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ORIGINAL ARTICLE

Combined importance–performance map analysis (cIPMA) in partial least squares structural equation modeling (PLS–SEM): a SmartPLS 4 tutorial

Marko Sarstedt[1,2] · **Nicole F. Richter**[3] · **Sven Hauff**[4] · **Christian M. Ringle**[5,6]

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Abstract
Recent research on partial least squares structural equation modeling (PLS–SEM) extended the classic importance–performance map analysis (IPMA) by taking the results of a necessary condition analysis (NCA) into consideration. By also highlighting necessary conditions, the combined importance–performance map analysis (cIPMA) offers a tool that enables better prioritization of management actions to improve a key target construct. In this article, we showcase a cIPMA's main steps when using the SmartPLS 4 software. Our illustration draws on the technology acceptance model (TAM) used in the cIPMA's original publication, which features prominently in business research.

Keywords cIPMA · Importance–performance map analysis (IPMA) · Necessary condition analysis (NCA) · Partial least squares (PLS) · PLS–SEM · Structural equation modeling (SEM) · Technology acceptance model (TAM)

Introduction

Partial least squares (PLS) is a composite-based approach to structural equation modeling (SEM) that allows estimating complex interrelationships between constructs and their indicator variables (Hair et al. 2017; Lohmöller 1989; Wold 1982). PLS has gained much prominence in marketing applications of SEM, as evidenced in various reviews across different subfields (e.g., Guenther et al. 2023; Sarstedt et al. 2022, 2024; Wang et al. 2023). In recent years, researchers have introduced various extensions that expand on the original PLS–SEM algorithm and statistics (Hair et al. 2022, 2024). One such extension is the importance–performance map analysis (IPMA) that interprets the composite scores that the PLS–SEM algorithm generates as indicative of construct performances (Ringle and Sarstedt 2016; Streukens et al. 2017). The core of the IPMA is a two-dimensional map that contrasts these performance scores with the constructs' total effects (i.e., the importance) on a specific target construct. The IPMA has been used in a variety of contexts, including research on customer loyalty (Damberg et al. 2022), sustainable consumption (Saari et al. 2021), and technology adoption (Mkedder and Özata 2024).

A potential limitation in the application of the standard IPMA is that it is restricted to a sufficiency logic. According to this logic, combinations of antecedent constructs are sufficient for impacting the target construct and each construct's influence can, in principle, be compensated for by the others. This logic differs from the necessity perspective that has recently experienced more coverage in the marketing literature through the introduction of the necessary condition analysis (NCA; Dul 2016; 2020; Dul et al. 2021). The NCA identifies necessary conditions by establishing whether a specific condition must be present so that an outcome can exist. In other words, it establishes whether the absence of a specific condition prevents the outcome from existing. In the case of a necessary condition, the analysis can also quantify

✉ Marko Sarstedt
sarstedt@lmu.de

1 LMU Munich School of Management, Ludwig-Maximilians-University Munich, Ludwigstraße 28 RG/III, 80539 Munich, Germany

2 Faculty of Economics and Business Administration, Babeş-Bolyai University, Cluj-Napoca, Romania

3 University of Southern Denmark, Odense, Denmark

4 Helmut Schmidt University, Hamburg, Germany

5 Institute of Management and Decision Sciences, Hamburg University of Technology, Hamburg, Germany

6 James Cook University, Townsville, Australia

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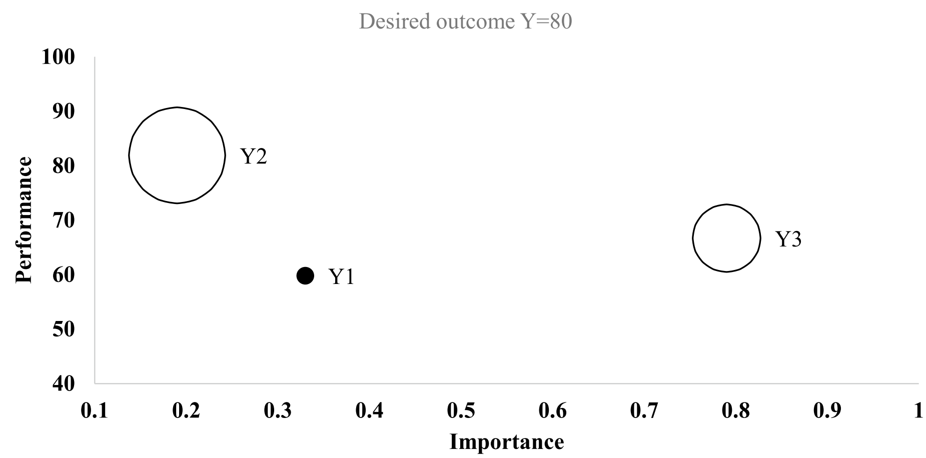


Fig. 1 Combined importance–performance map analysis (cIPMA) example

the level of an antecedent variable that must be achieved so that a specific outcome level in the target becomes possible. Originally proposed in a standard regression context, Richter and Hauff (2022) and Richter et al. (2023b, 2020) suggested using PLS–SEM-based composite scores as input for the NCA. Several authors have used this approach to introduce a necessity perspective into their PLS–SEM analyses (e.g., Sukhov et al. 2022; Tan et al. 2024; Tiwari et al. 2024).

Hauff et al. (2024) have recently merged these perspectives into a unifying analysis framework called combined IPMA (cIPMA). Their cIPMA introduces the results from the NCA as an additional dimension in an importance–performance map—see Riggs et al. (2024) for an initial application. Figure 1 shows a sample map from a cIPMA analysis. This hypothetical example considers three antecedent constructs with different total effects on the target construct (i.e., importance, shown on the *x*-axis) and the average construct values (i.e., performance, shown on the *y*-axis). The map also distinguishes between constructs with high versus low necessity effect sizes. Constructs that are *not* necessary for achieving the target construct's desired level are shown as black circles (Y_1 in Fig. 1), while the necessary constructs are displayed as white circles (Y_2 and Y_3 in Fig. 1). The size of the white circles indicates the percentage of observations whose case values are below those required for achieving a specific value in the target construct. Researchers have to specify this target value a priori, based on theoretical considerations or managerial requirements. In this example, the target value is set to 80. The larger the white circle, the larger the percentage of cases that have *not* achieved the necessary condition's required level. Consequently, large white circles indicate that, from a necessity perspective, researchers should focus their attention on this aspect.

Running a cIPMA requires some data management effort as researchers need to combine elements from different analysis steps. Addressing this concern, this tutorial article illustrates the main steps of a cIPMA using SmartPLS 4 (Ringle et al. 2024), currently the most prominent software for conducting PLS–SEM analyses (e.g., Cheah et al. 2023b; Sarstedt and Cheah 2019). Our illustrations draw on the same model and dataset as in Hauff et al. (2024) to facilitate the method's implementation and interpretation of results.

Case study illustration using SmartPLS 4

Hauff et al. (2024) outline an eight-step procedure for systematically applying the cIPMA (Fig. 2). Since this tutorial article endeavors to explain how to initiate the

