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Must-have, or maybe not? A sensitivity-based extension to necessary condition analysis☆

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ABSTRACT

The necessary condition analysis (NCA) has become a prominent method for identifying must-have factors required for an outcome. With increasing sample sizes, identifying such must-have factors becomes difficult as extreme responses are more likely to occur. Addressing this concern, we introduce a novel method, the *NCA with an effect size sensitivity extension* (NCA-ESSE), which allows researchers to better understand the sensitivity of the NCA results to extreme response patterns. We offer guidelines for the NCA-ESSE method's use and illustrate its efficacy using a well-known job satisfaction model. By extending NCA's capabilities to assess the sensitivity of necessary conditions, our research enhances the method's practical utility and helps ensure the robustness and replicability of its outcomes and conclusions.

1. Introduction

Necessity logic and necessary conditions have gained significant relevance across various academic research domains, as highlighted in recent reviews (e.g., Bokrantz & Dul, 2023; Dul et al., 2023; Dul et al., 2021; Richter & Hauff, 2022). The necessary condition analysis (NCA; Dul, 2016, 2020, 2025a) has emerged as a valuable method that enables scholars to identify necessary conditions and to test necessity-based arguments in samples of various size (Dul, 2023, 2024). Marketing researchers have, for example, used the NCA to identify the degree to which purchase intention is a necessary condition for sustainable buying behavior (Frommeyer et al., 2022), to assess whether hedonic motivation is necessary for app use (Cassia & Magno, 2024), to explore necessary conditions for Metaverse shopping (Pillai et al., 2025), and to examine the role of safe customer experience dimensions as necessary conditions for customer well-being (Rahman et al., 2026). In human resource management (HRM) and organizational research, studies have drawn on the NCA to examine HRM practices required for key outcomes, such as employee satisfaction and performance (Hauff et al., 2021) and to assess whether cultural intelligence is a necessary condition for performance in intercultural teams (Richter et al., 2021).

Grounded in necessity logic (e.g., Goertz, 2017), the NCA allows researchers to assess whether necessary conditions act as constraints, bottlenecks, or critical factors that need to be overcome to achieve a specific outcome (Dul, 2016; 2020, Chapter 2). In essence, an outcome Y (e.g., app usage, performance) can only be achieved if the necessary cause X (e.g., hedonic motivation, cultural intelligence) is present or at a certain level. In other words, 'If not X, then not Y' (e.g., without hedonic motivation individuals will not use an app, or without cultural intelligence intercultural teams will not perform well). To identify such conditions, the NCA contrasts a potential necessary condition X and an outcome variable Y in a scatterplot. The aim is to distinguish areas without observations from those with observations to identify areas where X needs to be at a certain level for Y to occur.

The scatter plot in Fig. 1 illustrates this concept. The area without observations in the upper left corner (i.e., the ceiling zone) indicates that X is a necessary condition for Y, as there is no high Y outcome at low levels of X—for example, no high app usage at low levels of hedonic

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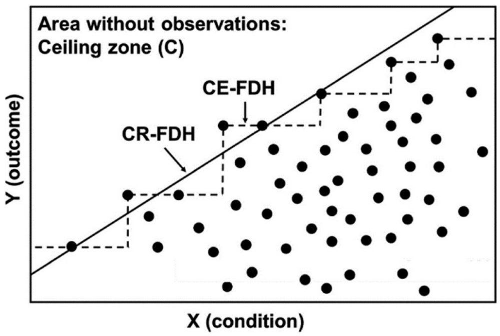


Fig. 1. NCA scatter plot example with ceiling lines (adopted from Richter et al., 2023b).

motivation, or no strong intercultural team performance at low levels of cultural intelligence. The ceiling envelopment-free disposal hull (CE-FDH) and regression-free disposal hull (CR-FDH) lines in Fig. 1 separate the ceiling zone at the upper left corner from the area with observations at the bottom right corner in the scatter plot. By calculating the ratio between the ceiling zone and the entire area potentially containing observations (i.e., the scope), the NCA determines the effect size (i.e., the ceiling zone divided by the scope). A larger ceiling zone implies a higher NCA effect size, which denotes the relevance of a necessary condition for accomplishing a certain outcome (Dul, 2016).

Dul (2024) distinguishes two types of perspectives when working with the NCA: the deterministic perspective and the typicality perspective. Under the deterministic perspective, a single case demonstrating the outcome Y without the necessary cause X falsifies the necessity concept ('If not X, then always not Y'). On the contrary, a typicality necessity builds on the idea of explaining phenomena in terms of what is typical (e.g., Wagner, 2020). It is expressed as 'If not X, then *typically* not Y.' The typicality perspective therefore allows for flexibility, implying that researchers should discard exceptional cases (e.g., extreme or unplausible cases such as a respondent who opted for the lowest possible customer satisfaction level and the highest possible customer loyalty outcome) before conducting an NCA (Dul, 2021). For example, Frommeyer et al. (2022) examined whether purchase intention is a necessary condition for the actual purchase of sustainable clothing, and following the typicality perspective in their NCA, deleted nine exceptional cases from a sample of 833 respondents (i.e., 1 %) in order to show an otherwise masked necessity effect of intention on sustainable clothing purchases (Frommeyer et al., 2022, p. 208). Specifically, the authors scrutinized individual answering patterns, deleted exceptional cases (of low intention paired with high purchases), and subsequently reran the NCA on the reduced dataset. Frommeyer et al.'s (2022) study thereby showcases one way to handle exceptional cases in an NCA context, but a holistic method for identifying, quantifying, and deciding how to deal with such cases and how to evaluate the adjusted solution has not yet been developed. Although this issue can arise in all NCA applications, it is especially problematic in larger datasets, where exceptional cases are more likely to occur. For example, a large dataset may comprise some (few) observations with a high level of an outcome Y at a low level of condition X, which would appear in the upper left corner of Fig. 1. These observations with exceptional response combinations substantially reduce or even completely eliminate the ceiling zone. Even if these exceptional observations constitute only a very small share of the dataset, their presence can prevent the identification of a necessary condition—despite most of the data suggesting a pattern consistent with such a condition. This is because under the deterministic necessity logic a single observation with a high value on the outcome (e.g., customer loyalty) and low value on the input variable (e.g., customer satisfaction) suggests that the input variable is not necessary. Therefore, exceptional response combinations pose a challenge to identify necessity in the traditional NCA.

