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Importance and performance in PLS-SEM and NCA: Introducing the combined importance-performance map analysis (cIPMA)

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ABSTRACT

This research offers a novel approach that extends the application of importance-performance map analysis (IPMA) in partial least squares structural equation modeling (PLS-SEM) by incorporating findings from a necessary condition analysis (NCA). The IPMA comprises assessing latent variables and their indicators' importance and performance, while an NCA introduces an additional dimension by identifying factors that are crucial for achieving the desired outcomes. An NCA employs necessity logic to identify the must-have factors required for an outcome, while PLS-SEM follows an additive sufficiency logic to identify the should-have factors that contribute to high performance levels. Integrating these two logics into the performance dimension is particularly valuable for prioritizing actions that could improve the target outcomes, such as customer satisfaction and employee commitment. Although the combined use of PLS-SEM and NCA is a recent suggestion, this study is the first to combine them with an IPMA (i.e., in a combined IPMA; cIPMA). A case study illustrates the combined use of PLS-SEM and an NCA to undertake a cIPMA. This innovative approach enhances researchers' and practitioners' decision making, enabling them to prioritize their efforts effectively.

1. Introduction

Comparing attributes' performance and importance in order to produce a given outcome has a long tradition in the management discipline (Martilla and James, 1977). Researchers routinely visualize this interplay in a two-dimensional plot, in which the attributes are normally grouped into four quadrants that combine low and high importance and performance values. This plot is usually referred to as an importance-performance grid (Martilla and James, 1977), importance-performance matrix (Slack, 1994), a quality map (Kristensen et al., 2000), or, more broadly, an importance-performance map analysis (IPMA, Ringle and Sarstedt, 2016). The IPMA has become a standard tool for understanding where managerial improvement efforts should be focused (e.g., Sever, 2015; Skok et al., 2001). Nevertheless, authors from different disciplines and methodological backgrounds have encountered challenges when using the toolset, which – among others – relate to understanding importance and performance, as well as the threshold levels' definition (see, for instance, Oh, 2001).

The IPMA has also been used in the context of partial least squares structural equation modeling (PLS-SEM), a multivariate method for estimating complex interrelationships between constructs and their indicators (Hair et al., 2022, Chapter 1; Lohmöller, 1989, Chapter 2; Wold, 1982). In the past decades, the use of PLS-SEM evolved in marketing research (Guenther et al., 2023; Hair et al., 2012; Sarstedt et al., 2022), including retailing and consumer services (e.g., Cai et al., 2023; Huete-Alcocer and Hernandez-Rojas, 2022; Rodríguez et al., 2020). PLS-SEM facilitates an IPMA, due to the way the method estimates model parameters. Specifically, PLS-SEM calculates indicator variables' composites to represent the constructs in a statistical model. Researchers have used these composite scores as representations of the constructs' performance and compared them with the total effects that the constructs exert on a specific target (e.g., Kristensen et al., 2000; Ringle and Sarstedt, 2016; Streukens et al., 2017). The underlying IPMA draws on the average performance and importance scores and subsequently

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visualizes them in an importance-performance map.

Numerous studies have used the IPMA in a PLS-SEM context. For example, in the context of retailing and consumer services, Zhang et al. (2023) draw on the IPMA to investigate environmental stimuli's importance and performance for consumers' in-store purchase intentions via two consumer attitude constructs. In a technology acceptance model (TAM), whose use also features prominently in retailing and consumer services (e.g., Ng et al., 2022; Perez-Aranda et al., 2023; Shahidi et al., 2022), the IPMA can be used to compare the total effect of a technology's ease of use in terms of its intended usage (its importance for the target construct) with its potential users' average perceived ease of use (its performance). An IPMA's results therefore allow the identification of a target construct's highly important antecedents, that, however, exhibit relatively low performance. This information is crucial, since it indicates how action should be prioritized to improve these antecedent constructs, which will increase the target construct substantially. For instance, ease of use's high importance, combined with a technology's poor ease of use rating (i.e., a poor performance), indicates a specific need to improve this technology's ease of use to ultimately increase its usage.

Inherently, the IPMA's implementation follows an additive sufficiency logic according to which multiple antecedents could contribute to an outcome. Antecedent constructs that improve an outcome, namely those that show a low performance, but have a strong and significant total effect on an outcome, are prioritized, while those showing weak effects are not prioritized. However, it may well be that a certain antecedent construct with a relatively low importance (i.e., a weak effect regarding increasing the desired outcome) might still require particular attention when its absence prevents the outcome. For instance, an IPMA in the context of the TAM might ascertain that a technology's compatibility has relatively low importance for its use. Yet, if the compatibility doesn't meet a specific threshold, users would be unwilling to use the technology. Considering such interrelationships requires adopting a necessity perspective, which implies that an outcome – or a certain level of an outcome – could only be achieved if the necessary cause is in place or at a certain level.

To incorporate such a necessity logic, researchers can draw on the necessary condition analysis (NCA; Dul, 2016; 2020), which has recently gained prominence in many business research fields (for a recent review of the topics analyzed with an NCA, see Dul et al., 2023), either as a stand-alone method or in combination with PLS-SEM and other regression-based methods (Richter et al., 2022). The NCA seeks to identify necessary conditions representing constraints, bottlenecks or critical factors, which need to be solved or satisfied to achieve a certain outcome. Identifying such necessary conditions is highly relevant for management practice, since an outcome can only be achieved if the necessary condition is in place or is at a certain level (Dul et al., 2021; Hauff et al., 2021; Richter and Hauff, 2022). Importantly, antecedent constructs showing weak and nonsignificant PLS-SEM effects might be necessary conditions; that is, without these antecedents a certain outcome cannot be achieved. Failure to consider these antecedent constructs could therefore lead to incomplete recommendations. For example, in the context of retailing and consumer services, Pappas (2023) highlights the impact of recession and quality risks as constant necessary conditions for holidaymakers' purchasing intentions. Alyahya et al. (2023) use the NCA to reveal that moral obligation, moral accountability, perceived risk, perceived risk, and cost knowledge are necessary antecedents for consumers' purchase of remanufactured products.

The recently proposed combined use of NCA and PLS-SEM (Richter et al., 2020) has been acknowledged as "a unique contribution by comparing and combining approaches, demonstrating how NCA (which focuses on necessary conditions) can [*sic*] be used in combination with PLS-SEM (which focuses on sufficiency) to create a previously unrecognized way of assessing causality" (Bergh et al., 2022, p. 1842). In line with recent research work that adopted this multimethod approach (e.g., Bolívar et al., 2022; Richter et al., 2021; Sukhov et al., 2022; Tiwari et al., 2023), we argue that identifying necessary conditions could also enrich an IPMA by providing information about the antecedent constructs' necessity. This information provides researchers and practitioners with a more complete picture of the important and necessary antecedents, while also helping to complement an IPMA's results. By following the path model results of a technology's perceived usefulness, researchers assessing consumer acceptance of novel technologies might, for instance, find that these are of little importance, although they are a necessary condition for the technology's usage. In other words, the technology will not be used unless it is perceived as useful. While an antecedent construct with little importance according to its PLS-SEM results might receive little attention from a classic IPMA, it might represent a necessary condition, which would once again make it the focus of decision making when PLS-SEM is combined with an NCA.

Against this background, we first contribute to the field by discussing how importance and performance are understood in the context of PLS-SEM and an NCA, as well as how the two approaches complement one another in importance-performance analyses. Building on prior research in each field (e.g., Dul, 2016, 2020; Ringle and Sarstedt, 2016), we discuss the concepts of importance and performance in a PLS-SEM context – as implemented in an IPMA – and an NCA context. In addition, we present guidelines for a combined IPMA that builds on PLS-SEM and NCA results. By doing so, we extend the guidelines proposed in Richter et al. (2020), who did not address the IPMA (see also Richter et al., 2023b). Finally, we illustrate a combined IPMA by using an extended TAM and offering researchers implementing the approach a toolset, before concluding our research and outlining future research.

2. Importance and performance in PLS-SEM

PLS (Lohmöller, 1989, Chapter 2; Wold, 1982) is a composite-based approach to SEM in that it represents constructs as weighted sums of indicators (Hair et al., 2017; Sarstedt et al., 2016). Building on this characteristic, researchers have used composite scores produced by PLS-SEM to develop indices such as the Swedish Customer Satisfaction Barometer (Fornell, 1992) and the American Customer Satisfaction Index (Fornell et al., 1996). In the computation of these indices, the composite scores are conceived as performance values, reflecting the respondents' satisfaction with certain features or with the overall construct. For example, if all respondents show a maximum level of overall satisfaction, this translates into a 100 percent performance of this construct. Starting with Anderson and Mittal (2000) and Kristensen et al. (2000), follow-up research has contrasted these scores with measurement or structural model weights representing the importance of individual indicators or constructs for improving a certain target, such as firm profit. Jointly, these two dimensions define an importance-performance map's axes, which represent the average importance and performance scores with regard to a certain target construct.

With models' increasing complexity, which often span multiple layers of constructs, researchers usually draw on structural model total effects – that is, the sum of an antecedent construct's direct and all of its indirect effects on an outcome – to represent an IPMA's importance dimension (Hair et al., 2024, Chapter 4; Ringle and Sarstedt, 2016). That is, rather than restricting the analysis to a target's direct antecedents, the IPMA also considers indirectly related constructs (i.e., those that impact the outcome via one or more mediating constructs).

In the importance-performance map, the antecedent constructs' importance values are plotted on the *x*-axis and their performance values on the *y*-axis. Using this illustration, researchers could, for example, identify antecedent constructs that are relatively important regarding explaining the key target constructs of interest (i.e., those with a strong total effect) with a relatively low performance (i.e., low average latent variable scores). Such constructs would, specifically, be highly prioritized in order to achieve improvement, because they are especially important for the target construct, although they simultaneously perform relatively poorly.

