




# Fuzzy-Set Qualitative Comparative Analysis (fsQCA) in Organizational Psychology: Theoretical Overview, Research Guidelines, and A Step-By-Step Tutorial Using R Software

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**Abstract.** Fuzzy set qualitative comparative analysis (fsQCA) is a method for assessing the effects of configurations of variables leading to an outcome. The recent growth of interest in this technique in organizational psychology is proving this method to be an important tool for addressing new and decisive research hypotheses. However, the effectiveness of fsQCA is dictated not only by its general principles, but also by how well these are understood and applied in the research community. Consequently, a guide that covers the fundamental ideas and tenets of the approach is required to aid the research community in its comprehension and practical application. The current study seeks to offer an understanding of FsQCA by providing: (a) A complete description of the method highlighting some of the most important theoretical-methodological aspects; (b) a perspective on the most used guidelines and recommendations, and (c) step-by-step instructions on how to carry out FsQCA in R using the QCA package. Data from 120 employees and supervisors derived from a company based in central Italy were used to best illustrate how to carry out fsQCA. Codes for conducting the analyses from the QCA package for R accompany the tutorial and can be adapted to a new dataset.

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Throughout its history, organizational psychology research has recognized and attempted to explain the complexity of organizational phenomena (e.g., Dooley, 2008; Guastello & Liebovitch, 2008). Specifically, the underlying assumption is that psychosocial events cannot be exclusively traced back to a single isolated element, but rather to configurations of variables linked by complex relationships of interdependence (Crilly, 2013; Fiss, 2011; Ketchen, 2013; Misangyi et al., 2016). Configurations represent a specific combination of variables leading to a given outcome (e.g., Rihoux & Ragin, 2009) and are not new to social sciences. In fact, configurational hypotheses have been addressed for years in research by applying regression models to test

moderation effects (e.g., Grofman & Schneider, 2009). However, this methodological approach has a limit, the number of possible interaction terms maxes out at three variables (e.g., Dawson & Richter, 2006; Igartua & Hayes, 2021), thus leaving much of the possibilities for configurational testing out of its reach.

For this reason, a number of studies have started using alternative methodologies to further understand and explore the role of configurations in organizational studies (e.g., Ong & Johnson, 2021). One of these emerging methods is qualitative comparative analysis (QCA), and its variant fuzzy set qualitative comparative analysis (FsQCA). This family of methods belongs to the comparative case-oriented approach that combines concepts from set theory and Boolean algebra (e.g., Furnari et al., 2021). Although their prior application to case

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studies, those methods are currently adopted to analyze empirical data and generalize the results considering the possibility of replication in future research (Parente & Federo, 2019; Roig-Tierno et al., 2017).

Unlike correlational approaches based on additive and linear attributes, QCA methods identify the relationships and interdependencies of multiple factors related to a given criterion, allowing for the investigation of the conjunct, equifinal, and asymmetric effects (Fiss, 2011). In doing so these methods analyze patterns of variables that are jointly related to a dependent variable (Ragin & Fiss, 2008). For this reason, fsQCA is being increasingly applied in organizational psychology as it seems to represent a suitable option to effectively test configurational hypotheses and offer robust results to enrich the literature.

In recent years, an increasing number of studies adopting fsQCA have been published in the field of organizational psychology (e.g., Cangialosi et al., 2021), but, despite this, configurational theory and its application in research are still not sufficiently covered in organizational research (e.g., Meier, 2017; Ott et al., 2018). This is partially due to the lack of knowledge of the potential of this methodology, of which guidelines to follow, and of the actual procedures to be implemented.

In order to fill this gap and to further promote the correct application of fsQCA, the present study aims at three objectives: (a) To highlight some of the most relevant theoretical-methodological features of the method, (b) to offer a detailed description of FsQCA in its various phases by providing a perspective on the most frequently adopted guidelines and, (c) to provide step-by-step instructions on how to run FsQCA using the QCA package in R.

## Fuzzy Set Qualitative Comparative Analysis

### *Key Concepts behind the Methodological Approach*

Originating over three decades ago (Ragin, 1987), QCA has enriched the toolbox of empirical research methods. QCA is an analytic methodology that combines quantitative and qualitative techniques by using Boolean logic and set theory instead of correlation methods (Ragin, 2000, 2009; Ragin & Fiss, 2008). For this reason, in all QCA based methods independent and dependent variables are referred to as “conditions” and “outcomes”, respectively. A condition reflects the set membership of a variable used to explain the outcome and an outcome to a set membership in a variable explained by the conditions (Ragin, 1987). The method was initially restricted to small samples, but further advancements allowed for its usage for more numerous data (e.g., Parente & Federo, 2019).

QCA is composed of several variants, the two most common are crisp-set (csQCA) and fuzzy-set (fsQCA). CsQCA is the original form of QCA, and its objective was to simplify complex configurations with the use of Boolean logic. CsQCA employs categorical conditions, giving each condition a value of either 1 (membership) or 0 (non-membership), identifying combinations that consistently lead to a result using Boolean expressions that detect irrelevant conditions. The main concern with this approach is its limited applicability in the social sciences; in fact, the investigation phenomena are hardly attributable to dichotomies.

To overcome that limitation, the variant fsQCA was later developed (Ragin, 2000, 2009). Fuzzy sets are “a class of objects with a continuum of grades of membership. Such a set is characterized by a membership (characteristic) function which assigns to each object a grade of membership ranging between zero and one” (Zadeh, 1965, p. 338). The application of fuzzy sets to QCA allows the transformation of any value on an infinite continuum of degrees of membership ranging from 0 to 1 with 0.5 as the cross-over point or point of maximum ambiguity (Duşa, 2019). In terms of research applications in the social sciences, fsQCA has quickly surpassed its original counterpart (csQCA) due to its capacity to handle configurations of causal conditions based on the degree of membership as opposed to category memberships (Nikou et al., 2022; Pappas & Woodside, 2021).

### *Causal Complexity*

QCA allows the distinction of causes into necessary and sufficient conditions (Furnari et al., 2021; Misangyi et al., 2016x). Necessary conditions denote that the focal outcome can only be obtained in the presence of the causal factor, and sufficient conditions that the presence of the causal factor always results in the focal outcome (Fiss, 2007). However, in applied research contexts it is very rare to identify single conditions capable of being necessary or sufficient, more often it is conjunctions of conditions that are associated with an outcome. The development of the QCA methodology is therefore intrinsically linked to the so-called principle of causal complexity (Gerrits & Pagliarin, 2021).

Causal complexity in the social sciences can be defined as “a situation in which a given outcome may follow from several different combinations of causal conditions” (2008, p. 124). This definition of causal complexity entails three aspects:

*Conjunctural causation* – When a combination of conditions produces the outcome. The complex causality approach assumes that specific patterns and combinations of conditions lead to an outcome (Ragin, 2014). In other words, phenomena are seen as results of interconnected attributes as a total, and not of individual and

separable entities (Aus, 2009). From this standpoint, patterns and combinations of causal conditions are responsible for the outcome rather than individual independent variables. As a result, complex causality-based methods focus on identifying different conditions interact that produce the desired outcome, uncovering causal combinations or recipes.

