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Gain more insight from your PLS-SEM results: The importance-performance map analysis

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# Gain more insight from your PLS-SEM results

Importance-  
performance  
map analysis

## The importance-performance map analysis

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### Abstract

**Purpose** – The purpose of this paper is to introduce the importance-performance map analysis (IPMA) and explain how to use it in the context of partial least squares structural equation modeling (PLS-SEM). A case study, drawing on the IPMA module implemented in the SmartPLS 3 software, illustrates the results generation and interpretation.

**Design/methodology/approach** – The explications first address the principles of the IPMA and introduce a systematic procedure for its use, followed by a detailed discussion of each step. Finally, a case study on the use of technology shows how to apply the IPMA in empirical PLS-SEM studies.

**Findings** – The IPMA gives researchers the opportunity to enrich their PLS-SEM analysis and, thereby, gain additional results and findings. More specifically, instead of only analyzing the path coefficients (i.e. the importance dimension), the IPMA also considers the average value of the latent variables and their indicators (i.e. performance dimension).

**Research limitations/implications** – An IPMA is tied to certain requirements, which relate to the measurement scales, variable coding, and indicator weights estimates. Moreover, the IPMA presumes linear relationships. This research does not address the computation and interpretation of non-linear dependencies.

**Practical implications** – The IPMA is particularly useful for generating additional findings and conclusions by combining the analysis of the importance and performance dimensions in practical PLS-SEM applications. Thereby, the IPMA allows for prioritizing constructs to improve a certain target construct. Expanding the analysis to the indicator level facilitates identifying the most important areas of specific actions. These results are, for example, particularly important in practical studies identifying the differing impacts that certain construct dimensions have on phenomena such as technology acceptance, corporate reputation, or customer satisfaction.

**Originality/value** – This paper is the first to offer researchers a tutorial and annotated example of an IPMA. Based on a state-of-the-art review of the technique and a detailed explanation of the method, this paper introduces a systematic procedure for running an IPMA. A case study illustrates the analysis, using the SmartPLS 3 software.

**Keywords** Structural equation modeling (SEM), Partial least squares (PLS), Unified theory of acceptance and use of technology (UTAUT), SmartPLS, Importance-performance map analysis (IPMA)

**Paper type** General review



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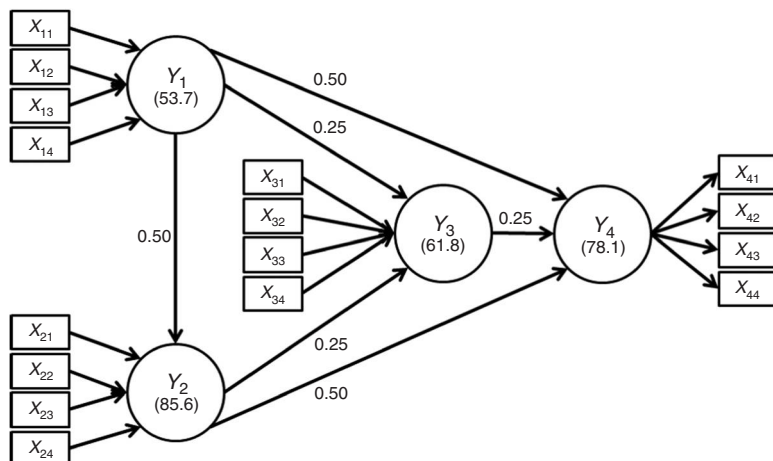
**Introduction**

Partial least squares structural equation modeling (PLS-SEM; Chin, 1998; Garson, 2014; Hair *et al.*, 2017; Lohmöller, 1989; Rigdon, 2013; Tenenhaus *et al.*, 2005; Wold, 1982) is a variance-based method to estimate path models with latent variables. The PLS-SEM approach is particularly useful when the study's focus is on the analysis of a certain target construct's key sources of explanation. For example, the technology acceptance model (TAM; Davis, 1989; Davis *et al.*, 1989) and its various extensions, such as the unified theory of acceptance and use of technology (UTAUT; Venkatesh *et al.*, 2003), are popular models for PLS-SEM applications in management information systems research. In the marketing field, the American Customer Satisfaction Index (ACSI) model (Anderson and Fornell, 2000; Fornell *et al.*, 1996) is another widespread PLS-SEM application. PLS-SEM enjoys rapidly increasing usage in various business disciplines, such as accounting (Lee *et al.*, 2011), family business (Sarstedt *et al.*, 2014), international business (Richter *et al.*, 2015), management information systems (Ringle *et al.*, 2012), marketing (Hair *et al.*, 2012), operations management (Peng and Lai, 2012), strategic management (Hair *et al.*, 2012a), and tourism research (do Valle and Assaker, 2015).

The purpose of this paper is to explain and illustrate the use of the importance-performance map analysis (IPMA; also called importance-performance matrix, impact-performance map, or priority map analysis), a useful analysis approach in PLS-SEM that extends the standard results reporting of path coefficient estimates by adding a dimension that considers the average values of the latent variable scores. More precisely, the IPMA contrasts the total effects, representing the predecessor constructs' importance in shaping a certain target construct, with their average latent variable scores indicating their performance (Fornell *et al.*, 1996; Martilla and James, 1977; Slack, 1994). The goal is to identify predecessors that have a relatively high importance for the target construct (i.e. those that have a strong total effect), but also have a relatively low performance (i.e. low average latent variable scores).

**Illustrative example**

To illustrate the concept of an IPMA, consider the PLS path model in Figure 1 with four constructs  $Y_1$ - $Y_4$ . In this PLS path model,  $Y_4$  represents the final target variable,



**Figure 1.**  
IPMA model

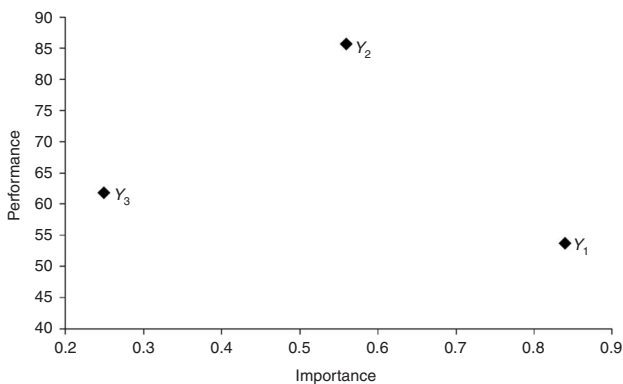
directly predicted by  $Y_1$ - $Y_3$ . Furthermore,  $Y_1$  and  $Y_2$  have indirect effects on  $Y_4$  via  $Y_3$ . Adding the predecessor constructs' direct and indirect effects yields their total effects on  $Y_4$ , which represent the importance dimension in the IPMA. In contrast, these constructs' average latent variable scores represent their performance, in the sense that high values indicate a greater performance.