To better illustrate the IPMA concept, consider the hypothetical path model in Fig. 1 (Panel A) with the four constructs Y_1 to Y_4. In this path model, Y_4 is the target construct. Based on the path coefficients, the antecedent constructs Y_1, Y_2, and Y_3 have direct effects on Y_4. In addition, Y_1 and Y_2 have indirect effects on Y_4 via Y_3, which are due to the corresponding direct effects' product (for further details, see Hair et al., 2024, Chapter 4). In this example, the indirect effects of Y_1 on Y_4 are computed as follows:

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

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

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

Hence, the total indirect effect of Y_1 on Y_4 is 0.25 + 0.03125 + 0.0625 = 0.34. Adding the direct effect of Y_1 on Y_4 (i.e., 0.50), as well as the antecedent constructs' total indirect effect (i.e., 0.34), we not only obtain the total effect of 0.5 + 0.34 = 0.84, but also the importance of Y_1 for the key target construct Y_4.

In contrast, the construct scores' average values represent their performance. Here, researchers could use the standardized construct scores or the unstandardized construct scores. The *standardized construct scores* are estimated on the basis of *z*-transformed standardized indicator data. The resulting standardized construct scores always have a mean value of zero and a standard deviation of 1. Since reporting mean values of zero for all the constructs is less useful for the IPMA, the procedure refers to the unstandardized construct scores.

The unstandardized construct scores depend on the indicators' scales

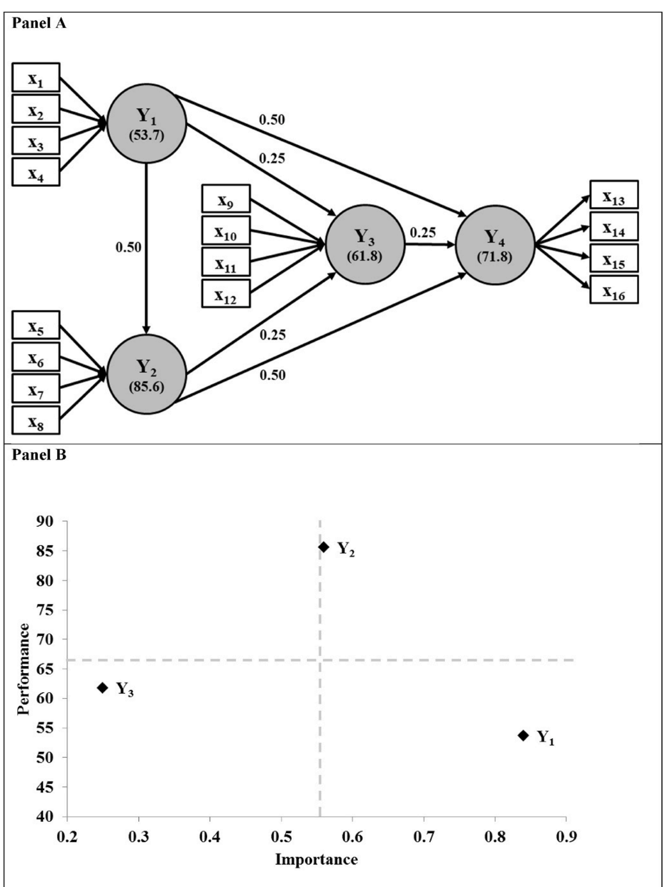

Fig. 1. Importance-performance map analysis example; adopted from Hair et al. (2024, Chapter 4).

(e.g., 1 to 5 or 1 to 7). If all the indicators are measured on the same scale (e.g., all on a scale from 1 to 5), their interpretation on the construct level is straightforward. However, their interpretation becomes ambiguous if different scales are involved (e.g., Ringle and Sarstedt, 2016; Hair et al., 2024, Chapter 4). For a better comparison of the performance levels, the unstandardized indicator data can be rescaled so that they all range between 0 and 100, with 0 representing the lowest and 100 the highest performance. The rescaling of an observation *j* with respect to indicator *i* proceeds via

$$x_{ij}^{rescaled} = \frac{E\left[x_{ij}\right] | - min[x_i]}{max[x_i] - min[x_i]} .100$$

where x_i is the *i*-th indicator in the PLS path model, E[.] represents indicator i's actual score of respondent *j*, and the min[.] and the max[.] represent the indicator's minimum and maximum values (Ringle and Sarstedt, 2016; Hair et al., 2024, Chapter 4). The indicator's minimum and maximum can refer to the theoretical minimum and maximum values (e.g., 1 and 7 when using a seven-point scale) or the empirical minimum and maximum values resulting from the sample data (e.g., 2 and 7, because no respondent evaluated the indicators below 2). It is easy to determine the theoretical minimum and maximum of an interval scale (e.g., 1 and 7 when using a seven-point scale). The use of other scales might not have a theoretical minimum or maximum, and the researcher could be advised or even forced to use the data at hand's empirical minimum or maximum.

The rescaled latent variable scores are a linear combination of the rescaled indicator data and the rescaled outer weights. 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. These weights are normalized per measurement model so that the sum of these final rescaled outer weights equals one. These rescaled outer weights allow us to determine the unstandardized rescaled construct scores that range between 0 and 100 (i.e., by the linear combination of the indicator data on a scale from 0 to 100 and the rescaled outer weights per construct). The average of these values represents the construct's performance score referred to in the IPMA in PLS-SEM (see values in brackets in the constructs in Fig. 1, Panel A).

Fig. 1 (Panel B) shows how the IPMA combines these two aspects graphically for the target construct Y_4. Two grey dashed lines divide the importance-performance map into four quadrants. The vertical line represents the mean importance and the horizontal line corresponds to the constructs' mean performance, computed as follows (Fig. 1, Panel A):

$$mean\ importance = \frac{(0.84 + 0.56 + 0.25)}{3} = 0.55, \text{ and}$$

$$mean\ performance = \frac{(53.7 + 85.6 + 61.8)}{3} = 67.03.$$

Researchers using the IPMA could use these average scores and plot them on an importance-performance map into four separate quadrants. However, researchers might rely on a different logic when dividing the four quadrants, such as previous knowledge or expert assessment. The combination of high/low importance and high/low performance induces specific recommendations, which antecedent constructs target through managerial activities (Ringle and Sarstedt, 2016).

3. Importance and performance in NCA

Unlike the classic IPMA, the NCA builds on a necessity logic to assess the antecedent constructs' importance and performance for an outcome. A necessity logic implies that an outcome can only be achieved if a specific condition is present (Dul, 2016, 2020, Chapter 2). A necessary condition therefore represents a constraint or a bottleneck that must be overcome to allow the outcome to exist. In order to detect necessary conditions in data sets, NCA uses ceiling line techniques to separate areas in scatter plots without observations from those with observations. By dividing the ‘empty’ space (also called the ceiling zone) by the entire area that includes observations (also called the scope), NCA calculates the necessity effect size *d*, which could be 0 if there is no empty space, and 1 if the maximum possible space is empty.

Consider, for example, a trichotomous case where the condition *X* and the outcome *Y* each have three levels, namely *low*, *medium*, and *high* (Fig. 2).[1] The effect size is calculated as $d = C/S$, with *C* being the ceiling zone and *S* the scope. The size of *C* is calculated by counting the number of ‘empty’ cells. *S* could be calculated as follows: $S = (q \times r) - q - r + 1$; where *q* is the number of *X* levels, and *r* is the number of *Y* levels. In our example, $S = (3 \times 3) - 3 - 3 + 1 = 4$. In Scenario A in Fig. 2, the effect size is $d = 1/4 = 0.25$; in Scenario B in Fig. 2, the effect size is $d = 3/4 = 0.75$ (for details on calculating the effect sizes see Dul, 2020, Chapter 4). The effect size therefore depends on how many of the total cells are empty. If only one cell is empty, the effect size is 0.25 (Fig. 2, Scenario A). If three cells are empty, the effect size is 0.75 (Fig. 2, Scenario B).

The effect size therefore specifies the extent to which *Y* is constrained by *X*. As an arbitrary benchmark, $0 \leq d < 0.1$ could be considered a ‘small effect,’ $0.1 \leq d < 0.3$ a ‘medium effect,’ $0.3 \leq d < 0.5$ a ‘large effect,’ and $d \geq 0.5$ a ‘very large effect’ (Dul, 2016). However, in order to conclude that a necessary condition hypothesis could be accepted, *d* should at least have a medium effect size (e.g., $d \geq 0.1$) and a statistical significance (e.g., with a *p* value lower than 0.05). Moreover, a necessary condition should always be theoretically supported (Dul, 2021a, Chapter 2; Dul et al., 2023).

In order to decide whether an identified effect size is satisfactory, researchers should always include contextual knowledge (Dul, 2020, Chapter 4). In fact, evaluating importance for an NCA could be perceived as less straightforward than for a PLS-SEM application. For example, to conclude that an effect size of 0.75 is more important than one of 0.25 might be misleading if a high *Y* level is always desired or needed from a practical perspective. In our trichotomous example, both effect sizes could be considered equally important, since both indicate that a specific *X* level is needed to achieve a high *Y* (i.e., a medium level of *X* in Scenario A and a high level of X in Scenario B). Conversely, an at least medium level and statistically significant effect size might not be important at all if it does not constrain the outcome’s desired level. For example, in Scenario A, the outcome of *Y* is not constrained by *X* if one only endeavors to achieve a medium *Y* level. In this case, the effect size of 0.25 is therefore of no practical importance. In contrast, in Scenario B, *X* represents a necessary condition to achieve a medium Y outcome level.

In the NCA context, performance should be understood in terms of how much of a specific condition’s required level has already been achieved. This can be analyzed from a case or sample perspective. From a case-level perspective, we could determine whether one case performs better than another case in terms of achieving the necessary level. For example, in Fig. 2, Scenario B, a case with a level of $X = $ *low* performs worse than a case with a level of $X = $ *medium* (although this is still not enough to achieve a high *Y* level). This case perspective could, for example, be particularly interesting if an organization wants to know how it compares to other organizations. From a sample perspective, we could analyze how many cases in a sample still need to achieve the condition’s required level. This sample perspective could, for example, be applied if an organization wants to obtain insights into its customers or employees. PLS-SEM analyses and the interpretation of a combined importance performance map analysis’s (cIPMA’s) findings focus on samples (or subsamples, such as specific groups of customers in a dataset), which makes the latter perspective particularly relevant when combining PLS-SEM-based IPMA results with NCA insights.

