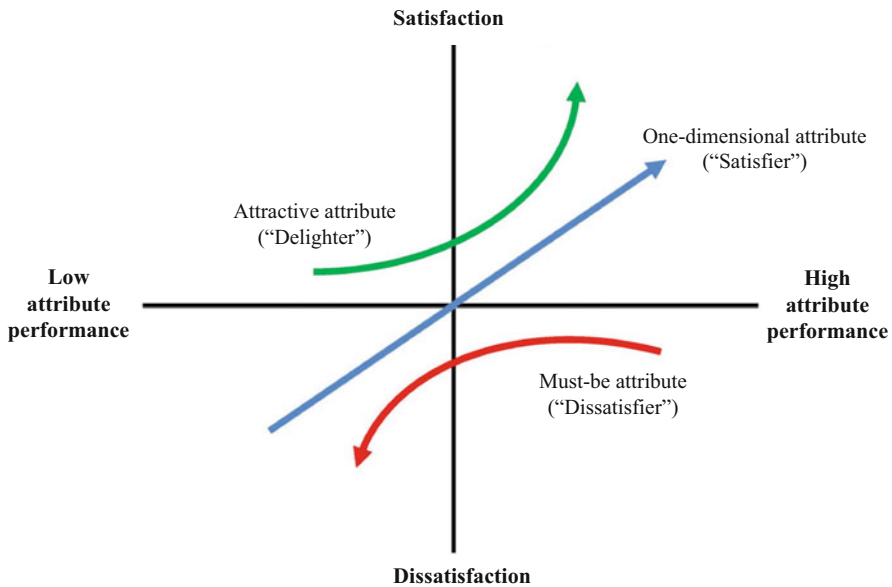


Fig. 17.3 Kano's model

Attractive attributes are attributes that increase satisfaction when fulfilled and have little influence on satisfaction ratings even when not fulfilled. Theoretically, *attractive* attributes are associated with customer delight, which is a positive emotion generally resulting from a surprisingly positive experience (Rust and Oliver 2000). In terms of functional form, *attractive* attributes are characterized by increasing returns. *Must-be* attributes cause dissatisfaction when absent but do not have an impact on satisfaction when present. Prospect theory (Kahneman and Tversky 1979), according to which “losses loom larger than gains,” provides a theoretical rationale for this pattern. The functional form associated with *must-be* attributes is characterized by decreasing returns. The third and final category of attributes consists of so-called *one-dimensional* attributes or performance attributes. These attributes lead to satisfaction if performance is high and to dissatisfaction if performance is low (Matzler et al. 2004). *One-dimensional* attributes are characterized by a linear functional form, implying that a change in attribute performance has a constant impact on satisfaction.

17.3.2.2 Nonlinearities in the Satisfaction-Loyalty Link

According to Anderson and Mittal (2000), the relationship between satisfaction and loyalty may also exhibit nonlinearity. Based on an overview of the literature, Dong et al. (2011) discern among five different functional forms that have been put forward and empirically tested regarding the satisfaction-loyalty relationship. What Dong et al. (2011) refer to as a linear, concave, and convex relationship coincides with the functional form associated with Kano’s *one-dimensional*, *attractive*, and *must-be* attributes, respectively. The two other functional forms discussed by Dong et al. (2011) include the S-shaped and inverse S-shaped function. An S-shaped function suggests decreasing returns for customers that are highly satisfied but increasing returns for customers who are less satisfied. The inverse S-shaped function implies increasing returns for customers who are highly satisfied and decreasing returns for customers with low satisfaction. Figure 17.4 summarizes the five functional forms of the satisfaction-loyalty relationship as presented by Dong et al. (2011).

17.4 IPMA: An Integrative Framework

This section outlines a three-stage integrative framework to conduct a strategically relevant IPMA. It is important to note that this framework, which is graphically presented in Fig. 17.5, implies that IPMA is more than just analytical approach.

That is, in order to be of true value, a strategically relevant IPMA requires addressing several key questions prior to the actual data analysis (e.g., the identification of attributes). This is reflected by stage 1 in Fig. 17.5. As indicated by stage 2 in Fig. 17.5, and in line with the discussion of possible nonlinearity in the relationships

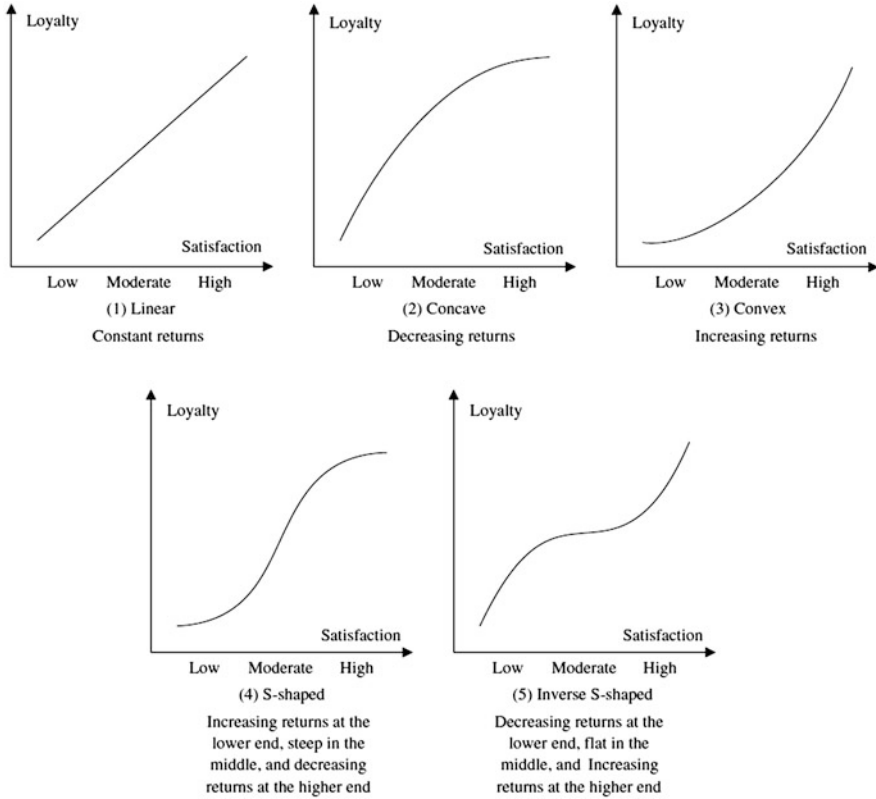


Fig. 17.4 Functional forms satisfaction-loyalty relationship (cf. Dong et al. 2011)

comprising a nomological network (i.e., the SPC), modeling the appropriate functional form is pivotal to adequately making strategic decisions involving resource allocation. As can be concluded from Fig. 17.5, several approaches are proposed to model nonlinear relationships. Finally, in stage 3, to make the transition from the statistical results to actionable practical implication, attention needs to be devoted to the interpretation of the results. Whereas the interpretation of the performance scores is rather straightforward, the interpretation of the importance scores will be relatively complex in case of nonlinear functional forms. Furthermore, stage 3 also includes (external) validation of the results. This is particularly relevant given the prediction-oriented nature of PLS-SEM (Shmueli et al. 2016; Carrión et al. 2016).