The IPMA combines these two aspects graphically by contrasting the (unstandardized) total effects on the  $x$ -axis with the latent variable scores, rescaled on a range from 0 to 100, on the  $y$ -axis. The result is a chart such as in Figure 2. For the results interpretation, we focus on constructs in the lower right area of the importance-performance map. These constructs have a high importance for the target construct, but show a low performance. Consequently, there is a particularly high potential to improve the performance of the constructs positioned in this area.

In Figure 2,  $Y_1$  is particularly important to explain the target construct  $Y_4$ . More precisely, a one-unit point increase in  $Y_1$ 's performance increases the performance of  $Y_4$  by the value of  $Y_1$ 's total effect on  $Y_4$ , which is 0.84 (*ceteris paribus*). Since the performance of  $Y_1$  is relatively low, there is substantial room for improvement, making the aspect underlying this construct particularly relevant for managerial actions. While this introductory example shows an IPMA on the construct level, the analysis can also be run on the indicator level. In this case, individual data points in the importance-performance map are derived from indicator mean values and their total effect on a particular target construct.

### The IPMA procedure

PLS-SEM studies that draw on IPMA results offer important insights into the role of antecedent constructs and their relevance for managerial actions (e.g. Grønholdt *et al.*, 2015; Höck *et al.*, 2010; Kristensen *et al.*, 2000; Martensen *et al.*, 2007; Martensen and Grønholdt, 2010). The IPMA also becomes particularly useful when contrasting PLS-SEM results from a multigroup analysis (Hair *et al.*, 2017; Sarstedt *et al.*, 2011), as several studies illustrate (Rigdon *et al.*, 2011; Schloderer *et al.*, 2014; Völckner *et al.*, 2010). However, to date, no comprehensive tutorial highlights the requirements for using the method, or offers a step-by-step introduction to its use. Against this background, this paper presents a state-of-the-art review and detailed explanation of



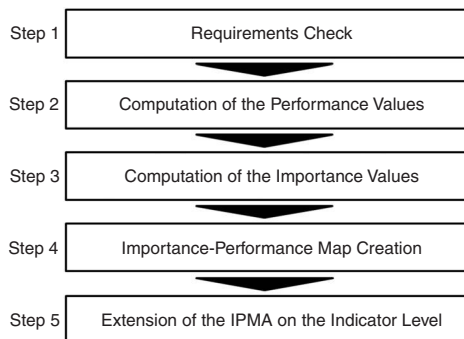
**Figure 2.**  
Importance-  
performance  
map of the target  
construct  $Y_4$

the IPMA. A case study on the TAM illustrates the analysis, using the SmartPLS 3 (Ringle *et al.*, 2015) software. The paper explains an IPMA by following the five-step procedure as shown in Figure 3.

When using an IPMA, the first step involves checking if the requirements for carrying out the analysis have been fulfilled (Step 1). The analysis proceeds with the computation of the latent variables' performance values (Step 2) and their importance values (Step 3). The importance-performance map creation for a selected target construct is based on these results (Step 4). Finally, the IPMA can be extended on the indicator level to obtain more specific information on the most effective managerial actions (Step 5). The following sections explain each step in greater detail.

### Step 1: requirements check

IPMA applications have to meet three requirements. First, the rescaling of the latent variable scores on a range from 0 to 100 requires all indicators in the PLS path model to use a metric or quasi-metric scale (Sarstedt and Mooi, 2014). Second, all the indicator coding must have the same scale direction. The minimum value of an indicator must represent the worst outcome and the maximum value must represent the best outcome of an indicator. Otherwise, we cannot conclude that higher latent variable scores represent better performance. If the indicator coding has a different direction compared to the other indicators in the measurement model (i.e. a high value represents a negative outcome), we must rescale the indicator. In this case, the indicator coding needs to be changed by reversing the scale (e.g. on a five-point scale, 5 becomes 1 and 1 becomes 5, 4 becomes 2 and 2 becomes 4, and 3 remains unchanged). Third, regardless of the measurement model being formatively or reflectively specified, the outer weights estimates must be positive. If the outer weights are negative, the latent variable scores will not fall within the 0-100 range, but would, for example, be between -5 and 95. Note that there are different reasons for (unexpected) negative outer weights. If an outer weight is negative and significant, the researcher should inspect the indicator and its scale. It may have another direction compared to the other indicators in the measurement model, which requires reversing the scale. In case of non-significant outer weights (with negative signs), the researcher may consider removing those indicators. Finally, negative outer weights might be a result of high indicator collinearity. For example, variance inflation factor values of 5 and higher indicate a potential collinearity problem (Hair *et al.*, 2017). In this case, the researcher may also consider removing indicators. However removing indicators from measurement models involves some additional considerations as explained by Hair *et al.* (2017; see Chapter 5) in more detail.



**Figure 3.**  
Steps of the  
importance-  
performance map  
analysis

While not being a formal requirement for running an IPMA, researchers should carefully consider PLS path model set-ups that favor IPMA use on the indicator level. When a latent variable of high priority for a specific target construct is identified, it is particularly advantageous to further analyze this predecessor construct's measurement model on the indicator level. Such an assessment is particularly useful when the measurement model is specified as formative – as is the case in our sample model in Figure 1. In this case, the indicators describe aspects that shape the corresponding construct, while their weights indicate each aspect's importance in this respect. Therefore, aspects underlying indicators with high weights should be given more attention to identify managerial actions aiming to improve the target construct's performance – see Höck *et al.* (2010) for an application. Note that the IPMA can be applied on any kind of PLS path model, regardless of whether the researcher specifies latent variables' measurement models as formative or reflective. The IPMA builds on the outer weights – as explained in more detail in the subsequent sections – and PLS-SEM always provides outer weights estimates, also when a measurement model is specified as reflective. In this context, it is important to note that the distinction between reflectively and formatively specified constructs refers to the ways how researchers develop proxies for conceptual variables and the resulting measurement approaches. While PLS-SEM readily processes reflectively and formatively specified constructs, it does so by linearly combining indicators to form composite variables. These composite variables are treated as proxies of the concepts under investigation (Rigdon, 2012, 2014) and serve as input for the IPMA in Step 2 (Figure 3). To represent formative measurement models, PLS-SEM draws on composite indicators – as opposed to causal indicators – which fully form the latent variable without an error term on the construct level (Bollen and Bauldry, 2011; Bollen and Diamantopoulos, in press). At the same time, PLS-SEM only approximates measures in reflective measurement models that draw on a factor model logic (Sarstedt *et al.*, 2016). While the “bias” that PLS-SEM produces when estimating common factor models is very small – provided that measurement models meet minimum recommended standards in terms of the number of indicators and indicator loadings – recent research has also introduced the consistent PLS approach that handles common factor model-based measures without limitations (Dijkstra and Henseler, 2015). Acknowledging the proxy character of the method (Rigdon, 2012; Sarstedt *et al.*, 2016), the following sections refer to the common denotation of reflective and formative measurement models and their standard treatment in PLS-SEM analyses.