In the case of multiple necessary conditions, a comparison of the different performance levels should help identify the conditions that require particular attention. For example, if almost all the cases have already achieved the required level, this condition might not be as imperative as one where many cases have not done so (Dul, 2021a, Chapter 4). Consequently, comparing different necessary conditions’ performance could help prioritize actions.

In sum, in order to assess the importance of different necessary conditions in the context of a cIPMA, we suggest that researchers should first evaluate whether a necessary condition is theoretically supported and whether it at least has a medium effect size and is statistically significant. Nevertheless, we do not recommend merely focusing on the effect size’s magnitude in order to understand its practical importance in a specific research project’s context. Instead, we propose defining a desired outcome (or target construct) level and assessing whether this level could only be achieved with a specific level of the condition. This could be done by using the information inherent in the ceiling line, which could also be illustrated in tabular form in a bottleneck table. The first column of such a table shows the outcome’s different levels, while the next one displays the condition’s corresponding critical levels; that is, the levels that need to be satisfied to achieve the outcome (as we will illustrate in the following sections). Consequently, the ultimate assessment of a cIPMA’s importance depends on the outcome or target construct’s desired level (i.e., the *Y* level), which the researcher specifies. In order to analyze performance, we suggest that cIPMA refers to the number of cases below the necessary levels, which will prioritize the necessary conditions’ identification.

4. Guidelines for a combined importance-performance map analysis

Richter et al. (2020) provided guidelines to combine PLS-SEM with NCA, which we will extend to accommodate the cIPMA (see also Richter et al., 2023b). Fig. 3 shows our extended guidelines, whose additional steps (printed in bold) we will discuss in detail. These additional steps relate to the further requirements checks in Step 4, to running the cIPMA and transferring the latent variable scores in Step 5, to the specific settings to run the NCA in Step 6, and to an enriched interpretation of the findings in Step 8. Please note that we also update some of the steps outlined in Richter et al. (2020) (marked with * in Fig. 3).

4.1. Measurement scales of indicators (step 2)

The IPMA usually relies on the unstandardized latent variable scores, which are being rescaled on a scale from 0 to 100 to aid the interpretation of the constructs’ performances. Using the rescaled latent variable scores in the NCA will provide the same necessity effect sizes as when applying the method to the (standardized or unstandardized) latent variable scores from a PLS-SEM analysis, as long as the indicators used to measure a construct are measured on the same scale.[2] For this reason, we recommend applying the cIPMA to models where each construct relies on indicators that are measured on the same (theoretical) scale. That is, while one constructs’ indicators may draw on a 7-point Likert scale only, another construct’s indicators may rely on a 5-point rating scale only. Researchers must not use differently scaled indicators in the measurement model of a single construct when running the cIPMA.

[1] We refer to a trichotomous illustration here to facilitate interpretation; however, the NCA is not limited to specific measurement levels. For more information, see Dul (2020, Chapter 3). Also note that the symbols used in the NCA context have a different meaning than in the PLS-SEM context. While the latter usually uses Y to denote latent constructs and X to denote indicators, the former uses Y for outcomes and X for conditions.

[2] Note that the bottleneck levels differ due to the different scales involved. Also note that this statement refers to the standardized, unstandardized or rescaled scores calculated in the IPMA context on the basis of a linear transformation. Other forms of transformation, particularly non-linear transformations, should be carefully considered, since they could affect the NCA’s results.

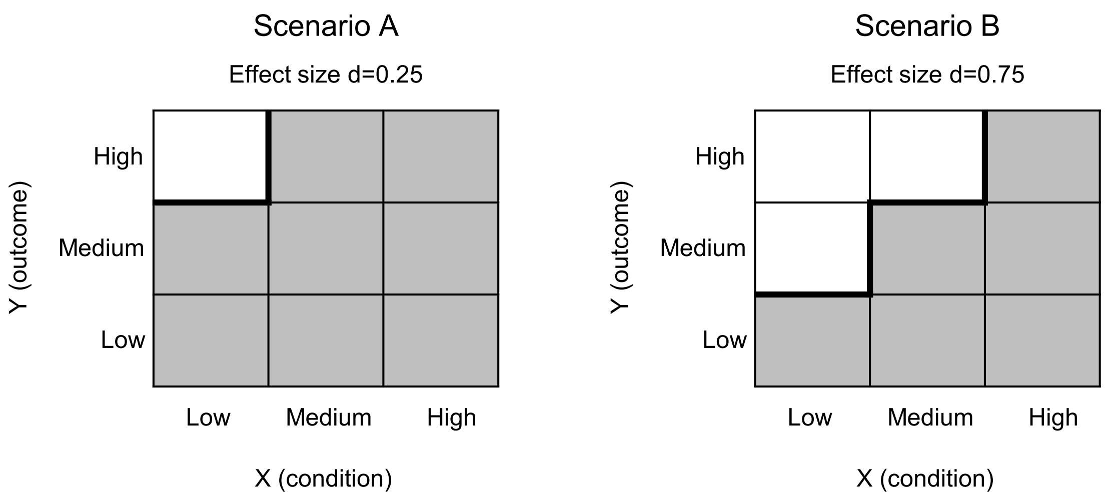

Fig. 2. Trichotomous necessary conditions.

4.2. Additional requirements check when evaluating measurement models (step 4)

In the context of PLS-SEM, IPMA requires the outer weights estimates to be positive, regardless of whether the measurement model is formatively or reflectively specified. If the outer weights are negative, the (rescaled) latent variable scores will not fall within the 0–100 range (but would, e.g., be between −5 and 95) (Ringle and Sarstedt, 2016). If an indicator's outer weight is unexpectedly negative and significant, researchers are advised to examine the indicator and its scale. The scale or question should not have a different direction (e.g., reverse-scale items) compared to the measurement model's other indicators. If the negative outer weights are nonsignificant, researchers should consider removing them. Finally, negative outer weights could be a result of high indicator collinearity, which the variance inflation factor values of 5 and higher indicate (Hair et al., 2019). In this case, researchers should again consider removing the indicators. However, they should note that removing indicators from measurement models means taking more considerations into account, which Hair et al. (2022, Chapter 5) explain in more detail.

4.3. Run the IPMA and transfer the latent variable scores (step 5)

Researchers should rely on the *theoretical* minimum and maximum scores of the indicator scales when running the IPMA; for instance, 1 and 5 on a scale that ranges from 1 to 5. This way, the latent variable scores can be interpreted in the form of percentage values from 0 to 100. If a respondent, for instance, answered a 3 on a scale that ranges from 1 to 5, the rescaling indicates a mediocre performance of the trait that the indicator expressed. After running the IPMA, the rescaled latent variable scores need to be exported into a new data file that serves as input for the NCA. If the aim is to later extend the IPMA to the indicator level, we recommend that researchers also export the rescaled indicator data.

4.4. Run the NCA (step 6)

In step 6, researchers should run the NCA in order to identify potential necessary conditions. The NCA can be conducted with a free R package (Dul, 2022). Alternatively, the SmartPLS 4 software (Ringle et al., 2022) also supports the NCA (see also Cheah et al., 2023; Richter et al., 2023b; Hair et al., 2024, Chapter 4; for basic guidelines on how to conduct and report NCA results, see also Dul et al., 2023). The NCA draws on the endogenous construct's (constructs') and their direct antecedent constructs' latent variable scores, as well as on the potential indicator scores if there are formative measurement models (as explained by Richter et al., 2020; Richter et al., 2023b; Hair et al., 2024, Chapter 4). The NCA could refer to the input data's empirical or theoretical scope. In the NCA context, the general recommendation is to use the empirical scope, as it produces a more conservative estimation of the effect size (Dul, 2020, Chapter 4) – we concur with this recommendation. That is, we use the rescaled latent variable scores from the IPMA in PLS-SEM as input data and refer to their empirical scope (which may not necessarily be from 0 to 100).

Creating bottleneck tables helps researchers assess their necessary conditions' importance and performance. A bottleneck table is a tabular representation of the ceiling line. The first column of this table displays different levels of the outcome, while the next column or columns display the condition or conditions' corresponding levels. The levels of the outcome and the levels of the condition(s) can be displayed in different ways (Dul, 2021a, Chapter 4.3). The NCA package in R produces (as a default) bottleneck tables in which, for example, both the outcome and the condition(s) are displayed as percentage ranges, with a level of 0% corresponding to the lowest observed values and a level of 100% to the highest observed values (that is, it refers to the values' empirical range). An alternative is to display the outcome and the condition(s) in terms of their actual values. Actual values are those used as input for the analysis; that is, if researchers use rescaled latent variable scores, these are the actual values. Note that the use of percentage ranges and actual values will provide the same results when researchers use rescaled latent variable scores with an actual minimum of 0 and a maximum of 100.

By referring to these bottleneck levels, researchers can select a specific outcome level and determine which level of a condition is necessary for its achievement. The bottleneck table can also be used to determine the antecedent constructs' performance from a necessity logic perspective. Therefore, the bottleneck table needs to be displayed as percentiles of the antecedent constructs, which provide the percentage and number of cases that do not reach the required level for a corresponding outcome level.

The NCA usually produces bottleneck tables with ten equidistant steps when, for instance, using percentage ranges from 0 to 100 (0, 10, 20 etc.). In order to offer a combined interpretation of the findings, we recommend specifying a performance level of interest for the dependent or target constructs in respect of which the antecedent constructs' levels will be evaluated in more detail. Researchers could determine the target construct's or constructs' desired performance level by building on expert knowledge, typical standards in the research context, or on ambitious aims forming the project's background. For instance, in job

Step 1: Specify the research objective and theoretical background

Outline hypotheses along the sufficiency and the necessity logic (for the latter, see Bokrantz & Dul, 2023; Richter & Hauff, 2022).*

Step 2: Prepare and check the data

Sample size: Follow the guidelines on sample size as outlined in a PLS-SEM context by, for instance, referring to published power tables (Hair et al., 2022, Chapter 1).

Data distribution: Report information on the data distribution (Hair et al., 2012).