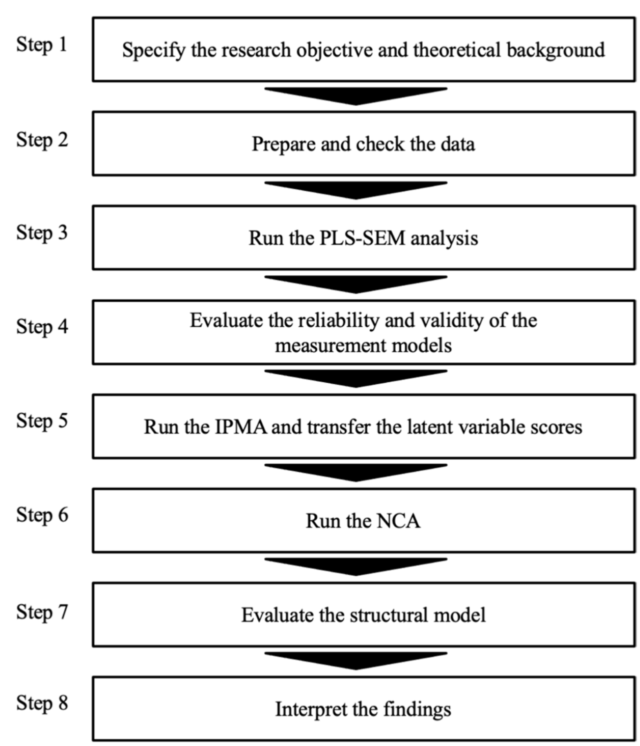


Fig. 2 A systematic procedure for running the cIPMA

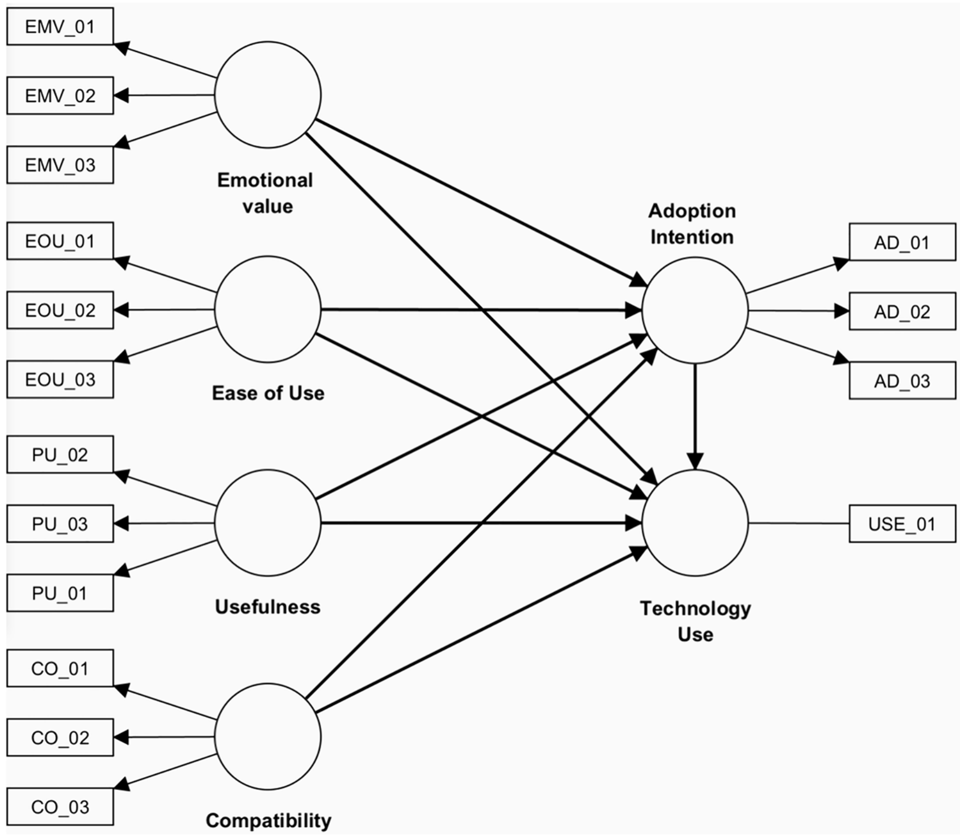


Fig. 3 Extended technology acceptance model (TAM)

analyses and extract the relevant information from the output by using SmartPLS 4 software (Ringle et al. 2024), we focus on Steps 5 and 6, but also comment on the other elements of the analysis.

The authors illustrate the cIPMA's application by using an extended version of Davis's (1989) technology acceptance model (TAM; Fig. 3), which has served as a blueprint for researching consumer behavior in various contexts. The dataset used in the illustration draws on $N = 174$ responses from French consumers. Richter et al.'s (2023a) article introduces the dataset in detail.

The model and the dataset are included in SmartPLS 4 as a sample project, which we can install in the software with a mouse click. Do so by going to the Project window, click on **Regression/PROCESS** under **Sample projects** and thereafter select **NCA (extended TAM)** from the drop-down menu (Fig. 4). SmartPLS will include a new sample project in the Workspace menu on the right of the window (Fig. 5). Note that this project already includes the final NCA model and the dataset derived from the IPMA analysis. However, to demonstrate the analysis steps, we start by analyzing the PLS path model; do so by double-clicking on *PLS–SEM for extended TAM* (Fig. 5).

SmartPLS then opens the **Modeling** window with the TAM readily specified (Fig. 6). Following the procedure that Hauff et al. (2024) outlined, the next step would be to run the standard PLS–SEM algorithm (i.e., by selecting **Standardized** for the *Type of results* option in the PLS–SEM algorithm's start dialog; Step 3 in Fig. 2). Assess the measurement models' reliability and validity in respect of these outcomes (Step 4 in Fig. 2). As part of this analysis, we also need to check whether all the indicator weights are positive. Here, we do not present the detailed analysis, which follows the well-known standards in PLS–SEM, but refer the reader to Richter et al. (2020) and to Hauff et al.'s (2024) Table A2 (in their "Appendix").

We continue our illustration by running the IPMA (Step 5 in Fig. 2). To do so, we click on **Calculate** in the menu bar and select the option **Importance–performance map analysis (IPMA)** (Fig. 6). In the menu that opens, we choose *Technology Use* as the target construct, and *All predecessors of the selected target construct* under the **IPMA results** (Fig. 7, left tab). The lower part of the dialog box shows the indicators' observed minimum and maximum values and the theoretical minimum and maximum values (**Scale min** and **Scale max**), which the software derives from the data structure. We see that the theoretical values in this illustration correspond to those considered in the original survey (i.e., the complete theoretical scales were used by respondents). If this were not the case, the estimated average performance values of the constructs would be biased along the empirical range of the indicators. In this case, PLS–SEM

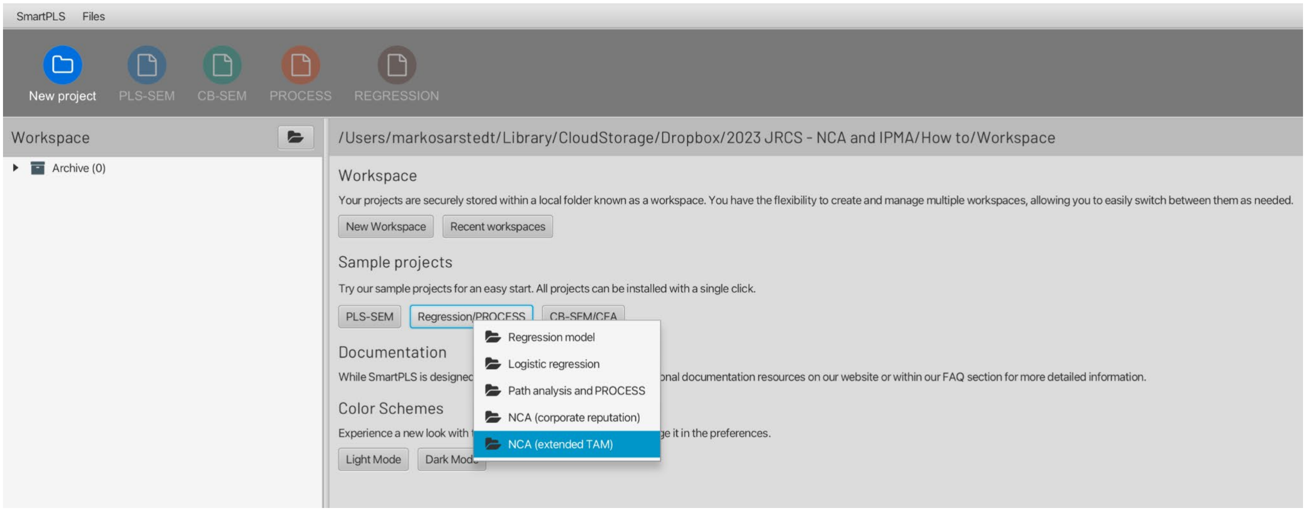


Fig. 4 SmartPLS Project window

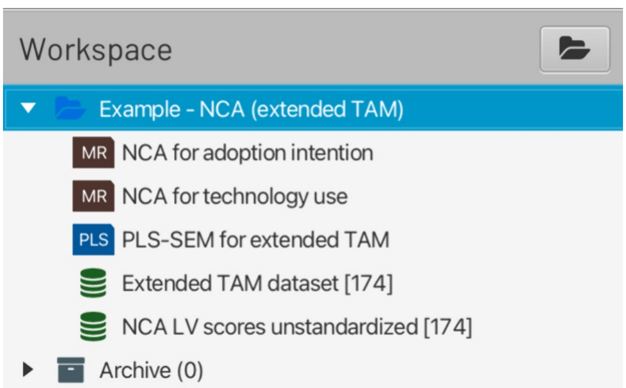


Fig. 5 Workspace

researchers advise to manually adjust the theoretical values in the **Data** window (i.e., by correcting the **Scale min** and **Scale max** in SmartPLS where necessary), which we could access by double-clicking on the dataset in the **Workspace** (Fig. 5). This is followed by clicking on **Setup** in the menu bar, where we can ultimately implement the desired changes and **Update** the file. To continue with the IPMA, we click on the **PLS setup** tab and select the settings shown in Fig. 7 (right tab), before clicking on **Start calculation**.

Next, the SmartPLS software shows the estimates in the **Results** window. Figure 8 shows the graphical output of the results report. The numbers in the constructs are the average performance scores (i.e., the average rescaled constructs scores, which range from 0 to 100). For example, while *Compatibility* has a performance score of 61.557, *Ease of use* achieves a considerably higher performance score of 75.640. The numbers on the arrows represent the direct effects between the constructs.

To extract the total effects that the antecedent constructs have on the final target construct (*Technology use*), click on **Final results → Total effects**. Figure 9 shows that *Adoption intention* has the strongest total effect, followed by *Emotional value*, *Usefulness*, and *Compatibility*.