Two additional remarks concerning the framework in Fig. 17.5 need to be made. First, the steps in Fig. 17.5 are presented sequentially. However, for some decisions, these steps are interrelated. Whenever that is the case, it is explicitly mentioned. Second, although this chapter focuses in particular on the modeling of nonlinear relationships, the presented framework is also applicable to models that consist of only linear relationships. Rather, the basic IPMA, which assumes only linear

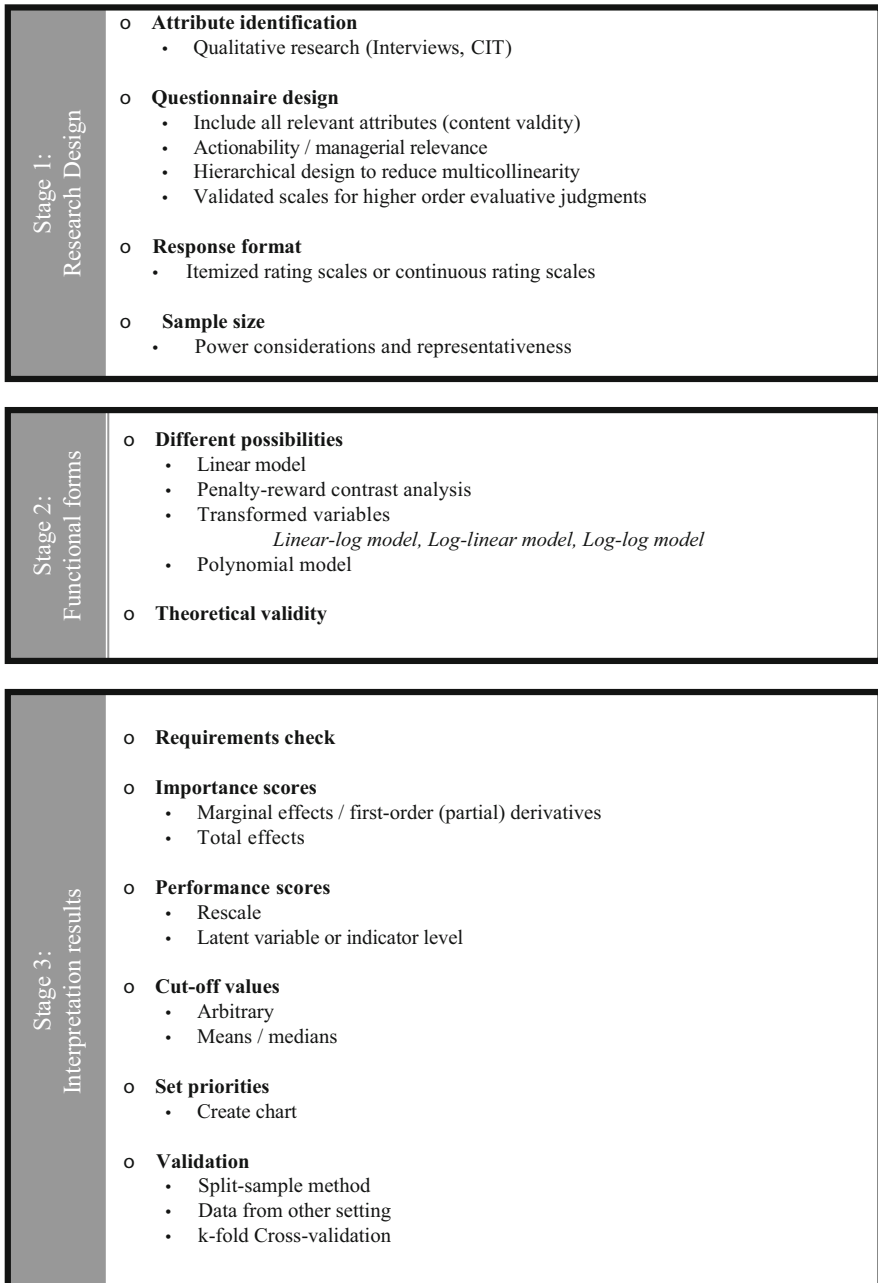


Fig. 17.5 IPMA: an integrative framework

relationships, can be considered as a special, very restricted case of the more advanced model that accounts for nonlinearity.

17.4.1 Stage 1: Research Design

A truly actionable IPMA is more than an analytical approach and requires several key considerations in the research design stage, such as attribute identification and questionnaire design.

17.4.1.1 Attribute¹ Identification

Conducting a series of interviews is often an excellent first step in identifying the relevant attributes, as the validity of the results of the IPMA depends on the completeness of the set of attributes under consideration. Or as Anderson and Mittal (2000) put it: the set of attributes should be as distinct and as broad as possible. An alternative method, preferably to be used in conjunction with interviews, is to use critical incident technique (CIT) data to identify active and/or salient sources of (dis)satisfaction. Moreover, the process of attribute identification needs to be repeated from time to time, as the list of attributes predicting overall satisfaction is likely to change due to a change in customer needs.

A frequently encountered issue involves the number of interviews that needs to be conducted. There is no fixed number that can be put forward here, but the saturation rule of Strauss and Corbin (1990) is a useful guideline. According to this rule, the researcher needs to continue conducting interviews until no new information comes to light (i.e., saturation point). Furthermore, in contrast to quantitative research, the samples used in interviews and other forms of qualitative research are not meant to be representative of the underlying population (see also Malhotra et al. 2012).

17.4.1.2 Modeling Attributes

Closely related to identification of the attributes is the specification of the accompanying measurement model. Several aspects need to be considered here. First, and also mentioned previously, is that attributes may be defined at the indicator or latent variable level. Second, although Fishbein's (1967) attribute model that is typically used in customer satisfaction research (see also Sect. 17.3.1) implies a formative

¹Attribute identification is a term that is often used in the customer satisfaction research/SPC. More generally, what we refer to as attributes can be considered as the drivers or input variables of various kinds in an IPMA.

measurement model, Ringle and Sarstedt (2016) state that reflective measurement models can also be used to measure the latent constructs underlying an IPMA.

Although formatively and reflectively specified constructs can act as exogenous constructs (i.e., drivers) in an IPMA, formatively specified constructs are preferred for reasons of actionability and thus strategic relevance of the IPMA (see also Ringle and Sarstedt 2016, p. 1869).

17.4.1.3 Questionnaire Design

Data for an IPMA typically stem from (satisfaction) surveys. Consistent with the need to identify the complete set of relevant attributes (see Sect. 17.4.1.1), the key term for the design of the questionnaire is content validity. This means that all elements relevant to the customer in a particular situation need to be included. To achieve this, the output from the qualitative research conducted to identify the relevant attributes serves as input for the design of the questionnaire. Furthermore, whenever possible one is advised to use validated scales. This is typically the case for constructs that serve as target or intermediary constructs in an IPMA such as, in casu, loyalty intentions, and satisfaction.

Multicollinearity is a common issue in analyzing IPMA data, especially for formatively measured constructs. Although there are several technical ways to deal with this problem, the multicollinearity problem can be minimized through the design of the questionnaire. To do so, Mikulić and Prebežac (2009) suggest the following guidelines for questionnaire design. First, there should not be any overlapping between the conceptual domains of attributes, and the predictors should be on the same level of abstraction. Second, employ a so-called hierarchical design in which the different hierarchical levels measure attribute performance at various levels of abstraction. For an example of this latter recommendation, see the work of Dagger et al. (2007). The use of a hierarchical level model reduces multicollinearity as it decreases the number of independent variables per equation. Guidelines on how to model higher-order constructs in a PLS-SEM context can be found in Becker et al. (2012).

17.4.1.4 Response Formats

The estimation of (non)linear models requires metric data. Rating scales such as Likert scales are most often used in marketing research and are generally considered metric when at least five response categories are employed (Weijters et al. 2010). From a strict methodological point of view, Dawes (2008) concludes that the number of categories (i.e., five, seven, or ten) is trivial in case of regression-based techniques. However, Preston and Colman (2000) suggest that researchers should opt for seven, nine, or ten categories to warrant optimal levels of reliability, validity, discrimination power, and respondent preference. In terms of the analytical approaches to be discussed in the subsequent section, the use of Likert scales is

a feasible option in the penalty-reward analysis, the linear model, the log-linear model, the linear-log model, and the log-log model.

In contrast, for a polynomial model, the use of Likert-type scales is not suitable (Finn 2011; Russell and Bobko 1992; Carte and Russell 2003) as it causes information loss that may result in an unknown systematic error. Hence, for polynomial models, the use of continuous rating scales is needed (see also Russell and Bobko 1992).

17.4.1.5 Sample Size

Similar to other analytical approaches, the needed sample size for a (PLS-SEM based) IPMA needs to be driven by statistical power considerations (Marcoulides et al. 2009) as well as representativeness (Streukens and Leroi-Werelds 2016).

