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When Predictors of Outcomes are Necessary: Guidelines for the Combined Use of Partial Least Squares Structural Equation Modeling (PLS-SEM) and Necessary Condition Analysis (NCA)

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Abstract

Purpose. This research introduces the combined use of partial least squares structural equation modeling (PLS-SEM) and necessary condition analysis (NCA) that enables researchers to explore and validate hypotheses following a sufficiency logic, as well as hypotheses drawing on a necessity logic. Our objective is to encourage the practice of combining PLS-SEM and NCA as complementary views of causality and data analysis.

Design/methodology/approach. We present guidelines describing how to combine PLS-SEM and NCA. These relate to the specification of the research objective and the theoretical background, the preparation and evaluation of the dataset, running the analyses, the evaluation of measurements, the evaluation of the (structural) model and relationships, and the interpretation of findings. In addition, we present an empirical illustration in the field of technology acceptance.

Findings. The use of PLS-SEM and NCA allows researchers to identify the (must-have) factors required for an outcome, that is necessity logic, as well as the (should-have) factors that contribute to a high-level outcome, namely additive sufficiency logic. The combination of both logics enables researchers to test their theoretical arguments more precisely and offers new avenues to test theoretical alternatives for established models.

Originality/value. We provide insights into the logic, assessment, challenges, and benefits of NCA for researchers familiar with PLS-SEM. This novel approach enables researchers to substantiate and improve their theories and helps practitioners disclose the must-have and should-have factors relevant to their decision making.

Keywords: necessary condition analysis; NCA; partial least squares; PLS; PLS-SEM; structural equation modeling; SEM; technology acceptance model; TAM

INTRODUCTION

For information systems to be effective in organizations, they must be used; they cannot be effective if not used. Hence, usage is a necessary condition for systems to contribute to success. Without usage, failure is guaranteed! However, usage alone may not be sufficient for success, since other requirements, such as the correct use and a change of organizational workflows in line with the system flows, could also play a role in information system effectiveness. Hence, there are must-have and should-have factors for the success of information systems. The existence of both – necessary conditions or must-have factors and sufficient conditions or should-have factors – is common in many fields of research. Studies in the field of operations management demonstrate that these must-have factors are common when trying to understand how to successfully implement operations management practices, such as business process re-engineering, just-in-time (JIT), total quality management, and enterprise resource planning (see Dul et al., 2010 who reviewed four major journals in the field of operations management and identified 32 examples of necessary condition hypotheses in previous studies). We introduce a combination of research techniques that assists the identification of both necessary conditions/must-have factors and sufficient conditions/should-have factors of an outcome.

In information systems research, as in several fields of management research, partial least squares structural equation modeling (PLS-SEM) has become a standard multivariate analysis technique to investigate causal-predictive relationships (Khan et al., 2019, Richter et al., 2016a, Hair et al., 2012b, Hair et al., 2012a, Ringle et al., 2012). The method is used to create path models with (weighted composites of variables that are stand-ins for) latent variables and to estimate their relationships[1]. This method empirically substantiates the determinants (X) that lead to an outcome (Y) (Sarstedt et al., 2017). Authors who interpret their PLS-SEM findings normally use expressions such as 'X increases Y' or 'a higher X leads to a higher Y' (e.g., Lin & Lin, 2019, Richter et al.,

[1] The weighted composites are not assumed to be identical to latent variables, but to be good approximations for latent variables (see Rigdon, 2012). Henceforth, we use the term latent variable for these weighted composites.

2019). The interpretation of relationships between the determinants and the outcome therefore follows a *sufficiency logic* (Mandel & Lehman, 1998, Dul, 2016a). Understanding relationships in terms of sufficiency logic is extremely relevant. Researchers, for instance, aim to understand the factors that lead to a stronger intention to use certain technology (e.g., Mathieson, 1991; Lin and Lin, 2019) by applying different theories and models of technology acceptance; or they aim to understand the factors that contribute to the success of implementing technologies in firms (e.g., Aladwani, 2001). We may, for instance, assume that the enjoyment of using a technology is a should-have factor, based on the proposition that greater enjoyment leads to higher technology use.

While, according to a sufficiency logic, a determinant (e.g., enjoyment) may be sufficient to produce the outcome (e.g., the use of a technology), it may not be necessary. The absence of enjoyment could be compensated by other determinants, for example a positive evaluation of the technology's usefulness. By contrast, *necessity logic* implies that an outcome – or a certain level of an outcome – can only be achieved if the necessary cause is in place or is at a certain level. For instance, a positive evaluation of an information system may be “a necessary but not always sufficient condition for system use” (Mathieson, 1991: p. 173), or an information system can only contribute to success in an organization if it is used (Mathieson, 1991). To express necessity, researchers refer to expressions such as ‘X is needed for Y’, ‘X is a precondition for Y’, or ‘Y requires X’ (Dul, 2020). Accordingly, the necessary condition – being a constraint, a bottleneck, or a critical factor – must be satisfied to achieve a certain outcome. Other factors cannot compensate in a situation where a necessary condition is not satisfied; that is, if determinant X is a necessary condition for outcome Y, Y will not be achieved if X is not in place. We may, for instance, assume that the perceived usefulness of a technology is a precondition for technology use.

Authors in management and information systems research, who acknowledge this logic, complement their PLS-SEM analyses with qualitative comparative analysis (QCA) and mostly use fuzzy-set QCA (e.g., Duarte & Pinho, 2019, Reyes, 2018, Mikalef & Pateli, 2017; see also the overview in Seny Kan et al., 2016). In fuzzy-set QCA, both the X and Y variables are calibrated into set membership scores and the researchers focus on whether combinations or configurations of the (calibrated) X variables are sufficient but not necessary for an outcome Y (e.g., Duarte & Pinho, 2019). Thereby, QCA is also able to analyze necessary conditions, but only to a limited extent. QCA's necessity statements are binary and ignore variations in degree (for a detailed discussion see Dul, 2016b, Vis & Dul 2018). Another methodology, which allows the identification of necessary conditions, is necessary condition analysis (NCA) (Dul, 2016a, Dul et al., 2020). NCA is a powerful tool since it can identify the degree of a necessary condition that needs to be satisfied to achieve a certain level of a desired outcome (without any pre-calibraion). By using NCA we can, for example, predict the necessary degree of perceived usefulness of an information system to achieve a certain level of system use; likewise, we can predict the critical level of usage that is necessary in an organization to ensure that information systems contribute to success. Although NCA is a rather new methodology, it has already received significant attention in management research (e.g., Hauff et al., 2019, Richter et al., 2020, Arenius et al., 2017, Sousa & Da Silveira, 2017) and is recommended for the analysis of necessary conditions (Fainshmidt et al., 2020).

The sufficiency and necessity perspectives, including the research techniques that allow their implementation, are highly relevant in information systems (e.g., Dul et al., 2010; Ringle et al., 2012). For instance, researchers and practitioners must understand the factors that lead to a stronger intention to use certain technology, as well as the factors that are necessary conditions for this use (Mathieson, 1991, Lin & Lin, 2019). Therefore, they aim to determine the factors that produce the best possible outcome (i.e., the should-have factors; sufficiency logic) and those that are critical for an outcome (i.e., the must-have factors; necessity logic). Importantly, the should-have factors can only increase an outcome after the must-have factors have been taken care of. If necessary conditions are ignored or neglected in a field where we theoretically assume they exist, the result will be incomplete findings and recommendations. The should-have factors identified by standard PLS-SEM can only unfold if the must-have factors perform at the required level. PLS-SEM is the correct approach to identify the determinants that can increase an outcome. NCA identifies the conditions or the level of specific conditions that a certain outcome or a specific level of an outcome demands, and the conditions identified via NCA need to be taken care of first. This joint application of PLS-SEM and NCA has the potential to advance theory development and the generation of actionable implications for research and business practice.