Dul (2021) sought to address this concern by proposing a routine to identify individual outliers, which are then sequentially removed to assess their influence on the necessity effect size. Although helpful, this procedure depends largely on the researcher's manual inspection of individual cases, which becomes practically unfeasible, particularly with larger datasets. Neither visual inspection, nor individual testing can efficiently handle even 1 % of cases in a large dataset with thousands of observations.

To bridge this gap in research, we develop a statistical method—the *NCA with an effect size sensitivity extension* (NCA-ESSE). The NCA-ESSE analyzes the X and Y variables' joint distribution to explore the bivariate space that their value pairs cover to identify and quantify necessity. Drawing on a benchmark distribution, the method facilitates calculating expected changes in the ceiling zone for different threshold levels and corresponding necessity effect sizes. We offer guidelines and illustrate how to use the NCA-ESSE method on an empirical HRM example. Our research thus provides a decision aid for researchers who want to apply a typicality perspective on necessity, especially when working with larger datasets. Based on our findings, we recommend adopting the NCA-ESSE method in diverse contexts and exploring alternative parameter settings to ensure robust and reliable results.

2. The effect size sensitivity method: Concept and background

The aim of the NCA-ESSE method is to quantify necessity effect sizes, allowing for a defined share (e.g., 1 %) of extreme response combinations that populate the ceiling zone in the analysis. Rather than deleting observations from the dataset, the method computes alternative NCA ceiling lines without considering a certain share of extreme observations. The NCA-ESSE thereby quantifies the increase in effect size that results from allowing extreme value-combinations in the ceiling zone by comparing it to the increase obtained from a theoretical benchmark distribution of value-pairs for the two variables.[1] In the following, we introduce the mathematical background of our method.

Evaluating necessary conditions with an NCA can be viewed as examining the joint distribution of the two variables, namely condition X and outcome Y. By analyzing the joint distribution, we explore the bivariate space that their value pairs cover to identify and quantify necessity. Mathematically, the joint distribution $f(X = x, Y = y)$ describes the likelihood of all possible combinations of values that X and Y could take jointly over the entire range of both variables. For the continuous case, the joint probability density function (PDF), which gives the density of the probabilities of each pair of values (x, y), can be used to quantify this likelihood. For the discrete case, the joint distribution is represented by the joint probability mass function (PMF), $P(X = x, Y = y)$, which specifies the probability of each discrete value pairs.

Since we are not interested in single points, but in spaces, we consider the variables' joint cumulative distribution function (CDF). This function describes the probability of X and Y simultaneously assuming values less than, or equal to, the specific thresholds x and y. The joint CDF $F(x, y)$ for two continuous random variables X and Y, is defined as

$$F(x, y) = \int_{-\infty}^{x} \int_{-\infty}^{y} f(u, v) du\, dv \quad (1)$$

[1] Note that the procedure will always lead to an increase in effect size for continuous variables because it systematically shifts the ceiling line. However, for discrete variables, the ceiling zone and thus the effect size may remain constant. The important question is whether these increases are larger than what one would expect when the data does not follow a necessary condition (e.g., randomly distributed data combinations).

where $f(.,.)$ is the joint PDF.[2] Conversely, the joint CDF $F(x,y)$ of two discrete random variables X and Y, is given by

$$F(x,y) = \sum_{u \le x} \sum_{v \le y} P(u,v) \tag{2}$$

where $P(.,.)$ is the joint PMF.

To quantify the joint CDF, one could make distributional assumptions about the two variables (i.e., both are multivariate normally distributed or uniformly distributed), thereafter identifying the distribution parameters from the given sample (i.e., mean and variance or min and max), and mathematically integrating them over the constructed distribution function.

Alternatively, we can create a non-parametric estimate by using the joint empirical cumulative distribution function (joint ECDF). The joint ECDF for two continuous random variables X and Y is defined as $F_{ECDF}(x, y) = P(X \le x, Y \le y)$, where $F_{ECDF}(x,y)$ represents the proportion of observations in the sample such that $X \le x$ and $Y \le y$. If—as often done in the NCA—we focus on the upper left corner (i.e., we want to investigate whether a high level of X is necessary for a high level of Y), we can simply estimate the joint ECDF as $F_{ECDF\_NCA}(x,y) = P(X \le x, Y \ge y)$.

The ceiling zone in an NCA scatter plot can therefore be described as the area where $F_{ECDF\_NCA}(X = x, Y = y) = 0$ (i.e., where the joint ECDF is zero). The CE-FDH line is given by the (x,y) combinations that mark the transition from $F(x,y) = 0$ to $F(x,y) > 0$. This ceiling line has 100 % accuracy, meaning that it does not allow any observations above the ceiling line.[3] Having defined the ceiling line, we can carry on as usual and calculate the NCA's effect sizes. Our method is therefore different from the current practice in NCA in that we use the joint distribution concept and the ECDF to determine the CE-FDH ceiling line. More specifically, it allows us to examine other thresholds (e.g., 1 % or 5 % of the ECDF) to define the ceiling lines that mark the transition between, for example, 99 % of the response combinations in the (observed) joint distribution and the 1 % of the "extreme" or "atypical" observations. We refer to these as the CE-$FDH_{1\%}$ and CE-$FDH_{5\%}$ ceiling lines, whereas the CE-$FDH_{0\%}$ equals the regular CE-FDH ceiling line in the NCA.[4] These new ceiling lines allow for constructing alternative spaces and NCA effect sizes that, for example, represent the space covered by 1 % of the observations relative to 99 % of the rest of the observations. This analysis allows us to understand the NCA effect size's sensitivity when using shifts in the joint distribution thresholds to define necessity. In other words, we implement the NCA's typicality logic with a specific form of sensitivity method that is based on varying ECDF thresholds. We therefore call the method NCA-ESSE (i.e., an *NCA with an effect size sensitivity extension*).