SmartPLS can display the standard importance–performance map (Fig. 10), which we can access by clicking on **Quality criteria → Importance–performance map**. However, the software currently (version 4.1.0.3) does not include a feature for creating a combined importance–performance map. To create such a combined map, we need to save these importance and performance scores as input for the cIPMA. For example, researchers could copy and paste the results on an Excel spreadsheet similar to the one which we provide as a cIPMA example on the following webpage: https://www.pls-sem.net/downloads/additional-useful-downloads/.

Having extracted the importance (i.e., total effects) and performance scores, we need to export the rescaled latent variable scores into a separate dataset for processing in the NCA. Do so by clicking on **Create data file** in the menu bar (Fig. 8). In the dialog box that opens (Fig. 11), we specify a file name (e.g., *Latent variable scores for the NCA*), check the box next to **Rescaled latent variable scores**, and confirm by clicking on **Create**. SmartPLS will now generate a new dataset under the project. Next, we click on **Edit** followed by **Back** to return to the Project window (Fig. 12). The new dataset called *Latent variable scores for the NCA* is now shown under the *PLS–SEM for extended TAM* project.

We next initiate the NCA by using the previously extracted latent variable scores as input (Step 6 in Fig. 2). We do so by clicking on **Regression** in the menu bar. In the

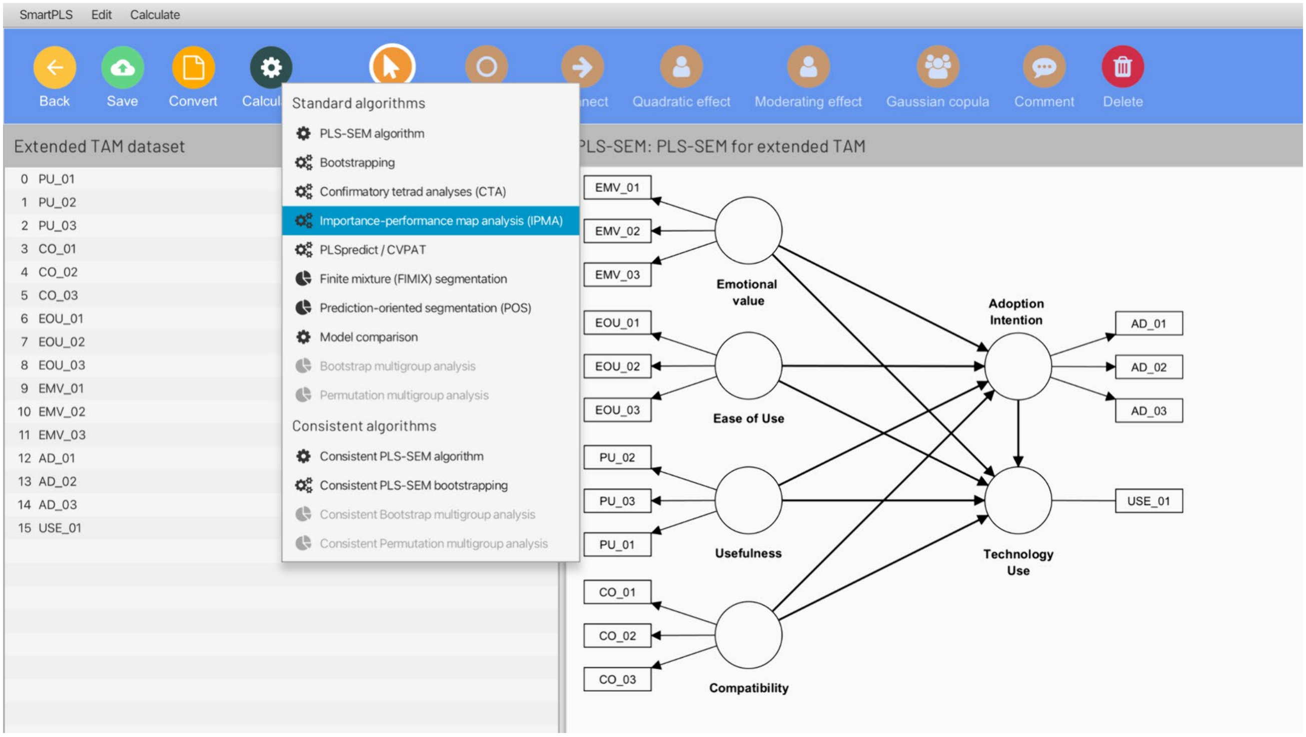


Fig. 6 Modeling window

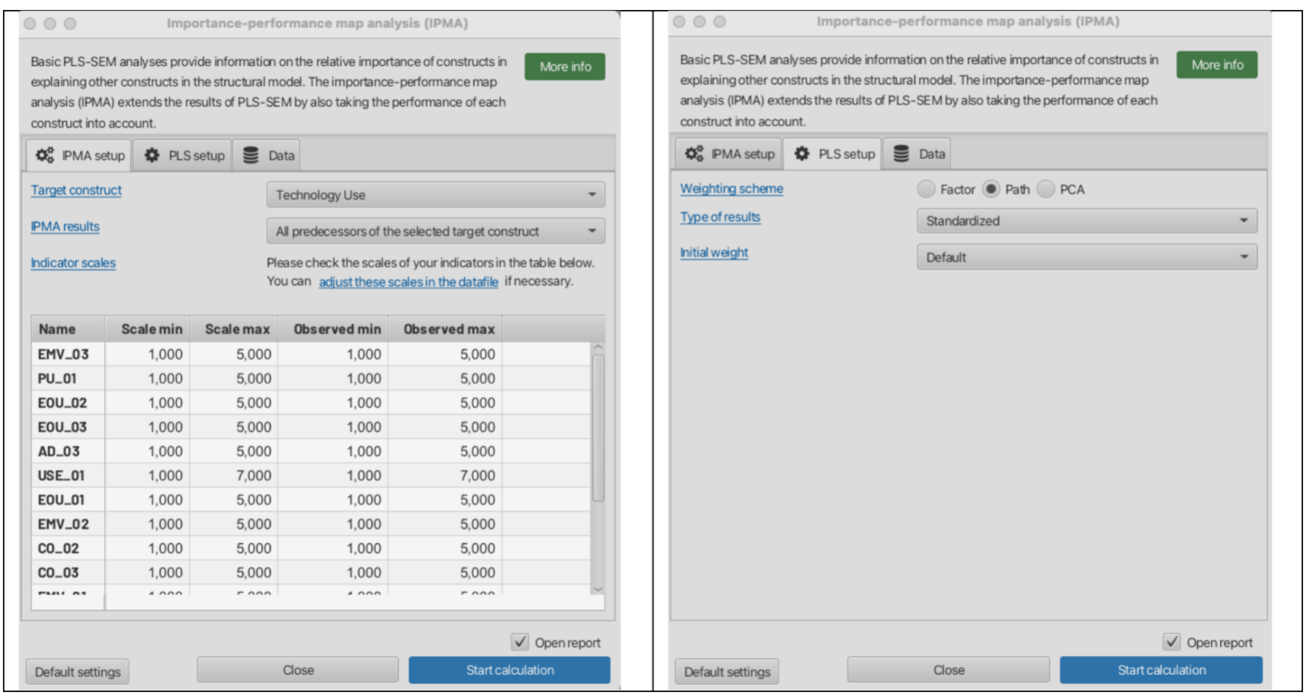


Fig. 7 IPMA dialog box

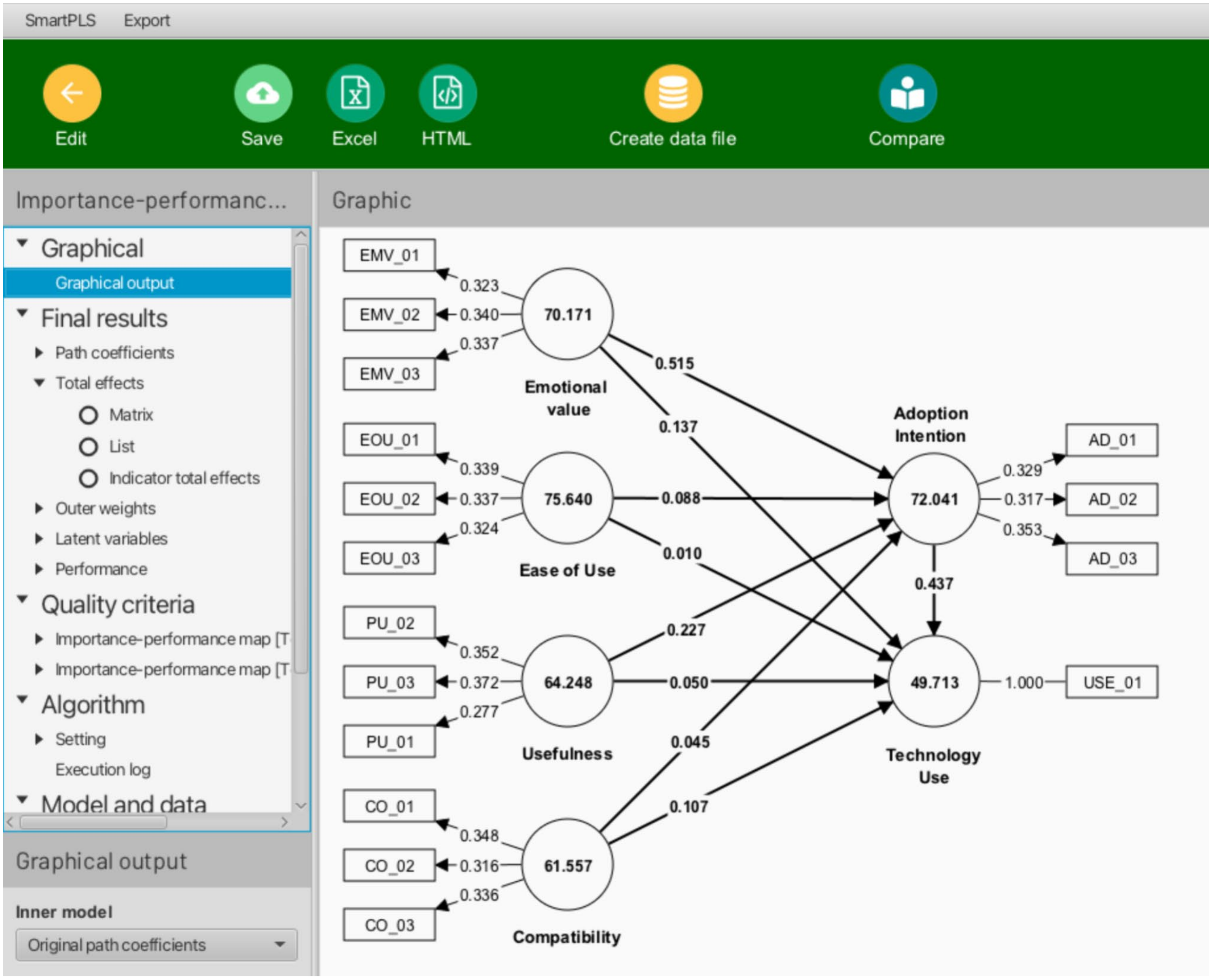


Fig. 8 IPMA results