17.4.2 Stage 2: The Functional Forms of the Relationships

Several approaches exist to model nonlinear relationships in a PLS-SEM context. Three alternative methods are discussed and compared below: the penalty-reward contrast analysis (PRCA), polynomial model, and analysis with transformed variables (i.e., linear-log, log-linear, and log-log models).

17.4.2.1 Penalty-Reward Contrast Analysis

Probably the most frequently used analytical approach in modeling the different types of attributes as implied by the Kano model is PRCA. Examples of studies employing PRCA include the work of Matzler et al. (2004), Busacca and Padula (2005), and Conklin et al. (2004).

PRCA analyzes the impact of high and low attribute performance on satisfaction by using two dummies, say D_i^L and D_i^H , for each attribute i (Mikulić and Prebežac 2011). The coding of the two dummies for attribute i is done as follows: $(D_i^L, D_i^H) = (1, 0)$ indicates “low attribute performance,” $(D_i^L, D_i^H) = (0, 1)$ indicates “high attribute performance,” and $(D_i^L, D_i^H) = (0, 0)$ indicates “average attribute performance.”

Running a PRCA thus implies that for each attribute, two coefficients are obtained: one to reflect the impact when performance is low, say β_i^L , and one to reflect the impact when performance is high, say β_i^H . Figure 17.6 presents the PRCA model in a PLS-SEM context. The model in Fig. 17.6 focuses on a single attribute measured by a single item. Moreover, satisfaction acts as target construct and is, consistent with the literature, measured by two reflective items. For academic research, it may be of interest to formally assess the nature of the attributes involved (e.g., see Mittal et al. 1998; Streukens and De Ruyter 2004). This can be done by

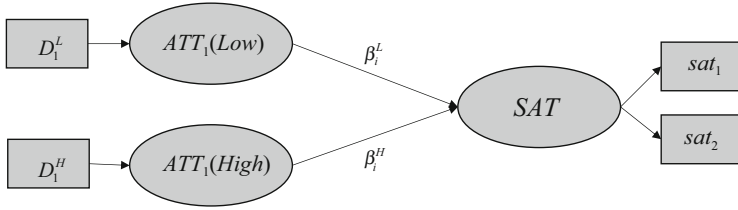


Fig. 17.6 PRCA in PLS-SEM

testing the following null hypothesis using the procedure outlined in Streukens and Leroi-Werelds (2016):

$$H_0 : \beta_i^L = \beta_i^H$$

If this null hypothesis cannot be rejected, the attribute can be regarded as a *one-dimensional* or linear attribute. Conversely, if the null hypothesis is rejected, then the attribute is either an *attractive* attribute (i.e., $\beta_i^L < \beta_i^H$) or a *must-be* attribute (i.e., $\beta_i^H < \beta_i^L$).

Despite its simplicity, several key disadvantages are associated with the use of PRCA. First, PRCA does not really capture nonlinearity. At best, it addresses whether the relationship between attribute performance and overall satisfaction is (a)symmetric. In the case of a symmetric relationship, low and high attribute performances have an equal impact on overall satisfaction. In the case of an asymmetric relationship, low and high attribute performances have a different impact on overall satisfaction. For more information on (a)symmetric relationships, the reader is referred to the work of Matzler et al. (2004). Second, as pointed out by Mikulić and Prebežac (2011), standardized coefficients for the PRCA dummies (as in PLS-SEM) may yield misleading results if the dummies have unequal distributions of zeros and ones, which is typically the case. Although a notable disadvantage, it can be circumvented by using the unstandardized model coefficients for model interpretation.

17.4.2.2 Polynomial Models

Polynomial models offer a flexible approach to capture a wide variety of functional forms without having to specify a specific form of nonlinearity a priori. Likewise, assessing whether nonlinearity is significant is straightforward in the case of polynomial models as it can be directly concluded from the statistical significance of the higher-order terms (Finn 2011; Dong et al. 2011). When modeling the link between attribute performance and overall satisfaction as implied by the Kano model, the quadratic model presented in Eq. (17.3) would apply:

$$SAT = \beta_1 ATT_i + \beta_2 ATT_i^2 \tag{17.3}$$

Assessing the statistical significance of the model parameters reveals information about the functional form of the relationship between attribute performance and overall satisfaction. That is, in the case $\beta_1 > 0$ and $\beta_2 = 0$, a linear functional form is implied (“one-dimensional attribute”); if $\beta_2 < 0$, the relationship displays decreasing returns (*must-be* attribute); if $\beta_2 > 0$, the relationship exhibits increasing returns (*attractive* attribute). To capture the five different functional forms for the satisfaction-loyalty relationship as proposed by Dong et al. (2011), a cubic model, as presented in Eq. (17.4), is needed.

$$\text{LOY} = \beta_1 \text{SAT} + \beta_2 \text{SAT}^2 + \beta_3 \text{SAT}^3 \quad (17.4)$$

This cubic model is able to capture the five functional forms displayed in Fig. 17.4. The pattern of the model coefficients contains information about the functional form. If $\beta_1 > 0$ and $\beta_2 = \beta_3 = 0$, a linear functional form is implied; if $\beta_2 < 0$ and $\beta_3 = 0$, the relationship is concave; if $\beta_2 > 0$ and $\beta_3 = 0$, the relationship is convex; if $\beta_3 < 0$, an S-shaped relationship exists; and if $\beta_3 > 0$, the relationships are characterized by an inverse S-shaped pattern.

The approach to estimate a polynomial PLS-SEM model depends on the nature of the exogenous’ construct measurement model (see also Henseler et al. 2012; Fassott et al. 2016). In case of a formative exogenous construct, the two-stage approach needs to be used.²

In the first stage, the PLS-SEM model without the quadratic effect is estimated to obtain estimates for the latent variable scores. These latent variable scores are saved for further analysis. In the second stage, the quadratic term is added to the model. The indicator of this quadratic term is the squared value of the relevant latent variable score obtained in stage 1. Furthermore, the latent variable scores obtained in the previous stage act also as indicators of the first-order term in the model and the endogenous construct, respectively. Figure 17.7 graphically presents the two-stage approach for a formative exogenous construct assessing attribute performance. Note that, although in Fig. 17.7 the formative exogenous construct only has a single indicator, the approach is readily applicable to multi-item formative exogenous constructs. Likewise, the approach can be easily extended to higher-order polynomial effects.

As evidenced by Henseler and Chin (2010), the analytical approach to be used for reflective exogenous construct is less straightforward, as the optimal choice depends on the objective of the researcher. Henseler and Chin (2010) distinguish three different types of research objectives: assessing the significance of the polynomial effect (case 1), finding an estimate for the true parameter of the polynomial effect

²Technically, the hybrid approach is also a feasible approach (see also Henseler et al. 2012). However, as this approach is not available in any of the standard PLS-SEM software packages, this approach will not be discussed in this chapter.

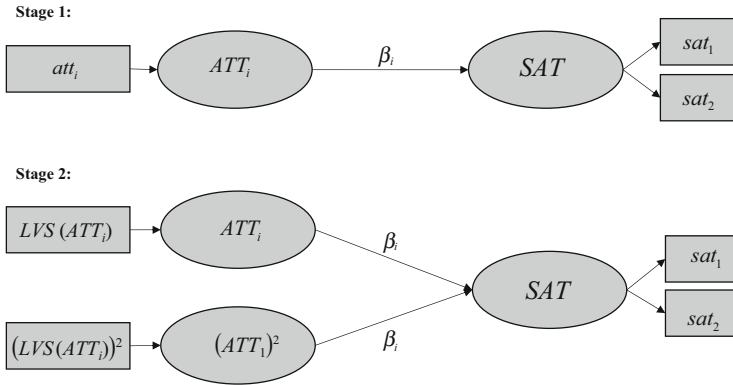


Fig. 17.7 Two-stage approach PLS-SEM (quadratic effect)

(case 2), and predicting the endogenous construct (case 3). All three cases will be discussed below.

Case 1: Assessing the Statistical Significance of the Polynomial Effect If the researcher is primarily interested in the significance of the polynomial effect, the two-stage approach is the method of choice. Here, a similar approach as outlined above for formative exogenous constructs applies.