Outliers: Perform an outlier analysis by following common guidelines, such as examining observations that show a z-score > 3 (Sarstedt & Mooi, 2019, Chapter 5).*

Measurement level/coding of scales: Use metric or quasi-metric data (i.e., interval-scaled, such as Likert scales); ensure that the direction of the scale/coding corresponds to the theoretically assumed relationships, otherwise revert to or flip the scale. **Ensure that the indicators used to measure a construct draw on the same scale (e.g., all indicators on a scale from 1 to 5).**

Step 3: Run the PLS-SEM analysis

Use PLS-SEM to estimate the latent variable scores, the structural model relationships, and their significance (Hair et al., 2022, Chapter 6).

Step 4: Evaluate the reliability and validity of the measurement models

Make use of the assessment guidelines in the PLS-SEM context to evaluate the measurement models' quality (e.g., Guenther et al., 2023; Hair et al., 2022, Chapters 4 and 5; Sarstedt et al. 2021). In respect of reflective constructs, evaluate their loadings, Cronbach's α / composite reliability / ρ_A, the average variance extracted, and the heterotrait-monotrait ratio. In respect of formative constructs, perform a redundancy analysis, evaluate the variance inflation factors, and the indicator weights' significance and relevance. If required, make improvements.

Additional requirements check: The outer weights' estimates need to be positive in all the measurements models (i.e., the formative and the reflective). In the case of nonsignificant negative outer weights, and / or a VIF of 5 and higher in the measurement models, researchers could, given the considerations in Hair et al. (2022, Chapter 5), consider removing the indicator.

Step 5: Run the IPMA and transfer the latent variable scores

Run the IPMA in PLS-SEM using the theoretical minimum and maximum values of the indicator scales as input (Ringle & Sarstedt, 2016).

Export the rescaled latent variable scores (and, if desired, the rescaled indicator data) to a new file and import the new data file into R or SmartPLS.

Step 6: Run the NCA

Run the NCA in SmartPLS (see also Richter et al., 2023b) or R (default settings; i.e., use the empirical scope of the input data; 10,000 permutations) (Dul, 2020, Chapter 4). Run the analysis for the hypothesized relations or all the relations: Dependent = endogenous latent variable score(s), independent = preceding latent variable scores. Select the ceiling line based on theory or data pattern (Dul, 2020, Chapter 4).* **Refer to the input data's empirical scope.**

Create a bottleneck table: Choose the desired level for the target construct (building on your knowledge of the field) and ensure that the bottleneck table identifies this level.

Step 7: Evaluate the structural model

After evaluating the VIFs of the inner model, evaluate the PLS-SEM model along the standard assessment criteria, especially the coefficient of determination (R^2), the path coefficients' statistical significance and relevance, and the predictive power (Guenther et al., 2023; Hair et al., 2022, Chapter 6; Sarstedt et al. 2021; Sharma et al., 2023; Shmueli et al., 2019).*

Visually inspect the scatter plot of the NCA results; inspect outliers as an NCA-specific robustness check (Dul, 2021a, Chapter 3.8 and Chapter 4.6). In case of outlier elimination, return to Step 3; otherwise continue.*

Evaluate the necessity effect size *d* and its statistical significance (Dul, 2016; 2020, Chapter 4).

Step 8: Interpret the findings

Produce an extended IPMA chart: Position constructs on the basis of the standardized total effects on the *x*-axis (importance) and the average latent variable scores' performance on the *y*-axis (performance); use the information from the NCA to indicate whether a construct is necessary or not (e.g., using a color code), and to indicate how they perform in terms of necessity (e.g., by adjusting the positioned antecedent constructs' size). Researchers may use our Microsoft Excel template for this purpose (https://www.pls-sem.net/downloads/).

Note: *indicates that steps are updated compared to Richter et al. (2020)

Fig. 3. An extended step-by-step guide in the context of a combined IPMA (cIPMA).
Note: *indicates that steps are updated compared to Richter et al. (2020).

satisfaction studies, this could be employees' job satisfaction score of 70 (on a scale from 0 to 100) (as in Hauff et al., 2015), while in a marketing project on customer satisfaction this could be a benchmark level of 75 or more, depending on the industry (on a scale from 0 to 100) (American Customer Satisfaction Index, 2022; Rigdon et al., 2010). Depending on these levels, researchers might need to change the presentation of the steps in their bottleneck tables to show the target constructs' selected performance level (e.g., increasing the number of steps from 10 to 20 will provide information on the 0, 5, 10, 15 etc. levels).

4.5. *Interpret the findings (step 8)*

The findings' interpretation leverages both the PLS-SEM results regarding the constructs' importance and performance values, and the NCA results regarding the corresponding necessity conditions. In order to facilitate the interpretation, researchers should produce a figure that clarifies the antecedent constructs' importance and average performance – in a standard PLS-SEM-based IPMA – as well as providing information on whether these antecedent constructs are necessary conditions for the selected outcome level and, if so, how they perform. Fig. 4 shows an example of such a graphical illustration.[3] The chart presents the PLS-SEM-based IPMA results; that is, the antecedent constructs' total effects on the target construct (importance) on the *x*-axis and their average rescaled scores (performance) on the *y*-axis. In addition, the chart distinguishes between necessary and not necessary constructs; that is, constructs that show at least a medium effect size and have statistical significance and those that do not. Constructs that are not necessary for achieving the target construct's desired level are displayed as black circles, while necessary constructs are displayed as white circles. In respect of the example shown in Fig. 4, we assume a desired level of the target construct of $Y = 80$. Next, building on the target construct's desired level, the chart uses the bottleneck table information to identify the percentage of cases remaining below the antecedent constructs' required levels (provided in the percentile display). The size of the bubbles of each of the antecedent constructs that are necessary conditions reflects this information. The larger the bubbles, the larger the percentage of cases that have not achieved the necessary condition's required level. Large bubbles therefore indicate that, from a necessity perspective, researchers should focus their attention on this aspect. Examining the results in Fig. 4, we find that Y_1 is not a necessary condition for improving the target construct, while Y_2 and Y_3 are. It also becomes obvious that many cases have not achieved the required Y_3 level. This makes Y_3 highly relevant, since investments in other constructs will not increase the outcome in these cases unless the Y_3 bottleneck is solved. Improving Y_3's performance is therefore very important in this situation in order to enable the target construct Y_4's desired performance.

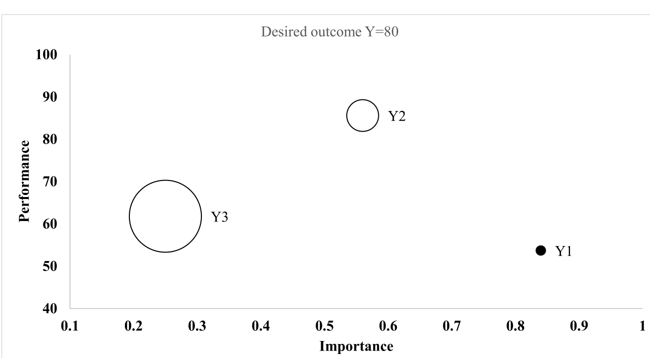

Fig. 4. Combined IPMA (cIPMA).
Note: Extension of the example given in Fig. 1, Panel B. For the desired level of the outcome: ● = construct is not necessary; ◯ = construct is necessary. The bubble sizes represent the percentage of cases that have not achieved the required desired level outcome.

By integrating information from the NCA, specifically from the bottleneck tables, the cIPMA enables an enriched interpretation of the findings, which we characterize in Fig. 5. For example, constructs mapped in the upper right corner – despite their high importance – are often outside the researcher's focus, as they have already achieved a high performance level. However, if the NCA results suggest that these constructs have not achieved a sufficient necessity level, their improvement should still be prioritized. Similarly, constructs positioned in the lower left quadrant (i.e., those that have a low importance and performance) should not be written off as irrelevant per se. If these constructs do not achieve a desired necessity level, actions for improvement should be taken. The interpretation of the other cases in these quadrants (e.g., constructs achieving a satisfactory necessity level) and in the other two quadrants is analogous.

5. Illustrative example of a combined importance-performance map analysis

While various models are suitable to serve as an example (e.g., Le et al., 2024; Siyal et al., 2024), we illustrate the application of a cIPMA by drawing on an extended TAM version (Davis, 1989), which has served as a blueprint for researching consumer behavior in various marketing and consumer behavior contexts. Richter et al. (2020) introduced the conceptual model and the relevant theoretical arguments and hypotheses in their demonstration of PLS-SEM's and NCA's combined use. The data and PLS-SEM analysis are also well documented. Consequently, we do not present all the steps in detail, but concentrate on aspects that are relevant for the cIPMA.

5.1. *The conceptual model, data, and PLS-SEM analyses (steps 1 to 3)*

The TAM under consideration comprises two endogenous constructs: the *behavioral intention* to adopt a technology, which leads to the actual *technology use* (e.g., Ajzen, 1991; Davis et al., 1989; Sheppard et al., 1988; Turner et al., 2010). It has four key exogenous constructs that precede behavioral intention and technology use: *compatibility*, which reports the innovation's fit with the customer's lifestyle and values, the perceived *usefulness* and perceived *ease of use*, and the *emotional value*, which measures whether customers enjoy or have positive feelings when using a product (Sheth et al., 1991). Fig. 6 indicates the conceptual

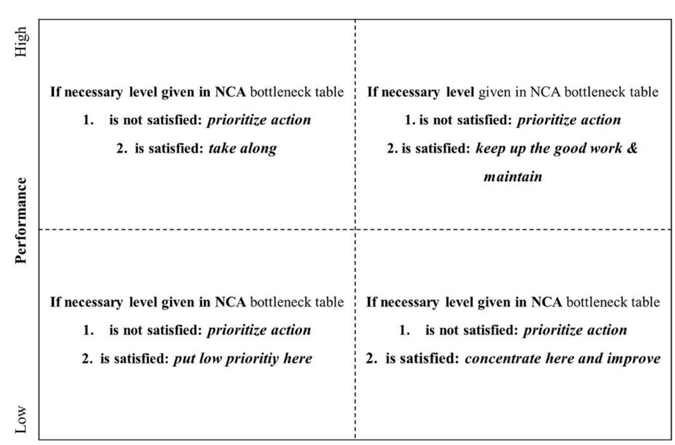

Fig. 5. Managerial recommendations based on the combined IPMA (cIPMA).

[3] Under https://www.pls-sem.net/downloads, we provide a Microsoft Excel template for downloading in order to produce this kind of indication.