*Causal asymmetry* – When an outcome can result from the presence or from the absence of a given condition. According to the complex causality perspective, the fact that A causes B does not imply that B is connected to A in the same way (Vassinen, 2012). Moreover, the combination of factors that lead to the presence of a result might differ from those leading to the absence of the same outcome. In other words, it is not necessary for factors causing the absence of one outcome to be the opposite of those causing the presence of that same outcome, as conditions “found to be causally related in one configuration may be unrelated or even inversely related in another” (Meyer et al., 1993, p. 1178). Consequently, methods adopting a complex-causality perspective need to test outcomes for the presence and absence of conditions leading to both the outcome and its absence.

*Equifinality* – When there is more than one path leading to the same outcome. The concept of equifinality entails the existence of multiple distinct configurations of conditions leading to the same outcome (Nikou et al., 2022). The principle says that the same results may be reached regardless of the solutions or paths used therefore, different causal recipes may yield the same outcome (Rippa et al., 2020; Rubinson et al., 2019; Schneider & Eggert, 2014).

Therefore, methods based on assumptions of causal complexity, like QCA, aim at providing multiple causal recipes composed of non-mutually exclusive conjoint attributes equally sufficient to the occurrence of an outcome (Gerrits & Pagliarin, 2021).

## Hands On Tutorial for Using FsQCA

### Sample Description

This section is aimed at showing the principal distinct procedures of performing FsQCA using a data set from an Italian manufacturing company (see Appendix). The data analysis focuses on 4 dimensions of the work-based learning scale (Nikolova et al., 2014), specifically learning through reflection (LTR), learning through experimentation (LTE), learning from colleagues (LFC), and learning from supervisors (LFS) as conditions. Work-based learning is defined by the perception of informal learning opportunities available in the workplace (e.g., Cangialosi et al., 2020). The scale comprises a total of 12 items, 3 for each dimension. Example of an items are

“in my work I am given the opportunity to contemplate about different work methods” for LTR; “in my job I can try different work methods even if that does not deliver any useful results” for LTE; “my colleagues are eager to collaborate with me in finding a solution to a work problem” for LFC; “my supervisor tips me on how to do my work” for LFS. As the outcome the example concentrated on the innovative work behavior (; Janssen, 2000), representing the intentional creation, introduction, and application of new ideas within a work role, group, or organization, in order to benefit role performance, the group, or the organization (p. 228). The scale includes 9 items, one example is “in my job I generate original solutions for problems”. Both scales were previously adopted and validated in the Italian language (e.g., Battistelli et al., 2022; Cangialosi et al., 2019).

The various steps and procedures were performed using the QCA package (Duşa, 2019) in R Core Team<sup>1</sup>. Before presenting the main steps of FsQCA, it is important to note that statistical methods traditionally used to test the reliability and validity of constructs should be performed previously. These measures are particularly important when the values derive from rating scales used to measure opinions, attitudes, or behaviors, which are the most frequent in the organizational literature. However, the present study will only present the results without showing how to perform these tests as they are out of the spectrum of QCA-related methods.

The McDonald's coefficient was computed in order to assess the reliability of the research variables with values ranging above the recommended cut-off of .70 (Nunnally, 1978; innovative work behavior [IWB],  $\omega = .95$ ; LTR,  $\omega = .89$ ; LTE,  $\omega = .88$ ; LFC,  $\omega = .85$ ; LFS,  $\omega = .85$ ). Additionally, confirmatory factor analysis was used to assess the measurement's validity for the proposed model. In the present study, all indices indicated good fit to the data for the five-factor solution:  $\chi^2(179) = 267.464$ , comparative fit index (CFI) = .949, Tucker-Lewis index (TLI) = .940, root mean square error of approximation (RMSEA) = .064, standardized root mean square residual (SRMR) = .063 with the factor loadings ranging from .61 to .89.

### Calibration

The first step of fsQCA is to carry out the data calibration procedure. This process allows for the transformation of the values of the study variables from raw numerical data into membership scores, or fuzzy sets

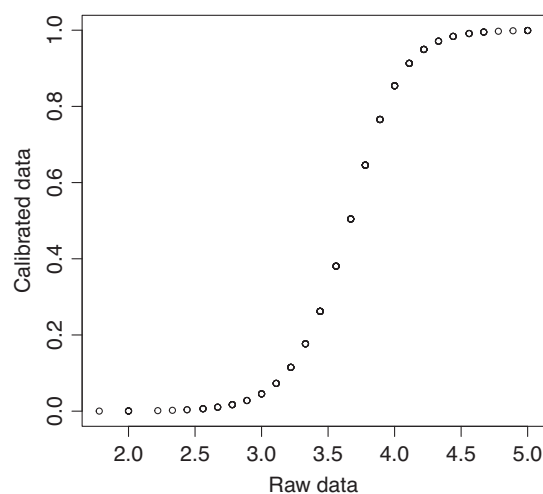
<sup>1</sup>R Core Team. (2022). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. <https://www.R-project.org/>

(Duşa, 2019). Most types of data can be calibrated into fuzzy scores (e.g., test results, performance ratings, socio-demographic indicators, etc.); however, as typically psychosocial research relies on survey responses, it is important to note that where a variable includes several items, the calibration process works with the average aggregate value of the construct. Fuzzy sets are pseudo-continuous measures ranging from 0 to 1 (Ragin, 2000). From a set theory perspective this implies that the level of values is reflective of the degree of inclusion to a specific set: The more the condition belongs to the set the higher the value associated with it, where 1 represents full membership in a set, 0 no membership and 0.5 represents the point of maximum ambiguity.

There are different approaches to this procedure, however, the so-called direct calibration is emerging as common practice in the field as it leads to results that are directly comparable with others found in the literature (Pappas & Woodside, 2021). The direct calibration requires indicating three anchoring values for full inclusion, full exclusion, and the cross-over point. In practical terms this means that specific values must be established to determine what can be regarded as low levels (no membership to a set), high levels (full membership in the set), and, additionally, a crossover point where values cannot be classified high or low (neither in nor out the set). As a result, the calibration process will allocate fuzzy scores ranging from 0.50 to 1 to raw values between the full inclusion anchor and the point of maximum ambiguity, and from 0 and 0.50 to those between the point of maximum ambiguity and the full exclusion anchor.

The anchors should be selected based on theoretical or substantive principles (Ragin, 2009; Schneider & Wagemann, 2010) and replicability of the process is ensured by transparency when defining them (Greckhamer et al., 2018). The anchor selection can be guided by allocating a particular value point on the Likert or aided by statistical measures, such as percentiles. The most common anchor values for full exclusion, crossover, and full inclusion are, respectively for a 7-point Likert scales 2, 4, and 6 (e.g., Meuer, 2014) and for 5-point Likert values 2, 3, and 4 (e.g., Pappas & Woodside, 2021). As per, the percentiles approach, the usual anchor values 5th, 50th, and 95th percentiles (Pappas & Woodside, 2021); however, the 20th, 50th, and 80th percentiles are also considered appropriate choices when data are asymmetrical or that do not conform to normality assumptions (Pappas, 2017).

