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Applying configurational analysis to IS behavioural research: a methodological alternative for modelling combinatorial complexities

Yong Liu,* József Mezei,†,¶ Vassilis Kostakos‡ & Hongxiu Li§

*Department of Information and Service Economy, Aalto University School of Business, Helsinki, Finland, email: yong.liu@aalto.fi, †Department of Information Technologies, Åbo Akademi University, Turku, Finland, ‡Department of Computer Science and Engineering, University of Oulu, Oulu, Finland, §Information Systems Science, Department of Management and Entrepreneurship, Turku School of Economics, University of Turku, Turku, Finland, and ¶RiskLab Finland, Arcada University of Applied Sciences, Helsinki, Finland

Abstract. *An important limitation of regression-based analysis stems from the assumption of symmetric relationships between variables, which is often violated. To overcome this limitation within IS research, we propose the use of the fuzzy-set qualitative comparative analysis (FsQCA) method. The paper elaborates on the rationale for applying this approach to IS behavioural research and how to tailor FsQCA for this purpose. A systematic interpretation of the technique covering its mathematical properties and advanced features is provided. Drawing from an illustrative study of mobile government services adoption by residents of rural areas, the paper demonstrates FsQCA's potential to supplement regression-based IS behavioural research, by (i) examining asymmetric relationships between a set of antecedents and the IS phenomenon of interest, (ii) providing nuanced coverage of necessary and sufficient conditions for emergence of an IS behavioural outcome, and (iii) identifying various configurations of conditions in association with users' demographic characteristics.*

Keywords: fuzzy-set qualitative comparative analysis, FsQCA, configurational analysis, multiple regression analysis, structural equation modelling, causal asymmetry

Introduction

Scientific tools are not neutral: tools-in-use shapes how we think and theorize (Gigerenzer, 1991). Without exception, this applies also to the dominance of regression-based analysis in IS behavioural research, in which researchers frequently utilize multiple measurement indicators in questionnaire-based surveys to collect empirical data on users' perceptions of diverse IS attributes when explaining various IS use phenomena, such as (continuous) intention to use and actual usage. Regression analysis – in particular, the structural equation modelling technique – has become a key tool used by scholars to model and interpret such phenomena. In this paper, we highlight one important bias of such tools: their assumption that relationships between variables are symmetric. In fact, these relationships are often asymmetric; therefore, a suitable alternative to regression analysis is needed and one such approach would be the use of configurational analysis.

Configuration theory argues that combinations of varying initial conditions can lead to the same outcome. Accordingly, the relationship between an outcome and its preconditions is often asymmetric rather than symmetric (Ragin, 2000; Fiss, 2007; Park & El Sawy, 2012; Woodside, 2013). For instance, different user groups may decide to adopt a technology by considering different sets of its attributes (Rogers, 1983; Venkatesh *et al*., 2003). Certain users may decide not to use a technology until a certain condition is satisfied, even though the given condition alone cannot result in their intention to use. Such asymmetric relationships and combinatorial complexities cannot be modelled by conventional regression-based methods (RBMs). However, applying a configurational approach can offer insights into problems of these types, particularly with regard to IS user behaviour.

To this end, we propose using a set-theoretical configurational analysis technique, fuzzy-set qualitative comparative analysis (FsQCA), as a methodological alternative to supplement mainstream RBMs in IS user behavioural research. Developed by Ragin (1987, 2000), FsQCA has become one of the most popular configurational analysis techniques. It has recently gained popularity amongst scientists across a broad spectrum of social science disciplines, though not the IS community. The possibilities of this technique offer IS scholars a new data analysis tool, new perspectives for theorizing, and an enhanced understanding of IS user behaviour (c.f. El Sawy *et al*., 2010).

In this study, we (i) elaborate on configuration theory and the rationale for embracing configurational analysis in IS behavioural research, (ii) systematically establish FsQCA as an effective instrument to detect configurations of an IS behaviour outcome, and (iii) demonstrate how to apply the technique to IS behavioural research by means of an illustrative study examining adoption of mobile government services.

Configuration theory and approach

To date, IS behavioural research has been grounded mostly in the use of RBMs, including multiple regression analysis (MRA) and structural equation modelling (SEM). These methods are aimed at understanding the problem from the perspective of variance theories, in which a predictor variable is posited to be both a necessary and a sufficient condition for the outcome (El Sawy *et al*., 2010). Therefore, a symmetric relationship is assumed between the variables in RBMs (Morris, 2005; Woodside, 2013); i.e. a change in the 'cause' variable results in a change in the 'effect' variable, and a low (or high) value of the effect variable corresponds to a low (or high) value of the cause variable. Consequently, asymmetric relationships are beyond the scope of RBMs. While RBMs *can* model the interaction effect of two predictors on an outcome variable, the relationship between the interaction variable and the outcome variable is assumed to be symmetric.

Configuration theory, however, allows the modelling of asymmetric relationships between variables (Matzler *et al*., 2004; Fiss, 2007; El Sawy *et al*., 2010; Woodside, 2013) because it views phenomena as clusters of interconnected elements that must be simultaneously understood as a holistic integrated pattern (El Sawy *et al*., 2010). This has two implications. Firstly, a predictor can have an asymmetric relationship with the outcome variable, while a predictor may be *insufficient* for the outcome to occur, it can serve as a *necessary* condition for the outcome variable (Fiss, 2007; Woodside, 2013). Specifically, a necessary condition represents a condition that is present – to some degree, in the fuzzy set theory sense – in every case that results in the specific outcome, while sufficiency indicates a condition whose presence guarantees the specific outcome. Secondly, a variable may affect the outcome only given the presence or absence of one or more additional variables (Fiss, 2007; El Sawy *et al*., 2010). In other words, multiple variables can act together to bring about the outcome of interest and different 'recipes' may exist for combining variables, known as *configurations*. Configuration theory strongly resonates with the theories of equifinality in management literature (Fiss, 2011), which posit that 'a system can reach the same final state from different initial conditions and by a variety of different paths' (Katz & Kahn, 1978, p. 30).

For our purposes, a 'configuration' is defined as a specific set of causal variables that, when working together, bring about an outcome of interest (Rihoux & Ragin, 2009; Ragin, 2000). To identify configurations in phenomena reliably, qualitative comparative analysis (QCA) is applied to estimate the causal contribution of various *possible configurations* to the expected outcome. Among the main variants of QCA are crisp-set QCA, multi-value QCA, and FsQCA (Schneider & Wagemann, 2010). We focus on FsQCA, one of the most general versions of QCA without posing a significant increase in the computational cost of performing the analysis. Additionally, although with many problems the limited modelling capabilities of multi-value QCA would seem a sufficient extension to crisp-set QCA, there are some serious pitfalls to be considered with respect to its interpretability and the way it is affected by limited diversity in the dataset as compared to FsQCA (Vink & Van Vliet, 2009).