Against this background, this paper's objective is to introduce the combined usage of PLS-SEM and NCA. We offer guidelines for researchers to complement their PLS-SEM analyses with NCA, and therefore to explore and validate propositions and hypotheses along sufficiency and necessity logics. First, we briefly describe the basic principles of NCA, it being relatively new to the field of information systems. Second, we develop guidelines that facilitate the process of applying PLS-SEM in combination with NCA. Third, as an illustrative example, we apply these guidelines to an extended technology acceptance model (TAM; Davis, 1989), that is of high relevance in information systems research (e.g., Gao et al., 2015, Aldás-Manzano et al. 2009, Park & Chen, 2007). Finally, the paper concludes with a discussion of the advantages of the presented multi-method approach, by leveling critical comments on the applicability of NCA, and by indicating avenues for further research.

NECESSARY CONDITIONS ANALYSIS

Originally developed by Dul in 2016, NCA is a relatively new approach and data analysis technique that enable the identification of necessary conditions in data sets (Dul, 2016a, Dul, 2020). Instead of analyzing the average relationships between dependent and independent variables, NCA aims to reveal areas in scatter plots of dependent and independent variables that may indicate the presence of a necessary condition (Figure 1). While ordinary least squares (OLS) regression-based techniques, such as PLS-SEM, establish a linear function, that is a dashed line through the center of the relevant data points (see Figure 1), NCA determines a *ceiling line* on top of the data. Figure 1 represents two default ceiling lines: (1) The ceiling envelopment - free disposal hull (CE-FDH) line, which is a non-decreasing step-wise linear line (step function); and (2) the ceiling regression - free disposal hull (CR-FDH) line, which is a simple linear regression line through the CE-FDH line.

INSERT FIGURE 1 HERE

The ceiling line separates the space with observations from the space without observations. The larger the empty space, the larger the constraint that X puts on Y. The ceiling line also indicates the minimum level of X that is required to obtain a certain level of Y. For example, in Figure 1, X must have at least a level of 6 to achieve a level of Y = 8. There is no Y of 8 or higher for X values that are below 6. This NCA outcome differs from the interpretation of linear regression where an increase of X leads, on average, to an increase of Y. Alternatively, the *bottleneck table* presents the ceiling line results in a tabular form. The first column of the table shows the outcome, whereas the next column represents (and additional columns represent) the condition(s) that must be satisfied to achieve the outcome. The results of both the outcome and the condition(s) may refer to the actual values, percentage values of the range, and percentiles. In Figure 1, the bottleneck table indicates the same relationships as the ceiling line, namely that for an outcome of Y = 8, X needs to be at a level of 6. For instance, if Y measures an information system's success on a 0-10 scale and X measures the system use on a 0-10 scale, the scatter plot indicates that system use is a necessary condition for success, whereas the bottleneck table specifies the levels of usage that are necessary for certain levels of success, for example that the system use must be at a level of 6 to achieve a success level of 8.

Two key NCA parameters are the ceiling accuracy and necessity effect size *d*. The ceiling accuracy represents the number of observations that are on or below the ceiling line divided by the total number of observations, multiplied by 100. While the accuracy of the CE-FDH ceiling line is per definition 100%, the accuracy of the other lines, for instance the CR-FDH, can be less than

100%. There is no specific rule regarding the acceptable level of accuracy. However, a comparison of the estimated accuracy with a benchmark value (e.g., 95%) can assist to assess the quality of the solution generated (Dul, 2016a). The necessity effect size *d* and its statistical significance indicate whether a variable or construct is a necessary condition. *d* is calculated by dividing the 'empty' space (called the ceiling zone) by the entire area that can contain observations (called the scope). Thus, by definition, *d* ranges between $0 \leq d \leq 1$. Dul (2016a) suggested that $0 < d < 0.1$ can be characterized as a small effect, $0.1 \leq d < 0.3$ as a medium effect, $0.3 \leq d < 0.5$ as a large effect, and $d \geq 0.5$ as a very large effect. In line with these suggestions, previous studies have used the threshold of $d = 0.1$ to accept necessity hypotheses (e.g., Karwowski et al., 2016, van der Valk et al., 2016). However, the absolute magnitude of *d* is only indicative of the substantive significance, that is the meaningfulness of the effect size from a practical perspective. Therefore, NCA also enables researchers to evaluate the statistical significance of the necessity effect size yielded by a permutation test, which should also be considered when deciding about a necessity hypothesis (Dul et al., 2020).

An NCA can be performed with a free software package that is implemented in R (Dul, 2019; see also the accompanying quick start guide: www.erim.eur.nl/necessary-condition-analysis/). The software's main functions are to draw ceiling lines, to calculate all NCA parameters (e.g., ceiling zone, scope, and effect size), and to generate the bottleneck tables and p-values.

THE COMBINED USE OF NCA AND PLS-SEM

In its original form, NCA is limited to analyzing relationships between observable characteristics (e.g., regarding sales, the absence or presence of a certain characteristic) or indices created by researchers (e.g., an index of business performance). However, the analysis can easily be extended to unobservable, latent concepts, such as user satisfaction, use intention, and perceived usefulness, by computing factor scores or composite scores of the indicators used to measure these concepts. We suggest using the composite scores of PLS-SEM because their generation considers the context of the structural model, which represents the underlying theory and corresponds with the idea to test necessities in the context of PLS-SEM (e.g., Hair et al. 207b; Rigdon et al. 2019). The PLS-SEM method estimates individual indicator weights, thereby accounting for measurement errors inherent in the indicators (Henseler et al., 2014). The weights are derived as part of the PLS-SEM algorithm and can either take the form of correlation weights or regression weights, referred to as Mode A and Mode B. Researchers usually use Mode A to estimate reflectively specified constructs and Mode B to estimate formatively specified constructs (Sarstedt et al., 2016). Using the indicator weights as input, PLS-SEM computes composite scores for each construct as linear combinations of the corresponding indicators that demonstrated good reliability, compared to other forms of creating composites (e.g., Henseler et al. 2014). These scores can then be used in an NCA to examine necessary conditions. However, this step of the analysis requires reliable and valid input measures. Hence, during the first step of the analysis, researchers must ensure that their construct measures meet all quality criteria.

The following guidelines facilitate the process of applying PLS-SEM in combination with NCA. These recommendations relate to the specification of the research objective and the theoretical background, the preparation and evaluation of the dataset, running the analyses, the evaluation of measurement models, the evaluation of the model and relationships, and the interpretation of findings. Figure 3, at the end of this section, summarizes the recommendations indicated below.

Specify the research objective and theoretical background

The first step in both procedures relates to the theoretical background and research objective (see Richter et al., 2016b; Dul, 2020). Accordingly, when combining the use of PLS-SEM and NCA, the researcher is advised to first review and outline the specific theoretical arguments on potential sufficient and necessary conditions that guide the analyses. The path model in PLS-SEM represents hypotheses on the relationships between different latent variables, based on theoretical reasoning and the researchers' experience or logic (Hair et al., 2017a). Researchers assume that exogenous variables are determinants that explain or predict the endogenous variables along a sufficiency logic. We find that theoretical models in many fields refer to necessities which have not been empirically tested, and therefore they have the potential to enrich empirical testing and, accordingly, theorizing (e.g., Hauff et al., 2019). Furthermore, there may be intuitive arguments regarding necessary conditions that could serve a more exploratory approach.

Prepare and check the data

Before analyzing the data, it is necessary to prepare the dataset and check its appropriateness for the analyses. First, consider the *size of the sample*. For NCA, no specific minimum sample size thresholds are required to technically run the analysis. Hence, sample size considerations should follow the guidelines, outlined in the PLS-SEM context, that revert to power tables to determine the technically required minimum number of observations (Hair et al., 2017a). For instance, assuming the commonly used level of statistical power of 80%, the researcher needs a sample size of 156 to detect R^2 values of at least 0.10 with a 5% probability of error in a path model with a maximum number of 10 arrows pointing at a construct (see Cohen, 1992).