Since we systematically shift the joint distribution's threshold, we usually expect an increase in the ceiling zone and, thus, an increase in the necessity effect size.[5] To enable a meaningful interpretation of this increase, we advise scholars to compare increases in the observed joint distribution to the expected increases in other theoretical joint distributions. This involves, for example, comparing the shift in the empirical distribution relative to a joint uniform distribution. The underlying reason for using a joint uniform distribution is that any observation within our scope (the range of possible X and Y combinations) is assumed to be equally likely. We then compare the expected increase in the 1 % threshold's space from our observed distribution to the theoretical distribution to determine whether this increase is only due to chance or reflects an actual necessary condition in the underlying data.

3. Steps of the NCA-ESSE

A systematic application of the NCA-ESSE method follows the steps shown in Fig. 2. Step 1 starts with the standard NCA to determine whether extreme responses potentially mask necessity conditions. This may occur when NCA results suggest the absence of necessary conditions, despite strong theoretical justification and practical plausibility. Step 2 then involves running the NCA-ESSE method. Step 3 is optional and involves a certain threshold selection, results presentation and their evaluation.

The initiation of the NCA-ESSE method (in Step 2) involves deciding the sensitivity threshold range, and the percentage point increments. We recommend a threshold range from 0 to 5 % to prevent a too high number of observations allowed to populate the ceiling zone. Furthermore, we recommend using 0.5 percentage point increments to achieve relatively fine granularity while maintaining computational efficiency. However, the choice will ultimately also depend on the size of the available data. Larger datasets may allow smaller increment steps and consequently also a smaller threshold range. When evaluating results, we recommend that researchers focus on the magnitude of the NCA effect size changes. These can be graphically represented in an inverse elbow function analysis. We also advise researchers to consider a benchmark distribution, which demonstrates the theoretical changes of the NCA effect sizes for the chosen joint distribution. In this study, we select a joint uniform distribution of the variables as the theoretical benchmark distribution.[6] Thus, we calculate expected changes in the ceiling zone when using different thresholds for this theoretical distribution and compute corresponding effect sizes to serve as benchmark results.

The optional Step 3 involves selecting a certain threshold and evaluating and presenting the results for this selection in more depth. This step is particularly relevant when the NCA-ESSE reveals a large effect size increase in the range of investigated thresholds, which entails a substantial change of the NCA findings and conclusions to support theoretical hypotheses. This analysis can be especially valuable when working with a dataset that does not reveal a relevant and significant effect size for a theoretically assumed necessary condition in the standard NCA (i.e., for a deterministic perspective with threshold 0 %); yet, the NCA-ESSE indicates practically meaningful and statistically significant effect sizes above 0.1 within the examined range of thresholds. In the following, we will apply the NCA-ESSE method to an empirical example to illustrate these steps and decisions.

4. Empirical illustration

4.1. Data and necessary conditions

To empirically demonstrate the NCA-ESSE method we draw on Drabe et al. (2015) who present a research model that examines the impact of various job characteristics on job satisfaction (controlling for gender, different age groups, and countries in their regression analyses). While the original study uses data from the work orientation III module of the International Social Survey Programme (ISSP) collected in 2005 (ISSP Research Group, 2013), we follow Sarstedt and Danks (2022) whose job satisfaction study draws on more recent ISSP data (ISSP Research Group, 2017). We focus on the following seven key job

[2] Note that u and v are auxiliary variables over which integration (or summation) of the densities (or probabilities) is done until reaching the thresholds x and y of the variables X and Y.

[3] Note that the combinations of points (x,y) that mark the CE-FDH ceiling line can be used for estimating a regression that characterizes the CR-FDH ceiling line.

[4] Similarly, one can also construct corresponding CR-$FDH_{1\%}$ or CR-$FDH_{5\%}$ ceiling lines. While this approach may appear similar to quantile regression, it is conceptually quite different as it only uses observations that are exactly on the respective percentile of the joint distribution for estimating the regression.

[5] We note that the ceiling zone must not always increase but can also remain constant, while it can never decrease.

[6] While the benchmark distribution builds on the assumption that all observations are equally likely, assuming individual case weights is also feasible.

Step 1: Run the standard NCA
Step 2: Apply the NCA-ESSE method and assess sensitivity to different thresholds
- Select range and increment for the thresholds
- Calculate new ceiling lines and NCA effect sizes for these thresholds
- Compare against a theoretical distribution

Step 3 (optional): Select the threshold and further evaluate the results

Fig. 2. Steps of the NCA-ESSE.

characteristics that explain job satisfaction (v44): job security (v22), high income (v23), high advancement opportunities (v24), interesting job (v25), independent work (v26), good relations between management and employees (v42), and good relations between workmates/colleagues (v43); the items in brackets show the variable names in the ISSP dataset. Job satisfaction is measured on a 1 to 7 scale and the other variables are measured on a 1 to 5 scale. While the aim of the analysis is to empirically demonstrate the NCA-ESSE method, the HRM literature offers explicit arguments for the inclusion of these variables from a necessity perspective (Hauff et al., 2021; Lepak et al., 2006). The ability, motivation, and opportunity (AMO) model (Appelbaum et al., 2000; Bailey, 1983) provides theoretical support for the prevalence of necessity conditions in job satisfaction models like the one used in our study. For instance, certain levels of M- and O-enhancing HRM practices are necessary for high employee performance. M-enhancing HRM practices (e.g., performance- based compensation, incentives and benefits, promotion opportunities, and job security) provide employees with motivation by linking their work efforts to external rewards (e.g., Deci et al., 1989). Hauff et al. (2021) note that a baseline level of M-enhancing HRM practices is necessary for achieving high employee performance, since a minimum degree of motivation is required to elicit desirable work behaviors (e.g., Cummings & Schwab, 1973). These authors also argue that O-enhancing HRM practices (e.g., job autonomy, organizational participation) shape the organizational conditions in which employees work (e.g., Ryan & Deci, 2000). Because such external conditions are essential for eliciting employees' discretionary effort (e.g., Blumberg & Pringle, 1982; Peters & O'Connor, 1980), a certain level of these practices is likewise necessary to attain high employee performance (Hauff et al., 2021).