### Step 2: computation of the performance values

The indicator data determines the latent variable scores and, thus, their performance. Similarly, when conducting an IPMA on the indicator level, the mean value of an indicator represents its average performance. When computing average values on the construct or indicator level, it is important to remember that indicators may be measured on different scales. For examples, some indicators may use a scale with values from 1 to 5, while others use a scale with values from 1 to 7, or from 1 to 9. To facilitate the interpretation and comparison of performance levels, the IPMA rescales indicator scores on a range between 0 and 100, with 0 representing the lowest and 100 representing the highest performance. Since most researchers are familiar with interpreting percentage values, this kind of performance scale is easy to understand. The rescaling of an observation  $j$  with respect to indicator  $i$  proceeds via:

$$x_{ij}^{\text{rescaled}} = \frac{E[x_{ij}] - \min[x_i]}{\max[x_i] - \min[x_i]} \cdot 100, \quad (1)$$

where  $x_i$  is the  $i$ th indicator in the PLS path model;  $E[.]$  represents indicator  $i$ 's actual score of respondent  $j$ ,  $\min[.]$  and  $\max[.]$  represent the indicator's minimum and maximum value. It is important to note that the minimum and maximum values refer to the potential values on a certain scale (e.g. 1 and 5 on a 1-5 scale) and not the minimum and maximum values of the actual responses (e.g. 2 and 4 on a 1-5 scale). Hence, if respondents use lowest actual response is 2 but the scale has a minimum value of 1, it is mandatory to use the 1 as minimum value for rescaling. For example, according to this formula, a value of 4 on a 1-5 scale becomes  $(4-1)/(5-1) \cdot 100 = 75$  while a 4 on a 1-7 scale becomes  $(4-1)/(7-1) \cdot 100 = 50$ . All data points used for estimating the PLS path model are rescaled this way.

Table I shows an excerpt of the original indicator data ( $n=300$ ) used to estimate the sample model from Figure 1. All indicators are measured on a scale from 1 to 5. Table II shows the indicator data from Table I, rescaled on a range from 0 to 100, which serve as input for the computation of the rescaled latent variable scores. In addition, the mean values of the rescaled indicators represent their performance values (e.g. 79 for indicator  $x_{11}$  and 77.5 for indicator  $x_{12}$ ), which are later used for the IPMA on the indicator level.

The rescaled latent variable scores are a linear combination of the rescaled indicator data and the rescaled outer weights – regardless whether the measurement model of a latent variable is reflective (i.e.  $Y_4$ ) or formative (i.e.  $Y_1$ - $Y_3$ ). To obtain the rescaled weights, we must first compute the unstandardized weights by dividing the standardized weights by the standard deviation of its respective indicator.

**Table I.**  
Original  
indicator data

Case	$x_{11}$	$x_{12}$	$x_{13}$	$x_{14}$	$x_{21}$	$x_{22}$	$x_{23}$	$x_{24}$	$x_{31}$	$x_{32}$	$x_{33}$	$x_{34}$	$x_{41}$	$x_{42}$	$x_{43}$	$x_{44}$
1	5	2	1	5	3	3	4	5	5	2	4	3	1	2	4	3
2	4	5	2	3	5	4	5	3	4	1	1	2	3	5	4	3
3	4	1	3	4	5	3	4	5	5	3	5	3	3	5	3	1
4	1	3	2	1	3	2	2	4	1	4	1	3	5	1	4	4
5	3	2	1	3	5	1	2	3	5	2	2	3	1	3	4	5
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
299	2	4	3	4	4	3	3	4	4	2	2	1	2	5	4	3
300	2	4	3	1	5	2	3	5	1	1	4	3	4	2	1	5
Mean value	4.2	4.1	3.4	2.3	3.6	4.5	3.4	3.1	3.4	4.7	4.4	4.6	3.4	4.2	4.5	4.2

**Table II.**  
Rescaled  
indicator data

Case	$x_{11}$	$x_{12}$	$x_{13}$	$x_{14}$	$x_{21}$	$x_{22}$	$x_{23}$	$x_{24}$	$x_{31}$	$x_{32}$	$x_{33}$	$x_{34}$	$x_{41}$	$x_{42}$	$x_{43}$	$x_{44}$
1	100	25	0	100	100	25	75	50	50	50	75	100	0	25	75	50
2	75	100	25	50	75	0	0	25	100	75	100	50	50	100	75	50
3	75	0	50	75	100	50	100	50	100	50	75	100	50	100	50	0
4	0	50	25	0	0	75	0	50	50	25	25	75	100	0	75	75
5	50	25	0	50	100	25	25	50	100	0	25	50	0	50	75	100
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
299	25	75	50	75	75	25	25	0	75	50	50	75	25	100	75	50
300	25	75	50	0	0	0	75	50	100	25	50	100	75	25	0	100
Mean value	79.0	77.5	59.5	33.5	66.0	87.5	59.5	53.0	59.5	91.5	85.5	90.0	59.5	79.0	88.5	79.0

While the standardized outer weights originate from the standard PLS path model estimation, the estimation of each indicator's standard deviation is based on the original indicator data. For example, if  $x_{11}$  has a standardized weight of 0.2 and a standard deviation of 1.619, the resulting unstandardized weight is 0.124. Table III shows the (standardized and unstandardized) indicator weights along with the indicators' standard deviations with regard to our sample model in Figure 1.

Finally, we rescale the unstandardized outer weights so that their sum equals one per measurement model. For this purpose, we need to divide each indicator's unstandardized weight (e.g. 0.124 for indicator  $x_{11}$ ) by the sum of the unstandardized weights of all the indicators that belong to the same measurement model. For  $Y_1$ , the sum of all the unstandardized indicator weights is  $0.124 + 0.168 + 0.191 + 0.406 = 0.889$ . Therefore, for indicator  $x_{11}$ , we obtain the unstandardized and rescaled outer weight of 0.139 after dividing 0.124 by 0.889. The final column in Table III shows the results of the rescaled outer weights.