Second, consider the *distribution of the data*. NCA is not bound to certain distributional characteristics of the data. Likewise, PLS-SEM proves to be robust to non-normal data distributions (e.g., Cassel et al., 1999, Reinartz et al., 2009). However, highly skewed data may inflate (bootstrap) standard errors and reduce statistical power (Chernick, 2008), which is why, at the very least, it is advisable to report information on the data distribution (Hair et al., 2012b).

Third, *detect outliers* and perform an outlier analysis. This step is important in an NCA context because a single case can reduce or even eliminate the empty space and, thus, reduce the necessity effect size (Dul, 2016a, 2020). Outliers can come in the form of errors that are part of the data collection process, such as sampling errors (e.g., non-coverage), or data entry errors. Similarly, errors can occur in data management, for example when transforming the data (Sarstedt

& Mooi, 2019). These outliers can safely be removed on condition that the underlying process is transparent. However, exceptionally high, or low values can also be a part of reality, making the observations "promising candidates for theory building because they defy expected cause-and-effect relationships" (Gibbert et al., 2020; see also Danks et al. 2019). This, particularly, applies to NCA since an outlier can represent a 'best case' where a high level of the desired outcome can exist with or without a minimum level of the condition.[2]

To identify outliers and more specifically errors, we recommend two basic steps. If the data is normally – or almost normally – distributed, check observations that show a z-score > 3 (see Aggarwal, 2017; Hair et al., 2017a). If the data is skewed, the aforesaid may not be an appropriate strategy. In this case, the easiest way forward is to check the scatter plots and to identify rare combinations of variables (see Sarstedt & Mooi, 2019). Checking the scatter plots is especially important in the context of NCA since it allows the identification of cases which are above or around the NCA ceiling line (Dul, 2020). In addition to these basic tests, researchers can make use of the PLSpredict procedure (Hair et al., 2020, Shmueli et al., 2016, 2019) to assess a model's out-of-sample predictive power (e.g., Hair et al., 2019b). Furthermore, more advanced methods are presented by Aggarwal (2017).

Fourth, it is necessary to assess the *measurement levels* and *coding of scales*. NCA can be applied to binary, discrete, and continuous variables (Dul, 2016a). Even though specific model setups and analyses allow the use of PLS-SEM with binary or categorical data (e.g., Hair et al., 2018), researchers should preferably use metric or interval-scaled, quasi-metric data for their analyses (Hair et al., 2017a). In many management studies, Likert-type scales are used, which work well with both techniques. A particularity of NCA is that, currently, the NCA software only searches for empty spaces in a scatter plot's upper left-hand corner. However, NCA is not limited

[2] There are different views on the role of outliers in NCA. In a deterministic view on necessity, every single case can falsify a necessity theory. In a more probabilistic view on necessity, few exceptions above the ceiling line are acceptable. For a detailed discussion see Dul (2020).

to situations where the presence of a condition is necessary for the presence of an outcome (i.e., the presence of X is necessary for the presence of Y), but can also be applied to different combinations of the condition's and the outcome's presence and absence (e.g., the absence of X is necessary for the presence of Y). Researchers only need to ensure that the coding of their variables correspond to the analytical procedure implemented in NCA, for example by flipping the coding.

Run the PLS-SEM analysis

The PLS-SEM analyses can start after preparing and checking the data. Researchers can create and estimate PLS path models by using software, such as SmartPLS 3 (Ringle et al., 2015).

Evaluate the measurement models

The reliability and validity of measurements are crucial when performing a PLS-SEM and an NCA. While NCA does not provide specific criteria to test for the construct measures' reliability and validity, it is assumed that the researcher has checked this in advance (Dul, 2016a). PLS-SEM offers routines to test for the measurements' reliability and validity before interpreting the structural model relationships. Corresponding guidelines have been well documented in textbooks (e.g., Garson, 2016; Hair et al., 2017a; Ramayah et al., 2016) and journal articles (e.g., Hair et al. 2019a), and comprise: (1) the evaluation of the loadings, Cronbach’s alpha, composite reliability, ρ_A as a compromise measure between the latter two, the average variance extracted, and the heterotrait-monotrait ratio for reflective constructs; and (2) redundancy analysis, variance inflation factors, and an evaluation of the indicator weights' significance and relevance for formative constructs. More recently, Hair et al. (2020) subsumed these guidelines under the label of confirmatory composite analysis; a procedure that facilitates the confirmation of composite measures in the context of a nomological network.

Transfer the latent variable scores

NCA can be applied to any type of variable, including constructs. However, the NCA software does not include the possibility of linking single indicators to constructs. Thus, being interested in understanding whether the relations within a PLS-SEM model also represent necessary conditions, we need to export the latent variable scores from PLS to a file that can be imported in NCA, for example an Excel file saved in CSV format.[3] Depending on the measurement model of the latent variables, we suggest the exporting of different scores (see Figure 2). For a PLS path model's *reflective constructs*, namely with relationships from the construct to the indicators, we recommend focusing on the latent variable scores for both the exogenous and endogenous constructs in the NCA. For *formative constructs*, namely with relationships from the indicators to the construct, we recommend focusing on the latent variable scores in the case of endogenous constructs, as the objective is usually to explain or understand the relation to the construct. For the exogenous constructs, we recommend including the latent variable scores and the individual indicators, as we may want to complement the analysis on the construct level with analyses for the individual indicators (see below).

INSERT FIGURE 2 HERE

Run the NCA

Once we have exported all relevant variables to a separate file and imported them into R, we can run the NCA. While the PLS-SEM analysis allows the estimation of multiple relationships in a path model, NCA is bivariate in nature because the necessity of one X for Y does not depend on the necessity – or potential necessity – of other factors. Accordingly, if a path model comprises different endogenous constructs, we may need to perform different NCAs for each of the

[3] In this context, please note that the NCA software requires missing values to be empty cells; hence, we may need to replace missing value qualifiers, such as 999, in advance. (see DUL, J. 2019. Necessary condition analysis (NCA) with R. R package version 3.02 ed.).

endogenous constructs. The analyses are always calculated with the latent variable scores of the exogenous and endogenous constructs. If one or more of the exogenous constructs is a formative construct, we recommend running additional analyses using the single indicator(s) of the formative construct(s). Therewith, we can test whether the individual indicators forming the construct are necessary conditions to be satisfied so that a certain outcome can occur. This will complement the findings that we automatically generate in the PLS-SEM context via the formative indicators' weights and significance.

Evaluate the structural model

The evaluation of relationships in the structural model in PLS-SEM and between the variables in an NCA are strongly interrelated with the content-wise interpretation of findings. To guide this step, both techniques have standard assessment criteria to evaluate the relationships between variables. In the PLS-SEM context the standard assessment criteria are the coefficient of determination (R^2), and the statistical significance and relevance of the path coefficients (for an overview of the more specific guidelines on how to perform these evaluations, see Hair et al., 2019a). Moreover, recent research calls for the routine use of the PLSpredict procedure (Hair et al., 2020, Shmueli et al., 2016, 2019). Before evaluating these criteria, the researcher, in a PLS-SEM context, is advised to test for multicollinearity in the structural model using the variance inflation factors (Becker et al., 2015).

In the NCA context, the necessity effect size *d* and its statistical significance are essential to understand whether a variable or construct is a necessary condition for an output. Furthermore, researchers should check for the ceiling accuracy (if going for other than the CE-FDH ceiling line) that facilitates the assessment of the quality of the solution generated (Dul, 2016a).

Interpret the findings

When it comes to the interpretation of relationships, we identify three relevant scenarios: First, an exogenous construct may be a relevant determinant and a necessary condition of an endogenous construct. This would undermine the construct's strong practical relevance because a certain level of the construct – and we can even specify this level using the bottleneck table – is necessary for the outcome. Moreover, a further increase in the construct may trigger a further increase in the outcome (the researcher is advised to check the levels in the bottleneck table and, if questioned, to perform a PLS-SEM analysis on the data that exceed the bottleneck level). Second, an exogenous construct may be an endogenous construct's relevant determinant, but not its necessary condition. Hence, an increase in the construct will on average lead to an increase in the outcome. However, no minimum level of the construct is required to ensure the occurrence of the outcome. Third, an exogenous construct may not be an endogenous construct's relevant determinant but could be a necessary condition. In this case, there is, from a managerial perspective, no point in increasing the exogenous construct's performance above the level necessary to achieve the level of interest in the endogenous construct. Yet, this level should be achieved to ensure the existence of the outcome. Table 1 summarizes the interpretations of these three scenarios.