The calibration process is carried out through the mathematical estimation of the degree of membership for any given raw number by calculating the equivalent of the log odds (Duşa, 2019). Many types of functions can be used to aid this procedure (e.g., Thiem, 2014). Nevertheless, a logistic function is frequently preferred



**Figure 1.** Calibrations of Raw Data into Fuzzy Scores using the Logistic Function for Calculating the Degree of Membership of IWB

as it allows accounting for the normal distribution of data points. By giving more weight to the cross-over point, the logistic function accounts for the fact that values that are normally distributed tend to cluster around the mean (Duşa, 2019). Figure 1 illustrates the numerical relationship between raw data and calibrated values resulting from the logistic function. Raw data (1–5) is presented on the horizontal axis while fuzzy scores (0–1) are presented on the vertical axis. The figure shows each original value converted into a fuzzy score, starting with the low scores in the lower left and gradually moving towards the high ones in the upper right.

Once the calibration process is completed, it is important to subsequently verify that no fuzzy scores fall on the value of 0.50. Because the point of maximal ambiguity cannot be characterized as belonging to or not belonging to the set, configurations with at least one condition at the crossover point are unavoidably excluded from the analysis (Wagemann et al., 2016). To avoid this occurrence, researchers commonly add a constant of 0.001 to the original fuzzy scores (e.g., Fiss, 2011).

The presented study adopts the direct approach for calibration and selects the 20th, 50th, and 80th percentiles as anchor values (see Table 1). After loading QCA package in R and having imported the data, percentiles are computed and subsequently used as anchor values. The calibration is performed with the calibrate function, with the selection of the three breakpoints (from the lowest to the highest) and the specification of the choice of the logistic function. In addition, fuzzy scores of 0.50 are replaced with 0.501 to prevent dropping significant configurations from the subsequent analyses. As a result of the calibration process, all values of study variables are subsequently transformed into fuzzy scores.

```
> library(QCA);
> ##Importing Data
> df <- read.csv(file="Desktop/datapro.csv", header=TRUE, sep=";", dec = ",")
```

```
> ##Percentiles
> quantile(df$LTR, probs=c(.20, .5, .80))
  20%    50%    80%
2.666667 3.333333 4.333333
> quantile(df$LTE, probs=c(.20, .5, .80))
  20%    50%    80%
2.000000 2.333333 3.066667
> quantile(df$LFC, probs=c(.20, .5, .80))
  20%    50%    80%
3.000000 3.666667 4.333333
> quantile(df$LFS, probs=c(.20, .5, .80))
  20%    50%    80%
3.000000 3.333333 4.000000
> quantile(df$IWB, probs=c(.20, .5, .80))
  20%    50%    80%
2.755556 3.333333 4.000000
```

```
> ##Calibration
> df$F_LTR <- calibrate(df$LTR, type = "fuzzy",
+                       thresholds = "e=2.666667, c=3.333333, i=4.333333",
logistic = TRUE)
> df$F_LTE <- calibrate(df$LTE, type = "fuzzy",
+                       thresholds = "e=2.000000, c=2.333333, i=3.066667",
logistic = TRUE)
> df$F_LFC <- calibrate(df$LFC, type = "fuzzy",
+                       thresholds = "e=3.000000, c=3.666667, i=4.333333",
logistic = TRUE)
> df$F_LFS <- calibrate(df$LFS, type = "fuzzy",
+                       thresholds = "e=3.000000, c=3.333333, i=4.000000",
logistic = TRUE)
> df$F_IWB <- calibrate(df$IWB, type = "fuzzy",
+                       thresholds = "e=2.755556, c=3.333333, i=4.000000",
logistic = TRUE)
```

```
> ##Crossover point
> df[df == 0.500000000] <- 0.501
```

**Table 1.** Calibration Values

	IWB	LTR	LTE	LFC	LFS
20 <sup>th</sup> percentile	2.76	2.67	2.00	3.00	3.00
50 <sup>th</sup> percentile	3.34	3.34	2.34	3.67	3.34
80 <sup>th</sup> percentile	4.00	4.34	3.07	4.34	4.00

*Note.* IWB = innovative work behavior; LTR = learning through reflection; LTE = learning through experimentation; LFC = learning from colleagues; LFS = learning from supervisors.

### Necessity Conditions Analysis

The second step of the fsQCA is the necessity conditions analysis. This is carried out to check whether any of the conditions is necessary for the outcome. A condition is defined as necessary when the result does not occur in its absence and while this type of causal relationship may not be sufficient to trigger the result by itself, is deemed a necessary portion of the causal mix (Duşa, 2019). For example, if learning from the supervisor is a necessary condition for IWB, this entails that an employee can only have high levels of IWB when the levels of learning from



the supervisor are also high; however, this doesn't translate into the fact that learning from the supervisor alone is causing employees' IWBs.

Due to the asymmetrical proprieties of this methodological approach, in the analysis of necessity it is important to test both the presence and absence of each condition on the result and its negation. This is because converting any value to its opposite does not necessarily mean an explanation for the opposite of the result. For instance, if high levels of learning from the supervisor are found necessary for IWB, this doesn't automatically imply lack of IWB is due to a low level of learning from the supervisor.

The verification of the absence of a relationship of necessity among variables is critical. However, as the organizational field typically analyzes issues characterized by a complex network relationship of multiple variables, it is extremely rare to find a necessary condition that alone can offer a substantial causal contribution.

In fsQCA, conditions are considered necessary when their consistency value is greater than 0.90 in the analysis of necessity, which translates into that at least 90% of the observations showing high-levels of the outcome also have high-levels of the condition. Although this threshold is set to account for data noise, randomness, and measurement inaccuracies (Ragin, 2000; Schneider & Wagemann, 2010), even when the consistency value surpasses 0.90, the result can be subject to Type 1 errors (Ragin, 2006).

This case is referred to as triviality, as opposed to relevance; a trivial condition can be described as a much larger set than the outcome. An example of this could be the necessity of a minimum amount of job tenure for innovation. An employee must have at least a minimal experience on the job in order to generate, promote and implement new and useful ideas in a workplace. But this is a trivial necessary condition because the mere presence of job tenure is an overarching condition that does not directly cause individual innovation.

To measure the relative importance of a condition in the causal mix and avoid Type 1 errors coverage scores can be adopted as an auxiliary indicator (Schneider & Wagemann, 2010). Coverage scores represent the percentage of X that is covered by Y, or more precisely by the intersection of X and Y, assuming that Y is already a (perfect) subset of X (Duşa, 2019). Therefore, a rule of thumb is that a condition is necessary when it concurrently shows consistency above 0.90 and coverage above 0.60 (Mattke et al., 2021).