Since *circa* 1995, QCA has gradually come to be used by scientists from quite varied research backgrounds (c.f. Skarmeas *et al*., 2014): political parties (Gordin, 2001), policy analysis (Blake & Adolino, 2001), social movements (Nomiya, 2001), social and political change (Berg-Schlosser & De Meur, 1994), addictive behaviour (Eng & Woodside, 2012), linguistics (Mendel & Korjani, 2012), and welfare states (Peillon, 1996). In the last two years, rapid expansion of QCA's use and its widespread use in the social sciences have occurred on account of recent advances in FsQCA, particularly within business and management research in examination of phenomena such as organizational innovation (Ganter & Hecker, 2014), successful product innovation (Cheng *et al*., 2013), inter-organizational technology transfer (Leischnig *et al*., 2014), and tourism behaviour (Woodside *et al*., 2011).

Relevance to IS

Configuration theory was originally developed in the context of organizational research (c.f. Fiss, 2007; Woodside, 2013). Hence, some researchers have sought to introduce configurational analysis to IS research with a focus on *organizational* performance (Fichman, 2004; El Sawy *et al*., 2010; Park & El Sawy, 2012; Wendler *et al*., 2013; Chong *et al*., 2013).

The work of Fichman (2004) was probably the first to introduce the concept of QCA to the IS community. This research focused on organizational IT innovations. Chong *et al*. (2013) and Wendler *et al*. (2013) are more recent examples of those applying QCA application in IS research. Efforts by other researchers can be seen in the work of El Sawy *et al*. (2010) and of Park & El Sawy (2012). In a research commentary, El Sawy *et al*. (2010) proposed that configuration theory offers a different paradigmatic lens for better understanding the complexity of digital ecodynamics. More recently, Park & El Sawy (2012) have applied FsQCA to identify different configurations that result in a similar level of competitive firm performance, in which multifaceted roles of IT capability are reported.

Despite valuable insights, configurational analysis is still '*a method which is nearly unrecognized within our discipline to date*' (Wendler *et al*., 2013, p. 1457). The uptake of this method in the IS community may be impeded by IS scholars' unfamiliarity with the approach and by its rapid evolution. In this regard, the paper represents an attempt to increase awareness and demonstrate application of the FsQCA approach in hopes of generating greater insights in the IS community.

Secondly, the study provides theoretical support for incorporating configurational analysis into IS behavioural research through comparison of the features of FsQCA with those of conventional RBMs. Discussion of the use of configurational analysis has thus far focused predominantly on (IS) organizational research. Theories and methods developed for the organizational research may not fit the context of user behavioural research, and vice versa. For instance, is it rational to model asymmetric relationships in IS behavioural research, given the predominant assumption of symmetric relationships between variables in our research tradition? Hence, another contribution of our work is to apply the method to IS behavioural research. We elaborate on our rationale next.

Asymmetric effects of determinants on IS behaviour

IS behavioural research has focused mostly on detecting the *causality* of IS use phenomena, with RBMs being the main approach utilized; thereby, causal symmetry has been assumed. However, causal asymmetry is also found within IS behavioural research.

Under assumptions of causal symmetry, the results of correlation or regression analysis are determined by the association pattern of two variables. Consider Figure 1, for instance, which presents a scatterplot of two variables: perceived usefulness (USE) and the behavioural intention to adopt mobile government services. A five-point Likert scale from 'Disagree' (1) to 'Agree' (5) is utilized for the data collection. The correlation between the two variables is positive ($r = 0.365$) and significant ($p < 0.001$), implying that when users perceive the technology to be more useful they are more likely to adopt it. For RBMs, the highlighted data points in the top left and bottom right appear to be 'noise' in the hypothesized symmetric and positive relationship, and they contribute to the unexplained part of behavioural intention. However, these samples contain important information and are

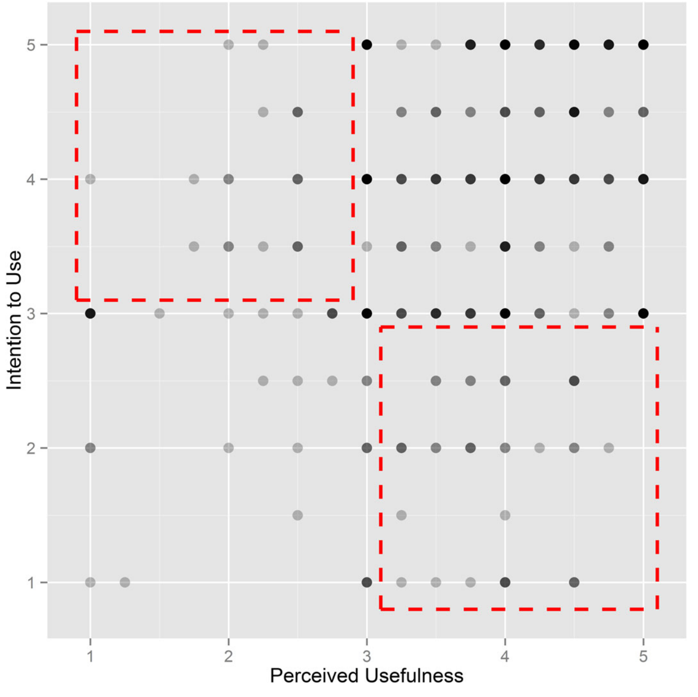

Figure 1. A scatterplot of two IS perceptual variables.

evidence of asymmetry. For instance, as is indicated in Figure 1, many users who do not perceive a technology to be useful may still intend to adopt it, while some users who perceive the technology as useful are unwilling to do so. Consequently, systematic explanation of the mechanism underlying these asymmetric relationships may offer important insights.

Merits of using QCA in IS behavioural research: comparison to RBMs

RBMs enjoy a long history of popularity in the social sciences, although several constraints have been reported (Woodside, 2013; Woodside & Zhang, 2013; Skarmeas *et al*., 2014). Hence, we should state that the aim of this section is not to suggest that prior RBM studies were inappropriately constructed. Instead, we seek to highlight the advantages of FsQCA as an instrument for supplementing RBM-based IS research.

Firstly, MRA and SEM adopt a 'net effect' estimation approach: they estimate the effect size of each independent variable with reference to the dependent variable after controlling for the impact of other independent variables in a model. In consequence, the estimated net effect of the independent variables may fluctuate between being significant and insignificant, depending on the presence or absence of additional independent variables (Woodside, 2013). Armstrong (2012) noted that adding variables to an equation does not mean controlling for variables in non-experimental settings, because predictors typically co-vary with each other. This phenomenon actually lends support to configurational analysis: it is the presence or absence of other particular factors that gives meaning to a variable (c.f. Fiss, 2007).

Secondly, RBMs examine the extent to which symmetric relationships exist between a set of independent variables and a dependent variable (Woodside, 2013). In other words, low or high values of a variable, *X*, are associated respectively, with low or high values of a variable, *Y*, and vice versa (Figure 2(B)). A symmetric relationship between *X* and *Y* indicates that *X* is both a necessary and a sufficient condition for *Y*. In contrast, in an asymmetric relationship *X* may be either a sufficient or a necessary condition for Y.