INSERT TABLE 1 HERE

INSERT FIGURE 3 HERE

Figure 3 summarizes the aforesaid guidelines to combine PLS-SEM and NCA in the form of a step-by-step roadmap for researchers. This roadmap is a mixture of steps that must be performed, one after the other, to continue with specific analyses (e.g., it is necessary to transfer the latent variable scores to run the NCA on the construct level) and includes a sequence that we deem useful when combining the two methods (e.g., running the NCA as soon as we have ensured an appropriate measurement at the construct level).

AN ILLUSTRATIVE EXAMPLE

Specify the research objective and theoretical background (Step 1)

To illustrate the use of NCA in combination with PLS-SEM, we draw on an extended technology acceptance model (TAM). Understanding why consumers accept, buy, and use certain technology or not is of major importance to any company in the technology industry. Researchers have been studying the antecedents of technology use for decades and have proposed different models in this regard – among others, the TAM (Davis, 1989), further extensions of the TAM (Venkatesh & Bala, 2008, Venkatesh & Davis, 2000), and the unified theory of acceptance and use of technology (UTAUT) model (Venkatesh et al., 2003, Venkatesh et al., 2012). Theories that underpin most of these models are the theory of reasoned action (Ajzen & Fishbein, 1980) and the theory of planned behavior (Ajzen, 1991). Based on these theories, we use a conceptual model that includes two widely accepted endogenous constructs: the *behavioral intention* to adopt a technology, which leads to the actual *technology use* (Ajzen, 1991, Davis et al., 1989, Sheppard et al., 1988, Turner et al., 2010).

We refer to four key antecedents of behavioral intention and technology use and therewith to four exogenous constructs. Building on innovation diffusion theory (Rogers, 2003), we integrate *compatibility*, which reports the innovation's fit with the customer's lifestyle and values, and which relates to the perceived characteristics of an innovation. Furthermore, we integrate two of TAM's classical antecedents (see the line of argument in Moore & Benbasat, 1991), namely perceived *usefulness* and perceived *ease of use.* We also argue that the intention to adopt an innovation and its use also depend on the question whether customers enjoy or have positive feelings about the use of a product. Therefore, building on the theory of consumption values (Sheth et al., 1991), we add *emotional value* as a fourth key antecedent of adoption intention and technology use. For these constructs, theory suggests positive relationships with adoption intention and technology use; moreover, empirical research supports these positive relationships (e.g., Al-Jabri & Sohail, 2012, Weigel et al., 2014). As these relationships described above build on well-established theoretical arguments in the research field, we assume that there are sufficiency relationships – having the form that if the exogenous constructs increase, the endogenous constructs will also increase – between all exogenous and endogenous constructs illustrated in the model depicted in Figure 4.

INSERT FIGURE 4 HERE

The relationships between the constructs in the theoretical model are widely researched and interpreted from a sufficiency logic (e.g., Cheng, 2011, Ho & Wu, 2012, Agag & El-Masry, 2016). However, researchers in the field also refer to arguments on necessities. For example, Chau and Hu (2002) found that *compatibility* "[…] may represent a necessary but insufficient condition for technology acceptance" (Chau & Hu, 2002) and Holden & Rada (2011) assume that *usefulness* is a prerequisite for technology acceptance. Thus, the theoretical reasoning behind the intention's antecedents to adopt and use an innovation also include the idea of necessity (and a few authors have tested necessities in a more exploratory fashion using fsQCA and the UTAUT, e.g., Duarte & Pinho, 2019, Reyes-Mercado, 2018). Accordingly, NCA may be a valuable, additional analytical technique that, in the field, complements the sufficiency logic interpretations.

Prepare and check the data (Step 2)

Before running the analysis, we checked the size of the sample, the distribution of the data, outliers, the measurement levels, and coding of scales. The sample consists of responses from e-book reader adopters in France (N=174). The data was collected by means of a professional market research agency using an online survey on e-book readers and quota samples by age, gender, income, and regional distribution to ensure a good representation of the French population. The survey included questions about the items used in our constructs' measurement models. A single item measured on a 7-point Likert scale represents the target construct *technology use*; the remaining constructs use reflective measurement models with items measured on 5-point Likert scales. Appendix A1 documents all items and descriptive statistics. The results do not suggest any data entry or management errors. The scatter plots partially show influential cases on or around the ceiling line. However, we refrained from deleting these cases as we did not identify any measurement or sampling errors in respect of them. In addition, our assessment of the model's out-of-sample predictive power using PLSpredict does not indicate any groups of observations with exceptionally high prediction errors (see Step 7 for further information).

Run the PLS-SEM analysis (Steps 3)

We estimated the extended TAM by using the SmartPLS 3 software (Ringle et al., 2015). For this purpose, researchers can also use the plspm package for R (see Sanchez & Trinchera, 2012). Figure 5 presents the PLS-SEM results.

INSERT FIGURE 5 HERE

Evaluate the measurement models (Step 4)

We ran a confirmatory composite analysis (Hair et al., 2020) to assess the quality of the reflective measurement models. We found that all measures meet all the relevant PLS-SEM criteria (Hair et al., 2017a, Hair et al., 2019a). More specifically, internal consistency reliability, indicator reliability, convergent validity, and discriminant validity were established (see Appendix A2).

Transfer of latent variable scores (Step 5)

We exported all the latent variable scores from the PLS-SEM results to a CSV file, which we afterwards imported into R. Since all our constructs are measured using reflective measurement models, we did not integrate the single indicators into this file.

Run the NCA (Step 6)

To generate a comprehensive output, we ran multiple advanced NCAs; the R code to run NCA is indicated in Appendix A3. Since our model includes two endogenous constructs, namely *adoption intention* and *technology use*, we ran two NCAs and in each analysis we entered all exogenous constructs, that is *perceived usefulness*, *ease of use*, *compatibility*, and *emotional value*. We also tested whether adoption intention was a necessary condition for technology use. Figure 6 shows the scatter plots for all relevant relations. Table 2 presents the effect sizes. As the accuracy of the CE-FDH ceiling line is per definition 100%, we did not add a separate column for the ceiling line accuracy.

INSERT FIGURE 6 HERE

INSERT TABLE 2 HERE

Evaluate the structural model (Step 7)

We first assessed the partial regression results' collinearity in the structural model by analyzing the variance inflation factors (VIF), which were all clearly below the critical level of 5; the highest VIF in the structural model had a value of 3.054. Next, we focused on the R^2 values of the dependent constructs in the model (Hair et al., 2017a, Hair et al., 2019a). The extended TAM explains both *adoption intention* and *technology use* with relatively high R^2 values of 0.539 and 0.420. The PLSpredict procedure supports the assessment of the model's predictive relevance (Shmueli et al., 2016, Shmueli et al., 2019). The $Q^2_{predict}$ values are above zero and the PLS-SEM predictions' root mean squared error (RMSE) and mean absolute error (MAE) values are smaller than those of the linear model (LM) benchmark for all indicators of *adoption intention* and *technology use* (Table 3). A detailed analysis shows that the prediction errors are approximately normally distributed as evidenced in (absolute) skewness and kurtosis values between -2 and +2 (see also Field, 2009). The related PLSpredict analysis does not produce groups of observations with exceptionally high prediction errors.

Table 4 provides information on the relationships in the structural model and on their significance; we used the percentile bootstrapping procedure with 5,000 subsamples and report the 95% confidence intervals. The results show that *emotional value* has the strongest impact on *adoption intention* (path: 0.515; $p < 0.05$), followed by *perceived usefulness* (path: 0.227; $p < 0.05$). *Ease of use* and *compatibility* show no significant relationship with *adoption intention*. Adoption intention furthermore has a significant impact on technology use (path: 0.437; $p < 0.05$). The f^2 effect sizes further support these findings. *Emotional value* on *adoption intention* (0.336) has the largest effect size. Furthermore, *adoption intention* reports a medium effect size on *technology use* (0.152).