In the next step, the IPMA uses the rescaled indicator data (Table II) and the rescaled outer weights (Table III) to compute the rescaled latent variable scores by means of simple linear combinations. For example, the first data point in the vector of  $Y_1$ 's scores is:

$$100 \cdot 0.139 + 25 \cdot 0.189 + 0 \cdot 0.215 + 100 \cdot 0.457 \approx 64.3. \quad (2)$$

Table IV shows the resulting latent variable scores along with their mean values. In our example,  $Y_1$  has a mean value (i.e. performance) of 53.7,  $Y_2$  of 85.6,  $Y_3$  of 61.8, and  $Y_4$  of 78.1. These results serve as input for the importance-performance map's performance dimension.

### Step 3: computation of the importance values

A construct's importance in terms of predicting another directly or indirectly linked (target) construct in the structural model is derived from the total effect of the relationship between these two constructs. The total effect is the sum of the direct and

Latent variable	Indicator	Standardized outer weights	SD of the indicators	Unstandardized outer weights	Rescaled outer weights
$Y_1$	$x_{11}$	0.2	1.619	0.124	0.139
	$x_{12}$	0.3	1.789	0.168	0.189
	$x_{13}$	0.4	2.099	0.191	0.215
	$x_{14}$	0.5	1.231	0.406	0.457
$Y_2$	$x_{21}$	0.1	2.099	0.048	0.114
	$x_{22}$	0.1	1.101	0.091	0.218
	$x_{23}$	0.4	3.357	0.119	0.285
	$x_{24}$	0.4	2.504	0.160	0.383
$Y_3$	$x_{31}$	0.1	1.762	0.057	0.136
	$x_{32}$	0.1	1.744	0.057	0.137
	$x_{33}$	0.4	2.270	0.176	0.422
	$x_{34}$	0.4	2.653	0.151	0.361
$Y_4$	$x_{41}$	0.3	2.164	0.139	0.186
	$x_{42}$	0.3	1.874	0.160	0.215
	$x_{43}$	0.3	1.413	0.212	0.286
	$x_{44}$	0.3	1.291	0.232	0.313

**Table III.**  
Computation of  
unstandardized and  
rescaled outer  
weights



all the indirect effects in the structural model (Hair *et al.*, 2017). For example, to determine the total effect of  $Y_1$  on  $Y_4$  (Figure 1), we have to consider the direct effect of the relationship between these two constructs (0.50) and the following three indirect effects via  $Y_2$  and  $Y_3$ , respectively:

$$Y_1 \rightarrow Y_2 \rightarrow Y_4 = 0.50 \cdot 0.50 = 0.25$$

$$Y_1 \rightarrow Y_2 \rightarrow Y_3 \rightarrow Y_4 = 0.50 \cdot 0.25 \cdot 0.25 = 0.03125$$

$$Y_1 \rightarrow Y_3 \rightarrow Y_4 = 0.25 \cdot 0.25 = 0.0625$$

Adding up the individual indirect effects yields the total indirect effect of  $Y_1$  on  $Y_4$ , which is approximately 0.34. The total effect of  $Y_1$  on  $Y_4$  is 0.84 ( $= 0.50 + 0.34$ ), which expresses  $Y_1$ 's importance in predicting the target construct  $Y_4$ . Since total effects represent the sum of direct and indirect effects, the IPMA's importance dimension supports the interpretation of complex models including mediators or even multiple mediators.

The IPMA draws on unstandardized effects to facilitate a *ceteris paribus* interpretation of predecessor constructs' impact on the target construct. This interpretation of the unstandardized effects is analogous to that of unstandardized weights in OLS regression models (Hair *et al.*, 2010). More precisely, by drawing on unstandardized effects, we can conclude that an increase in a certain predecessor construct's performance would increase the target construct's performance by the size of its unstandardized total effect. To determine the significance of the total effects – for example, by means of bias-corrected and accelerated (BCa) confidence intervals (Hair *et al.*, 2017) – researchers need to run the bootstrapping routine. While a non-significant effect provides evidence that a total effect is zero in the population, researchers should retain the corresponding construct in the IPMA since this outcome may also represent a valuable finding (e.g. a company invests into the performance of a construct that has no effect), which also can change with different data, for instance, in alternative contexts of the analysis.

Table V summarizes all the total effects with respect to our target construct  $Y_4$ . Note that  $Y_3$  does not have an indirect effect on  $Y_4$ ; therefore, its total effect equals the direct effect of 0.25. At this point, after computing the importance and performance values, all information required to draw the importance-performance map is available.

Finally, the IPMA also supports path models with moderators. However, if one path relationship in a total effect is moderated, the interpretation of the total effect changes. More precisely, the path coefficient estimate of a moderated effect expresses the strength of the relationship between the two constructs when the moderator variable

	$Y_1$	$Y_2$	$Y_3$	$Y_4$
1	64.3	76.3	63.3	42.5
2	57.6	75.4	18.2	67.9
3	55.5	82.0	76.5	45.1
4	14.8	47.0	26.9	63.5
5	34.5	37.7	43.3	63.5
...	...	...	...	...
Computation of the rescaled latent variable scores	299	62.4	22.9	63.3
	300	69.4	47.1	50.6
	Mean value	53.7	85.6	61.8
				78.1

**Table IV.**  
Computation of the rescaled latent variable scores

has the value 0 in case researchers follow standard procedure and standardize the moderator's indicators prior to the analysis (for more details see Hair *et al.*, 2017). This interpretation, however, complicates any comparison of total effects that include moderating effects with those that lack a moderating effect. With multiple moderators in a total effect or moderated mediation effect, the interpretation of IPMA's importance dimension becomes difficult. Therefore, we generally advise against the inclusion of moderators in an IPMA.

#### Step 4: importance-performance map creation

The IPMA focuses on one key target construct of interest in the PLS path model. Therefore, the first step in creating an importance-performance map requires selecting the target construct of interest. In our example,  $Y_4$  represents such a key target construct (Figure 1). The importance and performance values of  $Y_4$ 's predecessor constructs (i.e.  $Y_1$ - $Y_3$ ) allow creating the importance-performance map of  $Y_4$ . Table VI summarizes the values of this map's importance and performance dimensions – as obtained by the previous IMPA steps.