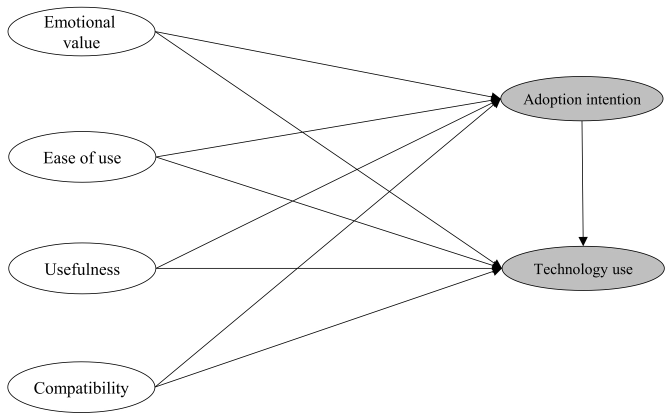

Fig. 6. Conceptual model.

model.

We used a sample of e-book reader adopters in France ($N = 174$) and collected responses via an online survey. We implemented a single item and a 7-point Likert scale to measure the target construct *technology use*; the remaining constructs used reflective measurement models with items measured on 5-point Likert scales (for more information on the sample and descriptive statistics, see Table A1 in the Appendix and Richter et al., 2020). That is, the indicators used to measure a specific construct are all measured on the same scale. The dataset is freely accessible via Richter, Hauff, Kolev, and Schubring (2023a). We used the data to estimate the extended TAM by means of the SmartPLS 4 software (Ringle et al., 2022) – for details on the model estimation, see Richter et al. (2023b).

5.2. Evaluate the reliability and validity of the measurement models (step 4)

The measurement and structural models demonstrated appropriate statistical quality when evaluated by means of the standard assessment criteria (see Table A2 in the Appendix and Richter et al., 2020). To finalize Step 4, we need to conduct an additional IPMA requirements check. We do so by evaluating whether the outer weights in our model are positive, which they are (Table A2 in the Appendix). We therefore continue with the analyses without making further changes.

5.3. Run the IPMA and transfer the latent variable scores (step 5)

We run the IPMA in PLS-SEM, using the SmartPLS 4 software (Ringle et al., 2022). Since all the respondents made use of the entire scale range at the indicator level, the empirical and theoretical scales at the indicator level are identical. Hence, we do not need to adjust the scale's theoretical minimum and maximum values in the IPMA. Following our guideline, we specified the analysis such that it produces rescaled latent variable scores on a scale from 0 to 100. After running the IPMA, we create a new data file with the rescaled scores for our NCA.

5.4. Run the NCA (step 6)

We use the rescaled latent variable scores to run the NCA on the construct scores generated in PLS-SEM. In the NCA, we use the empirical scope (to run the NCA in R, see Dul (2021b); please note that the NCA itself is a bivariate analysis not influenced by the other analyzed relationships). We create bottleneck tables to identify the antecedent constructs' necessary levels that need to be satisfied. Since we want to evaluate our findings based on an outcome level of technology use of 85 (see Steps 7 and 8), we increase the number of steps to 20 in order to produce bottleneck tables that display this outcome level. We create two bottleneck tables (based on the CE-FDH ceiling line technique), one with actual values, which provides the antecedent constructs' necessary levels that the different levels of technology use need to achieve, and one with percentiles for the conditions, which informs us about the number and percentage of cases that have not achieved the required antecedent construct levels for the corresponding levels of technology use (see next step).[4]

5.5. Evaluate the structural model (step 7)

In this step, we first evaluate the findings from the PLS-SEM analysis, including the IPMA. Thereafter we evaluate the NCA's findings. We illustrate the evaluation of the target construct *technology use*.

Analyzing the standardized total effects from the PLS-SEM analysis (Table 1), we find that adoption intention has the strongest significant impact on technology use (0.437), followed by emotional value (0.362). The other constructs' total effects are not significant. The constructs' average importance is 0.225. The explained variance of technology use is $R^2 = 0.420$.

The IPMA results show the rescaled latent variables' average performance scores (Table 2). Focusing on the direct antecedent constructs of technology use, we find that compatibility has the lowest average performance (61.557), while ease of use has the highest (75.640). This construct's minimum (case-specific) performance score is 16.871, which suggests that no respondent evaluated all of the ease-of-use indicators at the lowest level. Taken jointly, the antecedent constructs have an average performance of 68.731. On examining the IPMA results in full, we learn that all constructs perform at fairly similar levels, with adoption intention and emotional value having the largest importance for technology use.

Next, we turn to the NCA results. First, we inspect the scatter plots visually. We find that all the scatter plots show an empty space in the upper left corner, indicating potential necessary conditions (see Figure A1 in the Appendix). None of the scatter plots indicates single cases with a particular influence on the ceiling line (ceiling outliers) or the scope (scope outliers).

Next, we consider the necessity effect sizes *d*'s significance and size with regard to the target construct technology use. We followed Richter et al. (2020) and refer to the CE-FDH ceiling line (Table 3). We note that the selection of the ceiling (CE-FDH versus CR-FDH) line should be discussed based on (a) the data scaling (discrete versus continuous data), (b) the pattern of observations near the ceiling line (irregular versus linear), and (c) the potential theoretical ideas (indicating a straight ceiling line, see Dul, 2020, Chapter 4). We find that all the effect sizes are significant at $p < 0.05$ and at least medium in size.

Table 1
Total effects from the PLS-SEM analysis.

Construct	Technology use		Statistically significant ($p < 0.05$)?
	Total effects	95% bootstrap confidence intervals	
Emotional value	0.362	[0.200; 0.521]	Yes
Ease of use	0.049	[-0.110; 0.215]	No
Perceived usefulness	0.149	[-0.075; 0.357]	No
Compatibility	0.127	[-0.108; 0.365]	No
Adoption intention	0.437	[0.268; 0.609]	Yes

[4] In the Appendix, we offer a comparison of bottleneck tables for the standardized latent variable scores based on percentage ranges, the rescaled latent variable scores based on percentage ranges, and the bottleneck table for rescaled latent variable scores based on the actual values. We also comment on the differences (see Table A3 in the Appendix).

Table 2
Performance values of latent variables (rescaled).

Construct	Performance value, average	Performance value, minimum	Performance value, maximum
Technology use	49.713	0.000	100.000
Adoption intention	72.041	0.000	100.000
Emotional value	70.171	0.000	100.000
Ease of use	75.640	16.871	100.000
Perceived usefulness	64.248	0.000	100.000
Compatibility	61.557	0.000	100.000

Table 3
Necessity effect sizes (CE-FDH ceiling line).

Construct	Technology use	
	Effect size *d*	*p*-value
Emotional value	0.33	0.000
Ease of use	0.24	0.016
Perceived usefulness	0.24	0.001
Compatibility	0.21	0.000
Adoption intention	0.29	0.000

Table 4
Bottleneck table technology use, actual values (based on the rescaled PLS-SEM latent variable scores from 0 to 100).

Technology use	Adoption intention	Emotional value	Ease of use	Perceived usefulness	Compatibility
Actual values (rescaled 0–100)					
0	NN	NN	NN	NN	NN
5	NN	NN	25.373	NN	NN
10	NN	NN	25.373	NN	NN
15	NN	NN	25.373	NN	NN
20	NN	NN	25.373	NN	NN
25	NN	NN	25.373	NN	NN
30	NN	NN	25.373	NN	NN
35	33.833	49.650	33.469	15.702	25.518
40	33.833	49.650	33.469	15.702	25.518
45	33.833	49.650	33.469	15.702	25.518
50	33.833	49.650	33.469	15.702	25.518
55	33.833	49.650	33.469	15.702	33.696
60	33.833	49.650	33.469	15.702	33.696
65	33.833	49.650	33.469	15.702	33.696
70	33.833	49.650	33.875	48.127	33.696
75	33.833	49.650	33.875	48.127	33.696
80	33.833	49.650	33.875	48.127	33.696
85	75.000	49.650	66.904	66.212	33.696
90	75.000	49.650	66.904	66.212	33.696
95	75.000	49.650	66.904	66.212	33.696
100	75.000	49.650	66.904	66.212	33.696

Building on the scores presented in Table 4, we subsequently identify the value levels of our antecedent constructs that need to be satisfied for a desired level of technology use. In respect of our analysis, we assume a desired outcome level of technology use of 85, which is a rather conservative (i.e., high) benchmark. The corresponding levels are 75 for adoption intention, 50 for emotional value, 67 for ease of use, 66 for perceived usefulness, and 34 for compatibility. That is, to achieve a technology use score of 85 (on a scale from 0 to 100), we need to achieve a score of 75 for adoption intention (on a scale from 0 to 100), 50 for emotional value (on a scale from 0 to 100), etc.

In addition, in Table 5 we identify the percentage of cases that do not achieve the antecedent constructs' required levels. For example, 39.1% of all cases did not achieve the necessary level of adoption intention to enable a score of technology use of 85 (on a scale from 0 to 100). The corresponding percentages for the other antecedents are 5.7% for emotional value, 28.7% for ease of use, 47.1% for perceived usefulness, and 8.6% for compatibility. In the following, this information will be used to extend the initial IPMA results.

5.6. *Interpret the findings (step 8)*

In the following, we combine the results from Tables 1, 2 and 5 to design a combined importance-performance map that depicts its importance in the form of PLS-SEM's total effects, and as well as its average performance in the form of the average rescaled latent variable scores of adoption intention, emotional value, ease of use, perceived usefulness, and compatibility as obtained from the PLS-SEM analyses. In addition, the combined importance-performance map shows whether the antecedent constructs are necessary conditions for technology use or not, and, if they are necessary, how many of the cases do not achieve the required levels. Fig. 7 shows the combined importance-performance map.