Case 2: Finding Estimate of the True Parameter of the Polynomial Effect If the researcher is interested in finding an estimate for the true parameter of a polynomial effect, Henseler and Chin (2010) recommend using the orthogonalizing approach. Drawing upon Lance’s (1988) residual centering technique, orthogonalizing essentially involves creating polynomial terms that are uncorrelated with (i.e., orthogonal to) its lower-order constituents. In the relationship between satisfaction and loyalty, satisfaction is measured by two reflective indicators (i.e., sat_1 and sat_2). We follow the procedure outlined by Henseler and Chin (2010) and Little et al. (2006). The computations for the quadratic and cubic term and the accompanying PLS-SEM models for the orthogonalizing approach are presented in Figs. 17.8 and 17.9, respectively.

Case 3: Prediction of Endogenous Construct The third and final case that needs to be distinguished with reflective exogenous constructs occurs when a researcher strives for optimal prediction accuracy of the target construct. In this case, Henseler and Chin (2010) recommend using either the orthogonalizing approach (see also Figs. 17.8 and 17.9) or the product-indicator approach. For the relationship between satisfaction (two reflective items) and loyalty (three reflective items), the product-indicator approach is shown in Fig. 17.10.

As mentioned above, key advantages of the polynomial approach are that it is flexible and the user does not need to specify the exact functional form in advance. Moreover, the often mentioned disadvantage of multicollinearity can be relatively easily resolved by orthogonalizing the involved terms. An important drawback of

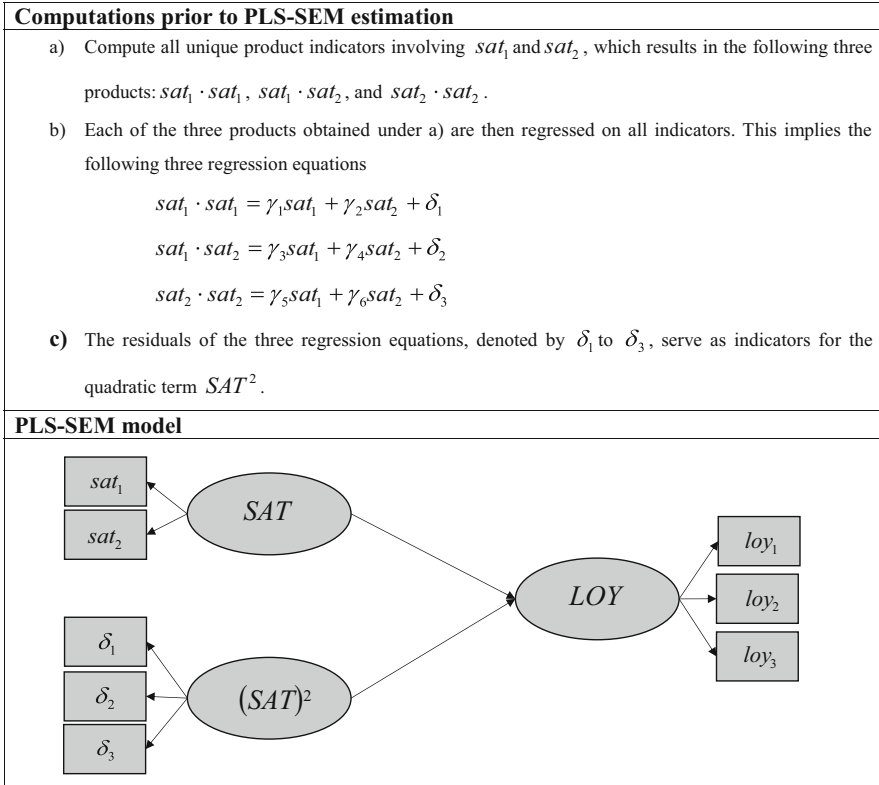


Fig. 17.8 Orthogonalization approach quadratic term

the polynomial model is the need for ratio-scaled data for the exogenous constructs (Carte and Russell 2003). Although Russell and Bobko (1992) recommend using continuous rating scales to solve this issue (see also Sect. 17.4.1.3), it needs to be acknowledged that for many constructs in business research, ratio scales do not exist. Although not impossible to create, it may represent a considerable challenge for researcher to develop ratio scales. Another disadvantage of the polynomial model is that it does not capture consistently decreasing or increasing returns (see also Streukens and De Ruyter 2004). For instance, the quadratic function describing the relationship between a *must-be* attribute and overall satisfaction may reach a maximum value after which the relationship under consideration becomes negative, which conflicts with the theory underlying the SPC.

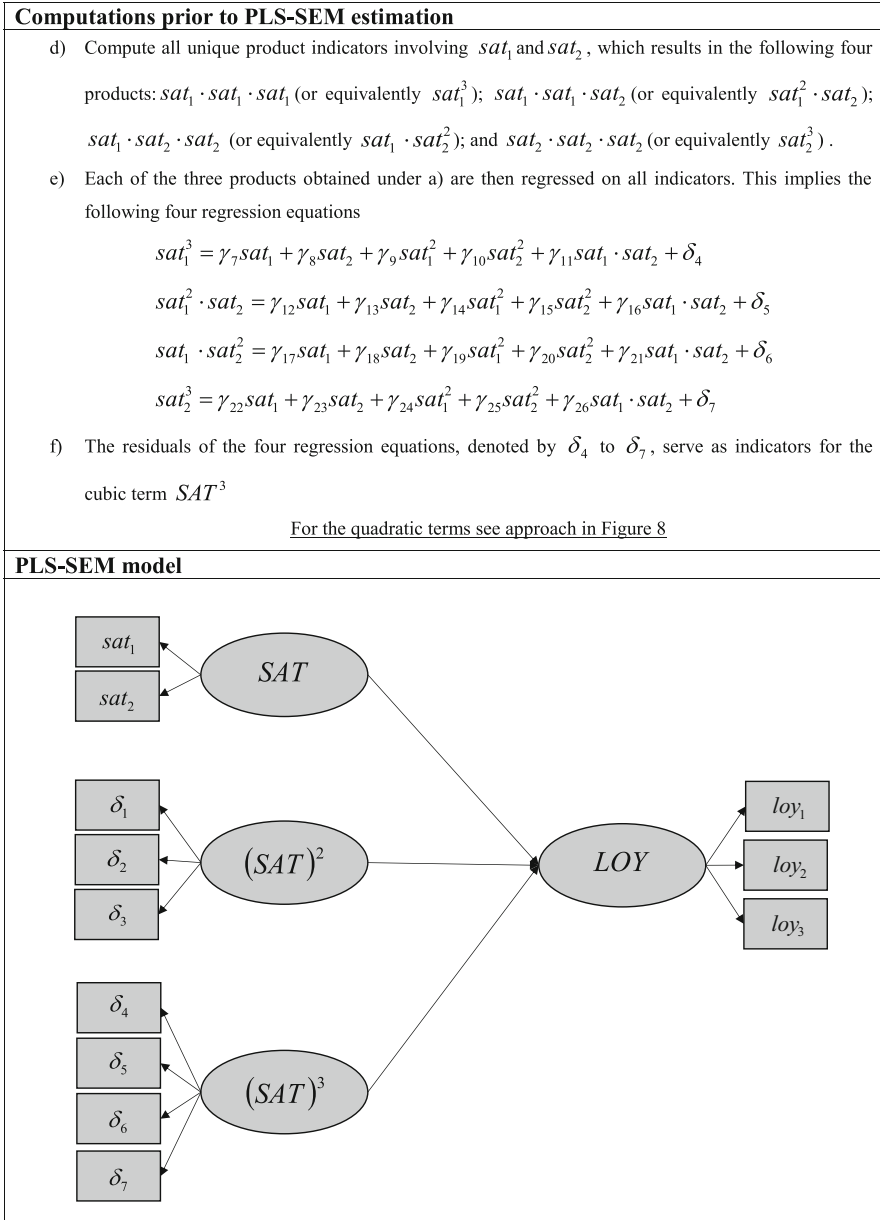


Fig. 17.9 Orthogonalization approach cubic term

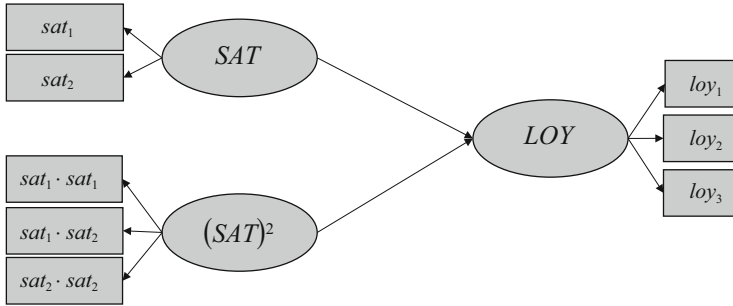


Fig. 17.10 Product-indicator approach (quadratic model)