INSERT TABLE 3 HERE

INSERT TABLE 4 HERE

The NCA's results (see Table 2) indicate that *usefulness*, *ease of use*, and *emotional value* are meaningful ($d \geq 1$) and significant ($p < 0.05$) necessary conditions for *adoption intention*. Furthermore, all determinants of *technology use* (*perceived usefulness*, *ease of use*, *emotional value*, *compatibility*, and *adoption intention*) are meaningful and significant necessary conditions. Each necessary condition can be assessed in detail with the bottleneck tables. For example, Table 5 highlights that in order to reach a 50%-level of *adoption intention*, three necessary conditions need to be in place: *perceived usefulness* at no less than 9.3%, *ease of use* at no less than 20%, and *emotional value* at no less than 25%.

INSERT TABLE 5 HERE

Interpret the findings (Step 8)

Our illustrative example covers Scenarios 1 and 3 (see Table 1) and supports the theoretical impact of *emotional value* and *usefulness* on *adoption intention* (see also the results of Hur et al., 2012, Cheng, 2011). Similarly, both *emotional value* and *usefulness* are necessary conditions. This reflects our Scenario 1.

Contrary to our assumptions but according to the PLS-SEM results, *ease of use* and *compatibility* did not have a significant impact; neither on *adoption intention*, nor on *technology use*. An interpretation of these findings could be that *ease of use* and *compatibility* play a subordinate role in adoption intention and technology use (e.g., Hu et al., 1999, Subramanian, 1994). However, the NCA results indicate that certain critical determinants were not identified by the standard PLS-SEM analysis. Whereas the PLS-SEM results indicate that *ease of use* and *compatibility* do not have a significant impact on *adoption intention* and *technology use*, the NCA results clearly highlights that these two constructs act as necessary conditions for both outcomes, as in our Scenario 3. These results support those authors who assume that *compatibility* represents a necessary but insufficient condition for technology acceptance (Chau and Hu, 2002). The findings even specify the critical levels of *compatibility* that are necessary (33.7%) to achieve, for instance, a relevant level of technology use in practical settings (60%). However, increasing *compatibility* to a higher level does not further increase *technology use*. This is an important finding since further investment in this and other drivers of *technology use* (e.g., *emotional value*) may be useless unless the necessary conditions have been taken care of. Only if the bottlenecks have been dealt with, will other investments be able to increase *adoption intention* and *technology use*.

These results show that NCA can complement the PLS-SEM analysis by emphasizing that not only significant but also nonsignificant determinants can constitute necessary conditions. Thus, both approaches, namely PLS-SEM and NCA, are essential for a comprehensive understanding of customers' technology and innovation acceptance.

DISCUSSION AND CONCLUSION

The objective of this paper is to introduce the combined usage of PLS-SEM and NCA. We believe that this multi-method approach is beneficial for different reasons. First, applying PLS-SEM and NCA can advance theorizing and theory testing. The main advantage of using both PLS-SEM and NCA lies in combining different views on causality, thereby adding value to the understanding of theoretical relationships between constructs. Although sufficiency logic and necessity logic represent two completely different causal logics, researchers – instead of distinguishing between both logics – often use them interchangeably and are imprecise when it comes to the empirical testing of their arguments (e.g., Hauff et al., 2019). Hence, we call on researchers to be more circumspect when formulating hypotheses and testing proposed effects. Specifically, when using expressions like ‘X is needed for Y’, ‘X must be there for Y to succeed’, ‘X is critical for Y’, ‘X is a precondition for Y’, and ‘Y requires X’, researchers must formally test these proposed effects using a methodology that is able to identify necessary conditions. By contrast, if we use expressions like ‘X increases Y’, ‘X contributes to Y’, and ‘a higher X leads to a higher Y’, we must ensure that we actually want to express sufficiency. In this case, the application of PLS-SEM is sufficient. Nevertheless, the combination of both methodologies and being more precise in translating theory to necessity logic or sufficiency logic arguments could lead to greater precision and theoretical clarity, as it requires the recognition of the differences between the two causal logics. We agree with the related arguments presented by Woodside (2013) and Gigerenzer (1991), namely that the availability and awareness of tools could shape the development of theory.

Second, the combined use of PLS-SEM and NCA can provide results that have increased practical value. By using PLS-SEM, researchers can identify the factors that produce the best possible outcome. Through NCA, researchers can identify those factors that are critical to achieve a certain outcome. Both issues, namely the should-have factors and the must-have factors, have high practical relevance. Indeed, practitioners often use the MoSCoW method to prioritize their activities; that is, at a particular point in time, they categorize activities as the *must-haves*, *should-haves*, *could-haves*, and *will not have*. PLS-SEM and NCA provide information on the first two categories. Notably, if there are any necessary conditions, they need to be taken care of first. Even if the should-have factors exert a major influence on the outcome, that is a high path coefficient in the PLS-SEM model, they will not have an effect unless the necessary conditions – namely the must haves, bottlenecks, critical factors, etc. – have been satisfied.

Third, the proposed multi-method approach can enrich many research fields. Recent research demonstrates the relevance of necessary conditions to theoretical reasoning in various fields (Hauff et al., 2019), and they play a similar important role in operations management and information systems research. The overview of necessary condition hypotheses in past studies – published in four major journals in the field of operations management – by Dul et al. (2010), provides a starting point to identify the fields that may profit from research on necessary conditions (Dul et al., 2010). For instance, McLachlin (1997) used a case-based research approach to test theory-based necessity propositions in the context of just-in-time manufacturing. He identified four management initiatives – the promotion of employee responsibility, teamwork, the provision of training, and the demonstration of visible commitment – that were necessary conditions for the implementation of just-in-time manufacturing. Through a more unstructured search in journals on operations management and information systems, we discovered further areas in which necessity arguments were prominent. For example, Domínguez-Escrig et al. (2018) – who analyzed the promotion of radical innovation through end-user computing satisfaction – indicate that for innovation to occur, it is necessary that employees share information and knowledge. Moreover, the outlining of necessities is quite common in research on the sharing, transferring, and creation of knowledge (e.g., Chi & Seth, 2009, Noorderhaven & Harzing, 2009). Furthermore, Marimon et al. (2016) argue and test the conditions necessary to achieve a true internalization of a strategic mission statement among stakeholders. They propose the development of a scale using, among others, confirmatory factor analysis and structural equation modeling. These and many other articles outline propositions and hypotheses that involve necessity thinking.

NCA is relatively new and sometimes there are misunderstandings and open aspects. However, critique and methodological reflections usually lead to advancement. Thiem (2018), for example, questioned the validity of NCA and argued that QCA is better suited to identify necessary conditions. However, the discussion thereof (Dul et al., 2018, also Vis & Dul, 2018) showed that Thiem's assessment was based on wrong assumptions. Indeed, NCA is not only a valid methodology to identify necessary conditions, but it also outperforms QCA in this respect since it not only allows an analysis of necessity in kind (i.e., in terms of X is necessary for Y) but also of necessity in degree (i.e., in terms of the level of X necessary for the level of Y). Similarly, by questioning the NCA significance test, Sojonen & Melin (2019) showed that the statistical test is valid and has a high power (Dul et al., 2019).

Through our guidelines, we hope to facilitate future research that jointly applies PLS-SEM and NCA. This research can address untested necessity statements that have been formulated in several research fields. Moreover, replications using the combined PLS-SEM and NCA approach present a promising avenue for future research, especially to substantiate and further develop existing knowledge on well-established models. A likewise interesting aspect is the application of NCA to test mediator models and to supplement group-specific PLS-SEM analyses (including models that involve moderation). Finally, cross-disciplinary applications of PLS-SEM in combination with NCA will support the presented guidelines and contribute to their improvement and extension.