The ISSP dataset contains 51,668 observations. For our empirical example, we filter those respondents who are currently in paid work as employees (giving us 22,789 usable responses). Furthermore, we apply case-wise deletion to deal with missing values and non-responses.[7] Hence, the final dataset for our empirical example contains 20,862 responses. For the results computations, we used the NCA package (Dul, 2025b) in the statistical software R (R Core Team, 2025) and our own R code for the NCA-ESSE method, which we made online available (see also Deer et al., 2025).[8]

4.2. Run the standard NCA (Step 1)

To begin with, we carry out a standard NCA, assuming that all job characteristics are necessary conditions for high job satisfaction.[9] The NCA results show that all effect sizes are zero. Accordingly, the NCA ceiling line charts of all the variables resemble the one shown in Fig. 3 for job security and job satisfaction. The observations fill the entire scatter plot area; that is, there is no ceiling zone (i.e., no area without observations) in the scatter plot. The NCA effect size is therefore also zero, and the bottleneck table shows "not necessary" for all levels of job satisfaction (NN; Table A1 in the Appendix).

According to the standard NCA, neither of the seven job characteristics is necessary for job satisfaction. However, assuming that employees do not need job security in order to be highly satisfied seems

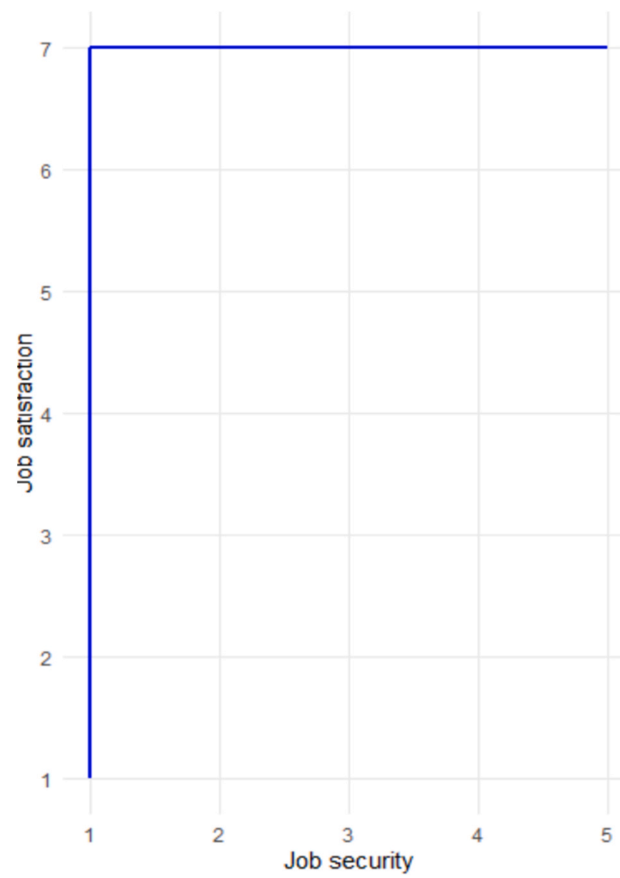


Fig. 3. Ceiling line chart.

[7] Alternatively, researchers may choose pairwise deletion for each pair of variables in the NCA(-ESSE). Such a step would retain more data for each individual NCA(-ESSE), but would result in different samples with different sizes across the analyses. For example, this would mean that the sample size for the analysis of job security as a necessary condition would be different from the sample size for the analysis of high income as a necessary condition for job satisfaction.

[8] The R code for the NCA-ESSE method in general as well as for our illustrative example can be accessed via https://osf.io/59ynt/. We anticipate that the NCA-ESSE will be integrated into packages of the statistical software R (e.g., NCA; Dul, 2025b) as well as into standard statistical software with a graphical user interface that support NCA (e.g., SmartPLS; Ringle et al., 2024).

[9] Note that the aim of this example is to demonstrate the empirical procedure rather than to focus on the model's theoretical aspects. To reinforce our illustration, we therefore focus only on employees who are in paid work, for whom such a logic is most likely to apply. Nevertheless, it should be clear that an application of NCA-ESSE in research projects and studies must always be based on theoretically substantiated hypotheses, which are of secondary concern in our illustration.

implausible and contradicts arguments in the HRM literature (e.g., Hauff et al., 2021). Focusing on job security, the data shows that 21 of the 20,862 responses (i.e., 0.1 %) show the highest level of job satisfaction and the lowest level of job security. This 0.1 % of cases, characterized by extreme and atypical value combinations, induce in a ceiling zone of zero—and consequently, an NCA effect size of zero for job security. Consequently, we decided to analyze the results in more detail by using the NCA-ESSE method.

4.3. Apply the NCA-ESSE method and assess sensitivity to different thresholds (Step 2)

For the application of the NCA-ESSE method, we choose a range from 0 % to 5 %, and 0.5 percentage point increment steps. In addition, we use the joint uniform distribution as a theoretical benchmark. For illustrative purposes, the analysis continues to focus on job security as a potential necessary condition for job satisfaction.[10] Fig. 4 shows the sensitivity plot; that is, it shows the NCA effect sizes obtained at different ceiling lines (thresholds); Table A2 in the Appendix shows the corresponding exact values. For example, the CE-FDH$_{0.5\%}$, where the ceiling line threshold is set at the 0.5 % level of the ECDF, results in an increase in the NCA effect size from zero to a substantial value of 0.167. With a CE-FDH$_{2\%}$, the NCA effect size even increases to a value of 0.375. As discussed before, we expect an increase in the NCA effect size at higher thresholds, because we systematically increase the ceiling zone by allowing more observations to populate this space. For example, with a CE-FDH$_{2\%}$ we allow 2 % of the observations to occur in the area above the ceiling line, where the observations are closest to the most extreme response. That is, extreme response combinations involving very low job security (e.g., a value of 1 for job security), and very high job satisfaction (e.g., a value of 7 for job satisfaction).