17.4.2.3 PLS-SEM with Transformed Variables: The Linear-Log Model and the Log-Linear Model

This section introduces two models with transformed variables, namely, the linear-log model and the log-linear model, that are directly related to the basic linear PLS-SEM model. The name “transformed variables” stems from the fact that by transforming either the criterion or predictor variable, the standard linear PLS-SEM model can be used to capture a nonlinear functional form. Given the log-linear and linear-log models’ kinship to the linear PLS-SEM model, the discussion of PLS-SEM with transformed variables will use the commonly-used linear model as a starting point. Although the focus in the sections below is on the relationship between attribute performance and overall satisfaction, the models can be readily applied to other relationships as well, e.g., the satisfaction-loyalty link.

The Linear Model For the simplest case of the relationship between overall satisfaction and performance of a single attribute, the linear model is defined as shown in Eq. (17.5):

$$SAT = \beta_i ATT_i \tag{17.5}$$

In terms of Kano’s framework, this linear model is suitable for capturing the relationship between performance on a *one-dimensional* attribute and a higher-order evaluative judgment such as customer satisfaction.

The Linear-Log Model Relationships which are characterized by decreasing returns can be captured by means of a so-called linear-log model, which is shown in Eq. (17.6). Compared to the linear model (see also Eq. 17.5), the linear-log model uses the natural logarithm of the original variable as predictor. In terms of Kano’s model, the linear-log model is suitable for modeling *must-be* attributes.

$$SAT = \beta_i \ln ATT_i \tag{17.6}$$

The Log-Linear Model In contrast to *must-be* attributes, the relationship between *attractive* attributes and a higher-order customer evaluative judgment displays

increasing returns. Also in this case, a simple variation of the basic model presented in Eq. (17.5) can be used to adequately capture this specific relationship. That is, increasing returns can be modeled by means of a log-linear model. Compared to the basic linear model, the log-linear model uses the natural logarithm of the original dependent variable as criterion. The general structure of a log-linear model is shown in Eq. (17.7):

$$\ln SAT = \beta_i ATT_i \tag{17.7}$$

Their obvious kinship to the linear model which is typically used and the ease with which the linear-log model and log-linear model can be implemented in a PLS-SEM context are key advantages of these models. To learn more about the implementation in a PLS-SEM context of the models implied by Eqs. (17.5)–(17.7), see the three upper panels in Fig. 17.11. Consistent with marketing literature and practice, single-item attribute performance measures are assumed, and a reflective multiple-item scale is assumed for the satisfaction construct in the models shown in Fig. 17.11.

It is important to stress that the models outlined in Eqs. (17.5)–(17.7) and shown in Fig. 17.11 require the specification of the functional form in advance. That is, one needs to know prior to the estimation whether one is dealing with a *one-*

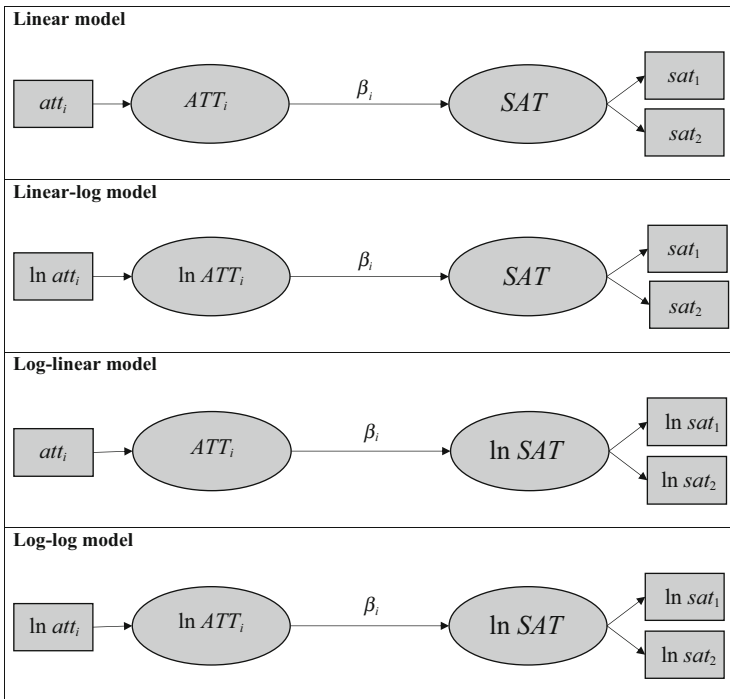


Fig. 17.11 PLS-SEM with transformed variables

dimensional, *must-be*, or *attractive* attribute. Although this may be perceived as a disadvantage, this drawback can be solved by carrying out an additional study in which Kano et al.'s (1984) approach to classifying attributes is applied. See the work of Mikulić and Prebežac (2011; pp. 48–51) for a detailed description of this attribute classification approach. Another problem arises when a relationship with increasing returns needs to be included in a single model that also needs to account for a linear relationship and/or a relationship displaying decreasing returns. Because the dependent variable of the log-linear model is different than the dependent variable of the linear and linear-log model, they cannot be included in a single model. For example, suppose attribute 1 (ATT_1) is a *one-dimensional* attribute, attribute 2 (ATT_2) is a *must-be* attribute, and attribute 3 (ATT_3) is an *attractive* attribute. Including *attractive* attribute ATT_3 in the same equation as ATT_1 and ATT_2 is not possible, as the dependent variable for the attribute ATT_3 differs from the dependent variable in modeling the impact of the latter two attributes (i.e., $\ln SAT$ vs. SAT). One possible way to overcome this problem is to estimate separate equations. However, this possibility is undesirable as it leads to biased coefficient estimates due to the omission of relevant variables.

17.4.2.4 PLS-SEM with Transformed Variables: The Log-Log Model

In line with its name, the log-log model involves taking the natural logarithm of both the dependent and independent variable. Departing from the basic model (see also Eq. 17.5), the log-log model is defined as shown in Eq. (17.8):

$$\ln SAT = \beta_i \ln ATT_i \quad (17.8)$$

The log-log model can account for all the functional forms implied by the Kano model without having to specify in advance the nature of the relationship. The magnitude of the model parameter β_i reveals the functional form best describing the relationship between variables involved. More specifically, $\beta_i = 1$ implies a linear relationship (i.e., *one-dimensional* attribute), $\beta_i > 1$ corresponds with increasing returns (i.e., *attractive* attribute), and $0 < \beta_i < 1$ reflects decreasing returns (i.e., *must-be* attribute). The fourth panel in Fig. 17.11 indicates how the log-log model can be applied in a PLS-SEM context. Just as for the other models related to the attribute performance-satisfaction link, a single-item attribute performance measurement model and a reflective multiple-item scale for satisfaction are assumed.

To understand the exact nature of the functional form (see, for instance, the work of Streukens and De Ruyter 2004), bias-corrected and accelerated bootstrap confidence intervals (see also Streukens and Leroi-Werelds 2016) need to be constructed to test whether $\beta_i = 1$, $\beta_i > 1$, or $0 < \beta_i < 1$.

Overall, in comparison to other models with transformed variables (i.e., log-linear model and linear-log model), the log-log model offers an elegant solution to the two drawbacks associated with the former type of models, namely, a priori

specification of functional form and incorporating *attractive* attributes in single models with *must-be* and/or *one-dimensional* attributes.