Total effects - Matrix

	Adoption Intention	Compatibility	Ease of Use	Emotional value	Technology Use	Usefulness
Adoption Intention					0.437	
Compatibility	0.045				0.127	
Ease of Use	0.088				0.049	
Emotional value	0.515				0.362	
Technology Use						
Usefulness	0.227				0.149	

Fig. 9 Total effects

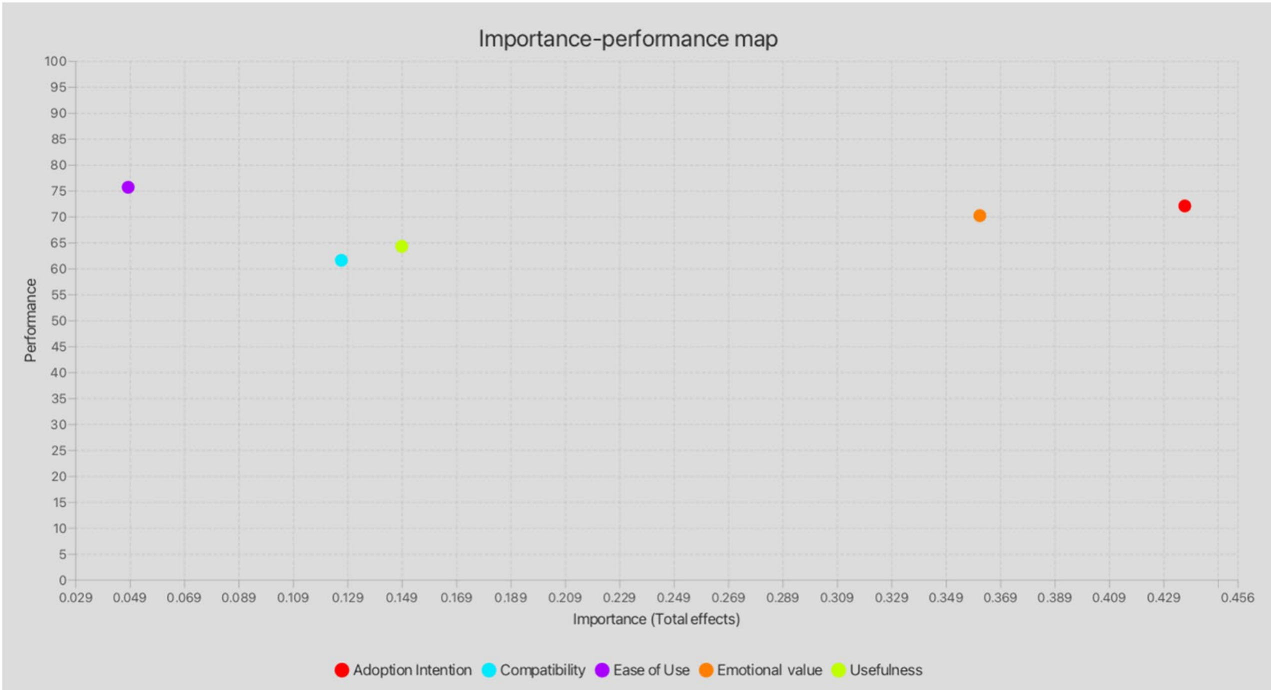


Fig. 10 Importance–performance map

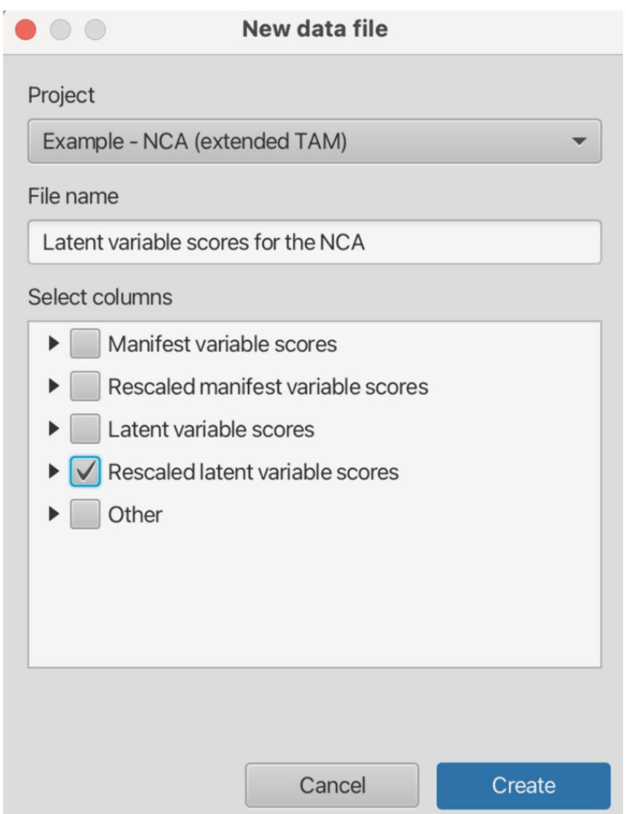


Fig. 11 Create data file dialog box

window that opens (Fig. 13), we have to specify the project to which the model should be assigned (here, *Example—NCA (extended TAM)*), the model type (here, *REGRESSION*), and the model's name (e.g., *cIPMA*). Next, we click on **Save** (Fig. 13).

In the window that opens, we first need to select the newly created *Latent variable scores for the NCA* dataset by clicking on the symbol above the variable list (Fig. 14). Then, we drag and drop the dependent variable (*LV scores—Technology use*) on the modeling window. Next, we need to drag and drop the independent variables (*LV scores—Adoption intention*, *LV scores—Compatibility*, *LV scores—Ease of Use*, *LV scores—Emotional value*, *LV scores—Usefulness*) on the box labeled *LV scores—Technology use* in the modeling window. Figure 15 shows the final modeling window. We can now run the analysis by clicking on **Calculate → Necessary condition analysis (NCA)**. In the dialog box that opens (Fig. 16), we choose **20** as the *Number of steps for bottleneck table* option as we are interested in identifying the necessary levels of the independent variables for a rescaled score of *Technology use* of 85 (which would not be shown, if we just selected the default 10 steps). Then, we click on **Start calculation**.