To aid decision making, Fig. 4 shows the changes in the NCA effect sizes when assuming that X and Y are jointly uniformly distributed (the theoretical distribution benchmark) for different ECDF thresholds. As expected, the NCA effect size also increases with higher ECDF threshold levels for such a theoretical distribution where all value pairs are equally likely to occur (and thus there is certainly no necessary condition). However, the increases observed in the empirical data are much larger than those for the reference distribution. This suggests the presence of a typicality necessary condition in the data.

Fig. 5 shows the different ceiling lines for job security and job satisfaction for alternative ECDF threshold levels. The ceiling lines are shifted further down to the right as we increase the threshold. These movements are much stronger than what would be expected from a uniform population of value pairs. The results highlight that for 99.5 % of the respondents, job security is a necessary condition for job satisfaction (effect size of 0.167). Assuming more liberal thresholds such as 98 % (i.e., CE-FDH$_{2\%}$) substantially increase the effect size to 0.375. These results suggest that for typical observations, it is highly unlikely to observe high satisfaction without high job security, thereby supporting a typicality necessary condition. We also complement the assessment using the permutation test for NCA (Dul, 2016) on the alternative ceiling lines (e.g., a CE-FDH$_{2\%}$) to check whether NCA effect sizes for different thresholds are significant. The results show that effect sizes up to a threshold of 2 % (i.e., CE-FDH$_{2\%}$) are significant.

These NCA-ESSE results allow us to discard the original NCA finding that there is no necessary condition for job satisfaction; instead, job security acts as a typicality necessary condition for job satisfaction. A comparable result can be obtained for the other regressors in the job satisfaction model.

[10] Note that the results of the other job characteristics (i.e., high income, high advancement opportunities, interesting job, independent work, good relations between management and employees, and good relations between workmates/colleagues) yield similar (sometimes even more pronounced) results.

4.4. Select the threshold and further evaluate the results (optional Step 3)

In this final (optional) step, we illustrate how researchers can use the results from the NCA-ESSE to select a specific threshold from the range previously considered for further in-depth evaluation and interpretation of the typicality necessary condition. We will use the theoretical benchmark to identify a reasonable empirical ECDF threshold for further assessment of the NCA results. As long as the increase in the NCA effect size is higher than that of the theoretical benchmark, it makes sense to use higher ECDF thresholds for the analysis. If these functions tend to show comparable slopes, this implies that moving the ceiling line frees the same amount of additional space as would be expected if all data points were equally likely. Thus, the additional effect size increment is not systematic but likely due to chance. At this point, we should stop and not further interpret the effect size increases as evidence of a necessary condition. For this reason, Fig. 6 shows the difference between the empirical and theoretical NCA effect size changes at different ceiling lines thresholds (see also the last column in Table A2 in the Appendix). For ECDF threshold levels up to 2 %, the increase in the empirical NCA effect size exceeds the increase expected from the theoretical benchmark distribution. Hence, we may select the solution at the 2 % threshold, beyond which further increases offer no clear improvement over what would be expected from a random distribution of data points. We also observe larger increases from 3 % to 3.5 % and 4.5 % to 5 %, but the increments in-between are smaller than those expected under a uniform distribution of data points and are therefore likely due to chance. Likewise, the effect sizes for 2.5 % and 3 % thresholds are not significant, further supporting the conclusion that there is no systematic improvement over a random distribution of data points beyond the 2 % threshold.

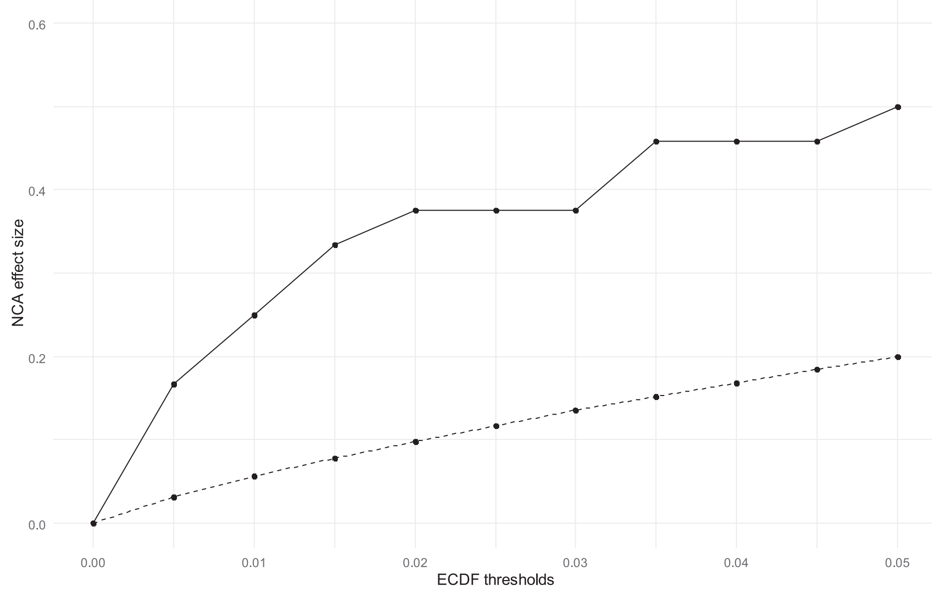
Once we have settled on a specific threshold, the analysis of the ceiling line chart (Fig. 5) and the bottleneck table (see, for example, Table A3 in the Appendix for CE-FDH$_{2\%}$) complements our understanding of the necessary condition that exists for most (i.e., here 98 %) but not all responses. Most importantly, we reveal a relevant effect size of 0.375 at the CE-FDH$_{2\%}$ (Table A2 in the Appendix), which supports the assumption that job security represents a typicality necessary condition for job satisfaction—an assumption, which is highly plausible based on theory and logic. Hence, in contrast to a standard NCA, we provide support for the finding that job security represents a typicality necessary condition for job satisfaction.

5. On the usefulness of the NCA-ESSE with smaller sample sizes

The logic and motivation behind the development and recommended application of NCA-ESSE apply not only to large datasets. Even with relatively small datasets, NCA results and conclusions can be misleading if extreme observations cause highly distorted outcomes.