We demonstrate asymmetric relationships in the following way. A typical case of an asymmetric relationship may involve a high value of *X* being associated with a high value of *Y*, while a high value of *Y* may not be associated with a high value of *X*. In this case, we claim that *X* is a sufficient condition for *Y*, as shown in Figure 2(C). On the other hand, it is possible for a high value of *X* not always to be associated with a high

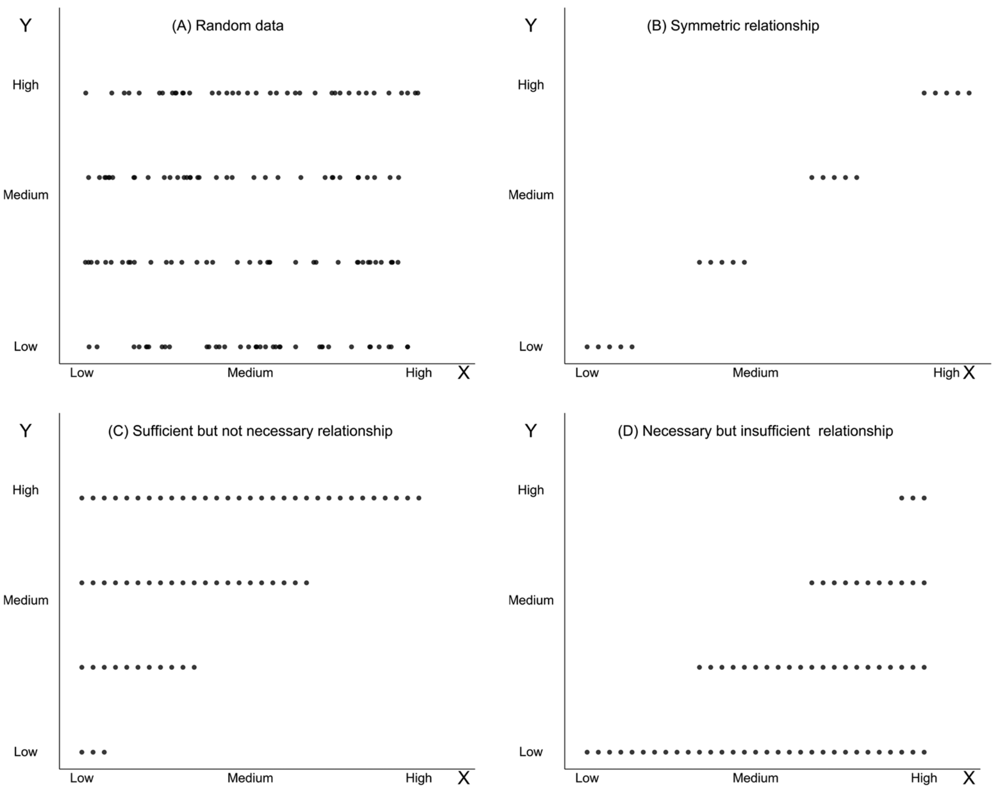

Figure 2. Visualization of symmetric (B), asymmetric (C and D), and random (A) dependencies between variables (adapted from Wu *et al*. (2014)).

value of *Y*, while a high value of *Y* is always associated with a high value of *X*. In this case, we claim that *X* is a necessary condition for *Y*, as shown in Figure 2(D). In addition, an insignificant symmetric relationship between two variables (as in Figure 2(A)) does not necessarily rule out the existence of asymmetric relationships – across parts of the sample.

Next, classic regression models treat variables as competing in explaining variance in outcomes rather than as showing how they cooperate or combine to create outcomes (Fiss, 2007), while configuration theory assumes that there is always more than one combination of conditions that gives rise to a given outcome. Similarly, this applies to the research on antecedents of IS behaviour: while there might be many significant antecedents of a particular IS outcome, these factors may not necessarily all co-exist to produce an effect, and also a single factor may not lead to the relevant outcome in the absence of other factors.

For instance, some individuals may adopt an IS mainly on account of peer influence, while others have an expectation of enhanced performance. In fact, evidence of these effects can be obtained from existing theories, such as the unified theory of acceptance and use of technology (Venkatesh *et al*., 2003) and innovation diffusion theory (Rogers, 1983), which show that users' demographic characteristics significantly alter the way they value the attributes of an IS. As IS behaviour tends to be motivated by different variables for different user groups, it is reasonable to assume that different configurations exist that generate a particular IS behaviour outcome.

Fourthly, users may not perceive all attributes of a given IS positively. A user who evaluates several attributes of the IS negatively may still adopt it on account of positive evaluation of other attributes. For instance, a considerable proportion of users may evaluate an iPhone as expensive (a negative perception) but still adopt it because they feel that using iPhones is 'cool' (a positive perception surrounding social image). Therefore, a positive perception as to social image is a necessary condition for iPhone adoption for those who perceive the price of an iPhone negatively. The negative perception of price, in combination with the positive perception of social image, forms a sufficient set of conditions (configuration) for iPhone adoption. However, this conditional combinatorial configuration cannot be detected by RBMs.

Finally, FsQCA can be more robust as compared to RBMs for two reasons. Firstly, while the results of RBMs can be sensitive to outliers, this is less likely to be an issue for FsQCA because its analysis relies on identifying subsets of the data (details are presented in Section 3). As every observation is translated into a combination of conditions, the inclusion or exclusion of a particular data point simply alters the evaluation of that combination and has no effect on the overall assessment of other causal combinations. Secondly, sample representativeness is less of an issue for FsQCA, because it does not hinge on the assumption that data are drawn from a given probability distribution (Fiss, 2011). This is because FsQCA, when evaluating a configuration, considers only the subset of samples affected by the configuration in the whole dataset. If a particular group of users have been over-represented or under-represented, there is little effect on the existence of other configurations.

Limitations of configurational analysis

It is important to point out that FsQCA does have some limitations. Firstly, RBMs are less demanding with respect to prior causal knowledge and have a clear empiricist foundation (Vis, 2012), whereas FsQCA relies on prior knowledge for the choice of the conditions and the outcome, and to simplify configurations. Secondly, the interpretation of the results gained by FsQCA is labour-intensive, carrying a high risk of subjective bias. This is especially true when one is interpreting complex solutions. Thirdly, FsQCA requires the calibration of data (Section 3), which is not necessary in RBMs. As Ragin (2008a) points out, this can be a disadvantage but also an advantage: if the researchers are knowledgeable enough about the underlying domain, the freedom to transform traditional variables into fuzzy values can significantly improve the analysis. Fourthly, there is also a lack of proper theoretical grounding when one is determining the precise threshold for various measurements in the application of FsQCA to assess causal configurations (Mendel & Korjani, 2012). A threshold value that is too low or high can result in too many or too few retrieved configurations respectively. Fifthly, FsQCA is sensitive to case selection, especially with a small sample size, and it cannot detect the solutions if the relevant sample cases are not included. This is a problem in studies with few cases, but when the data are collected from a random sample in sufficient numbers (where the threshold depends on the number of causal conditions to be considered), it is not a relevant issue. Sixthly, FsQCA lacks of proper procedures for assessing measurement error. Furthermore, FsQCA assesses the empirical relevance and set-theoretical importance of complex combinatorial pathways to the outcome but cannot identify the unique contribution of each individual condition (Skarmeas *et al*., 2014).