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APPENDIX

A1: Data description

Latent variable (measurement adapted from)	Indicator		Mean	Range [Min; Max]	S.D.	Excess kurtosis	Skewness
Emotional value, reflective (Sweeney & 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 & 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 (Moore & Benbasat, 1991, Antón et al., 2013)	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 (Moore & Benbasat, 1991, Huang & Hsieh, 2012)	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

A2: Results summary for (reflective) measurement models

<table>
<tr><th rowspan="3">Latent variable</th><th rowspan="3">Indicators</th><th colspan="3">Convergent validity</th><th colspan="3">Internal consistency reliability</th><th>Discriminant validity</th></tr>
<tr><td>Loadings</td><td>Indicator relia-bility</td><td>AVE</td><td>Compo-site relia-bility</td><td>Cronbach's alpha</td><td>Rho A</td><td rowspan="2">HTMT 95% bootstrap confidence interval does not include 1</td></tr>
<tr><td>>0.70</td><td>>0.50</td><td>>0.50</td><td colspan="3">0.70-0.95</td></tr>
<tr><td rowspan="3">Emotional value</td><td>EMV_01</td><td>0.891</td><td>0.794</td><td rowspan="3">0.853</td><td rowspan="3">0.946</td><td rowspan="3">0.914</td><td rowspan="3">0.917</td><td rowspan="3">Yes</td></tr>
<tr><td>EMV_02</td><td>0.950</td><td>0.903</td></tr>
<tr><td>EMV_03</td><td>0.929</td><td>0.863</td></tr>
<tr><td rowspan="3">Ease of use</td><td>EOU_01</td><td>0.784</td><td>0.615</td><td rowspan="3">0.697</td><td rowspan="3">0.873</td><td rowspan="3">0.783</td><td rowspan="3">0.873</td><td rowspan="3">Yes</td></tr>
<tr><td>EOU_02</td><td>0.878</td><td>0.771</td></tr>
<tr><td>EOU_03</td><td>0.840</td><td>0.706</td></tr>
<tr><td rowspan="3">Perceived usefulness</td><td>PU_01</td><td>0.722</td><td>0.521</td><td rowspan="3">0.642</td><td rowspan="3">0.842</td><td rowspan="3">0.723</td><td rowspan="3">0.753</td><td rowspan="3">Yes</td></tr>
<tr><td>PU_02</td><td>0.819</td><td>0.671</td></tr>
<tr><td>PU_03</td><td>0.856</td><td>0.737</td></tr>
<tr><td rowspan="3">Compati-bility</td><td>CO_01</td><td>0.901</td><td>0.812</td><td rowspan="3">0.779</td><td rowspan="3">0.914</td><td rowspan="3">0.858</td><td rowspan="3">0.859</td><td rowspan="3">Yes</td></tr>
<tr><td>CO_02</td><td>0.906</td><td>0.821</td></tr>
<tr><td>CO_03</td><td>0.840</td><td>0.706</td></tr>
<tr><td rowspan="3">Adoption intention</td><td>AD_01</td><td>0.933</td><td>0.870</td><td rowspan="3">0.889</td><td rowspan="3">0.960</td><td rowspan="3">0.938</td><td rowspan="3">0.939</td><td rowspan="3">Yes</td></tr>
<tr><td>AD_02</td><td>0.935</td><td>0.874</td></tr>
<tr><td>AD_03</td><td>0.960</td><td>0.922</td></tr>
</table>

A3: R code for running NCA

#Installation, update and loading of the NCA package

install.packages("NCA", dependencies = TRUE)

update.packages("NCA")

library(NCA)

#Read own data set “TIAM_FR” (exported LVS from PLS-SEM)

data <- read.csv("TIAM_FR.csv")

#Example of an advanced NCA analysis

model <- nca_analysis(TIAM_FR, c(“EmotionalValue”, “EaseofUse”, “Usefulness”, “Compatibility”), “AdoptionIntention”)

nca_output(model, plots=TRUE, summaries=TRUE, bottlenecks=TRUE, pdf=TRUE)

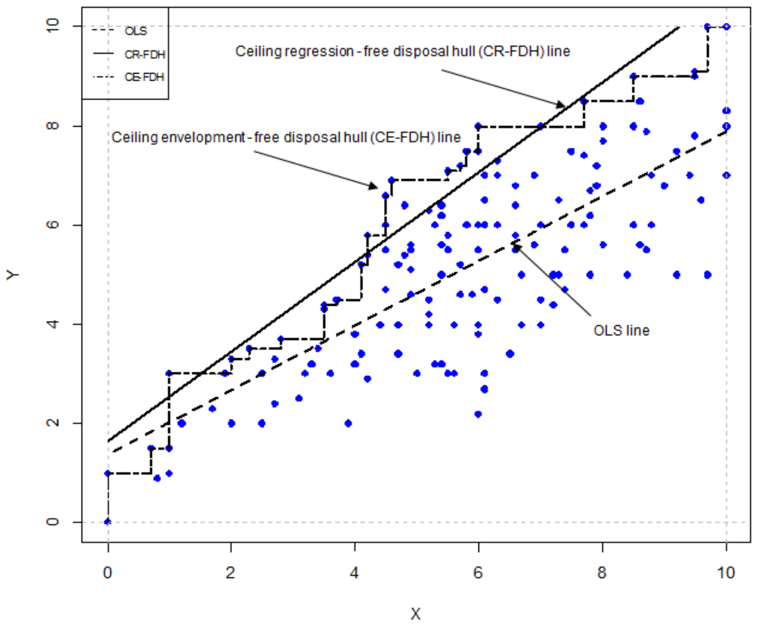
#Example of a significance test

model <- nca_analysis(TIAM_FR,c(“EmotionalValue”, “EaseofUse”, “Usefulness”, “Compatibility”), “AdoptionIntention”, ceilings="ce_fdh", test.rep=10000)

nca_output(model)

Figures

Figure 1: Scatter plot with OLS and ceiling lines, and bottleneck table



Bottleneck

(CE-FDH, actual values)

Y	X
0	NN
1	NN
2	1.00
3	1.00
4	3.50
5	4.10
6	4.50
7	5.50
8	6.00
9	8.50
10	9.70

Note: NN = Not necessary

Figure 2: Constructs/indicators to be tested in the NCA

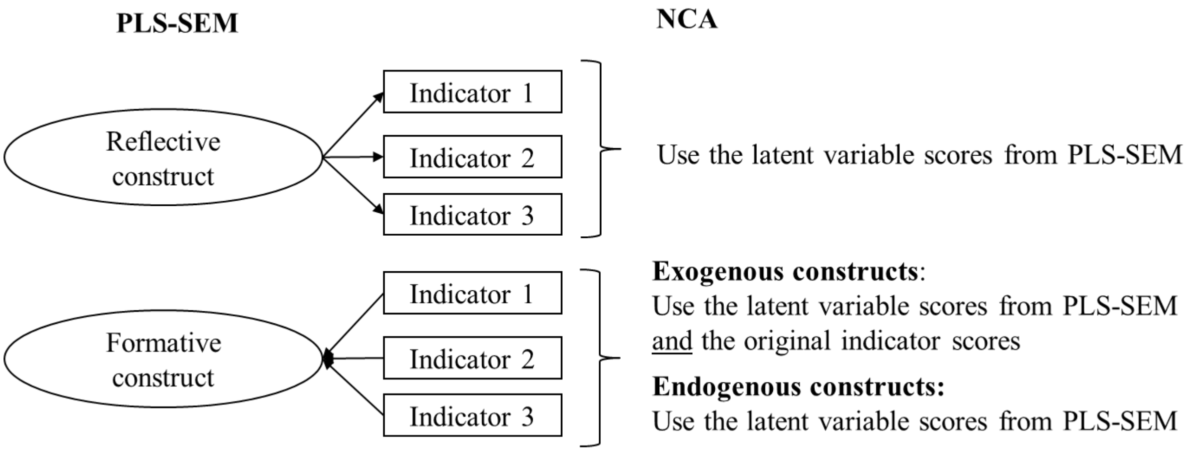


Figure 3: A step-by-step guide

Step 1	Specify the research objective and theoretical background

Outline hypotheses along sufficiency and necessity logic.