To demonstrate the robustness and usefulness of the NCA-ESSE method with smaller sample sizes, we randomly drew subsamples of 300 data points from the previously used full ISSP data (i.e., with 20,862 responses in this study). More specifically, we randomly drew 300 responses 10,000 times (without replacement) and then calculated the NCA-ESSE effect sizes for the different thresholds as done previously (i.e., from 0 % to 5 % with 0.5 % increments). Table 1 shows the summary statistics of the effect size estimates including the mean value, quantiles (Q), and standard deviation (SD) for the different thresholds across the 10,000 randomly drawn smaller datasets.

For a threshold of 2 % (i.e., the one that we identified as optimal in the previous analysis), we find that the mean (0.369) and median (0.375) effect sizes are very close (or equal) to the effect size estimate from the full dataset (0.375). Also, the variability (i.e., the SD) is reasonably small around these values. For smaller thresholds we find considerably larger variability. Interestingly, at a threshold of 0 %—which corresponds to the effect size estimates in a standard NCA—we observe the greatest variability in effect sizes. While only 26.5 % of the



Note: solid line = changes in NCA effect sizes using the CE-FDH$_{0\%}$ to CE-FDH$_{5\%}$ in the empirical dataset; dashed line = expected (theoretical) changes in NCA effect sizes from using the CE-FDH$_{0\%}$ to CE-FDH$_{5\%}$ on data following a joint uniform distribution of values as a benchmark

Fig. 4. Sensitivity plot.

samples yield an exact effect size of zero (as in the full dataset), 30.3 % are significantly different from zero at the 5 % confidence level based on the NCA permutation test (Dul et al., 2018).

The results can be interpreted in two ways: On the one hand, the full dataset can be viewed as a population reference, indicating a true effect of zero. From this perspective, the standard NCA results (i.e., the 0 % column in Table 1) based on the smaller samples would appear to produce an excessively high rate of false positives (i.e., 30.3 %). On the other hand, and in line with our proposed method, we argue that a small number of extreme responses in the full dataset may mask a true necessary condition. Accordingly, many of the smaller samples may detect this condition correctly, yielding a significant necessary condition effect for job security on job satisfaction. Either way, the results demonstrate that the standard NCA is highly sensitive to single extreme observations, which may paint a misleading picture of necessity conditions underlying the relations under consideration. These outcomes underscore that the NCA-ESSE method is beneficial not only for large datasets but also for smaller ones. We therefore recommend the routine application of the NCA-ESSE.

6. Conclusions and further research

The NCA is an important research method for empirically testing theoretically hypothesized and exploring potential necessary conditions, which has gained significant attention in recent research (e.g., Bachmann et al., 2024; Milovan et al., 2025; Quansah et al., 2025; Rahman et al., 2026; Vu & Tolstoy, 2025). However, extreme responses may challenge the robustness and replicability of NCA results in empirical applications. Our research extends the NCA's capabilities by introducing the NCA-ESSE method, which incorporates a typicality perspective by using varying ceiling line thresholds. In doing so, the method provides a decision aid to assess the sensitivity of NCA results, thereby improving the robustness of findings regarding the necessity of the studied variables, especially—but not exclusively—in large datasets.

NCA applications in different fields of business research normally use sample sizes of <1000 observations (e.g., Abner et al., 2023; Bouncken et al., 2023; Cassia & Magno, 2024; Damberg et al., 2024; Kardell et al., 2025; Richter et al., 2023a; Riggs et al., 2024; Sukhov et al., 2022; Tiwari et al., 2024). With the increasing availability of large datasets and with the growing number of discussions on how to best leverage such data (e.g., Hair & Sarstedt, 2021; Wenzel & Van Quaquebeke, 2017; Zhang et al., 2021), the NCA is likely going to be used in such research settings. However, the application of NCA to large datasets comes with significant challenges, as extreme data constellations that populate the entire scatterplot are more likely to occur. For example, scenarios such as the lowest possible level of job security paired with the highest possible level of job satisfaction may be rare but are more likely to emerge in large datasets. Although such combinations typically account for only a very small fraction of responses, their presence can easily falsify necessary conditions that may (typically) hold in most cases in the overall dataset. This challenge highlights the need for methods to identify and mitigate distortions arising from exceptional cases, thereby ensuring NCA outcomes' validity and robustness.

To overcome this limitation, we propose a systematic approach supported by an underlying statistical model, referred to as the NCA-ESSE method. This method assesses the sensitivity of the NCA to extreme responses and their potential to distort the results. By applying the NCA-ESSE method to Drabe et al.'s (2015) job satisfaction model, we demonstrate its utility in determining whether job security acts as a necessary condition for job satisfaction. While this illustration draws on a large dataset, we further illustrate NCA-ESSE's applicability and usefulness for smaller datasets. Our method contributes significantly to ensuring NCA outcomes' validity and robustness, positioning it as a valuable extension of the NCA methodological toolset.

There are several opportunities to further advance the NCA toolset based on this research and the proposed NCA-ESSE method. Future research should further refine the theoretical distinction between the deterministic and typicality perspectives on necessary conditions. Such a distinction should aim to characterize the observations that populate the ceiling zone and invalidate the deterministic necessity logic. A nuanced approach to handling these responses, including decisions on their classification as outliers or exceptional extreme response combinations could help further develop the method and its practical application.