SmartPLS now opens the results report that documents the metrics that are relevant for the NCA. Specifically, under **Final results → Ceiling line effect size overview** (Fig. 17), we can request the effect size *d*. We focus on the effect size for the CE-FDH ceiling line, which is the relevant

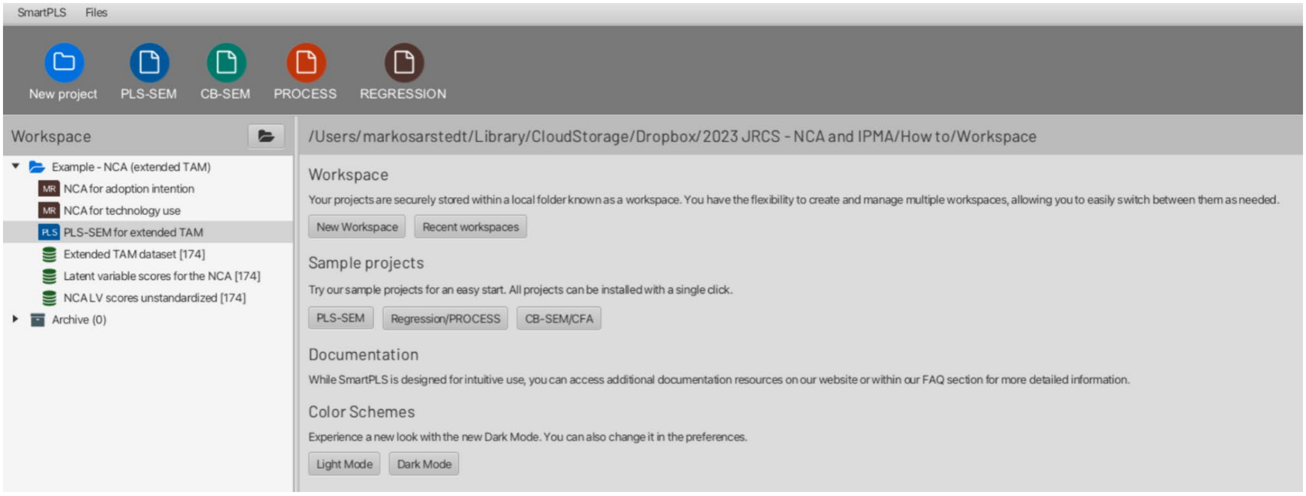


Fig. 12 SmartPLS project window with new dataset

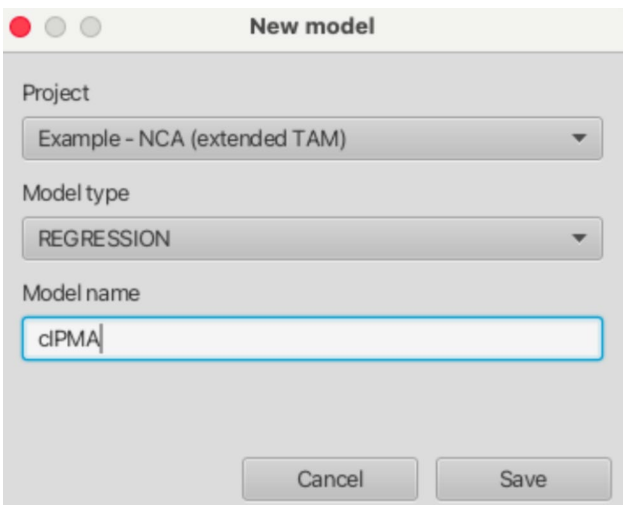
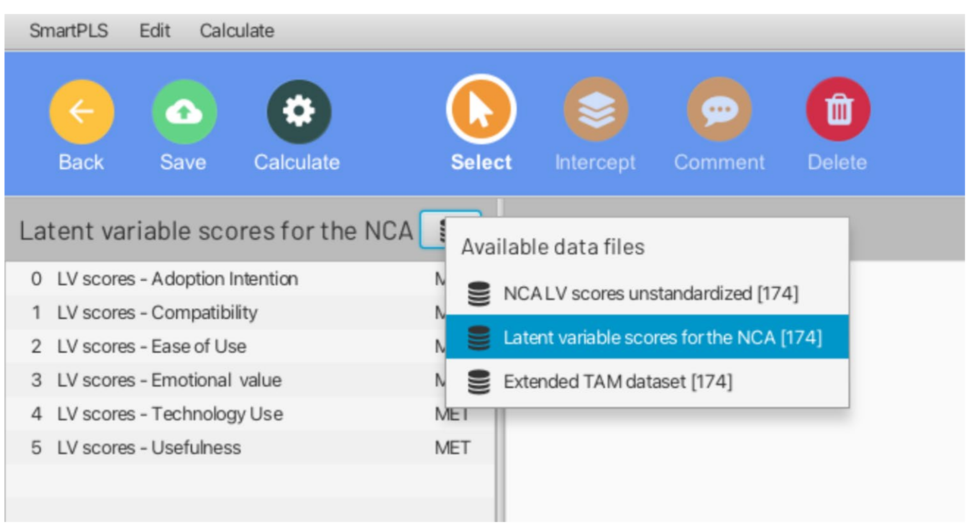


Fig. 13 Regression dialog box

line for our data (see Hauff et al. 2024). The results show that *Emotional value* has the strongest necessary effect size (0.331), followed by *Adoption intention* (0.294), and *Usefulness* (0.243). We need to substantiate these effect sizes' significances by running a permutation analysis. However, we will first complete the illustration of the NCA results' output that is useful for the interpretation of findings, before running the NCA permutation in SmartPLS (as we know which variables show significant necessity effect sizes from our previous studies). For our analyses, we would first identify the significance of effect sizes and may then need to go back to these outputs to not make interpretations on not significant necessity effects.

For the cIPMA, we identify the percentage of cases that do not achieve the antecedent constructs' required level to generate a specific level of *Technology use*. To request the corresponding table, go to **Final results → Bottleneck**

Fig. 14 Regression modeling window



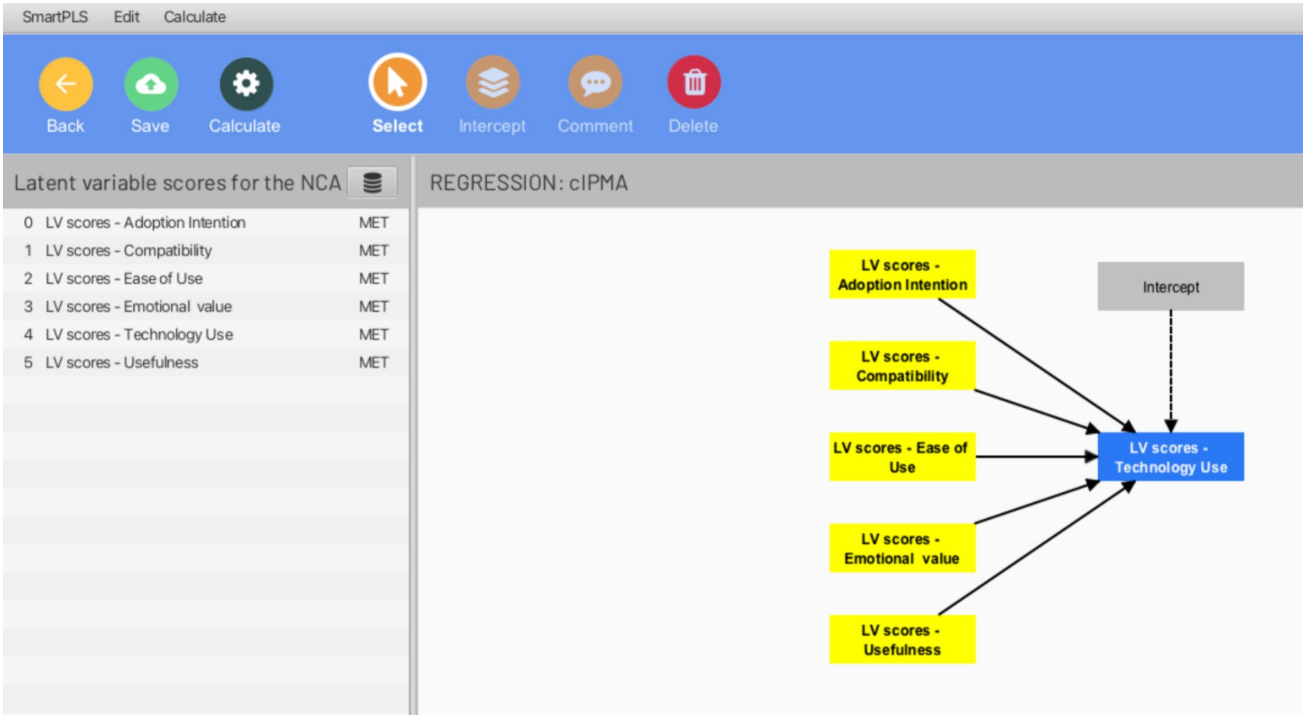


Fig. 15 Regression modeling window with model

tables—CE-FDH → Percentiles (Fig. 18). Hauff et al. (2024) assume a desired *Technology use* level of 85. Assuming this level, our results show that 39.080% of all cases did not achieve the necessary level of *Adoption intention* to enable such a *Technology use* score (see highlighted row in Fig. 18). Compared to *Adoption intention*, the percentage of cases that did not achieve the necessary level of *Compatibility* is considerably lower (8.621%).