The package QCA has the dedicated function `pofwith` a default value of the argument `relation = "necessity"`, which calculates both consistency and coverage, the first indicated with `inclN` and the latter with `covN`. An example of the applied function is reported below, complete results are reported in Table 2, showing that none of the study conditions is necessary to the outcome or its absence.

```
> ### Analysis of necessity
> pof("F_IWB <- F_LTR", data = fdata)

      inclN   RoN   covN
-----
1 F_IWB  0.680  0.768  0.705
-----

> pof("F_IWB <- ~F_LTR", data = fdata)

      inclN   RoN   covN
-----
1 F_IWB  0.450  0.628  0.423
-----
```

**Table 2.** Necessary Condition Analysis

	IWB		~IWB	
	Consistency	Coverage	Consistency	Coverage
F_LTR	0.680	0.705	0.443	0.471
~F_LTR	0.450	0.423	0.686	0.660
F_LTE	0.485	0.470	0.608	0.605
~F_LTE	0.617	0.621	0.473	0.488
F_LFC	0.722	0.795	0.431	0.487
~F_LFC	0.427	0.374	0.765	0.686
F_LFS	0.682	0.756	0.439	0.500
~F_LFS	0.437	0.378	0.718	0.638

*Note.* ~ indicates absence (i.e., low levels); IWB = innovative work behavior; LTR = learning through reflection; LTE = learning through experimentation; LFC = learning from colleagues; LFS = learning from supervisors.

**Table 3.** Truth Table

LTR	LTE	LFC	LFS	N	CONSISTENCY	PRI
0	0	0	0	4	.541	.188
0	0	0	1	6	.702	.440
0	0	1	0	5	.715	.531
0	0	1	1	3	.749	.567
0	1	0	0	7	.413	.145
0	1	0	1	12	.499	.179
0	1	1	0	1	.703	.385
0	1	1	1	5	.818	.684
1	0	0	0	2	.758	.440
1	0	0	1	6	.840	.680
1	0	1	0	1	.782	.606
1	0	1	1	23	.866	.819
1	1	0	0	8	.555	.226
1	1	0	1	16	.633	.439
1	1	1	0	6	.712	.440
1	1	1	1	15	.843	.760

Note. IWB = innovative work behavior; LTR = learning through reflection; LTE = learning through experimentation; LFC = learning from colleagues; LFS = learning from supervisors.

### Truth Table

The third step of fsQCA involves generating the truth table. This is done to identify all the possible combinations of conditions that are present in the data and evaluate how each combination is consistent with the outcome. In the truth table all potential combinations of conditions are comprised, consequently yielding  $2^k$  rows, ( $k$  = the number of conditions). In the presented example, the 4 study conditions produce 16 rows, one for each configuration. As displayed in Table 3 each row reports the presence (1; when the fuzzy score is greater than 0.5) and absence (0; when the fuzzy score is smaller than 0.5) of the conditions for each possible combination.

Following its generation, the truth table must subsequently be refined to allow systematic calculations for establishing which configurations are leading to the outcome. The refinement of the truth table is accomplished by assigning specific cut-offs to frequency and consistency values.

The frequency represents the number of cases ascribed to a given configuration. A threshold is necessary to ensure that the analysis for the evaluation of the relationships with the outcome is carried out on a sufficient number of cases. When setting a high-frequency threshold, the overall number of cases decreases, but there is an increment in the coverage of the sample that

is explained by the retained configurations. Conversely, with a low-frequency threshold, the overall number of cases increases, but the coverage of the sample decreases and resultant configurations are likely to be rare to the data reducing the stability for the subsequent analyses. In consequence, both may potentially result in findings that are not replicable. Hence, when choosing a frequency threshold, a balance must be struck between finding common configurations while keeping a sufficient pool of cases. The rule of thumb for determining a frequency threshold is 2 for small samples ( $N < 150$ ) and 3 or more for samples larger than that, as long as at least 80 percent of the cases are retained (Greckhamer et al., 2013; Fiss, 2011; Ragin, 2009).

After removing rows that fail to meet the frequency threshold, the truth table should be further refined for consistency. Consistency measures the degree of association of a configuration with the study result, that is the cooccurrence of the combination with high values of the outcome variable. A high consistency score indicates that the configuration consistently leads to the outcome, for instance, a consistency of 0.75 would indicate that 75% of the cases in the configuration share the same outcome. This measure can be compared to the concept significance in correlational methods with a minimum acceptable value of 0.75 (Greckhamer et al., 2018; Ragin, 2009). However, to increase the reliability of the results, the consistency threshold should be determined after a thorough inspection of the data. Finding natural breaking points in the consistency values has been suggested as a sound indicator for choosing the consistency threshold (Pappas & Wodside, 2021).

In addition, a second type of consistency should be used to further refine the truth table, the PRI consistency (i.e., Proportional Reduction in Inconsistency). A PRI cut-off is employed to deal with the issue of simultaneous subset relations (i.e., when configurations are related to both presence and the absence of the outcome). PRI cut-off should be set at a minimum of 0.50 (Greckhamer et al., 2018) and possibly close to consistency scores. When setting consistency and PRI cut-offs, the outcome for all configurations with a lower score than the selected ones, are automatically set to 0 and consequently excluded from the analysis.

In this study, the cutoff value was set at 3 for frequency, 0.75 for consistency, and 0.50 for PRI. The package QCA has a dedicated function called truthTable which allows the building of the truth table and its refinement based on given thresholds. Table 3 presents the unrefined truth table for the study variables, encompassing all 16 possible configurations.

```
> ##Truth table
> tt <- truthTable(fdata, outcome = "F_IWB", n.cut = 3, incl.cut = 0.75,
pri.cut = 0.5)
```

### Sufficiency Analysis

The final phase of FsQCA is the sufficiency analysis. Sufficiency can be defined as propriety whereby all cases possessing specific attributes experience the same given outcome. Hence, this type of analysis seeks to identify all the different configurations that consistently lead to the outcome. This process is carried out with the usage of the “Quine-McCluskey” algorithm for Boolean minimization (or logical reduction).

Boolean minimization reduces the complexity of all suitable configurations without dropping any relevant information (Ragin, 2014). This process involves detecting and omitting conditions that are logically redundant (“don’t care situation”). Those are the conditions present in a given configuration that do not really contribute to the outcome. For example, if by comparing two configurations that lead to the same result, one showing high and the other low levels on the same condition, it is possible to logically infer that the value of that condition is not relevant for the occurrence of the outcome. Logical minimization thus leads to configurations stripped of the redundant conditions.

Three sets of solutions (complex, parsimonious, and intermediate) are calculated for the sufficiency analysis. These types of a solution differ in how they deal with counterfactuals, combinations of conditions that have not reached the frequency threshold and therefore lack sufficient empirical evidence. In other words, those are the combinations that have an insufficient number of cases to make a meaningful inference about their relationship with the outcome. The complex solution fully excludes counterfactuals from the analysis whilst the parsimonious allows for any that can help provide a logically simpler solution. The intermediate solution makes use of “easy counterfactuals”, those who are theoretically plausible (Liu et al., 2017), which often-times translates into assuming their role in the outcome.