Another limitation of FsQCA is that it was originally developed to measure one-item factors. Therefore, latent variables cannot be directly utilized. Hence, we propose integrating the advantages of a measurement model test using SEM with an asymmetric relationship test using FsQCA (Park & El Sawy, 2012); i.e. after examination of the validity and reliability of latent variables through measurement model tests, the values of the latent variables should be transformed into fuzzy set values for further analysis with FsQCA.

FsQCA: CONCEPTS AND ANALYSIS

FsQCA was developed by the social scientist Charles Ragin (1987, 2000), who integrated fuzzy set and fuzzy logic principles with QCA; in FsQCA every variable is considered a (fuzzy) set. In the original form of QCA, Boolean sets are used as the basis for the analysis. For example, when we talk about the risk associated with an outcome, a case (which might be an organization or a respondent) is either risky or not risky and is associated with the value 1 or 0 respectively. In most situations, this binary classification is not sufficient to capture the real nature of an observation. In the ideal case, we would like to capture a degree of belonging: if a specific case can be classified as very risky, it belongs to the set of risky cases with a degree of 0.9, while a degree of 0.2 indicates low risk. The use of fuzzy set theory corresponds to the original intention of Zadeh (1965), who proposed fuzzy sets and fuzzy logic with broader applications for the social sciences, not solely for engineering and control theory (Seising, 2010).

Vis (2012) points out that a factor that definitely influences the outcome in only a small subset of cases becomes invisible in a regression-based analysis. FsQCA can identify the patterns that differ across subsets of cases easily and with less stringent data requirements than statistical advances. Compared to conventional RBMs such as MRA or SEM, FsQCA, as a configurational analysis approach, offers unique values and new capabilities for social scientists wishing to 'describe combinatorial complexities assuming asymmetrical relationships between variables, rather than symmetrical net effects that MRA and SEM usually estimate' (Skarmeas *et al*., 2014, p. 1796).

In a recent paper, Mendel & Korjani (2012) summarized the FsQCA method in 13 steps, to make it more approachable from a quantitative point of view. In the following discussion, we describe the most important steps in the analysis by focusing on the issues that highlight the differences between FsQCA and traditional statistical techniques. As is mentioned previously, the main goal with FsQCA is to identify combinations of conditions that result in a specific outcome. Two of the most important methodological differences result from this formulation: (a) in FsQCA, several combinations of (necessary and/or sufficient) conditions (that is, possible multiple solutions) can be identified, and (b) the effect of a given independent variable on the outcome is not quantified, because we are interested in the combinatorial effects (Woodside, 2013).

Data calibration

The initial step in the analysis is to convert the variables of the model into sets; this process is called data calibration in FsQCA terminology (Ragin, 2000). According to Ragin (2008a), there are two main types of data calibration: direct (identifying three qualitative breakpoints of the fuzzy sets) and indirect (rescaling the original measurements in line with qualitative assessments). Both approaches rely extensively on the substantive knowledge of the researchers in the calibration process. For this paper, we use direct calibration, and we discuss only this procedure in detail in the succeeding texts.

In some cases, it is sufficient to use crisp (0–1) sets to represent a variable: for example, the variable *gender*, when translated into a set, automatically becomes crisp as it can take only two values. For more complex variables, the original recommendation (and the calibration method used in the original software, and consequently in most of the applications) is to identify three values from the range of the variable that are to correspond to full-membership, the most ambiguous membership, and full non-membership. If the researcher does not have sufficient knowledge of the underlying variable, the most straightforward procedure is to use the three values 1, 0.5, and 0. The other values of the original variable are calibrated on the basis of a linear function to fit into these three values. For example, if a variable is measured on a five-item scale, the membership values for 1, 3, and 5 are 0, 0.5, and 1 respectively, and the memberships for 2 and 4 are assigned in keeping with the assumption of a linear membership function, in line with the researcher's substantive and theoretical knowledge. Substantive knowledge can refer to any knowledge that pertains to relevant information related to the problem domain, the measurement model, or the observed cases (sample). In other words, we use qualitative anchoring to establish a connection between a fuzzy membership function and the original data. In our analysis, for the binary variable gender we use membership values of 0 and 1. For other variables, measured on a five-item Likert scale, the two extreme items are translated to the membership values 0 and 1, and the intermediate items are assigned membership values in a sub-linear way, given values of 0.2, 0.4, and 0.7, instead of the equidistant choices 0.25, 0.5, and 0.75.[1] This means that a higher score on the Likert-scale is required from the respondent for intermediate memberships and reflects the general knowledge that the points on the Likert scale are not equidistant (Busch, 1993). In other words, using this substantive knowledge, instead of applying an equidistant division of the unit interval to calibrate a five-item scale (i.e. item i is assigned the membership value $(i-1)*0.25$), we can specify a (slightly) lower membership value for lower values of i. This indicates a higher standard for intermediate memberships. Transforming the middle point (neutral value) of a five-item scale into 0.5, the latter being the threshold for a configuration's selection in the frequency analysis would mean that a neutral opinion positively contributes to the evaluation of a configuration. To avoid this, we choose to use 0.4 and an intermediate membership value. In general, an understanding of the problem domain can offer information for calibration of an ordinal scale by means of a piecewise linear function (with different slopes on the subdomains).

In our analysis we made use of the FsQCA software developed by Ragin & Davey (2014), which uses the calibration values produced by a linear transformation function, but, in general, the choice of the three membership values and linearity is not necessary, because one can utilize the full [0,1] interval and use non-linear membership functions (Mendel & Korjani, 2012). The use of membership functions different from linear membership functions requires extensive knowledge of the underlying cases. This is a more feasible alternative when FsQCA is applied in reliance on a limited number of extensively analysed cases, for example individual organizations. If there is only a limited amount of information about the respondents in a questionnaire-based dataset, unless detailed knowledge is obtained about the utility functions of the respondents, it is unreasonable to translate an ordinal scale into a membership function that differs from a (piecewise) linear membership function.

Identifying the most important variable configurations

Once each variable is converted into a condition set, all possible variable combinations are evaluated, which means that with k condition sets there are 2^k possible combinations to be assessed. For example, in a simple case with two condition sets, here the USE and ease of use (EOU) of an IS, there are four logical combinations: 'USE and EOU', 'not USE and EOU', 'USE and not EOU', and 'not USE and not EOU'.