In the next step (Step 7 in Fig. 2), we need to evaluate the structural model in terms of PLS–SEM and NCA results. For the former, we refer the reader to Richter et al. (2023a) and move directly to testing whether the necessity effect size d is significant. We do so by returning to the **Modeling** window by clicking on **Edit** in the menu bar. Next, we go to **Calculate** and **NCA permutation**. In the dialog box that opens (Fig. 19), we retain the default settings (5000 permutations, parallel processing, a significance level of 0.05, and a fixed seed) and click on **Start calculation**. In the Results window that opens, we go to **Final results → Ceiling line effect size overview → CE-FDH**. We find that all necessity effect sizes are significantly larger than zero, since the estimates lie above the 95% percentile. For example, the necessity effect size of *Adoption intention* is 0.294, which is higher than the 95% percentile of 0.180 (Fig. 20). These results are further supported by the p values, which are all lower than 0.05.

Table 1 summarizes the results of the IPMA and the NCA. Specifically, the table shows the importance of constructs for *Technology use* and average performance scores from PLS–SEM. In addition, it shows the percentage of cases that do not meet the necessity condition (i.e., those cases that remain below the necessary level of 85 for *Technology use*), and the necessity effect size d, including the p value for each antecedent construct. In terms of the necessity conditions, we find that all antecedent constructs are indeed necessary, as their effect sizes are medium (i.e., $0.1 \leq d < 0.3$) and significant ($p < 0.05$).

We can now use the results from Table 1 to generate the combined importance–performance map with (1) the importance scores on the x-axis, (2) the performance scores on the y-axis, (3) the circle type indicating whether the antecedent construct is necessary (white = yes, black = no), and (4) the size of the white circles indicating the percentage of cases that do not achieve the required levels. To do so, we may use the Excel template, which we can access at https://www.pls-sem.net/downloads/additional-useful-downloads/. In our case, all five conditions are necessary, so we always use the percentage of cases that do not meet the required level as the input for the size of the white circle. If a condition is not necessary, the size of the black circle is standardized to 1.

Entering the values from Table 1 generates the combined importance–performance map shown in Fig. 21.[1] In line with Hauff et al. (2024), the results suggest that *Adoption*

[1] For clarity, we also included construct labels.

Fig. 16 NCA setup

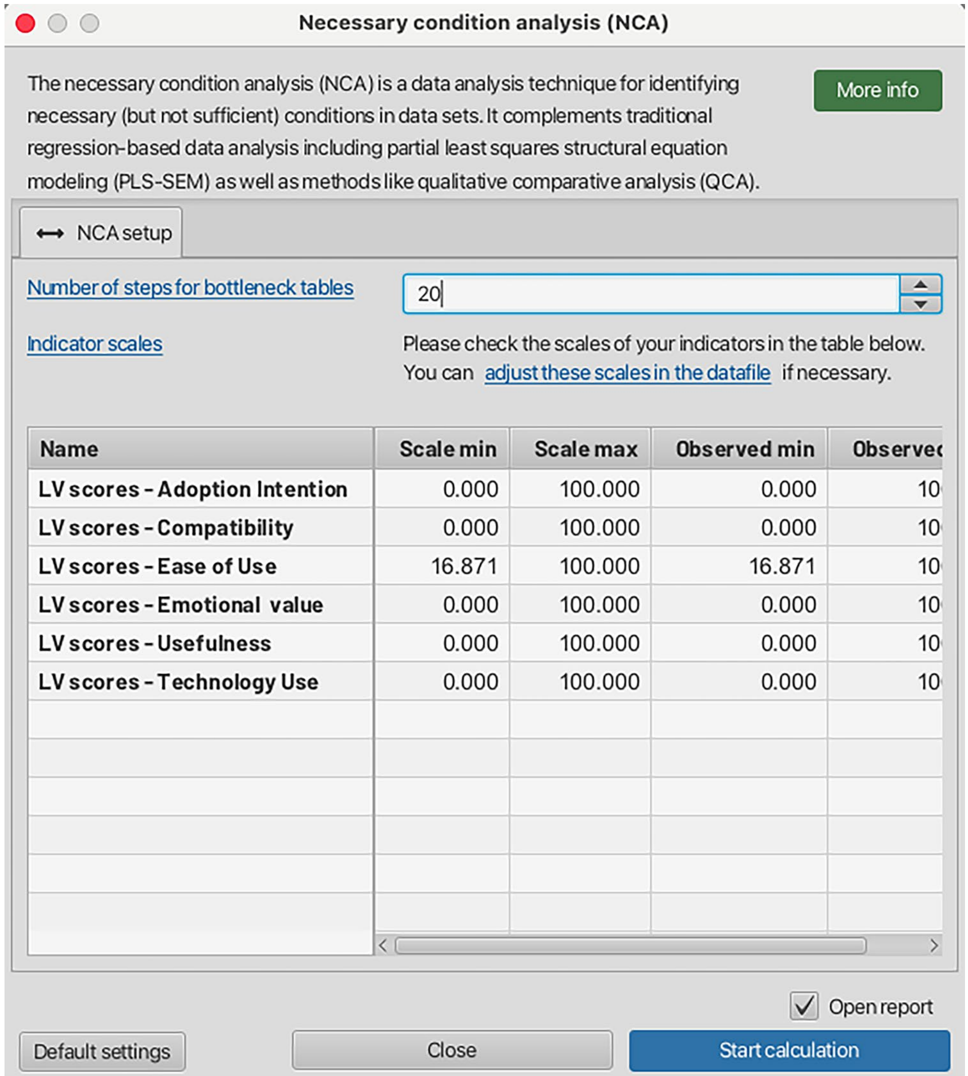
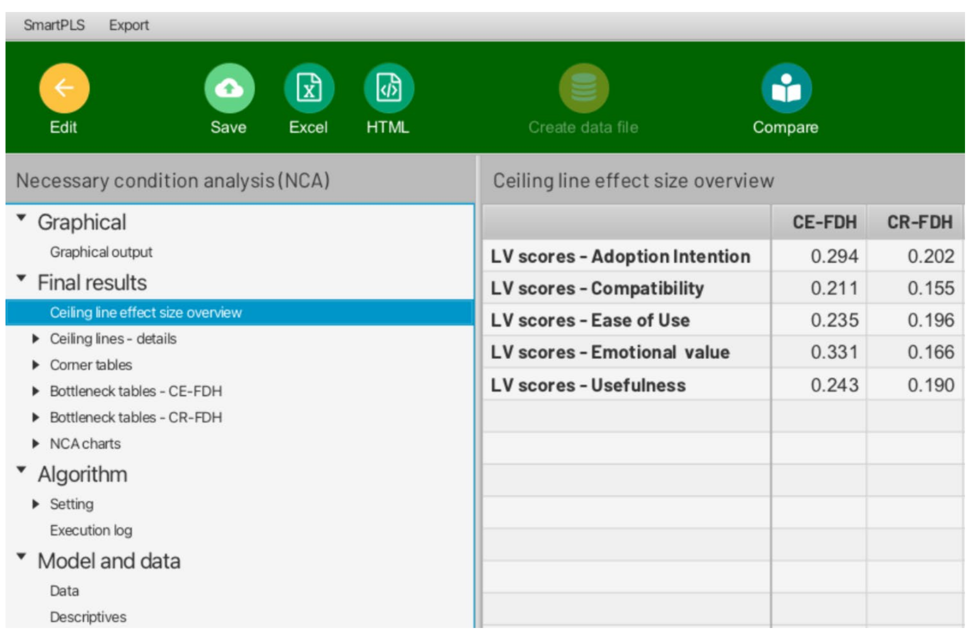
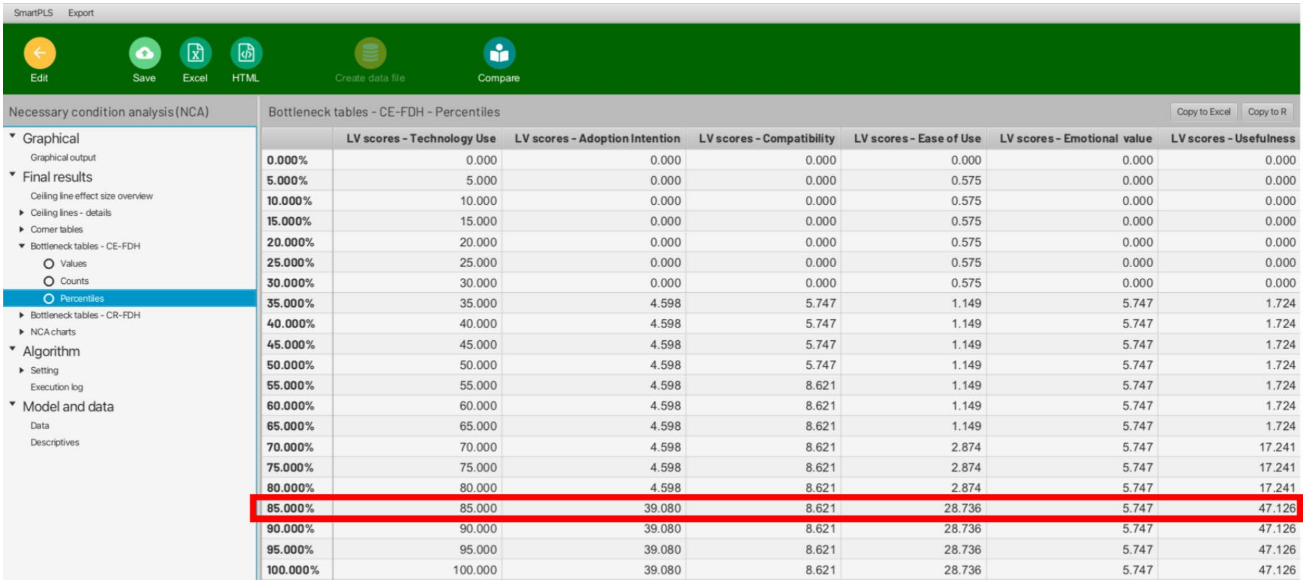