In line with our previous elaborations, we find that adoption intention, which is in the map's upper right corner, is highly important and already shows high performance. However, adoption intention still needs prioritization, as it is the necessary condition for the target construct, technology use. More specifically, 39% of the cases have not achieved adoption intention's required level. Moreover, perceived usefulness and ease of use, which are in the left quadrants, require prioritization even though they are of little importance and already perform relatively well. Both are necessary conditions, but many cases do not achieve the required levels (47% for perceived usefulness, 29% for ease of use). Failure to prioritize these constructs, which may seem negligible at first glance given the PLS-SEM results, would limit other activities' success regarding improving the technology use. These areas need to be addressed, because they are necessary conditions. Conversely, emotional value and compatibility are also necessary conditions, but only a few of these cases do not achieve the required levels (namely 6%, and 9%); consequently, these constructs are relatively less critical in a practical setting.

6. Conclusion

In this paper, we introduced an enriched understanding of importance and performance that combines insights from PLS-SEM and NCA. Our paper makes several beneficial contributions for researchers and practitioners aiming to profit from PLS-SEM, NCA, and importance-performance analyses in general.

Our overarching goal is to create awareness of a different logic for researchers and practitioners using PLS-SEM and IPMA; that is, the necessity logic, which offers several routes to complement findings from PLS-SEM's sufficiency thinking. First, it complements findings with a new perspective on importance. Constructs might have a low IPMA-based importance classification in PLS-SEM (i.e., when they show a relatively low association with a target construct and, therewith, less potential to induce an increase in the targeted outcome). However, such constructs might be highly important from a necessity perspective. If these constructs are bottlenecks, their desired level will not be achieved. Second, the cIPMA provides researchers with a deeper understanding of the relevant performance levels to be achieved, since the NCA's bottleneck information offers a fine-grained perspective on *how much* such information is actually needed to advance a target outcome to the next level. These insights benefit research investigating success's antecedents in various contexts (e.g., job satisfaction, team performance, and customer satisfaction to name but a few). In addition, such insights are of high practical value, as they allow actions to be clearly identified and prioritized and, moreover, provide information on how much to invest in certain improvements. Third, to further assess the performance achieved in a sample (which is the normal approach in the PLS-SEM context), we propose analyzing how many cases still need to achieve the condition's required level. In the case of multiple necessary

Table 5
Bottleneck table technology use: actual values for technology use (based on the rescaled PLS-SEM latent variable scores from 0 to 100) and the percentiles of antecedent constructs.

Technology use	Adoption intention		Emotional value		Ease of use		Perceived usefulness		Compatibility	
Actual values (rescaled 0–100)	Percentage (and number) of cases that do not achieve the necessary levels									
0	0	(0)	0	(0)	0	(0)	0	(0)	0	(0)
5	0	(0)	0	(0)	0.6	(1)	0	(0)	0	(0)
10	0	(0)	0	(0)	0.6	(1)	0	(0)	0	(0)
15	0	(0)	0	(0)	0.6	(1)	0	(0)	0	(0)
20	0	(0)	0	(0)	0.6	(1)	0	(0)	0	(0)
25	0	(0)	0	(0)	0.6	(1)	0	(0)	0	(0)
30	0	(0)	0	(0)	0.6	(1)	0	(0)	0	(0)
35	4.6	(8)	5.7	(10)	1.1	(2)	1.7	(3)	5.7	(10)
40	4.6	(8)	5.7	(10)	1.1	(2)	1.7	(3)	5.7	(10)
45	4.6	(8)	5.7	(10)	1.1	(2)	1.7	(3)	5.7	(10)
50	4.6	(8)	5.7	(10)	1.1	(2)	1.7	(3)	5.7	(10)
55	4.6	(8)	5.7	(10)	1.1	(2)	1.7	(3)	8.6	(15)
60	4.6	(8)	5.7	(10)	1.1	(2)	1.7	(3)	8.6	(15)
65	4.6	(8)	5.7	(10)	1.1	(2)	1.7	(3)	8.6	(15)
70	4.6	(8)	5.7	(10)	2.9	(5)	17.2	(30)	8.6	(15)
75	4.6	(8)	5.7	(10)	2.9	(5)	17.2	(30)	8.6	(15)
80	4.6	(8)	5.7	(10)	2.9	(5)	17.2	(30)	8.6	(15)
85	39.1	(68)	5.7	(10)	28.7	(50)	47.1	(82)	8.6	(15)
90	39.1	(68)	5.7	(10)	28.7	(50)	47.1	(82)	8.6	(15)
95	39.1	(68)	5.7	(10)	28.7	(50)	47.1	(82)	8.6	(15)
100	39.1	(68)	5.7	(10)	28.7	(50)	47.1	(82)	8.6	(15)

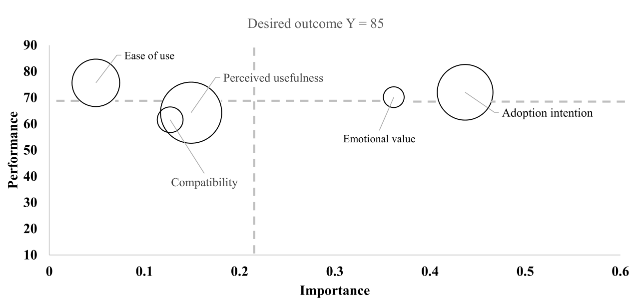

Fig. 7. Combined importance-performance map of technology use.

conditions, this information could help prioritize actions. Furthermore, our study also contributes to the broader research on importance and performance analyses, which face the challenge of having to define importance and performance, as well as the critical performance levels. We believe that the cIPMA is a step forward in this direction.

In addition to these contributions, there are also various areas on which future research could focus on. First, PLS-SEM and other methods that generate information on should-have factors, use the strength of the association between the constructs to determine the effect that an increase in the antecedent construct has on the target construct. These findings are mostly generated in respect of the full sample; that is, for all combinations of data involving low, medium, and high construct values. However, when combining PLS-SEM with NCA, it could be interesting to understand the association between the constructs involved when a specific bottleneck is bypassed. For instance, if the NCA points to a medium level antecedent construct being critical to achieve a desired high outcome level, it could be interesting to understand the association between the antecedent and the target construct of cases that have already achieved the required medium level. From a sufficiency logic perspective, this could ultimately represent an increase in the antecedent construct's further potential in the IPMA. Second, based on the PLS-SEM findings, the IPMA's importance refers to all of the involved constructs' total effects. In other words, they involve both the direct and indirect associations. These indirect or mediation effects are currently not explicitly considered in the proposed cIPMA. We therefore encourage future research to develop ideas for mediation relationships' analysis in the NCA context, which could ultimately be used in a cIPMA.

CRediT authorship contribution statement

Sven Hauff: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nicole Franziska Richter:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Marko Sarstedt:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Conceptualization. **Christian M. Ringle:** Writing – review & editing, Writing – original draft, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

This research uses the statistical software SmartPLS (https://www.smartpls.com). Christian M. Ringle acknowledges a financial interest in SmartPLS.

Data availability

Data available as part of a Data in Brief article (https://doi.org/10.1016/j.dib.2023.109190)

Appendix

Table A1
Data description

Latent variable (measurement adapted from)	Indicator		Mean	Range [Min; Max]	S.D.	Excess kurtosis	Skewness
Emotional value, reflective (Sweeney and Soutar, 2001)	EMV_01	Enjoyment	3.902	[1; 5]	0.842	1.942	−1.036
	EMV_02	Pleasure	3.724	[1; 5]	0.887	0.940	−0.675
	EMV_03	Relaxation	3.799	[1; 5]	0.877	1.465	−0.675
Ease of use, reflective (Moore and Benbasat, 1991)	EOU_01	Learning duration	4.011	[1; 5]	0.988	0.800	−0.996
	EOU_02	Operation	4.092	[1; 5]	0.811	0.798	−0.822
	EOU_03	Menu navigation	3.971	[1; 5]	0.867	1.201	−0.904
Perceived usefulness, reflective (Antón et al., 2013; Moore and Benbasat, 1991)	PU_01	General advantage	3.397	[1; 5]	0.970	−0.176	−0.296
	PU_02	Practical application	3.598	[1; 5]	1.055	−0.106	−0.585
	PU_03	Improvement of reading	3.293	[1; 5]	1.109	−0.534	−0.474
Compatibility, reflective (Huang and Hsieh, 2012; Moore and Benbasat, 1991)	CO_01	Reading behavior	3.299	[1; 5]	0.996	−0.238	−0.419
	CO_02	Consumption pattern	3.427	[1; 5]	0.991	0.259	−0.646
	CO_03	Reading needs	3.655	[1; 5]	0.992	0.430	−0.829
Adoption intention, reflective (Venkatesh et al., 2012)	AD_01	Future usage	4.023	[1; 5]	0.928	1.210	−1.046
	AD_02	Daily usage	3.776	[1; 5]	0.972	0.360	−0.712
	AD_03	Frequent usage	3.845	[1; 5]	0.925	0.869	−0.785
Technology use, single item (Venkatesh et al., 2012)	USE_01	e-books	3.983	[1; 7]	1.610	−0.894	−0.063

Table A2
Results summary of (reflective) measurement models

Latent variables	Indicators	Weights	Loadings	Indicator communality (squared loadings)	AVE	Composite reliability	Cronbach's α	ρ_A	HTMT 95% bootstrap confidence interval does not include 1
Emotional value	EMV_01	0.338	0.891	0.794	0.853	0.946	0.914	0.917	Yes
	EMV_02	0.375	0.950	0.903					
	EMV_03	0.368	0.929	0.863					
Ease of use	EOU_01	0.453	0.784	0.615	0.697	0.873	0.783	0.873	Yes
	EOU_02	0.371	0.878	0.771					
	EOU_03	0.380	0.840	0.706					
Perceived usefulness	PU_01	0.319	0.722	0.521	0.642	0.842	0.723	0.753	Yes
	PU_02	0.426	0.819	0.671					
	PU_03	0.491	0.856	0.737					
Compatibility	CO_01	0.396	0.901	0.812	0.779	0.914	0.858	0.859	Yes
	CO_02	0.357	0.906	0.821					
	CO_03	0.381	0.840	0.706					
Adoption intention	AD_01	0.345	0.933	0.870	0.889	0.960	0.938	0.939	Yes
	AD_02	0.347	0.935	0.874					
	AD_03	0.368	0.960	0.922					