To conclude this part on modeling different functional forms, Table 17.1 summarizes the advantages and disadvantages associated with the different approaches available to account for nonlinear functional forms. It is important to stress the role of theory in opting for the appropriate functional forms.

17.4.3 Stage 3: Interpretation of Results

The third and final stage of our framework focuses on the interpretation of the analytical results. This stage is critical in making the transition from statistical output to actionable results.

17.4.3.1 Requirement Check

Regardless of the measurement model being reflectively or formatively specified, an important requirement to determine the performance scores on the latent variable level is that all outer weights are positive (Ringle and Sarstedt 2016; Tenenhaus et al. 2005). Cenfetelli and Bassellier (2009) and Ringle and Sarstedt (2016) acknowledge the problem of co-occurrence of both positive and negative weights and warn for the adverse effects this may have on the interpretation of the results. Different reasons, conceptual as well as methodological, may underlie the co-occurrence of positive and negative weights. Depending on the cause, different courses of action are needed.

Conceptually, a negative indicator weight may result from the opposite formulation of the corresponding questionnaire item. In such instances, the researcher has to reverse the scale on which the item was measured.

Methodologically, negative indicator weights may be the result of multicollinearity. Inspection of the VIF values provides evidence of the existence of multicollinearity. In case of substantial multicollinearity (i.e., $VIF \geq 5$), the researcher may consider deleting indicators, constructing higher-order constructs, or combining collinear indicators into a single new composite indicator (see Hair et al. 2014, p. 125 for more information).

Dijkstra and Henseler (2011) propose the use of best-fitting proper indices (BFPI) to assure that the indicator weights (as well as the loading) for a formative measurement model are nonnegative (i.e., proper). Despite its apparent attractive features, a current drawback of using BFPI is that it is not, to the best of our knowledge, available in software packages such as SmartPLS 3 (Ringle et al. 2015).

Table 17.1 (Dis)advantages of the different approaches to model nonlinear effects

	Penalty-reward contrast analysis	Linear-log and log-linear model	Polynomial model	Log-log model
Advantages	<ul style="list-style-type: none"> • Easy to use 	<ul style="list-style-type: none"> • Models nonlinearity • Monotone function 	<ul style="list-style-type: none"> • Models nonlinearity Flexibility, allows also for modeled (inverse) S-shaped functions <ul style="list-style-type: none"> • Does not require a priori specification of functional form 	<ul style="list-style-type: none"> • Models nonlinearity • Monotone function Does not require a priori specification of functional form
Disadvantages	<ul style="list-style-type: none"> • Can model asymmetry, but not nonlinearity 	<ul style="list-style-type: none"> • A priori specification of functional form • Increasing returns cannot be modeled in a single equation with decreasing returns or a linear functional form 	<ul style="list-style-type: none"> • Requires ratio-scaled variables • Non-monotone function (theoretical validity) • Multicollinearity (can be solved by orthogonalization) 	<ul style="list-style-type: none"> • Only models linear, monotonically increasing and decreasing functions (i.e., no (inverted) S-shaped functions)

17.4.3.2 Importance Scores: Marginal Effects

To assess the impact or importance of a driver on the target, the structural model parameters play a pivotal role. In this respect, it is not necessarily the structural model parameters per se we are interested but rather the rate of change in a target construct for a driver or the driver's marginal effect. Mathematically, the first (partial) derivative of any type of equation gives the formula for the rate of change in the criterion variable for any predictor variable (Johnson et al. 1978; Stolzenberg 1980).

For a simple linear model (e.g., in the format of $SAT = \beta_i ATT_i$), the first derivative boils down to β_i and thus equals the structural model coefficient that can be readily derived from the PLS-SEM output. For all other functional forms discussed above, the marginal effect of a particular driver on a target construct is less straightforward but still can be derived from the PLS-SEM output. Just as for a simple linear function, the first derivative equals the marginal effect, but it yields a formula rather than a constant (see also Stolzenberg 1980). Table 17.2 summarizes the first derivatives for the different functions discussed in this chapter.

To arrive at the actual value reflecting the importance of a certain driver, the mean score of the latent or indicator variable is plugged into the equations listed in Table 17.2 (see also Roncek 1991, 1993).

In line with PLS-SEM's capability to integrally assess a nomological network of relationships, the importance rating equals the total effect of the driver on an endogenous construct of interest. That is, the idea of the total effects as expressed by Eq. (17.2) still applies when the nomological network contains one or more nonlinear effects. However, in this latter case, the formulae presented in Table 17.2 represent the different marginal effects that need to be used in combination with Eq. (17.2) to compute the total effect (see also Streukens et al. 2011).

17.4.3.3 Performance Scores

The determination of the performance scores in an IPMA remains unaffected by the nature of the relationships connecting the different constructs. Hence, the same guidelines as discussed in Sect. 17.2.2 apply. It should be noted the performance scores need to be calculated for the untransformed variables.

17.4.3.4 Cutoff Values

The definition of the quadrants remains arbitrary. See Sect. 17.2.4 for alternative ways to set the cutoff values that define the different quadrants.

Table 17.2 Marginal effects for the different functional forms

Approach	Accompanying function	Shape	Marginal effect
Penalty-reward contrast analysis	$SAT = \beta_1^L D_i^L + \beta_1^H D_i^H$	Piecewise linear	β_1^L or β_1^H
Linear model	$SAT = \beta_i ATT_i$	Linear	β_i
Linear-log model	$SAT = \beta_i \ln ATT_i$	Decreasing returns	β_i / ATT_i
Log-linear model	$\ln SAT = \beta_i ATT_i$	Increasing returns	$\beta_i \cdot e^{\beta_i ATT_i}$
Log-log model	$\ln SAT = \beta_i \ln ATT_i$	Various	$(SAT/ATT_i) \beta_i$
Quadratic model	$SAT = \beta_{1i} ATT_i + \beta_{2i} ATT_i^2$	Various	$\beta_{1i} + 2\beta_{2i} ATT_i$
Cubic model	$LOY = \beta_1 SAT + \beta_2 SAT^2 + \beta_3 SAT^3$	Various	$\beta_{1i} + 2\beta_{2i} SAT + 3\beta_{3i} SAT^2$

17.4.3.5 Setting the Right Priorities

Information on each driver in terms of performance and importance can be graphically presented in a two-dimensional map (see also Fig. 17.1). The subsequent resource allocation decisions are straightforward in case of linear functional forms but may be more complicated for nonlinear relationships. We summarize below the resource allocation guidelines proposed by Anderson and Mittal (2000) for *attractive* (log-linear model) and *must-be* (linear-log model) attributes. An important assumption regarding the guidelines below is that the relationships among subsequent constructs (e.g., the link between satisfaction and loyalty) are linear.

For *attractive* attributes that are characterized by both a high performance and a high importance score, the current investments should be maintained (“Keep up the good work”). When *attractive* attributes are characterized by low performance and low importance scores, no improvement initiatives need to be undertaken as an increase in performance will yield only a very limited increase in importance (i.e., flat part of the nonlinear relationship). *Must-be* attributes display diminishing returns, which means that the performance increases have a diminishing effect as the level of performance rises. Anderson and Mittal (2000) therefore recommend investments to improve the performance of *must-be* attributes which are important but on which the performance is still low.

17.4.3.6 Validation

In line with the prediction-oriented nature of PLS-SEM, being able to generate out-of-sample predictions from a model and to evaluate its predictive power is vital when conducting an IPMA (cf. Shmueli et al. 2016; Carrión et al. 2016). As outlined below, several approaches are available to assess the model’s predictive performance.

Carrión et al. (2016) strongly recommend the use of a split-sample approach (“holdout samples”) as a means for establishing whether or not a model has an adequate level of predictive performance. In their work, they provide an excellent overview of how to implement this in a PLS-SEM context.