Given a particular combination, we can then calculate the degree to which each case in our dataset supports it. This is done by calculating the minimum of the membership values of the conditions present in the combination, with the complementary value (i.e. 1 value) taken into

[1]Note that even though in this study we adopted a sub-linear way of assigning membership values, we do not object to the use of equidistant membership values. However, FsQCA users should be aware that some studies suggest that the intervals between values on a Likert scale cannot be presumed to be equal (Jamieson, 2004). In this illustrative work we demonstrate how it is possible to assign non-equidistant membership values, along with the rationale for doing so.

account when necessary. Continuing our previous example, let us assume that one respondent reported 0.7 for EOU and 0.4 for USE. From these figures, we calculate the degree for the four possible combinations. For instance, the combination USE and EOU is supported by this respondent degree: min (0.7, 0.4) = 0.4. On the other hand, the combination not USE and EOU is supported to the degree: min (1-0.4, 0.7) = 0.6. In crisp QCA, a combination is either fully supported or not supported at all by an observation. In FsQCA, the value 0.5 serves as the threshold value in the assessment of which combinations are supported to an acceptable degree.

The process we describe requires 2^{k}* (the number of cases) evaluations. However, Mendel & Korjani (2013) recently proved that for a given case there can be only one causal combination with an overall degree higher than 0.5, thereby greatly simplifying the calculations required. In comparison to the original exponential complexity of the FsQCA algorithm, this reduction represents a distinct advantage over other methods with respect to computational complexity.

In the next step we discard all combinations that are not supported by at least one case with a degree above 0.5. The remaining combinations are evaluated on the basis of two measures, in the following order:

- Frequency: The combinations that do not represent at least a predefined threshold number of cases are excluded from further analysis. For example if this predefined threshold is 10, a combination needs to have a membership value greater than 0.5 for *at least* 10 cases.
- Consistency: Every remaining combination at this point can be considered a potential fuzzy rule that provides a setting of conditions that may or may not result in the defined outcome. For checking whether these potential rules are indeed real, a fuzzy subsethood measure is defined, which is termed consistency. This measure captures the extent to which a given combination is a sufficient condition for the outcome. In other words, high consistency indicates that when the causal combination occurs, that case will lead to the outcome under consideration. The original recommendation by Ragin (2008a) is to exclude combinations with a consistency value lower than a threshold of 0.8, but this can be increased or decreased as the problem context dictates. In general, as we deal with several cases (respondents), the consistency for a particular combination is calculated as

$$Consistency = \frac{\sum_i \min(\text{support of combination for respondent}\, i;\ \text{membership of outcome for respondent}\, i)}{\sum_i \text{support of combination for respondent}\, i}$$

Continuing our example, we need to check which of the supported combinations is consistent with the outcome ‘Intention’. In our example we consider one respondent, and the only supported combination is not USE and EOU with support 0.6; therefore, the consistency of the rule ‘not USE and EOU leads to Intention’ has to be calculated. We assume that the respondent being considered belongs to the fuzzy set Intention with a membership value of 0.4. To calculate the consistency of this combination with the outcome Intention, we calculate min (support of combination, membership of outcome)/(support of combination) or min (0.6, 0.4)/0.6 = 0.67.

Therefore, this respondent is not sufficiently consistent (above 0.8) with the rule not USE and EOU leads to Intention'.

Obtaining the solution sets

After identification of all sufficient combinations, three solution sets can be obtained: complex, parsimonious, and intermediate solutions (Ragin, 2008a). Here, 'solution' refers to a combination of conditions that is supported by a high number of cases, where the rule 'the combination leads to the outcome' is consistent.

The set of *complex* solutions is obtained by taking the logical union of sufficient combinations identified in the previous step and simplifying these by applying traditional logical operations, i.e. union, intersection, and negation. This can be done in an algorithmic fashion via the Quine–McCluskey (QM) minimization method (Mendelson, 1970). To show an example, we suppose now that, additionally to USE and EOU, the variable G (gender) is included in the analysis, with 'G' representing females and negation, 'not G' representing males. We suppose that two configurations with high frequency and consistency were identified: 'USE and not EOU and G' and 'USE and not EOU and not G'. As the two configurations suggest, the presence of USE and lack of EOU results in intention to use for both genders; intuitively this could be simply expressed with the configuration USE and not EOU. As this statement holds for both genders, including two configurations simply conveys redundant information. Formally, taking the union of the two configurations (corresponding to the *or* operator) and using the property of associativity, we can derive that

$$
\begin{aligned}
&(USE \text{ and not } EOU \text{ and } G) \text{ or } (USE \text{ and not } EOU \text{ and not } G) = \\
&USE \text{ and not } EOU \text{ and } (G \text{ or not } G) = USE \text{ and not } EOU
\end{aligned}
$$

In this simple example we obtained the complex solution USE and not EOU by simplifying the configurations obtained in the previous step in the FSQCA process. In general, because the number of configurations identified can be very large, the number of complex solutions can be large and these may include configurations with several terms. This makes the interpretation of the solutions difficult and in most cases impractical (Mendel & Korjani, 2012). For this reason, they are usually simplified further into parsimonious and intermediate solutions.

For obtaining the set of *parsimonious* solutions, the QM method makes use of the combinations that were dropped in the frequency test. The parsimonious solutions can be seen as the causal combinations featuring the minimal number of conditions. To obtain the parsimonious solutions we make use of the information on the causal combinations that do not pass the frequency threshold in order to simplify the complex solutions through Boolean logic operations. Every complex solution includes at least one parsimonious solution. As the process for deriving parsimonious solutions makes very strong assumptions by utilizing information from all the combinations without considering sufficiency of frequency, they are usually not presented as the final solutions of the FsQCA analysis. However, they are necessary for calculating the intermediate solutions. To continue the example, we identify the complex solution USE and not EOU, and we conclude that the combination USE and EOU does not pass the frequency threshold test. By using logical operations thus

$$(\text{USE and not EOU}) \text{ or } (\text{USE and EOU}) = \text{USE and } (\text{EOU or not EOU}) = \text{USE},$$

we obtain the parsimonious solution 'USE'. While it provides a very simple explanation for understanding the underlying problem, the calculations make use of information that is not sufficiently supported by the data. For this reason, researchers, in general, have to be very careful when interpreting and presenting parsimonious solutions.

The *intermediate* solutions are obtained from the parsimonious and complex solutions through counterfactual analysis (Ragin, 2008a; Fiss, 2011), which builds on the domain knowledge of the researcher. Consequently, the set of intermediate solutions can vary with the person performing the analysis. The important condition in defining counterfactuals so as to simplify complex solutions into intermediate is that the researcher should rely on general, uncontroversial substantive knowledge. In general, the causal combinations contained in the set of intermediate solutions are included in the complex solutions but also contain the parsimonious solutions. For example, by using no substantive knowledge at all, the intermediate solutions are the same as the complex solutions. The traditional way of utilizing substantive knowledge is to specify whether the presence or absence of a condition (according to general knowledge) can be associated with the outcome variable. In counterfactual analysis, we consider every pair of complex and parsimonious solutions. If the parsimonious solution is contained in the complex solution and the substantive knowledge does not contradict the parsimonious solution, we simplify the complex solution by applying the knowledge. In our simple example, we have only one pair, USE and USE and not EOU. If the knowledge to be used states that, in general, 'not USE' is associated with the presence of the outcome variable (Intention), we do not perform counterfactual analysis as it contradicts the parsimonious solution. If the substantive knowledge shows that 'EOU' is, in general, associated with the outcome, because it does not contradict the parsimonious solution, we can remove its negation, 'not EOU' from the complex solution and thereby obtain the intermediate solution USE. In simple cases involving few variables and basic additional substantive knowledge, the intermediate solutions are identical to either parsimonious or complex solutions. However, in problems entailing several variables, intermediate solutions, on one hand, can simplify complex solutions into interpretable combinations while, on the other hand, overcoming the limitation of strong (and sometimes unjustified) assumptions used for deriving parsimonious solutions. A more detailed and mathematical oriented description of the steps in counterfactual analysis is provided by Mendel & Korjani (2012).