In addition, the complex solution offers all the possible combinations present after the application of logical operations. In general, the interpretation of complex solutions is quite difficult as they result in many configurations with several conditions. For this reason, researchers usually rely on parsimonious and

**Table 4.** Results of the Sufficiency Analysis

	IWB		~IWB	
	1	2	3	4
LTR	●	●	∅	
LTE	∅			•
LFC		●	∅	∅
LFS	•	●		∅
Consistency	0.847	0.828	0.847	0.894
Raw coverage	0.387	0.300	0.506	0.329
Unique coverage	0.288	0.200	0.262	0.085
Solution consistency	0.830		0.851	
Solution coverage	0.588		0.591	

*Note.* • indicates presence (i.e., high levels), ∅ indicates absence (i.e., low levels), blank space indicates “don’t care” (levels of the condition are not relevant to that configuration in regard to the outcome); Large circles suggest “core” or central conditions, while small circles indicate “contributing” or peripheral conditions; IWB = innovative work behavior; LTR = learning through reflection; LTE = learning through experimentation; LFC = learning from colleagues; LFS = learning from supervisors.

intermediate solutions for drawing their conclusions. The parsimonious solution is based on all possible simplifying assumptions and presents the “core conditions” which are important as are present in all three types of solution (Fiss, 2011). In the intermediate solutions appear both “core” conditions and the “peripheral” conditions which show in the intermediate solution and are eliminated in the parsimonious solution (Fiss, 2011).

The package QCA has a dedicated function called `minimize` which allows for the generation of the three solutions. Table 4 presents the intermediate result of the sufficiency analysis distinguishing core and peripheral conditions. By comparing the intermediate and parsimonious solutions core and peripheral conditions can be established. Each sufficient configuration presents values for raw coverage, unique coverage, and consistency, Table 5 contains the information for their interpretation.

```
> ## Boolean minimization
> #complex
> comsol <- minimize(tt, details = TRUE)
> #parsimonious
> parsol <- minimize(tt, include = "?", details = TRUE)
> #intermediate
> intsol <- minimize(tt, include = "?", dir.exp = "F_LFS, F_LFC, F_LTE,
F_LTR", details = TRUE)
> #intermediate
> intsol <- minimize(tt, dir.exp = "F_LFS, F_LFC, F_LTE, F_LTR", details =
TRUE)
```



```

> parsol

M1: F_LTR*~F_LTE + F_LTE*F_LFC*F_LFS -> F_IWB

          inclS  PRI  covS  covU
-----
1  F_LTR*~F_LTE 0.777 0.701 0.458 0.358
2  F_LTE*F_LFC*F_LFS 0.828 0.744 0.300 0.200
-----
M1 0.784 0.711 0.658

> intsol

From C1P1:

M1: F_LTR*~F_LTE*F_LFS + F_LTE*F_LFC*F_LFS -> F_IWB

          inclS  PRI  covS  covU
-----
1  F_LTR*~F_LTE*F_LFS 0.847 0.794 0.387 0.288
2  F_LTE*F_LFC*F_LFS 0.828 0.744 0.300 0.200
-----
M1 0.830 0.773 0.588
    
```

**Table 5.** Results Interpretation Parameters

Measures	Definition
Raw Coverage	The proportion of memberships in the outcome that is explained by each term of the solution.
Unique coverage	The proportion of memberships in the outcome that is explained solely by each individual solution term.
Consistency	The extent to which the configuration consistently exhibits the outcome.
Solution consistency	The degree to which membership in the solution is a subset of membership in the outcome.
Solution coverage	The proportion of memberships in the outcome that is explained by the complete solution.

*Note.* Adapted from Ragin (2006).

The results show the existence of two configurations sufficient for high levels of IWB. The first configuration is characterized by high levels of learning through reflection and low levels of learning through experimentation as core condition and high levels of learning from supervisors as peripheral. The second configuration is described by high levels of learning through reflection, learning from colleagues and learning from supervisors, all as core conditions. In addition, the results also highlight the existence of two configurations leading to low levels of IWB. The first configuration is characterized by low levels of learning through reflection and learning from colleagues as core conditions. The second is

characterized by low levels of learning from colleagues and learning from supervisors as core conditions with high levels of learning through experimentation as peripheral.

**Robustness Checks**

As an additional step, sensitivity analyses are performed to assess the robustness of the results after generating and reporting the solutions. This stage is necessary because FsQCA relies on guidelines and recommendations to determine thresholds, and, accordingly, it's key to control whether changing various parameters and cut-offs can significantly alter the results and subsequently report the extent of the change. To this end, common practices require the reporting of findings with different frequency, consistency, and PRI thresholds along with those performed on recalibrated data with alternative anchoring values.

Table 6 shows, as an example, the results of repeated analyses with different cut-offs and calibration levels for IWB. From the analysis of the table, the robustness of the original results can be inferred based on two criteria, the different results obtained have limited differences in terms of coherence and coverage and do not provide indications for different interpretations; and/or are in a subset relationship to the original results (Wagemann & Schneider, 2015).

**Conclusion**

The assumptions of causal complexity are inherent in psychosocial processes occurring in organizational environments, where multiple components jointly

**Table 6.** Robustness Checks

Changes in thresholds	Changes in solutions	Overall consistency	Overall coverage
Consistency set to 0.90	No solution is produced as none of the values in the outcome is explained	/	/
Consistency set to 0.85	The following configuration replace the original solutions: F_LTR*~F_LTE*F_LFC*F_LFS	0.866	0.350
Consistency set to 0.80	No changes	No changes	No changes
Frequency set to 1	The following configuration occurs in addition to the original solutions: F_LTR*~F_LTE*F_LFC*F_LFS	0.799	0.646
Frequency set to 5	No changes	No changes	No changes
PRI set to 0.60	No changes	No changes	No changes
PRI set to 0.70	The following configuration remains as the only solution: F_LTR*F_LFC*F_LFS	0.855	0.488
Calibration (.05,.50, .95)	F_LTR*~F_LTE*F_LFS is maintained, the second solution is replaced by LFC	0.769	0.879

*Note.* LTR = learning through reflection; LTE = learning through experimentation; LFC = learning from colleagues; LFS = learning from supervisors.

interact with one another (Fiss, 2011; Ott et al., 2018; Rihoux & Ragin, 2009). As a result, rather than single and isolated components, organizational phenomena can be more accurately explained by configurations leading to a certain criterion (e.g., Short et al., 2008). Therefore, methods like fsQCA designed to address configurational hypotheses have significant potential applications for organizational research (e.g., Parente & Federo, 2019; Schwab & Golla, 2021).

Compared to traditional analysis techniques, fsQCA is that it is well-suited to studying complex, non-linear relationships between variables (Schneider & Wagemann, 2010). It also allows researchers to analyze the effects of configurations of variables, rather than simply examining the effects of individual variables (Ragin, 2006). However, fsQCA can be computationally intensive, and the results are often difficult to interpret for researchers who are not familiar with the technique (Caren & Panofsky, 2015). Additionally, the validity and reliability of the results can be affected by the choice of membership functions and calibration methods used in the analysis (Schneider & Wagemann, 2010).

By employing the fsQCA approach effectively, organizational psychology can gain further insights into the nature of causal configurations. But for this to happen, continuous development and refinement of its application for research in organizational psychology is required. The fsQCA method has filtered in many ways within the research contexts, and great strides have been made in its dissemination, however, so far there has been a lack of dedicated work to inform the community of its practices and correct guidelines (Rihoux & Ragin, 2018). In order to fill this gap, this paper has introduced

fsQCA by providing a general overview of the method, offered guidelines for good practice which provide further background knowledge and know-how regarding the use of this method, and outlined a practical example with a step-by-step tutorial for utilizing QCA for R package.