Step 2	Prepare and check the data

- *Sample size*: Follow the guidelines on sample size outlined in a PLS-SEM context, for instance, by referring to published power tables published; see Hair et al., 2017a.
- *Data distribution:* Report information on the data distribution; Hair et al., 2012b.
- *Outliers:* Perform an outlier analysis following common guidelines, for instance, by looking at observations that show a z-score > 3; e.g. Sarstedt & Mooi, 2019.
- *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 or flip the scale.

Step 3	Run the PLS-SEM analysis

Use **PLS-SEM** to estimate the latent variable scores and structural model relationships and their significance; Hair et al., 2017a.

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 quality of measurement models: For reflective constructs, evaluate loadings, Cronbach's alpha / composite reliability / ρ_A , average variance extracted and heterotrait-monotrait ratio. For formative constructs, perform a redundancy analysis, evaluate the variance inflation factors, and the significance and relevance of the indicator weights. If required, make the necessary improvements; see Hair et al., 2017a and Hair et al., 2019a.

Step 5	Transfer the latent variable scores

Export the latent variable scores from the PLS-SEM model to an extra file and import the new datafile to R.

Step 6	Run the NCA

Use **R and the package for NCA** (default settings; 10,000 permutations); Dul, 2019.
Analyze hypothesized relations or explore all relations: Dependent = final level latent variable score(s), independent = all preceding latent variable scores and all formative indicators; repeat for all endogenous constructs.

Step 7	Evaluate the structural model

- After evaluating the VIFs of the inner model, evaluate the PLS-SEM model along the standard assessment criteria, most importantly the coefficient of determination (R^2), the predictive accuracy (Q^2), and the statistical significance and relevance of the path coefficients; Hair et al., 2019a.
- Evaluate the necessity effect size d and its statistical significance Dul, 2016a, Dul et al. 2020.
- Check the accuracy of the ceiling line (if going for other than the CE-FDH).

Step 8	Interpret the findings

Figure 4: Conceptual model

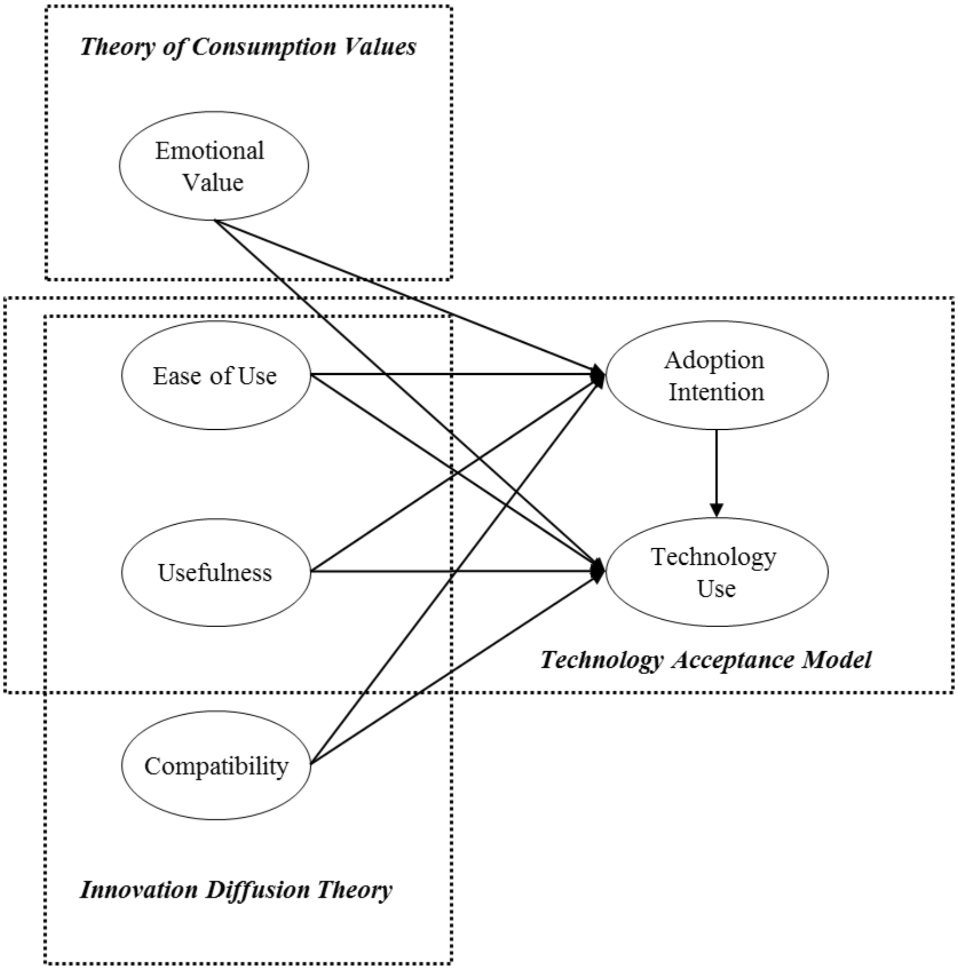
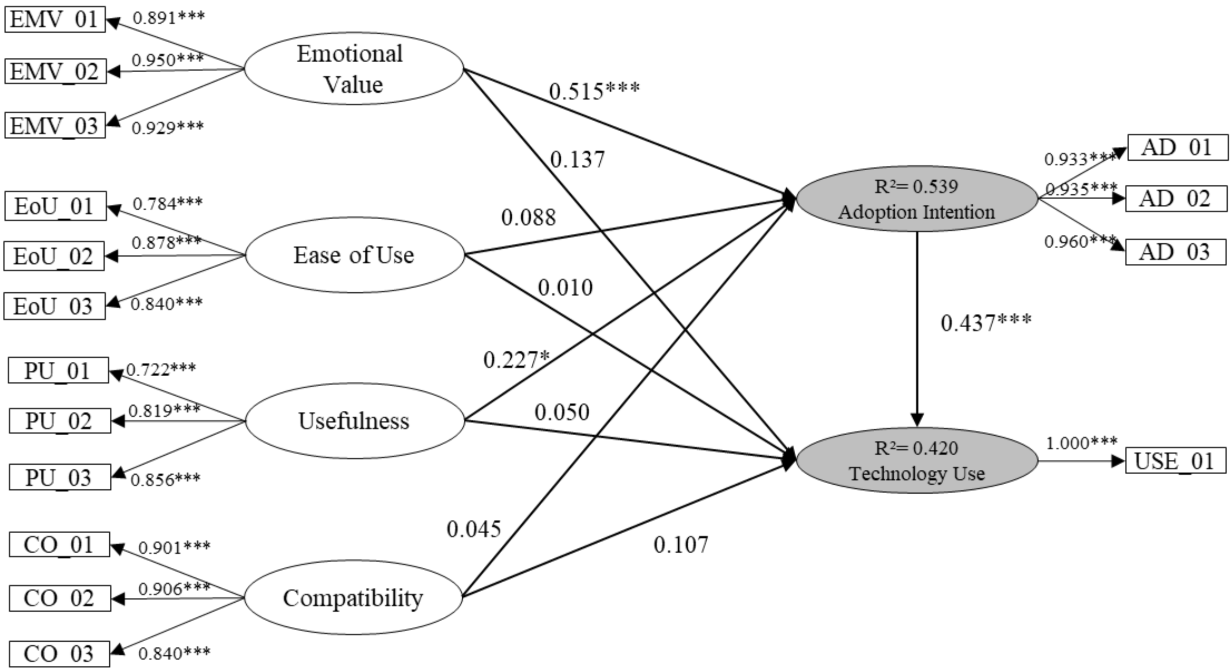
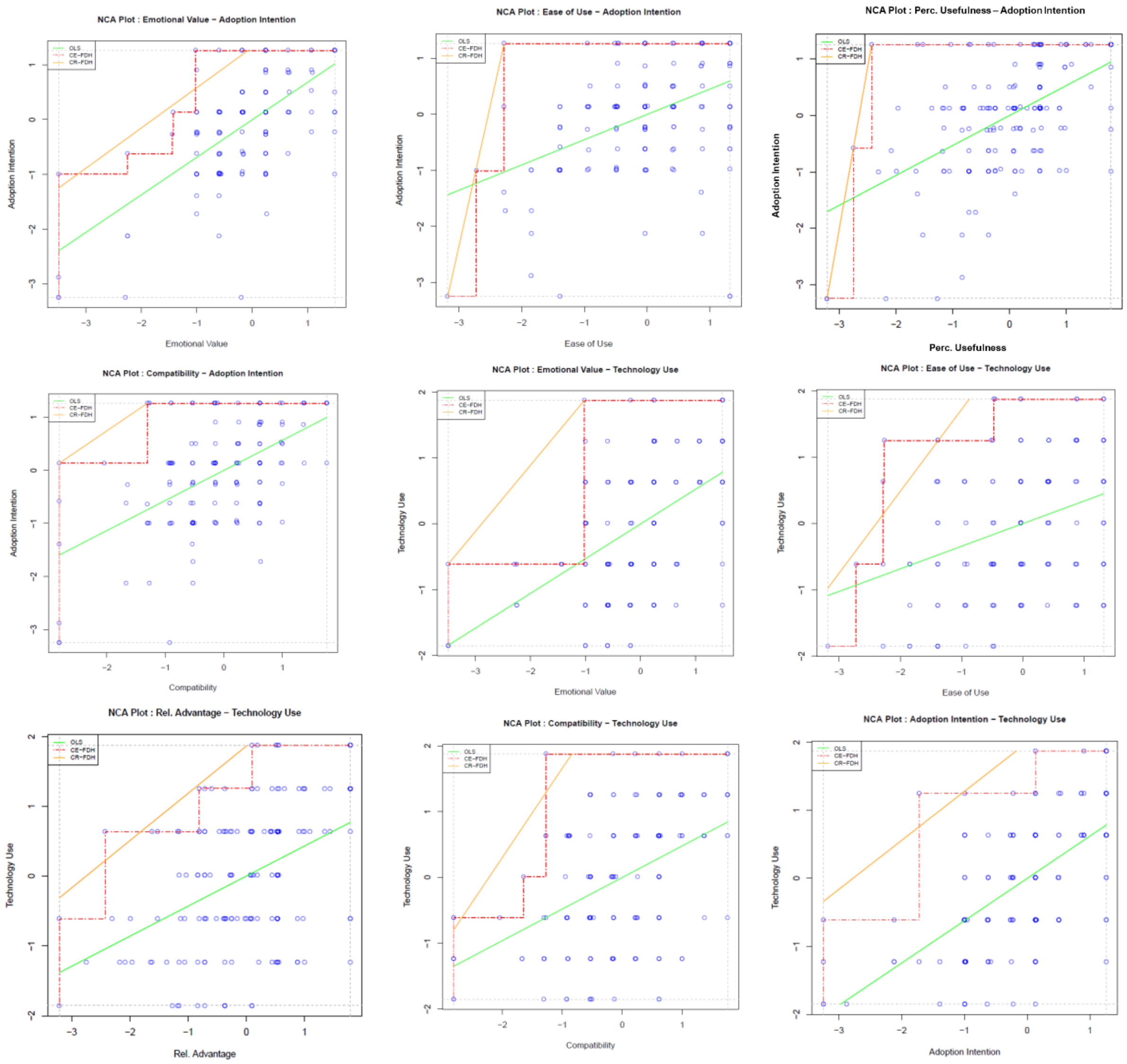