Interpreting and evaluating the solutions

After obtaining these three sets of solutions, we can classify causal conditions further, into core and peripheral conditions (Fiss, 2011). Core conditions are those conditions that are part of both parsimonious and intermediate solutions, while peripheral conditions are those that exist only in the intermediate solution but are eliminated in the parsimonious solution. This approach defines the causal coreness in terms of the strength of the evidence relative to the outcome, instead of the connectedness to other configurational elements (Fiss, 2011). In other words, as intermediate solutions are derived on the basis of substantive knowledge of the connection between conditions and the outcome variable, differentiating between core and peripheral conditions depends mainly on this knowledge rather than the relationship with other configurations. Specifically, for a core condition, the validity of both conditions (e.g. the presence of condition A and its counter-condition and the absence of condition A) is supported by the data. For a peripheral condition, only the condition itself in the configuration is supported by the data, while it is unclear whether the counter-condition is valid, because there is a lack of relevant data. Furthermore, a peripheral condition is not necessarily unimportant; a peripheral condition can often serve as a necessary condition in the configuration.

In this paper, we use both complex solutions and intermediate solutions to identify core and peripheral conditions, as recommended by, for example, Ragin & Sonnett (2005) and Ragin (2008a). The main reason behind this methodological choice is that both intermediate and parsimonious solutions require the researcher to make assumptions as to the presence or absence of various conditions. When one is obtaining parsimonious solutions, the analysis relies partly on the set of causal combinations that are not present with sufficient frequency in the dataset while the intermediate solutions are calculated through reliance on assumptions (the assumed knowledge of the researcher) surrounding the effect of individual conditions on the outcome. The assumptions could be made on the basis of prior studies; e.g. the presence of perceived USE should be associated with a high membership value for intention to use (based, for instance, on the technology acceptance model). However, we hypothesize that users with particular negative perceptions will also be able to adopt the technology. Using complex solutions enables presentation of all possible configurations.

Finally, in the last step in the analysis, the solutions can be evaluated by means of various coverage measures. The general term 'coverage' refers to the proportion of the sum of the membership values of supporting cases for a combination. Coverage is akin to effect size in statistical hypothesis testing (Woodside & Zhang, 2013). Coverage can be calculated in terms of a solution set (a set of configurations) or individual solutions. Depending on the group of evaluated configurations, a choice of solution, raw or unique coverage can be made, according to Mendel & Korjani (2012).

To illustrate the three coverage measures, we will use the example presented in Table 1. It includes four cases, three possible conditions (USE, EOU, and IMAGE), and the outcome variable Intention. The first four columns contain the membership values for the conditions and the outcome. We find that there are two configurations identified as solutions, Conf1 = USE and

Table 1. Example illustrating the various coverage measures

Case	USE	EOU	IMAGE	Intention	C1	C2	Overall support	C1 and Intention	C2 and Intention	Overall
1	0.7	0.8	0.6	0.9	0.7	0.6	0.7	0.7	0.6	0.7
2	0.5	0.6	0.3	0.7	0.5	0.3	0.5	0.5	0.3	0.5
3	0.7	0.3	0.8	0.9	0.3	0.7	0.7	0.3	0.7	0.7
4	0.3	0.7	0.8	0.2	0.3	0.3	0.3	0.2	0.2	0.2
Sum	2.2	2.4	2.5	2.7	1.8	1.9	2.2	1.7	1.8	2.1

EOU and Conf2 = 'USE and IMAGE'. The 'C1' and 'C2' columns present the support for the configurations, which is simply the minimum of the two values for the variables in a configuration, for example, C1 = min (USE and EOU). The column labelled 'Overall support' shows the support for the solution set (Conf1, Conf2), as the maximum of the values in the preceding two columns. The columns 'C1 and Intention' and 'C2 and Intention' show how consistent the configurations are with the outcome; for example C1 and Intention = min (C1, Intention). Finally, 'Overall' presents the overall consistency of the solution set (Conf1 and Conf2) as the maximum of the values in the preceding two columns.

The first coverage measure, *solution coverage*, is calculated for a solution set (not for an individual solution) and describes the sum of the values obtained from the join of the causal configurations and the outcome variable normalized by the sum of the membership values for the outcome variable (Mendel & Korjani, 2012). In other words, it measures to what extent the cases that indicate the presence of the outcome are covered by at least one of the configurations from the solution set. In our example, this can be calculated as the quotient of the sum of the columns Overall (the join of the two configurations and Intention) and Intention, which is 2.1/2.7 = 0.78.

The *raw coverage* of a specific solution is the join of the configuration and outcome normalized by the sum of the membership values for the outcome variable (Ragin, 2000; Ganter & Hecker, 2014). Raw coverage provides a measure estimating the extent (in a fuzzy sense) to which a solution covers the dataset; that is, in what percentage of the cases the configuration can be observed. In our case, the raw coverage of Conf1 is calculated as (using the values from the last row of Table 1)

$$\text{the sum for C1 and Intention}/\text{the sum for Intention} = 1.7/2.7 = 0.63$$

For Conf2, it can be calculated similarly as 1.8/2.7 = 0.67.

Unique coverage represents the contribution of a solution beyond what has already been interpreted via other solutions in a solution set (Ragin, 2000; Ganter & Hecker, 2014). In other words, it offers an estimate as to the cases that can be described by a specific configuration and not by any other configurations in the solution set. In our example, for a specific configuration it is the difference between the coverage of the whole solution set (precisely the solution coverage) and the raw coverage of the other configuration. For Conf1, it is

$$\text{solution coverage} - \text{raw coverage of Conf2} = 0.78\text{–}0.67 = 0.11,$$

while for Conf2, it is 0.78–0.63 = 0.15

Summary of FsQCA

As a point of reference, Table 2, in the succeeding texts, includes the definitions of important terms used in the foregoing description. For further review of the discussion in the preceding texts on applying FsQCA, we can summarize the process in terms of four main steps:

1 The calibration process: The variables of the model are converted into fuzzy sets through determination of an appropriate membership value. On the basis of this calibration, the values from the dataset containing the respondents' answers are transformed into fuzzy membership values.