Scatter plotting the information shown in Table VI allows us to create an importance-performance map as shown in Figure 2 at the beginning of this paper. The  $x$ -axis represents the importance of  $Y_1$ - $Y_3$  for explaining the target construct  $Y_4$ , while the  $y$ -axis depicts the performance of  $Y_1$ - $Y_3$  in terms of their average rescaled latent variable scores. For a better orientation, researchers may also draw two additional lines in the importance-performance map: the mean importance value (i.e. a vertical line) and the mean performance value (i.e. a horizontal line) of the displayed constructs (Figure 4). With regard to our example,  $Y_1$ - $Y_3$  have a mean importance of 0.55 and a mean performance of 67.0 (Table VI). These two additional lines divide the importance-performance map into four areas with importance and performance values below and above the average. Generally, when analyzing the importance-performance map, constructs in the lower right area (i.e. above average importance and below average performance) are of highest interest to achieve improvement, followed by the higher right, lower left and, finally, the higher left areas. Thereby, the importance-performance map provides guidance for the prioritization

Predecessor construct	Direct effect on $Y_4$	Indirect effect on $Y_4$	Total effect on $Y_4$	Are the total effects on $Y_4$ significant?
$Y_1$	0.50	0.34	0.84	Yes
$Y_2$	0.50	0.06	0.56	Yes
$Y_3$	0.25	–	0.25	Yes

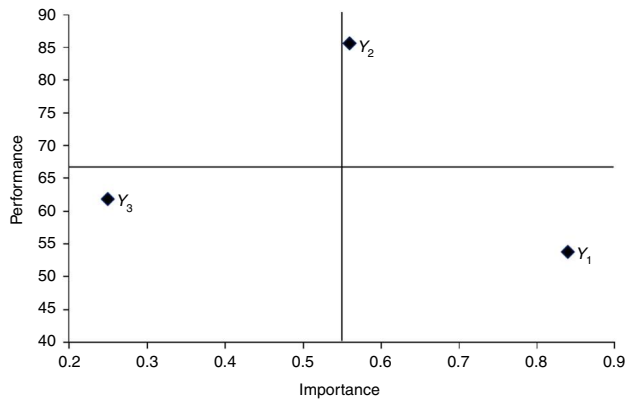
**Table V.**  
Direct, indirect,  
and total effects  
in the IPMA

**Notes:** All effects denote unstandardized effects. Significance testing uses the bootstrapping routine with 5,000 sample and no sign changes for determining the 95 percent BCa confidence intervals

	Importance	Performance
$Y_1$	0.84	53.7
$Y_2$	0.56	85.6
$Y_3$	0.25	61.8
Mean value	0.55	67.0

**Table VI.**  
Data of the  
importance-  
performance map for  
construct  $Y_4$

**Figure 4.**  
Adjusted importance-  
performance  
map of the target  
construct  $Y_4$



of managerial activities of high importance for the aspect underlying the selected target, but which require performance improvements.

In our example, the importance-performance map (Figure 4) shows that  $Y_1$  has a relatively low performance of 53.7. In comparison with the other constructs,  $Y_1$ 's performance is slightly below average. On the other hand, with a total effect of 0.84, this construct's importance is particularly high. Therefore, a one-unit increase in  $Y_1$ 's performance from 53.7 to 54.7 would increase the performance of  $Y_4$  by 0.84 points from 78.10 to 78.94. Hence, when managers aim at increasing the performance of the target construct  $Y_4$ , their first priority should be to improve the performance of aspects captured by  $Y_1$ , as this construct has the highest (above average) importance, but a relatively low (below average) performance. Aspects related to constructs  $Y_2$  and  $Y_3$  follow as a second and third priority.

#### Step 5: extension of the IPMA on the indicator level

The IPMA is not limited to the construct level. We can also conduct an IPMA on the indicator level to identify relevant and even more specific areas of improvement. More precisely, we can interpret the rescaled outer weights – as reported in formative measurement models – as an indicator's relative importance compared to that of the other indicators in a specific measurement model. Alternatively, the interpretation of the indicators' relative contribution can also draw on reflective measurement models but use the outer weights instead of the outer loadings. While the outer weights play no role in the assessment of the reflective measurement model's reliability and validity, they still represent each indicator's contribution to forming the composite variable that represents the construct in the PLS path model.

The importance values are derived from the indicators' total effects on the target construct, which is the result of multiplying the rescaled outer weights of a predecessor construct's indicators with its unstandardized total effect on the target construct. For example, with regard to the indicators of  $Y_1$ , we would multiply the rescaled outer weights of  $x_{11}$ - $x_{14}$  (i.e. 0.139, 0.189, 0.215, 0.457; Table III) with the unstandardized total effect of  $Y_1$  on  $Y_4$  in the structural model (i.e. 0.84). This analysis yields importance values of  $x_{11}$ - $x_{14}$  of, respectively, 0.117, 0.159, 0.181, and 0.384. The performance values are derived from the indicators' mean value of the rescaled data (i.e. 79, 77.5, 59.5, and 33.5; Table II). With this data for all indicators of  $Y_1$ ,  $Y_2$ , and  $Y_3$ , we can create an importance-performance map as

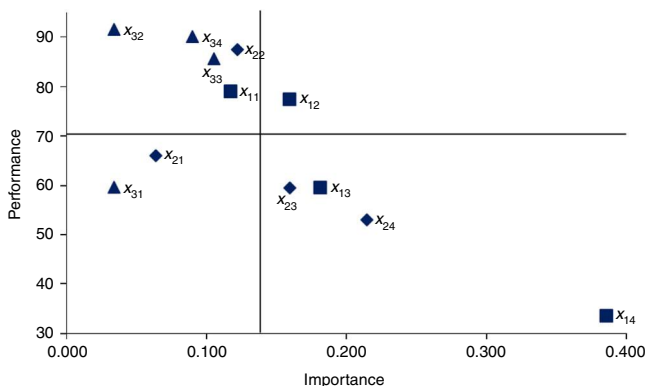
shown in Figure 5. In this figure, rectangles represent the indicators of  $Y_1$ , diamonds those of  $Y_2$ , and triangles those of  $Y_3$ .

Derived from this example, indicator  $x_{14}$  should have the highest priority for improvement, since it has the highest relative importance, but the lowest performance. A one-unit point increase in  $x_{14}$ 's performance increases the performance of  $Y_4$  by  $x_{14}$ 's importance value, which is 0.384 (ceteris paribus). Indicators  $x_{24}$ ,  $x_{13}$ ,  $x_{23}$ , and  $x_{12}$  follow with second to fifth priority. The other indicators shown in Figure 5 are less relevant for improving  $Y_4$ 's performance.