This article will contribute to the research community, in the hope of further stimulating interest in configurational approaches in the field of organizational psychology and serve as a useful starting point for readers who want to learn more about this methodology and provide an additional resource to help organizational psychologists deliver high-quality research.

## References

- Aus, J. P. (2009). Conjunctural causation in comparative case-oriented research. *Quality & Quantity*, 43(2), 173–183. <https://doi.org/10.1007/s11135-007-9104-4>
- Battistelli, A., Odoardi, C., Cangialosi, N., Di Napoli, G., & Piccione, L. (2022). The role of image expectations in linking organizational climate and innovative work behaviour. *European Journal of Innovation Management*, 25(6), 204–222. <https://doi.org/10.1108/ejim-01-2021-0044>
- Cangialosi, N., Battistelli, A., & Odoardi, C. (2021). Designing innovative jobs: A fuzzy-set configurational analysis of job characteristics. *Personnel Review*, 52(1), 382–399. <https://doi.org/10.1108/pr-02-2021-0105>
- Cangialosi, N., Deprez, G. R. M., Odoardi, C., & Battistelli, A. (2019). Work based learning: Italian adaptation of the Learning Potential of the Workplace Scale (LPW). *BPA Applied Psychology Bulletin*, 67(284), 31–44. <https://doi.org/10.26387/bpa.284.4>

- Cangialosi, N., Odoardi, C., & Battistelli, A. (2020). Learning climate and innovative work behavior, the mediating role of the learning potential of the workplace. *Vocations and Learning*, 13(2), 263–280. <https://doi.org/10.1007/s12186-019-09235-y>
- Caren, N., & Panofsky, A. (2015). The benefits of a qualitative approach to causal inference: Counterfactuals and case selection in the comparative method. *Sociological Methods & Research*, 44(2), 221–268.
- Crilly, D. (2013). Chapter 8. Corporate social responsibility: A multilevel explanation of why managers do good. In P.C. Fiss, B. Cambré, & A. Marx, (Eds.), *Configurational theory and methods in organizational research (Research in the sociology of organizations)*, Vol. 38, pp. 181–204). Group Publishing Limited. [http://doi.org/10.1108/S0733-558X\(2013\)0000038012](http://doi.org/10.1108/S0733-558X(2013)0000038012)
- Dawson, J. F., & Richter, A. W. (2006). Probing three-way interactions in moderated multiple regression: Development and application of a slope difference test. *Journal of Applied Psychology*, 91(4), 917–926. <https://doi.org/10.1037/0021-9010.91.4.917>
- Dooley, K. J. (2008). Organizational psychology. In S. J. Guastello, M. Koopmans, & D. Pincus (Eds.), *Chaos and complexity in psychology: The theory of nonlinear dynamical systems* (pp. 434–451). Cambridge University Press. <https://doi.org/10.1017/cbo9781139058544.015>
- Duša, A. (2019). *QCA with R*. Springer Cham. <https://doi.org/10.1007/978-3-319-75668-4>
- Fiss, P. C. (2007). A set-theoretic approach to organizational configurations. *Academy of Management Review*, 32(4), 1180–1198. <https://doi.org/10.5465/amr.2007.26586092>
- Fiss, P. C. (2011). Building better causal theories: A fuzzy set approach to typologies in organization research. *Academy of Management Journal*, 54(2), 393–420. <https://doi.org/10.5465/amj.2011.60263120>
- Furnari, S., Crilly, D., Misangyi, V. F., Greckhamer, T., Fiss, P. C., & Aguilera, R. V. (2021). Capturing causal complexity: Heuristics for configurational theorizing. *Academy of Management Review*, 46(4), 778–799. <http://doi.org/10.2139/ssrn.4158028>
- Gerrits, L., & Pagliarin, S. (2021). Social and causal complexity in qualitative comparative analysis (QCA): Strategies to account for emergence. *International Journal of Social Research Methodology*, 24(4), 501–514. <https://doi.org/10.1080/13645579.2020.1799636>
- Greckhamer, T., Furnari, S., Fiss, P. C., & Aguilera, R. V. (2018). Studying configurations with qualitative comparative analysis: Best practices in strategy and organization research. *Strategic Organization*, 16(4), 482–495. <https://doi.org/10.1177/1476127018786487>
- Greckhamer, T., Misangyi, V. F., & Fiss, P. C. (2013). Chapter 3. The two QCAs: From a small-n to a large-n set theoretic approach. In P.C. Fiss, B. Cambré, & A. Marx (Eds.), *Configurational theory and methods in organizational research (Research in the sociology of organizations)*, Vol. 38, pp. 303–309). Emerald Group Publishing Limited. [https://doi.org/10.1108/S0733-558X\(2013\)0000038007](https://doi.org/10.1108/S0733-558X(2013)0000038007)
- Grofman, B., & Schneider, C. Q. (2009). An introduction to crisp set QCA, with a comparison to binary logistic regression. *Political Research Quarterly*, 62(4), 662–672. <https://doi.org/10.1177/1065912909338464>
- Guastello, S. J., & Liebovitch, L. S. (2008). Introduction to nonlinear dynamics and complexity. In S. J. Guastello, M. Koopmans, & D. Pincus (Eds.), *Chaos and complexity in psychology: The theory of nonlinear dynamical systems* (pp. 434–451). Cambridge University Press. <http://doi.org/10.1017/CBO9781139058544.002>
- Igartua, J.-J., & Hayes, A. F. (2021). Mediation, moderation, and conditional process analysis: Concepts, computations, and some common confusions. *The Spanish Journal of Psychology*, 24, E49. <https://doi.org/10.1017/sjp.2021.46>
- Janssen, O. (2000). Job demands, perceptions of effort-reward fairness and innovative work behaviour. *Journal of Occupational and Organizational Psychology*, 73(3), 287–302. <https://doi.org/10.1348/096317900167038>
- Ketchen, D. J. (2013). Chapter 13. We try harder: Some reflections on configurational theory and methods. In P.C. Fiss, B. Cambré, & A. Marx (Eds.), *Configurational theory and methods in organizational research (Research in the sociology of organizations)*, Vol. 38, pp. 303–309). Emerald Publishing Limited. [https://doi.org/10.1108/s0733-558x\(2013\)0000038017](https://doi.org/10.1108/s0733-558x(2013)0000038017)
- Liu, Y., Mezei, J., Kostakos, V., & Li, H. (2017). Applying configurational analysis to IS behavioural research: A methodological alternative for modelling combinatorial complexities. *Information Systems Journal*, 27(1), 59–89. <https://doi.org/10.1111/isj.12094>
- Mattke, J., Maier, C., Weitzel, T., & Thatcher, J. B. (2021). Qualitative comparative analysis in the information systems discipline: a literature review and methodological recommendations. *Internet Research*, 31(5), 1493–1517. <https://doi.org/10.1108/intr-09-2020-0529>
- Meier, A. (2017). *The configurational perspective in organizational psychology: Fuzzy sets for novel insights* [Unpublished doctoral dissertation]. Universität Osnabrück.
- Meuer, J. (2014). Archetypes of inter-firm relations in the implementation of management innovation: A set-theoretic study in China's biopharmaceutical industry. *Organization Studies*, 35(1), 121–145. <https://doi.org/10.1177/0170840613495339>
- Meyer, A. D., Tsui, A. S., & Hinings, C. R. (1993). Configurational approaches to organizational analysis. *The Academy of Management Journal*, 36(6), 1175–1195. <https://doi.org/10.2307/256809>
- Misangyi, V. F., Greckhamer, T., Furnari, S., Fiss, P. C., Crilly, D., & Aguilera, R. (2016). Embracing causal complexity: The emergence of a neo-configurational perspective. *Journal of Management*, 43(1), 255–282. <https://doi.org/10.1177/0149206316679252>
- Nikolova, I., van Ruysseveldt, J., De Witte, H., & Syroit, J. (2014). Work-based learning: Development and validation of a scale measuring the learning potential of the workplace (LPW). *Journal of Vocational Behavior*, 84(1), 1–10. <https://doi.org/10.1016/j.jvb.2013.09.004>
- Nikou, S., Mezei, J., Liguori, E. W., & El Tarabishy, A. (2022). FsQCA in entrepreneurship research: Opportunities and best practices. *Journal of Small Business Management*, 1–18. <https://doi.org/10.1080/00472778.2022.2147190>