Table 2. Definition of the most important concepts in FsQCA

Concept	Definition
Configuration	A logical combination of causal conditions
Frequency	The number of cases for which a configuration achieves a membership value higher than 0.5 (Ragin, 2008b)
Consistency	The extent to which a given combination is a sufficient condition for the outcome (Ragin, 2008b)
Complex solutions	Solutions obtained by simplifying, through logical operations the configurations with sufficient frequency and consistency (Mendel & Korjani, 2012)
Parsimonious solutions	Solutions obtained by simplifying the complex solutions through use of information from the combinations dropped in the frequency test (Mendel & Korjani, 2012)
Intermediate solutions	Solutions obtained from the complex solutions via utilization of substantive knowledge in the form of the presence or absence of some causal conditions (Mendel & Korjani, 2012)
Core conditions	Causal conditions that appear in both the parsimonious and intermediate solutions (Fiss, 2011)
Peripheral conditions	Causal conditions that appear in the intermediate solutions, but not in the parsimonious solutions (Fiss, 2011)
Solution coverage	The proportion of cases (in terms of fuzzy membership value) that can be described by at least one configuration from a solution set (Ragin, 2000)
Raw coverage	The proportion of cases (in terms of fuzzy membership value) that can be described by the configuration (Ragin, 2000)
Unique coverage	The proportion of cases (in terms of fuzzy membership value) that can be described by a configuration appearing in a solution set but cannot be described by any other configuration from the set (Ragin, 2000)

2 Identification of the most important variable configurations: Each possible logical combination of the variables is evaluated for every respondent. The combinations that appear enough times and are consistent enough with the data are selected for further analysis.

3 Obtaining the solution sets: The configurations identified are simplified and combined through logical operations and counterfactual analysis via the use of additional statements based on the researcher's substantial knowledge. Three solution sets, complex, intermediate, and parsimonious, are identified.

4 Interpretation and evaluation of solutions and solution sets: The solutions identified are broken down further, into core and peripheral conditions. Additionally, various coverage measures are used to assess the quality of the solutions and solution sets.

Example: applying FsQCA to latent reflective variables for user perceptions

Variables for analysis and the context of survey-based research

A dataset from a survey-based questionnaire on rural residents' intention to use mobile government services was utilized in our study. Five variables are proposed as the antecedents of mobile government services adoption: perceived EOU, perceived (near-term) USE, perceived long-term USE, benevolence, and image. Definitions for these variables are given in Table 3.

Table 3. Definition of the latent variables.

Variables	Definition	Relevant studies
Perceived ease of use	Perceived ease of use refers to the degree to which a user believes that using mobile government services would be free of effort.	Davis (1989)
Perceived near-term usefulness	Perceived usefulness is defined as the degree to which an individual perceives that using a particular system would enhance his or her performance of access government information.	Davis (1989), Thompson *et al*. (1991), Chang & Cheung (2001), and Liu *et al*. (2010))
Perceived long-term usefulness	Perceived long-term usefulness refers to the degree to which a user believes the use of mobile government services may also bring about outcomes that have a pay-off in the future.	Thompson *et al*. (1991), Chang & Cheung (2001), and Liu *et al*. (2010)
Benevolence	Benevolence refers to an individual's belief that the trustee cares about her/him and acts in her/his interests.	Wang & Benbasat (2005)
Image	Image refers to citizens' perceptions that the adoption of mobile government services would enhance the adopters' status in the social system.	Phang & Li (2005 and Shareef *et al*. (2011)
Behavioural intention	Behavioural intention refers to a person's subjective probability that he/she will perform some behaviour.	Fishbein & Ajzen (1975)

Given that the reason for use of this dataset is to test FsQCA in IS behavioural research, justification of the subject of the survey questionnaire is not included. Hence, we simply provide a summary of prior studies showing the importance of the variables as antecedents of IS adoption in Table 3.

The questionnaire-based survey

A five-point Likert scale from Disagree (1) to Agree (5) was used to measure each perception item. The measurements for the constructs of our research model are derived from prior studies. The measurement for perceived EOU and near-term USE are derived from the work of Davis (1989). The items for measuring perceived long-term USE are based on the study by Liu *et al*. (2010) and Chang & Cheung (2001). The items for measuring image are adapted from the work of Lee & Kozar (2008) and Moore & Benbasat (1991). Finally, the items for benevolence and intention are derived from the measurements used by Wang & Benbasat (2005) and by Venkatesh *et al*. (2003) respectively. Note that in IS behavioural research, adoption intention is a frequently explored dependent variable, measuring the degree to which individuals are likely to adopt an IS (c.f. Fishbein & Ajzen, 1975). The IS adoption research offers insights into the antecedents driving the information systems adoption, which represents an important stream of IS behavioural research. The measurement conducted for latent variables can be found in Appendix A.

Twenty-one student volunteers, whose families live in the rural regions of China's Zhejiang province, were recruited to help us collect responses from the villages in which their families reside. Before the survey, the volunteers received training and the purpose of the research was clearly explained to all volunteers. The volunteers were requested to visit about 15–25 different rural families and collect a response from one person per family visited. We collected 433 responses, of which 409 were retained for analysis (responses that had missing values for latent variable measurement were removed from consideration).

Measurement validity and reliability

The construct validity of the measurement included in the questionnaire was assessed. Specifically, construct validity indicates the degree to which a factor accurately reflects the construct of interest (Gefen, 2000; Wade & Nevo, 2006). Construct validity is normally assessed via measurement of convergent validity and discriminant validity. The former denotes the degree to which the measurements of the constructs that are assumed to be theoretically related are actually related (Wade & Nevo, 2006). As is shown in Table 4, the values of Cronbach's alpha (α), composite reliability, and average variance extracted (AVE) for the constructs are all above the thresholds: 0.7, 0.7, and 0.5 respectively (Gefen, 2000). These results show that adequate convergent validity was obtained for the measurement scales.

Discriminant validity reflects the extent to which two variables that should not be related to one another are actually unrelated (Gefen, 2000; Wade & Nevo, 2006). As Table 5 shows, the square roots of AVE are higher than their correlations with other constructs. In addition, principal component analysis was conducted for further testing of the measurement validity, as shown in Appendix B. The results show that all items fit their respective factors quite well

Table 4. Reliability and convergent validity statistics

Construct (no. of items)	α	Composite reliability	Minimal factor loading	AVE
Near-term usefulness (4)	0.890	0.859	0.614	0.608
Perceived ease of use (4)	0.904	0.891	0.783	0.671
Benevolence (3)	0.912	0.892	0.816	0.734
Long-term usefulness (3)	0.907	0.858	0.785	0.668
Image (3)	0.952	0.915	0.871	0.783
Intention (2)	0.910	0.865	0.862	0.762

Table 5. Discriminant validity

Construct	NTU	EOU	BEN	LTU	IM	INT
Near-term usefulness (NTU)	**0.779**					
Perceived ease of use (EOU)	0.514	**0.819**				
Benevolence (BEN)	0.494	0.379	**0.856**			
Long-term usefulness (LTU)	0.607	0.462	0.407	**0.817**		
Image (IM)	0.335	0.442	0.442	0.457	**0.885**	
Intention (INT)	0.365	0.420	0.391	0.443	0.452	**0.873**

Note: The bold diagonals are the square roots of the AVEs of the individual constructs; off diagonal values are the correlations between constructs (all correlation values are significant at $p < 0.01$ level).

without any substantial cross loading over 0.4, indicating that there is sufficient discriminant validity (Fornell & Larcker, 1981; Gefen, 2000).