In case of small- to medium-sized samples, the abovementioned split-sample approach may not be feasible as partitioning the already relatively small sample size into a training and validation sample can introduce too much bias. For these situations, Shmueli et al. (2016) propose the use of a k-fold cross-validation approach. With regard to this k-fold cross-validation approach, which is available in SmartPLS 3 (Ringle et al. 2015) under the name “blindfolding,” Shmueli et al. (2016) and Rigdon (2014) rightly point out that the traditionally reported Stone-Geisser Q^2 statistics suffer from serious limitations and should only be used with the greatest care.

Another way of assessing predictive performance is to use samples from other contexts as validation samples. In a PLS-SEM context, this is demonstrated in the work of Miltgen et al. (2016). In a similar vein as the split-sample approach

suggested by Carrión et al. (2016), this approach involves using parameter estimates from the original sample to predict the outcomes in another external sample.

17.5 Empirical Illustration³

This fifth section demonstrates how the log-log model can be used in an IPMA. Data were collected from customers of a European DIY company whose business consisted of providing customers with the resources needed to install ventilation systems by themselves. All analyses were performed using SmartPLS 3 (Ringle et al. 2015).

17.5.1 Stage 1: Research Design

Based on interviews with a set of customers ($n = 10$), six attributes were identified as being drivers of customer satisfaction. These six items can be found in Table 17.3.

For each attribute, the questionnaire included a single item to tap customers' quality perceptions. The respondents were asked to rate each attribute's quality on a 9-point Likert scale (1 = very low quality, 9 = very high quality). In a similar vein, overall satisfaction was measured using single item in combination with a 9-point Likert scale (1 = very dissatisfied, 9 = very satisfied). The accompanying descriptive statistics can be found in Table 17.3. In total, an effective sample size of $n = 149$ was obtained.

As can be observed in subsequent figures, we employed a single-item measurement model for each attribute. Technically this implies that the IPMA at the latent construct level and IPMA at the indicator level coincide.

17.5.2 Stage 2: The Functional Forms of the Relationships

The log-log model was used to account for possible nonlinearity in the attribute-satisfaction relationships. The key advantage of the chosen approach is that one does not have to specify the functional form in advance. Prior to running the model in SmartPLS 3 (Ringle et al. 2015), the natural log transformation was performed on all variables involved. For reasons to be explained later on in Sect. 17.5.3, the researcher is advised to construct a data file that contains both the original variables and the transformed variables.

³All files pertaining to this application are available upon request from the first author.

Table 17.3 Results of empirical application

	Mean	SD	Performance (0–100%)	Unstandardized structural model coefficient	BCa percentile bootstrap CI	Marginal effect	BCa percentile bootstrap CI shape	Shape
Attribute: quality products (IQ01)	7.74	1.15	84.312	0.610	[−0.069;0.576]	–	–	–
Attribute: quality-provided tools (IQ02)	7.53	1.39	81.628	0.146	[−0.296;0.329]	–	–	–
Attribute: quality working plan (IQ03)	6.11	2.13	63.926	0.255	[0.028;0.451]	0.281	[−0.963;−0.364]	Decreasing returns
Attribute: quality delivery (PQ01)	5.79	2.38	59.815	0.314	[0.030;0.627]	0.370	[−0.964;−0.562]	Decreasing returns
Attribute: quality invoicing (PQ02)	5.68	2.43	58.473	0.084	[−0.151;0.374]	–	–	–
Attribute: quality-finished installation (OQ01)	7.96	0.99	82.681	0.023	[−0.099;0.151]	–	–	–
Overall satisfaction with company (SAT)	6.64	2.13	70.554					

Note: Marginal effects and the bootstrap confidence interval regarding functional form (shape) are only computed for significant attributes

To estimate the log-log model, the structural model as shown in Fig. 17.12 panel A is run. The unstandardized coefficients (cf. Hock et al. 2010) and the accompanying bias-corrected and accelerated percentile bootstrap confidence intervals based on 10,000 samples (cf. Streukens and Leroi-Werelds 2016) are presented in Table 17.3. Note that in SmartPLS 3 (Ringle et al. 2015), the option “importance-performance matrix analysis (IPMA)” was selected as this automatically yields the unstandardized coefficients and the rescaled performance scores.

Note that for the significant attributes, bootstrap confidence intervals were constructed to determine the shape of the functional forms describing the relationship between the attribute’s performance and overall satisfaction. Based on the results listed in Table 17.3, it can be concluded that the two significant attributes are so-called *must-be* attributes.

17.5.3 Stage 3: Interpretation

As evidenced in Table 17.1, the marginal effects for the log-log model depend on the value of the (in)dependent constructs involved. Hence, in order to obtain the appropriate importance scores for the situation at hand, the performance scores of the relevant variables need to be imputed in equations describing the marginal effects for the log-log model (see Table 17.2). For this aim, either the original *untransformed* variables or the *rescaled* performance of the *untransformed* variables, both of which can be found in Table 17.3, can be used. A quick way to obtain the *rescaled* performance scores of the *untransformed* variables is to run the PLS-SEM model with the untransformed variables (see also Fig. 17.12, panel B). This is the reason why the researcher was advised to store both the transformed and untransformed variables in a single data file. Table 17.2 contains the marginal effects for the different attributes. Also for this second estimation run, the option “importance-performance matrix analysis” was selected in the program. It is important to stress that the second estimation (estimation of model shown in Fig. 17.12, panel B) is technically not required to determine the performance scores. Rather, it is merely a handy shortcut to obtain the rescaled performance levels.

The actual IPMA chart can be created using Microsoft Excel. Although SmartPLS 3 (Ringle et al. 2015) can produce these charts automatically, the nonconstant marginal effects in the case of nonlinear functional forms cannot (yet) be taken into account by the program. The only data needed to construct the chart are the importance and performance scores described in the previous section and listed in Table 17.3. In Table 17.3, the entries in the column named “Performance (0–100%)” provide the x-axis coordinates (i.e., driver performance), and the entries in the columns named “Marginal effects” provide the y-axis coordinates (i.e., driver importance). The resulting chart, shown in Fig. 17.13, only contains two data points as we only include drivers that have a significant impact on the target construct.

The cutoff values for the axis are determined as follows. For the importance score, a cutoff value of 0.30 is used, which corresponds to a medium effect size