- Nunnally, J. C. (1978). An overview of psychological measurement. In B. B. Wolman (Ed.), *Clinical diagnosis of mental disorders* (pp. 97–146). Springer. [https://doi.org/10.1007/978-1-4684-2490-4\\_4](https://doi.org/10.1007/978-1-4684-2490-4_4)
- Ong, W. J., & Johnson, M. D. (2021). Towards a configural theory of job demands and resources. *Academy of Management Journal*, 66(1), 195–221. <https://doi.org/10.5465/amj.2020.0493>
- Ott, U., Sinkovics, R. R., & Hoque, S. F. (2018). Advances in qualitative comparative analysis (QCA): Application of fuzzy set in business and management research. In C. Cassell, A. L. Cunliffe, & G. Grandy (Eds.), *The SAGE handbook of qualitative business and management research methods* (pp. 414–430). Sage Publications Ltd. <https://doi.org/10.4135/9781526430236.n25>
- Pappas, N. (2017). Risks and marketing in online transactions: A qualitative comparative analysis. *Current Issues in Tourism*, 20(8), 852–868. <https://doi.org/10.1080/13683500.2016.1187586>
- Pappas, I. O., & Woodside, A. G. (2021). Fuzzy-set qualitative comparative analysis (fsQCA): Guidelines for research practice in information systems and marketing. *International Journal of Information Management*, 58, Article 102310. <https://doi.org/10.1016/j.ijinfomgt.2021.102310>
- Parente, T. C., & Federo, R. (2019). Qualitative comparative analysis: Justifying a neo-configurational approach in management research. *RAUSP Management Journal*, 54, 399–412. <https://doi.org/10.1108/rausp-05-2019-0089>
- Ragin, C. C. (1987). *The comparative method: Moving beyond qualitative and quantitative strategies*. University of California Press. <https://doi.org/10.1525/9780520957350>
- Ragin, C. C. (2000). *Fuzzy-set social science*. University of Chicago Press.
- Ragin, C. C. (2006). Set relations in social research: Evaluating their consistency and coverage. *Political Analysis*, 14(3), 291–310. <https://doi.org/10.1093/pan/mpj019>
- Ragin, C. C. (2009). Measurement versus calibration: A set-theoretic approach. In J. M. Box-Steffensmeier, H. E. Brady, & D. Collier (Eds.), *The Oxford handbook of political methodology* (pp. 174–198). Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780199286546.003.0008>
- Ragin, C. C. (2014). *The comparative method*. University of California Press. <https://doi.org/10.1525/9780520957350>
- Ragin, C. C., & Fiss, P. C. (2008). Net effects analysis versus configurational analysis: An empirical demonstration. In C. C. Ragin (Ed.), *Redesigning social inquiry: Fuzzy sets and beyond* (pp. 190–212). University of Chicago Press.
- Rihoux, B., & Ragin, C. C. (2009). *Configurational comparative methods: Qualitative comparative analysis (QCA) and related techniques* (Vols. 1–51). Sage Publications. <https://doi.org/10.4135/9781452226569>
- Rihoux, B., & Ragin, C. C. (2018). *Configurational comparative methods: Qualitative comparative analysis (QCA) and related techniques*. Sage Publications. <https://doi.org/10.4135/9781452226569>
- Rippa, P., Ferruzzi, G., Holienka, M., Capaldo, G., & Coduras, A. (2020). What drives university engineering students to become entrepreneurs? Finding different recipes using a configuration approach. *Journal of Small Business Management*, 61, 353–383. <https://doi.org/10.1080/00472778.2020.1790291>
- Roig-Tierno, N., Gonzalez-Cruz, T. F., & Llopis-Martinez, J. (2017). An overview of qualitative comparative analysis: A bibliometric analysis. *Journal of Innovation & Knowledge*, 2(1), 15–23. <https://doi.org/10.1016/j.jik.2016.12.002>
- Rubinson, C., Gerrits, L., Rutten, R., & Greckhamer, T. (2019). Avoiding common errors in QCA: A short guide for new practitioners. *Sociology*, 9, 397–418.
- Schneider, M. R., & Eggert, A. (2014). Embracing complex causality with the QCA method: An invitation. *JBM-Journal of Business Market Management*, 7(1), 312–328.
- Schneider, C. Q., & Wagemann, C. (2010). Standards of good practice in qualitative comparative analysis (QCA) and fuzzy-sets. *Comparative Sociology*, 9(3), 397–418. <https://doi.org/10.1163/156913210x12493538729793>
- Schwab, A., & Golla, S. (2021). Reconsidering configurational approaches to organizational paradox research. *Journal of Management Inquiry*, 30(3), 301–314.
- Short, J. C., Payne, G. T., & Ketchen, D. J. (2008). Research on organizational configurations: Past accomplishments and future challenges. *Journal of Management*, 34(6), 1053–1079. <https://doi.org/10.1177/0149206308324324>
- Thiem, A. (2014). Membership function sensitivity of descriptive statistics in fuzzy-set relations. *International Journal of Social Research Methodology*, 17(6), 625–642. <https://doi.org/10.1080/13645579.2013.806118>
- Vassinen, A. (2012). *Configurational explanation of marketing outcomes: A fuzzy-set qualitative comparative analysis approach* [Doctoral thesis, Aalto University]. <https://research.aalto.fi/en/publications/configurational-explanation-of-marketing-outcomes-a-fuzzy-set-qua>
- Wagemann, C., Buche, J., & Siewert, M. B. (2016). QCA and business research: Work in progress or a consolidated agenda? *Journal of Business Research*, 69(7), 2531–2540. <https://doi.org/10.1016/j.jbusres.2015.10.010>
- Wagemann, C., & Schneider, C. Q. (2015). Transparency standards in qualitative comparative analysis. *Qualitative & Multi-Method Research*, 13(1), 38–42.
- Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, 8(3), 338–353. [https://doi.org/10.1016/s0019-9958\(65\)90241-x](https://doi.org/10.1016/s0019-9958(65)90241-x)