Future research should further assess the applicability of the NCA-

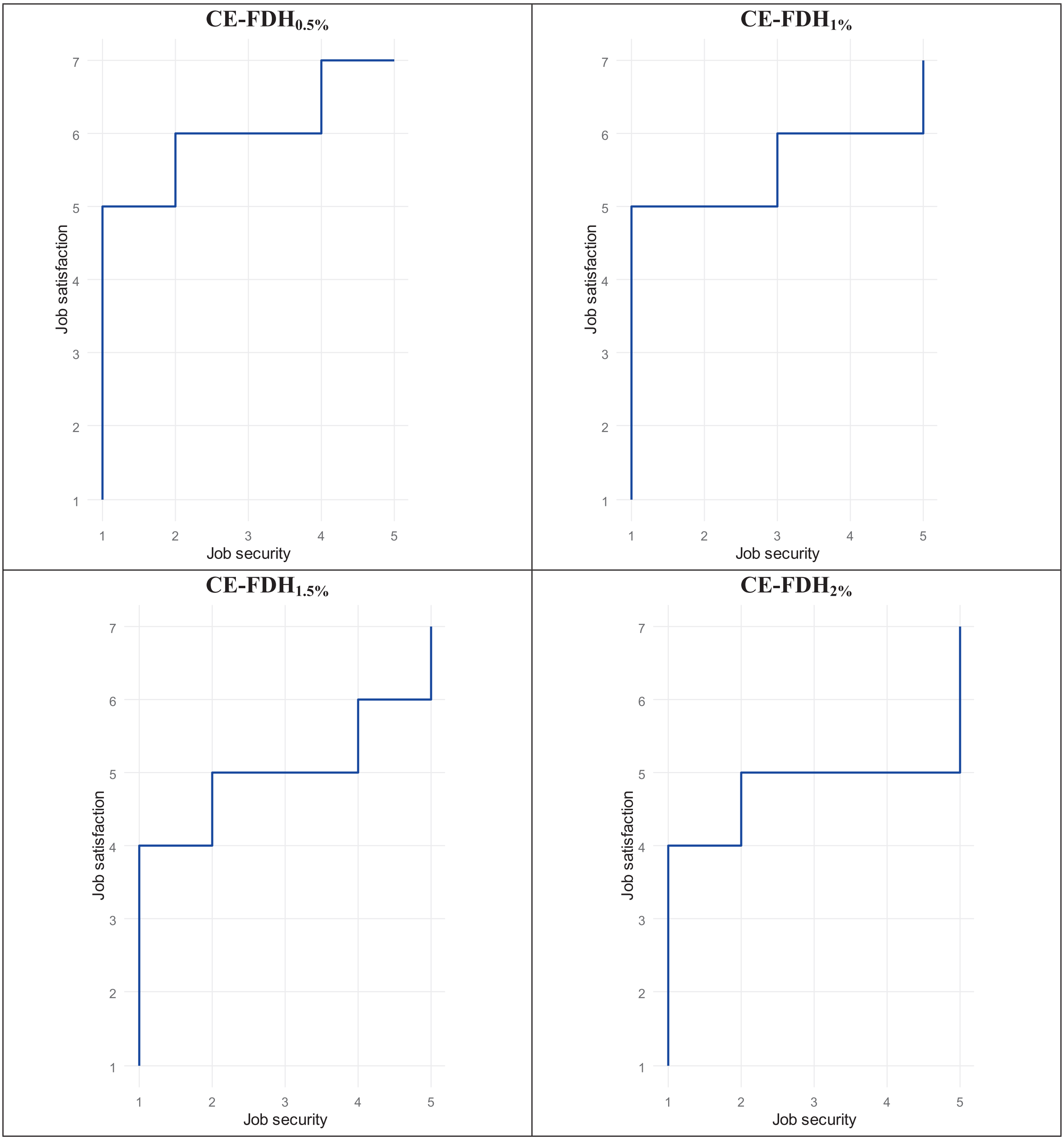


Fig. 5. NCA ceiling line charts for different ECDF thresholds.

ESSE method in a broad range of contexts. We see substantial potential in future studies that not only validate the general use of the NCA-ESSE method but also develop a more refined procedural model applicable across various NCA contexts. For example, in addition to the uniform distribution of variables used as a theoretical benchmark in this study, other benchmark distributions could be introduced for the NCA-ESSE toolbox such as a bi-variate normal distribution with a given (or empirically estimated) correlation. In addition, future research could improve how researchers select appropriate thresholds for presenting and interpreting results, or develop additional quality and assessment criteria to enhance the robustness of NCA-ESSE findings. We also see potential for future research to expand and discuss our statistical model and to apply probability-based assessments of necessary conditions that allow for more advanced forms of their testing.

Researchers could also build on the proposed NCA-ESSE method to discover heterogeneity in the NCA framework. While the method can be applied to different a-priori defined segments (e.g., frontline service employees vs. manufacturing jobs) to better understand differences in necessary conditions, future research may also explore methods to uncover unobserved heterogeneity. Analogous to iterative-reweighted regression approaches (e.g., Schlittgen et al., 2016), sets of data points identified on the grounds of the NCA-ESSE may be conceived as a

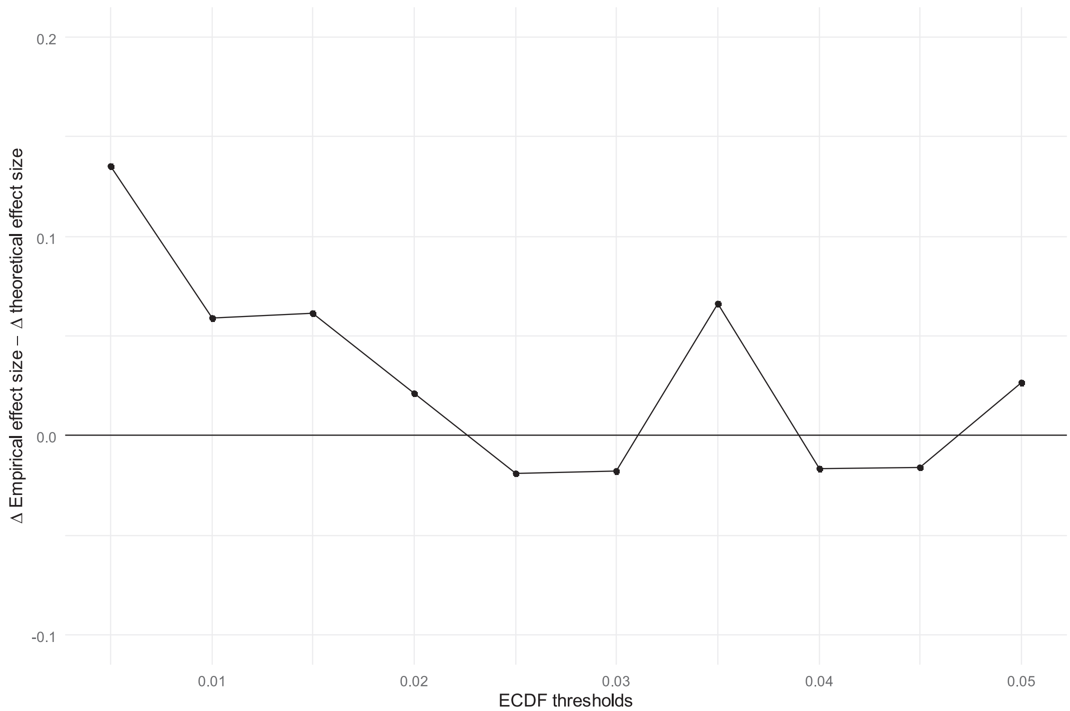


Fig. 6. NCA effect size differences between empirical and theoretical benchmark results.