Table A3
Bottleneck table in different formats

Bottleneck technology use, standardized latent variable scores percentage ranges (as in Richter et al., 2020)					
	Adoption intention	Emotional value	Ease of use*	Perceived usefulness	Compatibility
0	NN	NN	NN	NN	NN
10	NN	NN	10.2	NN	NN
20	NN	NN	10.2	NN	NN
30	NN	NN	10.2	NN	NN
40	33.8	49.6	20.0	15.7	25.5
50	33.8	49.6	20.0	15.7	25.5
60	33.8	49.6	20.0	15.7	33.7
70	33.8	49.6	20.5	48.1	33.7
80	33.8	49.6	20.5	48.1	33.7
90	75.0	49.6	60.2	66.2	33.7
100	75.0	49.6	60.2	66.2	33.7
Bottleneck technology use, rescaled latent variable scores, percentage ranges					
0	NN	NN	NN	NN	NN
10	NN	NN	10.2	NN	NN
20	NN	NN	10.2	NN	NN
30	NN	NN	10.2	NN	NN
40	33.8	49.6	20.0	15.7	25.5
50	33.8	49.6	20.0	15.7	25.5
60	33.8	49.6	20.0	15.7	33.7
70	33.8	49.6	20.5	48.1	33.7
80	33.8	49.6	20.5	48.1	33.7
90	75.0	49.6	60.2	66.2	33.7
100	75.0	49.6	60.2	66.2	33.7
Bottleneck technology use, rescaled latent variable scores, actual scores					
0	NN	NN	NN	NN	NN
10	NN	NN	25.4	NN	NN
20	NN	NN	25.4	NN	NN
30	NN	NN	25.4	NN	NN
40	33.8	49.6	33.5	15.7	25.5
50	33.8	49.6	33.5	15.7	25.5
60	33.8	49.6	33.5	15.7	33.7
70	33.8	49.6	33.9	48.1	33.7
80	33.8	49.6	33.9	48.1	33.7
90	75.0	49.6	66.9	66.2	33.7
100	75.0	49.6	66.9	66.2	33.7

*The standardized and rescaled latent variable scores produce the same bottleneck results if presented as percentage ranges, but differ regarding the actual values of the construct *ease of use*. This difference is due to the minimum value of ease of use being 16.9. Consequently, ease of use's potential values range from 16.9 to 100; that is, 83.1. Transferring the percentage ranges, for instance of 10.2 or 20.0, to rescaled actual scores therefore yields $16.9 + 0.102 \cdot 83.1 = 25.4$ or $16.9 + 0.200 \cdot 83.1 = 33.5$.

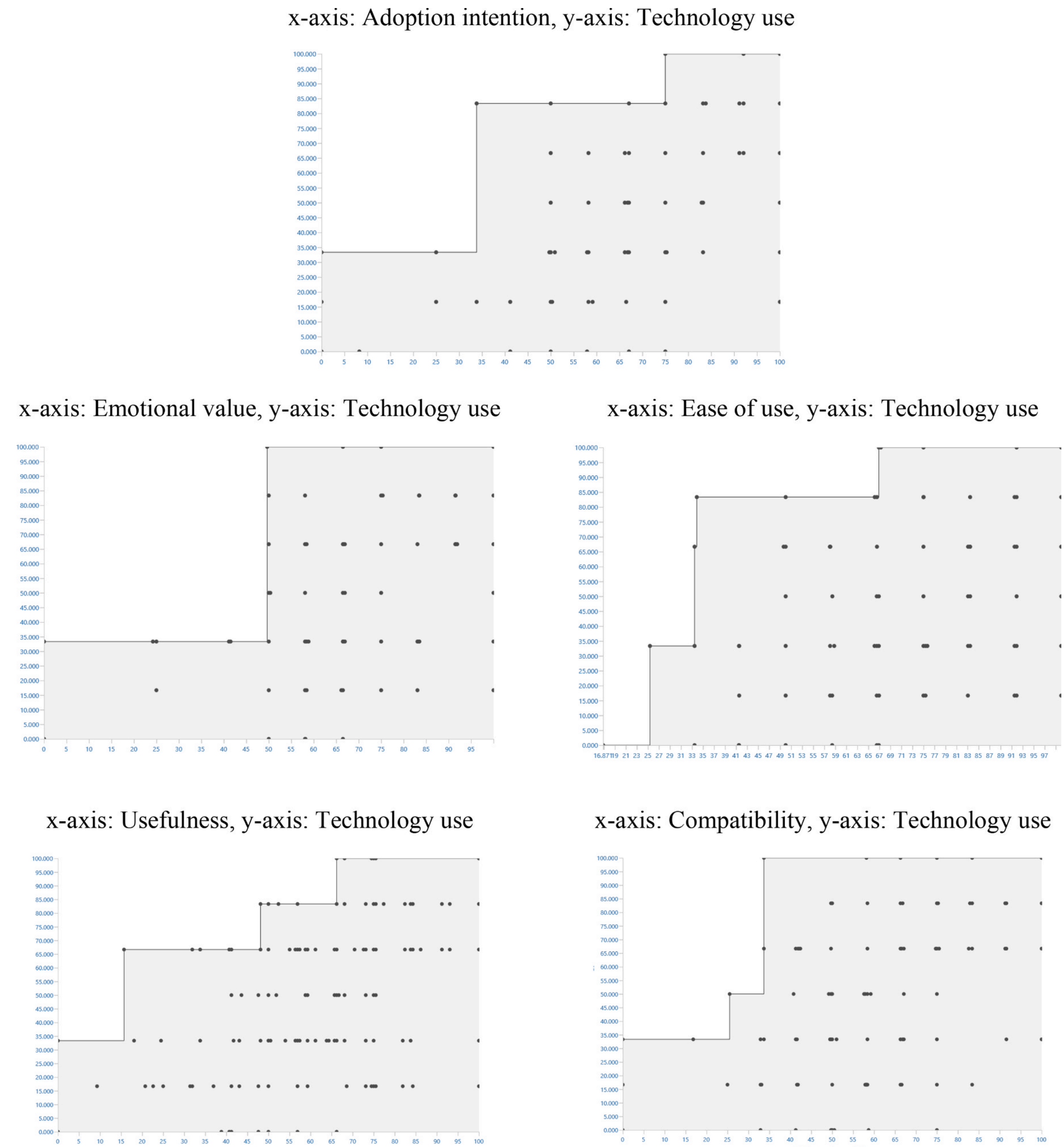

Fig. A1. NCA scatter plots with CE-FDH ceiling lines.

References

Ajzen, I., 1991. The theory of planned behavior. Organ. Behav. Hum. Decis. Process. 50, 179–211.

Alyahya, M., Agag, G., Aliedan, M., Abdelmoety, Z.H., Daher, M.M., 2023. A sustainable step forward: understanding factors affecting customers' behaviour to purchase remanufactured products. J. Retailing Consum. Serv. 70, 103172.

American Customer Satisfaction Index, 2022. Unparalleled Customer Intelligence. Retrieved from. https://www.theacsi.org/our-industries/.

Anderson, E.W., Mittal, V., 2000. Strengthening the satisfaction-profit chain. J. Serv. Res. 3 (2), 107–186.

Antón, C., Camarero, C., Rodríguez, J., 2013. Usefulness, enjoyment, and self-image congruence: the adoption of e-book readers. Psychol. Market. 30 (4), 372–384.

Bergh, D.D., Boyd, B.K., Byron, K., Gove, S., Ketchen, D.J., 2022. What constitutes a methodological contribution? J. Manag. 48 (7), 1835–1848.

Bolívar, L.M., Roldán, J.L., Castro-Abancéns, I., Casanueva, C., 2022. Speed of international expansion: the mediating role of network resources mobilisation. Manag. Int. Rev. 62, 541–568.

Cai, X., Cebollada, J., Cortiñas, M., 2023. Impact of seller- and buyer-created content on product sales in the electronic commerce platform: the role of informativeness, readability, multimedia richness, and extreme valence. J. Retailing Consum. Serv. 70, 103141.

Cheah, J.-H., Magno, F., Cassia, F., 2023. Reviewing the smartPLS 4 software: the latest features and enhancements. Journal of Marketing Analytics. Advance online publication.

Davis, F.D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly 13 (3), 319–340.

Davis, F.D., Bagozzi, R.P., Warshaw, P.R., 1989. User acceptance of computer technology: a comparison of two theoretical models. Manag. Sci. 35 (8), 982–1003.

Dul, J., 2016. Necessary condition analysis (NCA): logic and methodology of "necessary but not sufficient" causality. Organ. Res. Methods 19 (1), 10–52.

Dul, J., 2020. Conducting Necessary Condition Analysis. Sage, London.

Dul, J., 2021a. Advances in Necessary Condition Analysis. Online book retrieved from:, Version 0.1. https://bookdown.org/ncabook/advanced_nca2/.