Appendix

"TWB	LTR	LTE	LFC	LFS
1,88888889	2	2	1,66666667	1
1,22222222	2	3,66666667	2	2,66666667
1	1,66666667	2	2	2,33333333
3,66666667	4,33333333	2,66666667	3	4
3,33333333	3,33333333	3,33333333	3,66666667	2,66666667
3,66666667	1,66666667	1	3,33333333	3,66666667
2,22222222	3,33333333	3,33333333	2,66666667	4
4,11111111	5	3,66666667	3	4,66666667
2,11111111	3,66666667	4	2,66666667	3,33333333
2,44444444	3,33333333	3,33333333	2,66666667	3,66666667
2,11111111	3,33333333	4	2,33333333	3
3,44444444	2,33333333	3	3,33333333	3,33333333
2,11111111	3	2,33333333	2,66666667	3,33333333
2,22222222	3,66666667	3,33333333	2,33333333	3,33333333
1,22222222	3,66666667	4	2	2
3,66666667	4,33333333	4	4	2,66666667
4,88888889	4,33333333	3,66666667	3,66666667	4,33333333
2	3	4	2,66666667	3
3,33333333	4,33333333	2	3	3,66666667
2,22222222	3	3	2,66666667	2
2,77777778	2,33333333	3,66666667	3,33333333	2,66666667
1,88888889	2,66666667	3	2,33333333	3,66666667
2,77777778	2,33333333	3,33333333	3,33333333	4,33333333
4,55555556	4	1,33333333	4	4,66666667
2	2	3	3	3,33333333
3,11111111	2	2,66666667	3	3,33333333
3	3	2	3,66666667	3,33333333
3,77777778	5	1,66666667	4,33333333	4
3,33333333	4,33333333	4	4	4
3,33333333	3	1,66666667	3,66666667	3
3,66666667	3,66666667	2,66666667	3,66666667	2,33333333
4,11111111	3,33333333	2	4,33333333	3,33333333
3,77777778	3,33333333	1,66666667	3	4,66666667
3,77777778	3	1,66666667	4,33333333	2,33333333
3,88888889	3,66666667	2,33333333	4,33333333	4
3,44444444	4,33333333	1,33333333	4,33333333	3,66666667
2,11111111	1	2,66666667	4	3
2,77777778	2,33333333	3	3	3,66666667
2,77777778	3,66666667	2,66666667	3	2,66666667
3,11111111	2,66666667	1,66666667	4,33333333	2,66666667
2,33333333	3,33333333	2	3,33333333	3,33333333
3,33333333	2,33333333	2,66666667	3	4,66666667
3,77777778	3,33333333	3	4	4
2,66666667	2,33333333	1,66666667	3,33333333	3,33333333
3,11111111	4	2	4	4
2,33333333	1,33333333	2,33333333	3	3
3,55555556	5	3,33333333	2,33333333	3,33333333
3,33333333	3	1,66666667	3,66666667	2,33333333
3,11111111	4,33333333	3	3	3,66666667
3,44444444	4,33333333	3	3,66666667	3,33333333
3,77777778	3,66666667	2	3,66666667	4
3,22222222	4,33333333	2,66666667	3	3
3	2,66666667	2	4	3,33333333
3	4	2,66666667	3,66666667	3,33333333



Continued.

"IWB	LTR	LTE	LFC	LFS
4,11111111	3,33333333	2	4,33333333	3,33333333
2,33333333	2	2,66666667	3	2
3,11111111	3,33333333	3,33333333	3,66666667	3,33333333
3,22222222	2,33333333	1,66666667	3,66666667	3,33333333
3,33333333	3	2,33333333	3,33333333	3,66666667
3,44444444	3	3,33333333	3,66666667	4
3,44444444	1,66666667	2	3,33333333	3,66666667
4	3,33333333	2,33333333	3,66666667	3
3,66666667	3	2,33333333	3,66666667	3,33333333
2,88888889	3	2,33333333	3,66666667	3
4,22222222	3,66666667	1,66666667	4,33333333	3,33333333
3,88888889	4,66666667	1,66666667	4,66666667	4
3,77777778	3,66666667	3	3,33333333	4
3,66666667	3,66666667	2	3,33333333	4,33333333
3,77777778	3,33333333	2,66666667	4	3,33333333
4,22222222	5	1,66666667	4,66666667	4,66666667
3	3,66666667	2,33333333	4	2,66666667
1,88888889	4,66666667	2,33333333	4	3
3,33333333	2,33333333	3,33333333	4	4
4,11111111	4	1,66666667	4	3,66666667
4	3	2	4,33333333	3
2,33333333	2,66666667	2	3,66666667	3,66666667
4,55555556	4,33333333	2	4	3,66666667
3,77777778	3,33333333	2,33333333	3,66666667	3,33333333
3,77777778	4	2,33333333	4,33333333	3,66666667
3,44444444	4,66666667	2	4	3,33333333
2,33333333	2	2,33333333	3,66666667	4
3	4,33333333	2	4,66666667	4,66666667
3,33333333	2	3	4	3,33333333
3,11111111	4	3,33333333	3,66666667	3
2,77777778	2,33333333	1,66666667	4	2,66666667
4	4	2	4	4,66666667
3,33333333	3,33333333	1,66666667	4,33333333	3,66666667
3,55555556	4,33333333	2	4,33333333	4,66666667
3,77777778	2,66666667	2,66666667	4,66666667	5
3	2	1,66666667	4	4
4,22222222	4	2	4	3,33333333
3,66666667	3,66666667	2,33333333	4	3,66666667
3,22222222	4	2	4	3,33333333
3	3,66666667	2	4,66666667	3,33333333
4,88888889	3,33333333	2,33333333	4,66666667	5
2,88888889	3,33333333	2	3	2,66666667
2,55555556	3,33333333	3,33333333	3,66666667	4
3,66666667	3	2	4,66666667	3,33333333
3,44444444	3,66666667	1,33333333	3,66666667	3
4	4,33333333	2	3,66666667	3,66666667
4	3,33333333	2	4,33333333	3,33333333
3	3,33333333	1,66666667	4	2
2,88888889	4,66666667	2,66666667	3,33333333	3,66666667
3,55555556	4	2,33333333	4	3
2,66666667	3,33333333	2,33333333	4	2,66666667
3,44444444	3,66666667	3	4,33333333	4,33333333
3,77777778	3	2	4,66666667	3
4,77777778	3	3	4,33333333	4,66666667
2,77777778	3,33333333	2,33333333	4	3,33333333

*Continued.*

"IWB	LTR	LTE	LFC	LFS
3,33333333	4,33333333	3	4,66666667	3
4,11111111	4	2,66666667	4,33333333	4,66666667
4,33333333	4,33333333	4	4	4,33333333
4	5	3	4,33333333	4,66666667
4	3,66666667	2	4,66666667	3,66666667
5	5	1,66666667	5	4,66666667
3,22222222	5	3	5	3,33333333
3,66666667	4,33333333	3,66666667	4,33333333	4,33333333
4,55555556	2,33333333	3,66666667	4,33333333	4
4,66666667	4,33333333	2	5	4
4,66666667	4,33333333	2,66666667	4,66666667	4