Table 1
Summary statistics of CE-FDH effect size estimates.

ECDF threshold	0 %	0.5 %	1.0 %	1.5 %	2.0 %	2.5 %	3.0 %	3.5 %	4.0 %	4.5 %	5.0 %
Mean	0.099	0.185	0.288	0.322	0.369	0.387	0.419	0.434	0.462	0.473	0.493
Median	0.083	0.208	0.292	0.333	0.375	0.375	0.417	0.417	0.458	0.458	0.500
$Q_{2.5\%}$	0.000	0.000	0.167	0.208	0.292	0.292	0.333	0.375	0.375	0.375	0.417
$Q_{97.5\%}$	0.250	0.333	0.375	0.417	0.458	0.458	0.500	0.500	0.542	0.542	0.542
SD	0.081	0.077	0.060	0.054	0.043	0.041	0.043	0.043	0.041	0.039	0.035
Full data	0.000	0.167	0.250	0.333	0.375	0.375	0.375	0.458	0.458	0.458	0.500

Note: The results have been obtained by creating 10,000 randomly drawn datasets from the full data, each containing 300 responses; full data = 20,862 ISSP responses; ECDF = empirical cumulative distribution function; Q = quantile, SD = standard deviation; 0 % = standard NCA result; > 0% = NCA-ESSE results.

distinct segment, which should be separately analyzed. The analysis could then identify necessary conditions within a subset of observations, parallel to the NCA of the remaining data. In addition, researchers may theorize about necessity patterns that manifest as empty zones in more than one corner of the scatterplot. For example, they may posit that an optimal (neither very low nor very high) level of X is necessary for achieving a high level of the outcome Y. In such cases, both the upper left and upper right corners of the scatterplot will be empty. NCA allows for a combined test of these two necessity relations for a single factor by aggregating and evaluating the total empty zone (Dul, 2025a, Chapter 2.6). Researchers may consider expanding the NCA-ESSE method to test the effect size sensitivity in these or similar necessity patterns in various corners of the scatterplot in the future. Finally, future research should apply the NCA-ESSE method to the same model, but to data from different points in time. Such an analysis would allow researchers to demonstrate that our proposed method could provide robust and reliable results, also over time.

CRediT authorship contribution statement

Jan-Michael Becker: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Nicole Franziska Richter:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Christian M. Ringle:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Conceptualization. **Marko Sarstedt:** Writing – review & editing, Validation, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table A1
Bottleneck table of the CE-FDH line.

Job satisfaction	High Income	High Advancement opportunities	Job security	Interesting job	Independent work	Good relationships with managers	Good relationships with colleagues
1.000	NN	NN	NN	NN	NN	NN	NN
2.000	NN	NN	NN	NN	NN	NN	NN
3.000	NN	NN	NN	NN	NN	NN	NN
4.000	NN	NN	NN	NN	NN	NN	NN
5.000	NN	NN	NN	NN	NN	NN	NN
6.000	NN	NN	NN	NN	NN	NN	NN
7.000	NN	NN	NN	NN	NN	NN	NN

Note: NN = not necessary.

Table A2
NCA robustness outcomes.

ECDF threshold	Δ ECDF threshold	Empirical effect size	Permutation p-value	Δ Empirical effect size	Theoretical effect size	Δ Theoretical effect size	Δ Empirical effect size − Δ theoretical effect size
0.000	–	0.000		–	0.000	–	–
0.005	0.005	0.167	0.000	0.167	0.031	0.031	0.135
0.010	0.005	0.250	0.000	0.083	0.056	0.025	0.059
0.015	0.005	0.333	0.000	0.083	0.078	0.022	0.061
0.020	0.005	0.375	0.000	0.042	0.098	0.020	0.021
0.025	0.005	0.375	1.000	0.000	0.117	0.019	−0.019
0.030	0.005	0.375	1.000	0.000	0.135	0.018	−0.018
0.035	0.005	0.458	0.000	0.083	0.152	0.017	0.066
0.040	0.005	0.458	0.000	0.000	0.169	0.016	−0.016
0.045	0.005	0.458	0.000	0.000	0.185	0.016	−0.016
0.050	0.005	0.500	0.000	0.042	0.200	0.015	0.026

Table A3
Bottleneck table at the 2 % ECDF threshold (CE-FDH$_{2\%}$).

Job satisfaction	High Income	High Advancement opportunities	Job security	Interesting job	Independent work	Good relationships with managers	Good relationships with colleagues
1.000	NN	NN	NN	NN	NN	NN	NN
2.000	NN	NN	NN	NN	NN	NN	NN
3.000	NN	2	NN	NN	NN	NN	NN
4.000	2	2	NN	2	NN	2	NN
5.000	3	4	2	2	2	2	2
6.000	5	5	5	5	5	5	4
7.000	5	5	5	5	5	5	5

Note: NN = not necessary.

Data availability

The data is available at https://www.gesis.org/en/issp; the R Code is available at https://osf.io/59ynt/.

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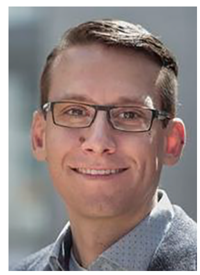

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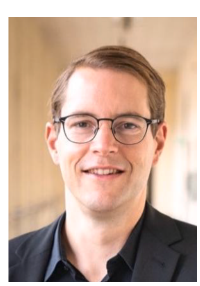

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