Dul, J., 2021b. Necessary Condition Analysis (NCA) with R. *A Quick Start Guide: 2 March 2021*. Online document retreived from:, Version 3.1.0. https://www.erim.eur.nl

/fileadmin/user_upload/_generated_/download/Quick_Start_Guide_NCA_3.1.0_March_2_2021.pdf.
Dul, J., 2022. R Package NCA: Necessary Condition Analysis. Version:, 3.2.0. https://cran.r-project.org/web/packages/NCA/index.html.
Dul, J., Hauff, S., Bouncken, R.B., 2023. Necessary condition analysis (NCA): review of research topics and guidelines for good practice. Rev. Manag. Sci. 17 (2), 683–714.
Dul, J., Hauff, S., Tóth, Z., 2021. Necessary condition analysis in marketing research. In: Nunkoo, R., Teeroovengadum, V., Ringle, C.M. (Eds.), Handbook of Research Methods for Marketing Management. Edward Elgar, pp. 51–72.
Fornell, C., 1992. A national customer satisfaction barometer: the Swedish experience. J. Market. 56 (1), 6–21.
Fornell, C., Johnson, M.D., Anderson, E.W., Cha, J., Bryant, B.E., 1996. The American satisfaction index: nature, purpose, and findings. J. Market. 60 (4), 7–18.
Guenther, P., Guenther, M., Ringle, C.M., Zaefarian, G., Cartwright, S., 2023. Improving PLS-SEM use for business marketing research. Ind. Market. Manag. 111, 127–142.
Hair, J.F., Hult, G.T.M., Ringle, C.M., Sarstedt, M., 2022. A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), 3 ed. Sage, Thousand Oaks, CA.
Hair, J.F., Hult, G.T.M., Ringle, C.M., Sarstedt, M., Thiele, K.O., 2017. Mirror, mirror on the wall: a comparative evaluation of composite-based structural equation modeling methods. J. Acad. Market. Sci. 45 (5), 616–632.
Hair, J.F., Risher, J.J., Sarstedt, M., Ringle, C.M., 2019. When to use and how to report the results of PLS-SEM. Eur. Bus. Rev. 31 (1), 2–24.
Hair, J.F., Sarstedt, M., Ringle, C.M., Gudergan, S.P., 2024. Advanced Issues in Partial Least Squares Structural Equation Modeling (PLS-SEM), 2 ed. Sage, Thousand Oaks, CA.
Hair, J.F., Sarstedt, M., Ringle, C.M., Mena, J.A., 2012. An assessment of the use of partial least squares structural equation modeling in marketing research. J. Acad. Market. Sci. 40 (3), 414–433.
Hauff, S., Guerci, M., Dul, J., van Rhee, H., 2021. Exploring necessary conditions in HRM research: fundamental issues and methodological implications. Hum. Resour. Manag. J. 31 (1), 18–36.
Hauff, S., Richter, N.F., Tressin, T., 2015. Situational job characteristics and job satisfaction: the moderating role of culture. Int. Bus. Rev. 24 (4), 710–723.
Huang, L.-Y., Hsieh, Y.-J., 2012. Consumer electronics acceptance based on innovation attributes and switching costs: the case of e-book readers. Electron. Commer. Res. Appl. 11 (3), 218–228.
Huete-Alcocer, N., Hernandez-Rojas, R.D., 2022. Do SARS-CoV-2 safety measures affect visitors experience of traditional gastronomy, destination image and loyalty to a world heritage city? J. Retailing Consum. Serv. 69, 103095.
Kristensen, K., Martensen, A., Grønholdt, L., 2000. Customer satisfaction measurement at post Denmark: results of application of the European customer satisfaction index methodology. Total Qual. Manag. 11 (7), S1007–S1015.
Le, H.T.P.M., Kim, D., Park, J., 2024. The way to generate customer citizenship behavior with customer experience. J. Retailing Consum. Serv. 76, 103608.
Lohmöller, J.-B., 1989. Latent Variable Path Modeling with Partial Least Squares. Physica, Heidelberg.
Martilla, J.A., James, J.C., 1977. Importance-performance analysis. J. Market. 41 (1), 77–79.
Moore, G.C., Benbasat, I., 1991. Development of an instrument to measure the perceptions of adopting an information technology innovation. Inf. Syst. Res. 2 (3), 192–222.
Ng, F.Z.-X., Yap, H.-Y., Tan, G.W.-H., Lo, P.-S., Ooi, K.-B., 2022. Fashion shopping on the go: a dual-stage predictive-analytics SEM-ANN analysis on usage behaviour, experience response and cross-category usage. J. Retailing Consum. Serv. 65, 102851.
Oh, H., 2001. Revisiting importance-performance analysis. Tourism Manag. 22 (6), 617–627.
Pappas, N., 2023. Came and gone? A longitudinal study of the effects of COVID-19 on tourism purchasing intentions. J. Retailing Consum. Serv. 72, 103269.
Perez-Aranda, J., Gonzáles Robles, E.M., Alarcón Urbistondo, P., 2023. Understanding antecedents of continuance and revisit intentions: the case of sport apps. J. Retailing Consum. Serv. 72, 103288.
Richter, N.F., Hauff, S., 2022. Necessary conditions in international business research: advancing the field with a new perspective on causality and data analysis. J. World Bus. 57 (5), 101310.
Richter, N.F., Hauff, S., Gudergan, S.P., Ringle, C.M., 2022. The use of partial least squares structural equation modeling and complementary methods in international management research. Manag. Int. Rev. 62 (4), 449–470.
Richter, N.F., Hauff, S., Kolev, A.E., Schubring, S., 2023a. Dataset on an extended technology acceptance model: a combined application of PLS-SEM and NCA. Data Brief 48, 109190.
Richter, N.F., Hauff, S., Ringle, C.M., Sarstedt, M., Kolev, A.E., Schubring, S., 2023b. How to apply necessary condition analysis in PLS-SEM. In: Latan, H., Hair, J.F., Noonan, R. (Eds.), Partial Least Squares Path Modeling: Basic Concepts, Methodological Issues and Applications. Springer, pp. 267–297.
Richter, N.F., Martin, J., Hansen, S.V., Taras, V., Alon, I., 2021. Motivational configurations of cultural intelligence, social integration, and performance in global virtual teams. J. Bus. Res. 129, 351–367.
Richter, N.F., Schubring, S., Hauff, S., Ringle, C.M., Sarstedt, M., 2020. When predictors of outcomes are necessary: guidelines for the combined use of PLS-SEM and NCA. Ind. Manag. Data Syst. 120 (12), 2243–2267.
Rigdon, E.E., Ringle, C.M., Sarstedt, M., 2010. Structural modeling of heterogeneous data with partial least squares. In: Malhotra, N.K. (Ed.), Review of Marketing Research, vol. 7. Sharpe, Armonk, NY, pp. 255–296.
Ringle, C.M., Sarstedt, M., 2016. Gain more insight from your PLS-SEM results: the importance-performance map analysis. Ind. Manag. Data Syst. 116 (9), 1865–1886.
Ringle, C.M., Wende, S., Becker, J.-M., 2022. SmartPLS 4. Oststeinbek: SmartPLS. Retrieved from. https://www.smartpls.com/.
Rodríguez, P.G., Villarreal, R., Valiño, P.C., Blozis, S., 2020. A PLS-SEM approach to understanding e-SQ, e-satisfaction and e-loyalty for fashion e-retailers in Spain. J. Retailing Consum. Serv. 57, 102201.
Sarstedt, M., Hair, J.F., Pick, M., Liengaard, B.D., Radomir, L., Ringle, C.M., 2022. Progress in partial least squares structural equation modeling use in marketing research in the last decade. Psychol. Market. 39 (5), 1035–1064.
Sarstedt, M., Hair, J.F., Ringle, C.M., Thiele, K.O., Gudergan, S.P., 2016. Estimation issues with PLS and CBSEM: where the bias lies. J. Bus. Res. 69 (10), 3998–4010.
Sever, I., 2015. Importance-performance analysis: a valid management tool? Tourism Manag. 48, 43–53.
Shahidi, N., Tossan, V., Bourliataux-Lajoinie, S., Cacho-Elizondo, S., 2022. Behavioral intention to use a contact tracing application: the case of StopCovid in France. J. Retailing Consum. Serv. 68, 102998.
Sheppard, B.H., Hartwick, J., Warshaw, P.R., 1988. The theory of reasoned action: a meta-analysis of past research with recommendations for modifications and future research. J. Consum. Res. 15 (3), 325–343.
Sheth, J.N., Newman, B.I., Gross, B.L., 1991. Why we buy what we buy: theory of consumption values. J. Bus. Res. 22 (2), 159–170.
Siyal, A.W., Chen, H., Jamal Shah, S., Shahzad, F., Bano, S., 2024. Customization at a glance: investigating consumer experiences in mobile commerce applications. J. Retailing Consum. Serv. 76, 103602.
Skok, W., Kophamel, A., Richardson, I., 2001. Diagnosing information systems success: importance-performance maps in the health club industry. Inf. Manag. 38 (7), 409–419.
Slack, N., 1994. The importance-performance matrix as a determinant of improvement Priority. Int. J. Oper. Prod. Manag. 44 (5), 59–75.
Streukens, S., Leroi-Erelds, S., Willems, K., 2017. Dealing with nonlinearity in importance-performance map analysis (IPMA): an integrative framework in a PLS-SEM context. In: Latan, H., Noonan, R. (Eds.), Partial Least Squares Path Modeling. Springer, Cham, pp. 367–403.
Sukhov, A., Olsson, L.E., Friman, M., 2022. Necessary and sufficient conditions for attractive public transport: combined use of PLS-SEM and NCA. Transport. Res. Pol. Pract. 158, 239–250.
Sweeney, J.C., Soutar, G.N., 2001. Consumer perceived value: the development of a multiple item scale. J. Retailing 77 (2), 203–220.
Tiwari, P., Kaurav, R.P.S., Koay, K.Y., 2023. Understanding travel apps usage intention: findings from PLS and NCA. Journal of Marketing Analytics. advance online publication.
Turner, M., Kitchenham, B., Brereton, P., Charters, S., Budgen, D., 2010. Does the technology acceptance model predict actual use? A systematic literature review. Inf. Software Technol. 52 (5), 463–479.
Venkatesh, V., Thong, J.Y.L., Xu, X., 2012. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. MIS Quarterly 36 (1), 157–178.
Wold, H., 1982. Soft modeling: the basic design and some extensions. In: Jöreskog, K.G., Wold, H. (Eds.), Systems under Indirect Observations: Part II. North-Holland, Amsterdam, pp. 1–54.
Zhang, P., Chao, C.-W., Chiong, R., Hasan, N., Aljaroodi, H.M., Tian, F., 2023. Effects of in-store live stream on consumers' offline purchase intention. J. Retailing Consum. Serv. 72, 103262.
Bokrantz, J., Dul, J., 2023. Building and testing necessity theories in supply chain management. J. Supply Chain Manag. 59 (1), 48–65.
Sarstedt, M., Mooi, E.A., 2019. A Concise Guide to Market Research: The Process, Data, and Methods Using IBM SPSS Statistics. 3, ed. Springer, Berlin, Heidelberg.
Sharma, P.N., Liengaard, B.D., Hair, J.F., Sarstedt, M., Ringle, C.M., 2023. Predictive model assessment and selection in composite-based modeling using PLS-SEM: extensions and guidelines for using CVPAT. Eur. J. Market. 57 (6), 1662–1677.
Shmueli, G., Sarstedt, M., Hair, J.F., Cheah, J., Ting, H., Vaithilingam, S., Ringle, C.M., 2019. Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. Eur. J. Market. 53 (11), 2322–2347.