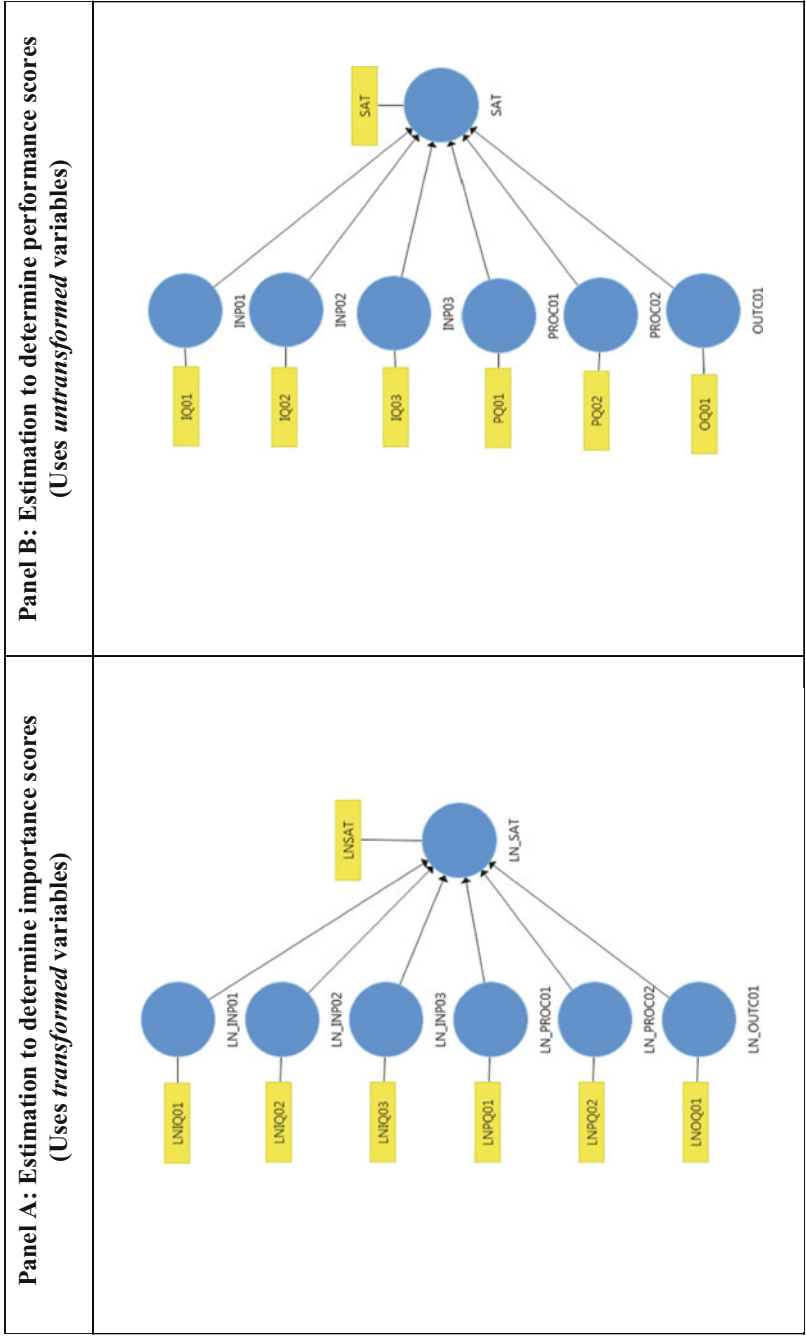


Fig. 17.12 PLS-SEM models accompanying empirical demonstration IPMA

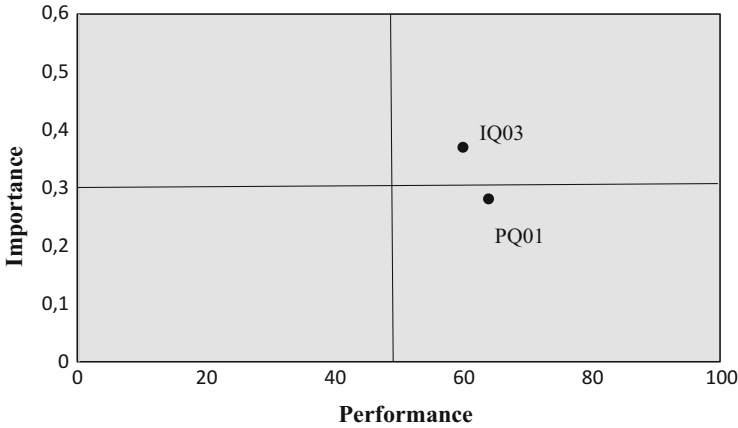


Fig. 17.13 IPMA chart empirical illustration

for correlation coefficients. For the performance score, the cutoff value equals 50, which is the midpoint of the 0–100 range to which the drivers are rescaled.

Based on the chosen cutoff values, attribute IQ03 (quality working plan) falls in the quadrant “Keep up the good work,” whereas attribute PQ01 (quality delivery) falls in the “Possible overdrive” quadrant. This would imply that investments to at least maintain the perceived performance of attribute IQ03 are warranted, whereas investments to maintain the perceived performance of attribute PQ01 are less relevant. Given that resources are scarce, one could even argue that resources currently spent on PQ01 could be (partly) reallocated to maintaining or even improving the performance on attribute IQ03.

Ideally, the final step involves the validation of the findings. Unfortunately, the sample size was too small to apply a split-sample procedure, nor was an external validation sample available.

17.6 Conclusion

In times when managers are increasingly held accountable for the financial performance implications of their strategic actions, IPMA is an effective method to help set priorities and to optimally allocate scarce resources. As convincingly argued by Ringle and Sarstedt (2016), IPMA adds valuable additional insights above and beyond the results of a standard PLS-SEM.

Consistent with the view expressed in the academic literature across various domains that the structural model relationships do not necessarily exhibit a linear functional form, a strategically relevant IPMA must be able to take into account possible nonlinearities in the inter-construct relations.

In response to the need for IPMAs that will contribute to optimal strategic decision-making, this chapter proposes an integrative IPMA framework in which the possibility of nonlinear functional structural relationships is explicitly accounted for. Although the suggested IPMA framework is applicable regardless of the analytical approach to model the involved relationships that ultimately yield the importance score, we have deliberately chosen to discuss the framework through a PLS-SEM lens. The value of PLS-SEM as a basis for an IPMA stems from the fact that PLS-SEM is capable of integrally estimating complex nomological networks of relationships and can take into account latent constructs as well.

Compared to previous IPMA guidelines, the proposed framework takes a broader perspective on IPMA than just a data analytical tool. Rather, designing and conducting an IPMA that is both managerially relevant and theoretically sound start already at the research design stage. Moreover, in line with PLS-SEM's prediction-oriented nature, validation is suggested to constitute an essential element of IPMA.

Within the proposed IPMA framework, the estimation of (possible) nonlinear relationships plays a dominant role. We compare and contrast several approaches to account for a variety of functional forms in a PLS-SEM context. Similar to the overall IPMA framework, the focus on PLS-SEM in modeling nonlinearities in no way limits the generalizability of our work.

Complementing existing work on modeling nonlinear function in a PLS-SEM context, this study introduces the log-log model as a flexible approach to capture all possible functional forms without having to specify the functional form in advance. Being a direct extension of the commonly used linear model, the log-log model will be easy to apply for most PLS-SEM users.

We drew upon the SPC to illuminate and empirically illustrate the ideas put forward in the suggested framework. Also regarding this choice, it is pivotal to stress that this does not limit the generalizability of our work in any way. Despite the focus on a specific substantive domain, we sincerely believe that access to the data and other files associated with our empirical application may have a positive impact on the practical implementation of our ideas. Hence, feel free to ask for them, use them, and adapt them to your own IPMA in the hope to arrive at a truly valuable IPMA and to get even more from your PLS-SEM results than ever before.

Regarding the link between overall satisfaction and loyalty, the literature proposes even a larger variety of functional forms that may describe this relationship. The log-log model is not capable of capturing all of the suggested functional forms by Dong et al. (2011). To account for all the possible functional forms of the satisfaction-loyalty link, a cubic model offers the most flexible approach. Similar to the log-log model, the cubic model does not require to specify the functional form in advance. However, a key drawback of the cubic model is that it requires the use of ratio data (Carte and Russell 2003), which may not always be possible to collect. Finally, although the current study focuses on customer satisfaction and PLS-SEM, the proposed IPMA framework and the approaches to capture nonlinear functional forms are also applicable in other contexts.

17.7 Limitations and Suggestions for Further Research

This study has not taken into account possible dynamic effects. Past research (e.g., Bolton 1998) has shown that changes in performance have a different effect on satisfaction depending on the duration of the relationship. In a similar vein, Mittal et al. (1999) provide empirical evidence that the nature of the attribute performance-satisfaction link may change over time. More research is needed on how these effects can be incorporated in an IPMA to optimize strategic decisions.

Closely related to the previous point is the recognition that the relationships in the SPC vary as a function of customer characteristics (e.g., see Garbarino and Johnson 1999; Mittal and Katrichis 2000). If customer characteristics that influence the relationships determining the importance scores in an IPMA can be identified beforehand, this problem may be solved by conducting a separate IPMA for each segment. If customer heterogeneity is unobserved, as is often the case, possible solutions may be found along the lines of FIMIX PLS-SEM. Hence, a promising avenue for future research is how to make strategic resource allocation decisions while taking into account observed customer heterogeneity.

Hopefully the integrative IPMA framework proposed in this chapter advances the existing knowledge and skills to make well-informed strategic decisions. The focus of the current chapter is on the increase in attribute performance and other constructs which ultimately translate into enhanced revenues (i.e., SPC). To fully understand the impact of investments associated with strategic decisions, both the revenues and the costs of the investment need to be taken into account (Zhu et al. 2004). As such, research that places the results from an IPMA in a larger investment framework, such as proposed by Streukens et al. (2011), might further increase the managerial relevance of the suggested framework.

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