Fig. 17 NCA output (I)

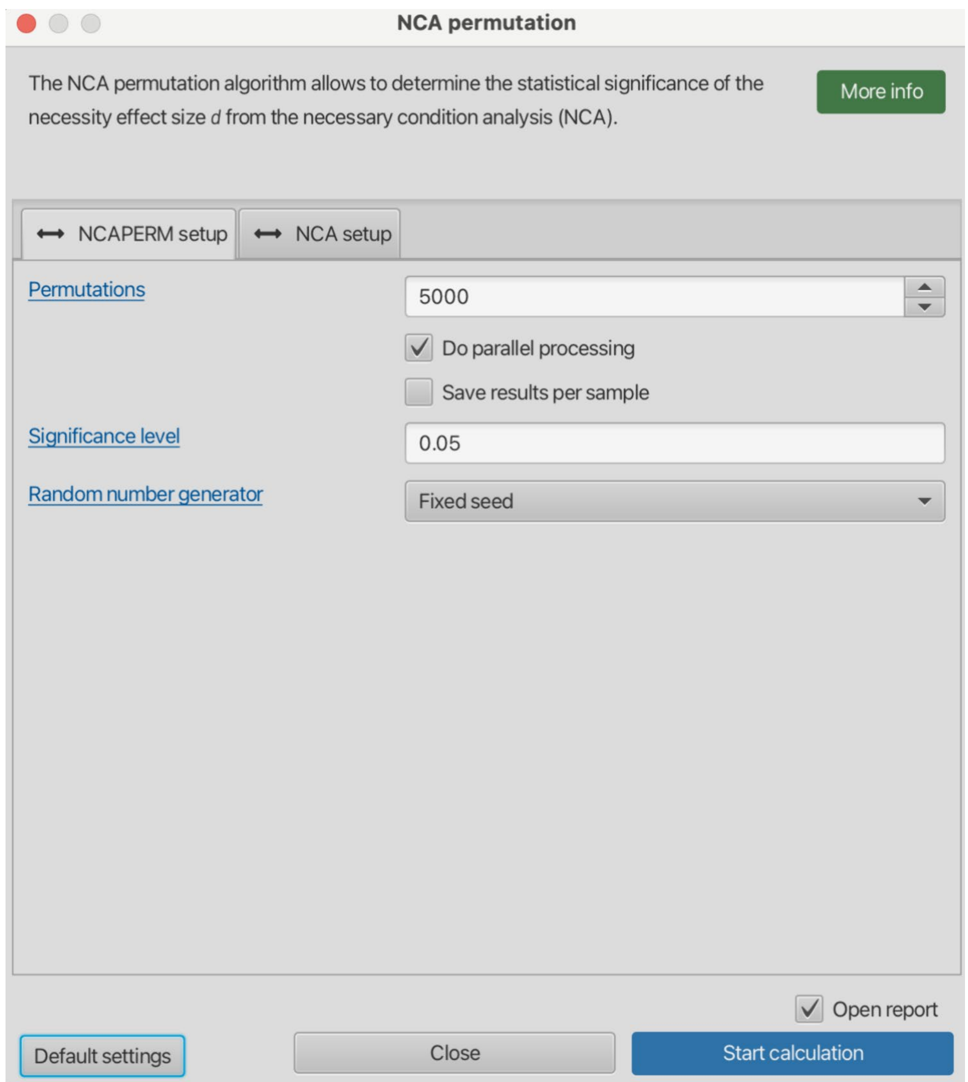




	LV scores - Technology Use	LV scores - Adoption Intention	LV scores - Compatibility	LV scores - Ease of Use	LV scores - Emotional value	LV scores - Usefulness
0.000%	0.000	0.000	0.000	0.000	0.000	0.000
5.000%	5.000	0.000	0.000	0.575	0.000	0.000
10.000%	10.000	0.000	0.000	0.575	0.000	0.000
15.000%	15.000	0.000	0.000	0.575	0.000	0.000
20.000%	20.000	0.000	0.000	0.575	0.000	0.000
25.000%	25.000	0.000	0.000	0.575	0.000	0.000
30.000%	30.000	0.000	0.000	0.575	0.000	0.000
35.000%	35.000	4.598	5.747	1.149	5.747	1.724
40.000%	40.000	4.598	5.747	1.149	5.747	1.724
45.000%	45.000	4.598	5.747	1.149	5.747	1.724
50.000%	50.000	4.598	5.747	1.149	5.747	1.724
55.000%	55.000	4.598	8.621	1.149	5.747	1.724
60.000%	60.000	4.598	8.621	1.149	5.747	1.724
65.000%	65.000	4.598	8.621	1.149	5.747	1.724
70.000%	70.000	4.598	8.621	2.874	5.747	17.241
75.000%	75.000	4.598	8.621	2.874	5.747	17.241
80.000%	80.000	4.598	8.621	2.874	5.747	17.241
85.000%	85.000	39.080	8.621	28.736	5.747	47.126
90.000%	90.000	39.080	8.621	28.736	5.747	47.126
95.000%	95.000	39.080	8.621	28.736	5.747	47.126
100.000%	100.000	39.080	8.621	28.736	5.747	47.126

Fig. 18 NCA output (II)

Fig. 19 NCA permutation dialog box



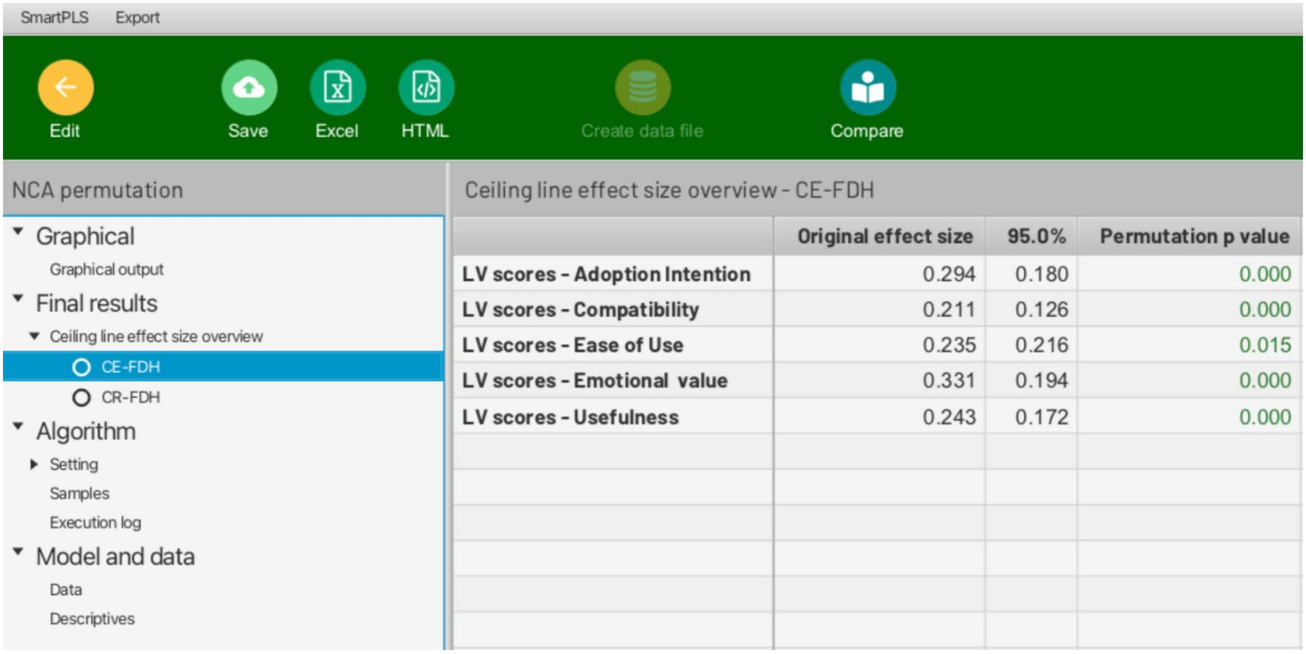


Fig. 20 NCA permutation results

Table 1 cIPMA results

Antecedent construct	Importance	Performance	Percentage of cases that do not meet the necessity condition[a]	Necessity effect size d (p value)
Adoption intention	0.437	72.041	39.080	0.294 (0.000)
Compatibility	0.127	61.557	8.621	0.211 (0.000)
Ease of use	0.049	75.640	28.736	0.235 (0.015)
Emotional value	0.362	70.171	5.747	0.331 (0.000)
Usefulness	0.149	64.248	47.126	0.243 (0.000)