### Empirical example

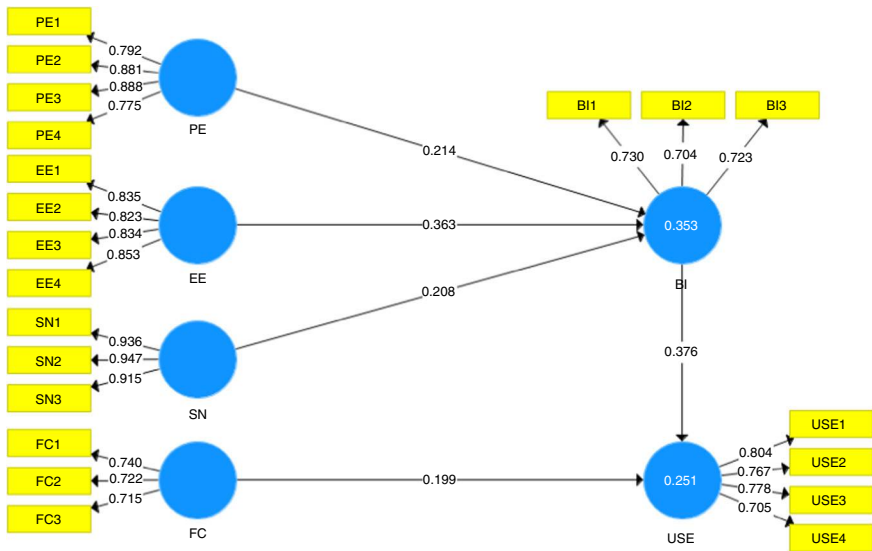
Investigating the user acceptance and usage of new IT is a perennial theme in mainstream MIS research. Path models explicating IT user acceptance, such as the TAM (Davis, 1989) and its extensions, for example, the UTAUT (Venkatesh *et al.*, 2003), are well known and have been extensively researched. In the light of the method's prediction orientation, researchers usually use PLS-SEM to estimate such models. However, despite PLS-SEM's popularity in this respect, prior research has not, to our best knowledge, yet applied the IPMA in this context. Researchers have thus missed an opportunity to use the available data to gain additional results and findings with which to enrich their conclusions.

In order to demonstrate the efficacy of the IPMA, we draw on data from a survey sample by Al-Gahtani *et al.* (2007) of 722 knowledge workers in Saudi Arabia voluntarily using desktop computer applications. These data were initially analyzed within the context of a modified UTAUT model that synthesized model elements from various other precedent user acceptance models, such as TAM and its extensions (e.g. TAM 2; Venkatesh and Davis, 2000). UTAUT postulates that four constructs act as determinants of behavioral intentions (BIs) to use and actual usage behavior: performance expectancy (PE) (i.e. the degree to which individuals believe that using the system will help them attain improved job performance), effort expectancy (EE) (i.e. the degree of ease associated with the use of the system), subjective norm (SN) (i.e. the degree to which individuals perceive that important others believe they should use computers), and facilitating conditions (FC) (i.e. the degree to which individuals believe that an organizational and technical infrastructure supports the use of the system). Figure 6 shows the model and the PLS-SEM results when using the empirical data and SmartPLS 3 software[1].



**Figure 5.**  
Adjusted  
importance-  
performance  
map of  $Y_1$ ,  $Y_2$ , and  $Y_3$ 's  
indicators on the  
target construct  $Y_4$

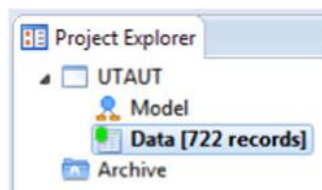
**Figure 6.**  
UTAUT model and  
PLS-SEM results



The evaluation of the measurement models by means of standard evaluation criteria (e.g. Chin, 1998, 2010; Hair *et al.*, 2011, 2013; Henseler *et al.*, 2012, 2017; Roldán and Sánchez-Franco, 2012; Tenenhaus *et al.*, 2005) supports the measures' reliability and validity. This also holds for discriminant validity assessment using Henseler *et al.*'s (2015) recently proposed HTMT criterion, which extends the standard measures used in Al-Gahtani *et al.* (2007). The results from bootstrapping with 5,000 samples using the no sign change option and the 95 percent BCa confidence intervals (Hair *et al.*, 2017) show that all the path coefficients are statistically significant. More specifically, PE, EE, and SN each have significant and positive effects on the BI to use the system. Similarly, the BI and FC each have significant and positive effects on the use behavior (USE). In addition, the bootstrapping results also substantiate that all total effects on the target construct USE are significant.

As a point of departure, we check the requirements for carrying out an IPMA (Step 1). After reviewing the questionnaire, we find that the indicator data are mostly on an interval scale from 1 to 7, in some cases from 0 to 6, and in others from 0 to 11. In respect of all the indicators, a higher value represents a better outcome (for the description of indicators, see Tables III-V in Al-Gahtani *et al.*, 2007). We, therefore, do not need to reverse the scale of any of the indicators. When double clicking on the data set in the SmartPLS Project Explorer (Figure 7), the data view opens (Figure 8), which

**Figure 7.**  
SmartPLS project  
explorer



Indicators	Indicator correlations	Raw File	Variable Number	Missing	Mean	Median	Min	Max	Standard deviation	Excess Kurtosis	Skewness
PE1			0.000	0.000	6.493	7.000	1.000	7.000	1.002	8.501	-2.657
PE2			1.000	0.000	6.342	7.000	1.000	7.000	1.069	5.208	-2.093
PE3			2.000	0.000	6.273	7.000	1.000	7.000	1.117	4.997	-2.057
PE4			3.000	0.000	6.277	7.000	1.000	7.000	1.124	4.077	-1.920
EE1			4.000	0.000	5.921	6.000	1.000	7.000	1.313	1.832	-1.381
EE2			5.000	0.000	5.705	6.000	1.000	7.000	1.258	0.575	-0.920
EE3			6.000	0.000	5.803	6.000	1.000	7.000	1.268	1.595	-1.233
EE4			7.000	0.000	5.837	6.000	1.000	7.000	1.314	1.853	-1.348
SN1			8.000	0.000	5.283	6.000	1.000	7.000	1.610	0.311	-0.914
SN2			9.000	0.000	5.292	6.000	1.000	7.000	1.601	0.375	-0.926
SN3			10.000	0.000	5.561	6.000	1.000	7.000	1.532	0.975	-1.158
FC1			11.000	0.000	5.900	6.000	1.000	7.000	1.321	2.075	-1.454
FC2			12.000	0.000	5.141	6.000	1.000	7.000	1.807	-0.137	-0.854
FC3			13.000	0.000	4.913	5.000	1.000	7.000	1.768	-0.331	-0.723
BI1			14.000	0.000	6.208	7.000	1.000	7.000	1.166	3.950	-1.883
BI2			15.000	0.000	5.918	6.000	1.000	7.000	1.273	0.460	-1.085
BI3			16.000	0.000	5.747	6.000	1.000	7.000	1.387	1.359	-1.241
USE1			17.000	0.000	4.655	5.000	1.000	7.000	1.542	-0.361	-0.889
USE2			18.000	0.000	5.327	6.000	1.000	6.000	1.206	3.910	-2.075
USE3			19.000	0.000	3.102	3.000	0.000	6.000	1.357	-1.076	-0.007
USE4			20.000	0.000	3.673	3.000	0.000	11.000	2.350	0.455	0.965