Figure 5: PLS path model and estimation results



Note: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Figure 6: Scatter plots



TABLES

Table 1: Relevant scenarios to interpret the findings

Scenario	PLS-SEM results	NCA results	Conclusion
1: Exogenous construct is a…	significant determinant	and a necessary condition	On average, an increase in the exogenous construct will increase the outcome. However, a certain level (see NCA bottleneck tables) of the exogenous construct is necessary for the outcome to manifest.
2: Exogenous construct is a…	significant determinant	but no necessary condition	On average, an increase in the exogenous construct will increase the outcome; no minimum level of the construct is needed to ensure that the outcome will manifest.
3: Exogenous construct is a…	nonsignificant determinant	but a necessary condition	A certain level (see NCA bottleneck tables) of the exogenous construct is necessary for the outcome to manifest. However, a further increase is not recommended, as it will not increase the outcome any further.

Table 2: NCA effect sizes

Construct	Adoption intention		Technology use	
	CE-FDH	p-value	CE-FDH	p-value
Emotional value	0.214	0.000	0.331	0.000
Ease of use	0.151	0.007	0.235	0.016
Perceived usefulness	0.119	0.002	0.243	0.001
Compatibility	0.082	0.011	0.211	0.000
Adoption intention			0.294	0.000

Table 3: PLSpredict indicator prediction summary

Endogenous construct's indicators	PLS-SEM			LM		PLS-SEM - LM	
	RMSE	MAE	$Q^2_{predict}$	RMSE	MAE	RMSE	MAE
AD_01	0.688	0.522	0.457	0.701	0.525	-0.013	-0.003
AD_02	0.757	0.559	0.399	0.795	0.591	-0.038	-0.032
AD_03	0.685	0.518	0.458	0.711	0.546	-0.026	-0.028
USE_01	1.366	1.115	0.289	1.397	1.142	-0.031	-0.027

Table 4: Path coefficients, f^2 effect sizes, total effects, and confidence intervals

	Path coefficients	**95% bootstrap confidence intervals** (paths)	**Significant ($p<0.05$)?**	**f^2 effect sizes**	**Total Effects**	**95% bootstrap confidence intervals** (total effects)
Emotional value on adoption intention	0.515	[0.349; 0.656]	Yes	0.336		
Emotional value on technology use	0.137	[-0.045; 0.316]	No	0.014	0.362	[0.200; 0.521]
Ease of use on adoption intention	0.088	[-0.063; 0.292]	No	0.012		
Ease of use on technology use	0.010	[-0.167; 0.170]	No	0.000	0.049	[-0.110; 0.215]
Perceived usefulness on adoption intention	0.227	[0.028; 0.396]	Yes	0.044		
Perceived usefulness on technology use	0.050	[-0.178; 0.255]	No	0.002	0.149	[-0.075; 0.357]
Compatibility on adoption intention	0.045	[-0.162; 0.272]	No	0.001		
Compatibility on technology use	0.107	[-0.133; 0.343]	No	0.006	0.127	[-0.108; 0.365]
Adoption intention on technology use	0.437	[0.268; 0.609]	Yes	0.152		

Table 5: Bottleneck table (percentages)

	Emotional value	Ease of use	Perceived usefulness	Compatibility	Adoption intention
Bottleneck adoption intention					
0	NN	NN	NN	NN	
10	NN	10.2	9.3	NN	
20	NN	10.2	9.3	NN	
30	NN	10.2	9.3	NN	
40	NN	10.2	9.3	NN	
50	25.0	20.0	9.3	NN	
60	41.2	20.0	15.7	NN	
70	41.5	20.0	15.7	NN	
80	49.6	20.0	15.7	32.9	
90	49.6	20.0	15.7	32.9	
100	49.6	20.0	15.7	32.9	
Bottleneck technology use					
0	NN	NN	NN	NN	NN
10	NN	10.2	NN	NN	NN
20	NN	10.2	NN	NN	NN
30	NN	10.2	NN	NN	NN
40	49.6	20.0	15.7	25.5	33.8
50	49.6	20.0	15.7	25.5	33.8
60	49.6	20.0	15.7	33.7	33.8
70	49.6	20.5	48.1	33.7	33.8
80	49.6	20.5	48.1	33.7	33.8
90	49.6	60.2	66.2	33.7	75.0
100	49.6	60.2	66.2	33.7	75.0