[a]Based on a desired *Technology use* outcome level of 85

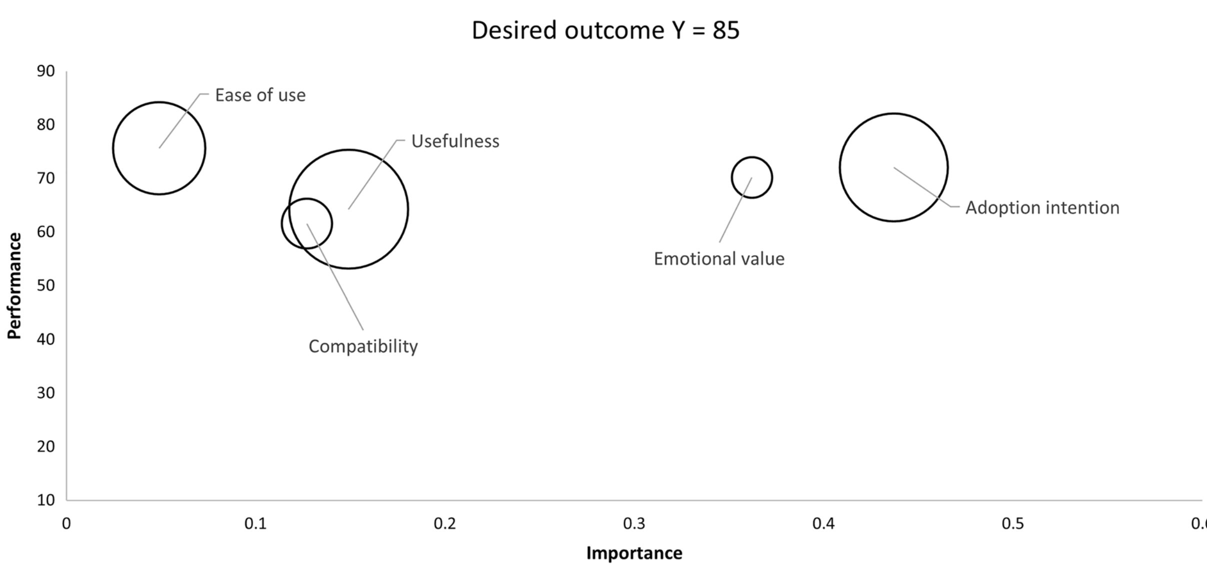


Fig. 21 Combined importance–performance map of the TAM

intention is highly important and already shows a high performance. The NCA adds to this basic IPMA result, since its results identify several necessary conditions for *Technology use*. Specifically, 39% of the cases did not achieve *Adoption intention*'s required level to produce the desired performance level of 85 for *Technology use*. Despite their relatively low importance obtained by PLS–SEM, *Usefulness* and *Ease of use* warrant attention, as many cases do not achieve the required levels (47% for *Usefulness*, 29% for *Ease of use*). Failure to do so would hinder *Technology use*'s improvement to the desired level. Finally, while *Emotional value* and *Compatibility* are also necessary, only few cases fail to achieve the required levels (namely 6%, and 9%). Consequently, these constructs should receive less priority.

Observations and conclusions

During the last decade, research on PLS–SEM has made considerable progress regarding advancing the method's capabilities—see, for example, Cheah et al. (2023a), Richter and Tudoran (2024), and Sarstedt and Liu (2024). One such extension is Hauff et al.'s (2024) cIPMA, which combines results from an IPMA and NCA to form a joint map that allows managerial actions seeking to improve a certain target construct. The IPMA may, for example, identify certain antecedent constructs of relatively minor importance and performance, while they are simultaneously necessary to realize a desired value of the target construct. Similarly, in the same context, a construct may be important, but not necessary. The cIPMA allows its users to identify such relationships and dependencies. To facilitate its adoption, this article demonstrates the implementation of the cIPMA by means of the SmartPLS 4 software, which features prominently in marketing research and beyond (e.g., Cheah et al. 2023b; Richter et al. 2022; Sarstedt and Cheah 2019). Our step-by-step illustration of how to run the cIPMA in SmartPLS helps researchers and practitioners to introduce a necessity perspective in their IPMA.

While the cIPMA offers a valuable way of combining sufficiency and necessity perspectives, future research should extend its scope further. For example, researchers may investigate routines that test the associations between the constructs involved in PLS–SEM when a specific bottleneck identified in the NCA is bypassed and their implications for the interpretation of should-have factors. Also, researchers may engage in discussing and evaluating if and how indirect or mediation effects could be integrated into the NCA and therewith cIPMA. Likewise, advancements such as in Streukens et al. (2017) who have extended the standard IPMA to accommodate nonlinear effects whose specification and estimation has become more prominent (Basco et al. 2021) may be integrated in a cIPMA context. Researchers may also engage further in the discussion of relevant aspects related to the philosophies (Dul 2024a) and core research design elements when triangulating routines and methods (e.g., related to sampling and sample size, see for instance, Dul 2024b).

The cIPMA also provides relevant input to further conceptualize on the importance–performance management toolset itself. Sever (2015), for instance, outlined that further conceptualization is needed with regards to the definition of the term importance, the definition of thresholds to demark the cut-off between high and low performance, and the differentiation of attributes positioned in the same quadrant and close to thresholds. The cIPMA offers input to all these areas of concern. The integration of the necessity logic into the IPMA does not only offer relevant new input to the definition of importance but can also aid the definition of relevant threshold levels and guide the interpretation of constructs positioned within quadrants of the map. Researchers engaged in the development of the managerial toolset are invited to combine and test our approach in combination with or contrast to previous developments (such as sensitivity analyses, iso-rating lines and further).

Finally, there is room for researchers to address the interpretation of findings when assumptions that underly our cIPMA approach are not met. This relates, for instance, to research designs in which constructs use indicators with different scales (e.g., a construct using indicators measured on a scale from 1 to 5 and 1 to 7). While all of the above are relevant areas to further advance the cIPMA and its related toolsets, we are confident that the method offers a valuable means to advance both managerial decision making and academic research.

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Data availability The dataset used and the Excel file employed for additional cIPMA analyses are publicly available on the website https://www.pls-sem.netunderDownloads. See also Richter et al. (2023a).

Declarations

Conflict of interest This research uses the statistical software SmartPLS 4 (https://www.smartpls.com/). Christian M. Ringle acknowledges a financial interest in SmartPLS.

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Marko Sarstedt is a Chaired Professor of Marketing at the Ludwig-Maximilians-University Munich (Germany) and an Adjunct Research Professor at Babeș-Bolyai-University Cluj-Napoca (Romania). His main research interest is the advancement of research methods to further the understanding of consumer behavior. His research has been published in Nature Human Behaviour, Journal of Marketing Research, Journal of the Academy of Marketing Science, Multivariate Behavioral Research, Organizational Research Methods, MIS Quarterly, and Psychometrika, among others. Since 2018, Marko has been named Member of Clarivate Analytics' Highly Cited Researchers List, which includes the "world's most impactful scientific researchers." More information about Dr. Sarstedt: https://linktr.ee/markosarstedt.

Nicole F. Richter is a Full Professor at the University of Southern Denmark. Her research focuses on international management with a special emphasis on cross-cultural aspects and the management of diversity. She is one of the leading experts for partial least squares structural equation modeling (PLS–SEM) and necessary condition analysis (NCA). Her publications have appeared in journals, such as the Journal of International Business Studies, Journal of World Business, Journal of Business Research, and Long Range Planning. Nicole is the Editor in Chief at the European Journal of International Management. More information about Dr. Richter: https://portal.findresearcher.sdu.dk/en/persons/nicole.

Sven Hauff is a Professor of Human Resource Management and Head of the Chair of Labor, Human Resources and Organization at the Helmut Schmidt University in Hamburg. His main research interests are in the interrelationships between the design of human resource management and its effects on employees and organizational performance. He is also interested in research methods with a particular focus on necessary condition analysis (NCA). His scientific works have been published in leading international journals such as Human Resource Management Journal, Human Resource Management, International Journal of Human Resource Management, and Journal of World Business. More information about Dr. Hauf: https://www.hsu-hh.de/apo/en/hauff-2.

Christian M. Ringle is a Chaired Professor and the Director of the Institute of Management and Decision Sciences at the Hamburg University of Technology (Germany), and an Adjunct Professor at the James Cook University (Australia). His research focuses on management and marketing topics, method development, business analytics, machine learning, and the application of business research methods to decision making. Since 2018, Christian has been included in the Clarivate Analytics' Highly Researchers list. He is a Co-developer and Cofounder of the statistical software SmartPLS. More information about Dr. Ringle: https://www.tuhh.de/mds/team/prof-dr-c-m-ringle.