## Importance-performance map analysis

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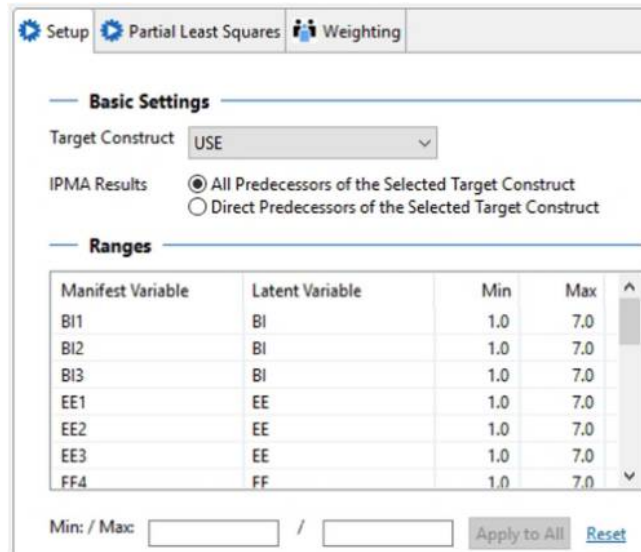
Figure 8.  
SmartPLS data view

provides further information on the data set (e.g. the missing value marker) and some descriptive statistics of the indicators.

Next, we inspect the signs of the outer weights. After running the PLS-SEM algorithm, SmartPLS opens the Results Report, which also displays the weights of all the indicators. All the outer weight signs are positive. Therefore, in line with IPMA Step 1, all the requirements for conducting the analysis have been fulfilled and we can continue the analysis.

We subsequently run the IPMA by clicking on Calculate→Importance-Performance Map Analysis (IPMA) in the SmartPLS menu bar. Alternatively, you can left-click on the Calculate wheel symbol in the tool bar, and select the corresponding option in the combo box that opens. In the dialog box that opens (Figure 9), we need to specify the target construct and decide whether to include all the predecessor constructs of that target variable, or only those that have a direct relationship with it. We select USE as the target construct and choose the All Predecessors of the Selected Target Construct option. Most importantly, we need to specify each indicator's minimum and maximum value required for the rescaling of the data to a 0-100 scale. As shown in Figure 9, SmartPLS automatically reads these minimum and maximum values from the data. However, if the respondents have not made use of the full scale (e.g. the actual minimum value is 2 instead of 1), SmartPLS cannot correctly rescale the data. Consequently, the rescaled latent variable scores will not be between 0 and 100 but, for instance, between -5 and 95. In such a case, we need to manually insert the true minimum value of the scale (e.g. 1 instead of 2) by clicking on the corresponding cell in the Min column. Alternatively, we can simultaneously specify the minimum and maximum value of all the indicators. To do so, enter the corresponding values next to Min/Max at the bottom of the dialog box and click on Apply to All. In our example, all the respondents made use of the full range of the indicator scales as indicated in the Min and Max columns of the SmartPLS Data View (Figure 8). We therefore maintain the default settings and proceed by clicking on Start Calculation.

**Figure 9.**  
SmartPLS IPMA  
dialog



SmartPLS now automatically computes the performance and importance values (Step 2 and 3) and creates the importance-performance map (Step 4). After completing the computations, SmartPLS opens the Results Report. Initially, it shows the results of the standardized path coefficients. Under Quality Criteria→Importance-Performance Map (USE) (Constructs), the report includes the importance-performance map as displayed in Figure 10. Under Final Results →Total Effects, SmartPLS displays the importance values in a matrix format. The graphical representation of the importance-performance uses the unstandardized total effects for the importance-dimension (x-axis), which you can access by clicking on the tabs Constructs, unstandardized and Indicators unstandardized. Under Final Results→Performance/Index, for the performance-dimension (y-axis), you can access the rescaled performance values of the latent and manifest variables (i.e. indicators) by means of the tabs LV Performances and MV Performances.

Not surprisingly, we find that the two direct predecessors, BI and FC, have a particularly high importance (Figure 10). Although performing at comparable levels, the FC construct has a considerably higher importance than the BI construct. Managerial actions should therefore prioritize improving the performance of the BI, which can be achieved by focusing on the predecessor construct of BI with the strongest impact on USE. As can be seen in Figure 10, EE has the strongest total effect on USE.

It is important to note that the graphical representation of IMPA results differs from the graphical PLS-SEM results illustration in SmartPLS. Instead of displaying the  $R^2$  values of the endogenous latent variables in the PLS path model (Figure 6), the IPMA results show the performance values of each latent variable (Figure 11); instead of displaying the standardized outer loadings or weights (Figure 6), the IPMA results show the unstandardized and rescaled outer weights of the measurement models regardless if they are formative or reflective (Figure 11).

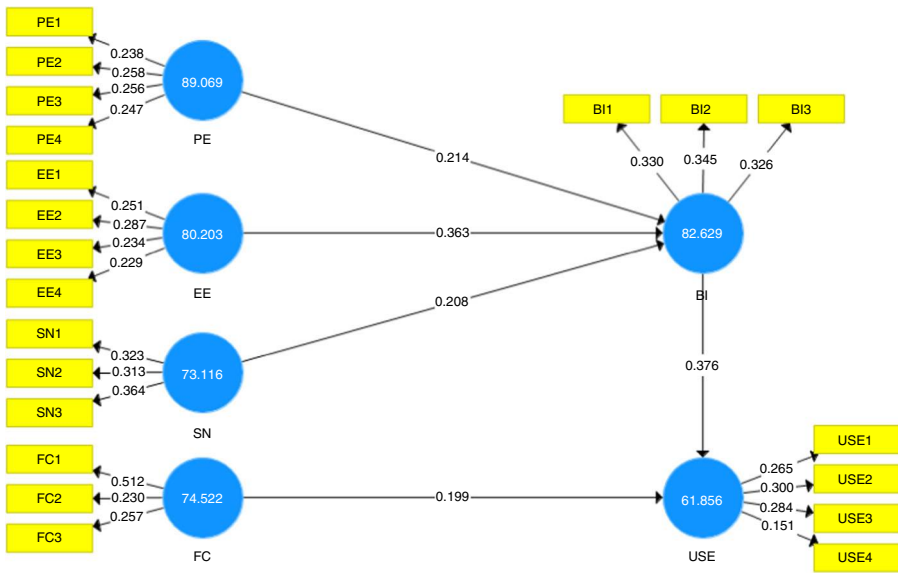
To gain more specific information on how to increase the performance of constructs, the following analyses focus on the indicator level (Step 5)[2].



**Figure 10.** Importance-performance map (construct level) of the target construct USE



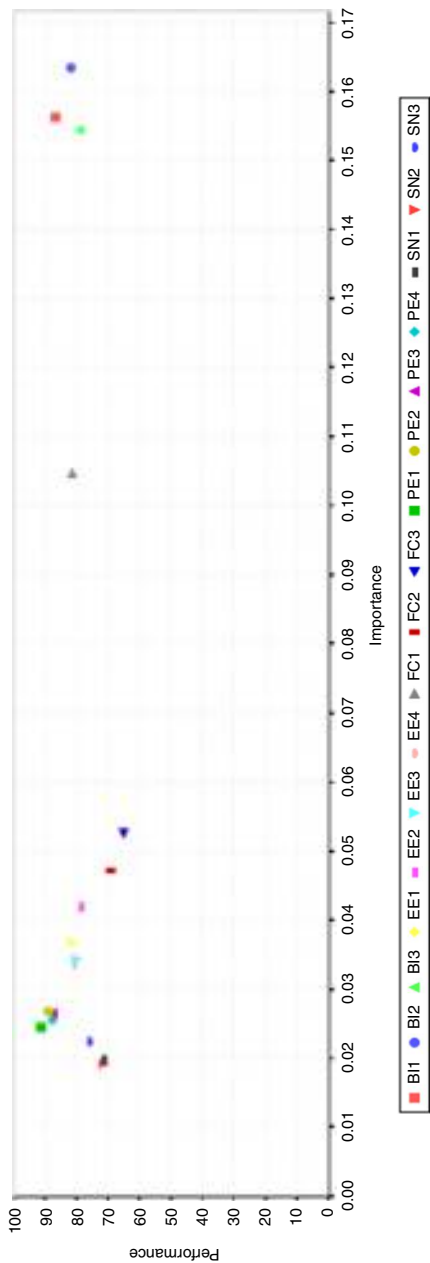
**Figure 11.**  
PLS path model and  
IPMA results



In the results report, under Quality Criteria→Importance-Performance Map (USE) (Indicators), SmartPLS shows the indicators' importance-performance map as displayed in Figure 12. For example, we find that the indicator EE2 ("It is easy for me to become skillful using computers") has a relatively high importance when focusing on the construct EE, while offering some room for performance improvement. Hence, performance improvements could focus on offering high-quality computer trainings to provide users with the skills and knowledge they need. As a direct consequence, the performance of the construct EE increases, which entails an improvement of the construct BI and the target construct USE. Similarly, other indicators (e.g. FC1, "I have the resources and the knowledge and the ability to make use of the computer") may gain particular attention regarding improving the USE.

**Summary and conclusion**

Review studies on the use of PLS-SEM (Hair *et al.*, 2012a, b; Ringle *et al.*, 2012; Sarstedt *et al.*, 2014) reveal that practically all researchers rely on standard PLS path model analysis, often ignoring more advances techniques, such as CTA-PLS (Gudergan *et al.*, 2008), FIMIX-PLS (Hahn *et al.*, 2002; Ringle *et al.*, 2010; Sarstedt *et al.*, 2011; Sarstedt and Ringle, 2010), PLS-POS (Becker *et al.*, 2015), moderator (Henseler and Chin, 2010; Henseler and Fassott, 2010), and multigroup analyses (Sarstedt *et al.*, 2011). The IPMA belongs to this suite of often neglected methods, but are particularly useful for generating additional findings and conclusions. By combining the analysis of the importance and performance dimensions, the IPMA allows for prioritizing constructs to improve a certain target construct. Expanding the analysis to the indicator level allows for identifying the most important areas of specific actions. These results are, for example, particularly important in studies researching the differing impacts that certain construct dimensions have on a phenomenon such as corporate reputation (e.g. Sarstedt *et al.*, 2013), or customer



**Figure 12.** Importance-performance map (indicator level) of the target construct USE

satisfaction (e.g. Ringle *et al.*, 2011). Another extension of the IPMA's use is in the context of a multigroup analysis. The IPMA allows for contrasting group results and for developing specific conclusions in respect of each group (Rigdon *et al.*, 2010, 2011; Schloderer *et al.*, 2014). However, researchers should refrain from using the IPMA if the analysis does not meet the requirements mentioned in Step 1 of the IPMA procedure (Figure 3) such as having only positive outer weights estimates in the measurement models.

As the IPMA assumes linear relationships, future research could focus on non-linear IPMA results (Anderson and Mittal, 2000; Eskildsen and Kristensen, 2006; Mittal *et al.*, 1998), making the analysis even more useful. For example, in the context of the Kano model, an IPMA could consider the differing role of delighters and basic needs (e.g. Kano *et al.*, 1984). If the performance of a delighter construct exceeds a certain threshold, further improvement of this construct's performance improves the target construct exponentially. Conversely, performance decreases in this construct generally have a lower effect on the target construct. The opposite holds for basic needs, where decreases in a corresponding construct's performance result in steep decreases in the target construct's performance. Exceeding the performance of basic needs above a certain threshold will, however, only marginally increase the target construct's performance. In this context, the penalty-reward contrast analysis of IPMA results (Matzler and Sauerwein, 2002; Matzler *et al.*, 2003) could be another promising avenue for future research. Given IPMA's capabilities and the additional benefit of potential extensions to non-linear effects, we expect that the much broader use of the method in future studies will extend the results presentations and allow more elaborate findings and conclusions.

### Notes

1. The original paper also considered a further model set-up with additional moderator variables (i.e. age, experience, gender, and voluntariness of use). However, in light of the problems that arise in the interpretation of total effects that include moderators, our analysis focuses on the first model in Al-Gahtani *et al.* (2007).
2. Note again that an IPMA on the indicator level is possible regardless of the predecessor constructs' measurement model specifications. However, an indicator-related analysis is particularly useful in formative measurement model settings.

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