We conducted a Harmon's one-factor test to examine the common-method bias (Podsakoff *et al.*, 2003). None of the factors was found to account for the majority of the covariance in the variables, which suggests that common method bias is unlikely to merit concern. In addition, a single factor model test was conducted. The single-factor model exhibited a poor fit (CMIN/DF = 22.95; $p < 0.001$; adjusted goodness-of-fit index (AGFI) = 0.376; normed fit index (NFI) = 0.475; incremental fit index (IFI) = 0.486; Tucker–Lewis index (TLI) = 0.420; comparative fit index (CFI) = 0.484; root mean square error of approximation (RMSEA) = 0.232), against the existence of common-method bias. In addition, the measurement model test shows good model fit (CMIN/DF = 3.33; $p < 0.001$; AGFI = 0.850; NFI = 0.931; IFI = 0.951; TLI = 0.938; CFI = 0.951; RMSEA = 0.076).

Calibration of the Likert scale to fuzzy sets

For performance of the FsQCA,[2] the variables were transformed into fuzzy sets through the use of three qualitative breakpoints: 1, 0.4, and 0. The calibration was performed in the R software environment (the code is provided in Appendix C), and the fuzzy truth table analysis was conducted afterwards by means of the software fs/QCA 2.0. For example when the fuzzy set for the variable EOU was constructed, a membership value of 1 was assigned to respondents who answered 5 in the questionnaire, 0 was assigned to an answer of 1, 0.4 was associated with 3, and the membership values for other answers were specified between these breakpoints – i.e.0.70 for an answer of 4 and 0.20 for 2. In this part of the analysis, perceived EOU, near-term USE, long-term USE, benevolence, image, and additionally gender were included in the model, to allow deriving the sufficient and necessary conditions for the outcome Intention. In creation of the fuzzy set for gender, male gender was coded with low membership (0) and female with high membership (1).

Results of FsQCA analysis

Proceeding from prior literature (Table 3), we set certain assumptions for the calculation: the presence of EOU, image, benevolence, and near-term and long-term USE should associate with the presence of intention to use. Also, we set gender as a 'both' condition, meaning that gender would be associated with intention to use regardless of whether it was present (female users) or absent (male users).

After calibrating the variables, we set the frequency cutoff at 3 and set the consistency cutoff value to 0.93 in order to identify the different solution sets. Tables 6 and 7 show the configurations of the intermediate and complex antecedent conditions that are related to high membership values in the outcome condition of behavioural intention to adopt mobile government services. The configurations in Table 7 are grouped on the basis of their core conditions. The raw coverage of the solutions is between 0.109 and 0.338, and the consistency values for all

[2]Please see the manual at http://www.u.arizona.edu/~cragin/fsQCA/download/fsQCAManual.pdf

Table 6. Intermediate solutions of the FsQCA method

Solution	Casual conditions: Gender	Near-term usefulness	Ease of use	Long-term usefulness	Benevolence	Image	Raw coverage	Unique coverage	Consistency	Solution coverage	Solution consistency
1	○					●	0.383	0.383	0.911	0.655	0.919
2	●		●	●	●		0.272	0.272	0.931		

Filled circles indicate the presence of the corresponding condition, while open ones symbolize the absence of the condition (in other words, the presence of the negation of the condition). Empty cells represent ‘Don’t care’ conditions. Furthermore, large circles refer to core conditions, while small circles indicate peripheral conditions.

Table 7. Complex solutions of the FsQCA method

Solution	Casual conditions: Gender	Near-term usefulness	Ease of use	Long-term usefulness	Benevolence	Image	Raw coverage	Unique coverage	Consistency	Solution coverage	Solution consistency
1a	○			•	•	●	0.338	0.015	0.956	0.637	0.933
1b	○	•	•		•	●	0.331	0.008	0.948		
1c	○	•	•	•		●	0.330	0.009	0.951		
1d	○	○	○	○	○	●	0.109	0.005	0.974		
2	●		●	●	●		0.272	0.271	0.931		

Filled circles indicate the presence of the corresponding condition, while open ones symbolize the absence of the condition (in other words, the presence of the negation of the condition). Empty cells represent ‘Don’t care’ conditions. Furthermore, large circles refer to core conditions, while small circles indicate peripheral conditions.

solutions are above 0.92. Ragin (2008a) suggests that gaps in the upper range of consistency are useful for establishing a consistency threshold and that a threshold below 0.75 indicates substantial inconsistency. The high consistency of all the reported solutions also indicates that a subset relation exists and supports an argument of sufficiency (Rihoux & Ragin, 2009).

For illustration of the relationships between the ‘Intention to adopt’ outcome and the complex solutions identified, the fuzzy membership values for an observation in the two fuzzy sets corresponding to Intention and the seven solutions identified can be depicted as in Appendix D. An observation supports the sufficiency of a causal combination if the fuzzy membership in Intention is higher than the membership in the combination (i.e. the point is above the diagonal line in the plots). As we can observe, most of the cases are above the diagonal; additionally all of the figures indicate an asymmetric relationship between intention and the antecedent combinations, supporting the appropriateness of FsQCA as a complement to RBMs.

Fiss (2011) has suggested that the configurations can be further classified, into first-order and second-order solutions, on the basis of the equifinality of the different core conditions exhibited. Using Fiss’s method (Fiss, 2011), we identify two first-order equifinalities of solutions, along with a second-order, within-type equifinality for solution 1 (1a, 1b, 1c, and 1d), as shown in Table 7.

The results in Table 6 show that, given our assumptions, there are two major configurations leading to intention to use. Specifically, for a group of male users, the presence of image is sufficient for obtaining intention to use, regardless of these users' perceptions of the EOU, benevolence, and near-term and long-term USE. In other words, solution 1 suggests a group of males seeking image-enhancement. Solution 2 presents a combination of the presence of EOU, long-term USE and benevolence for a group of female users. This suggests that certain female users are willing to adopt the technology if they have an aim of improvement in their quality of life in combination with a belief that the government is trustworthy in providing them with technology that can be easily used.

The unique coverage value in Table 6 suggests that configuration 1 uniquely covers 38.3% of the membership of the observations belonging to the fuzzy set 'Intention to use', while solution 2 uniquely covers 27.2% of the membership values. Therefore, solution 1 is a more prevalent recipe than configuration 2 for facilitating adoption of the technology.

Table 7 provides more detailed information for determination of the features of the user groups that are specified in the intermediate solutions (Table 6). For instance, solutions 1a, 1b, 1c, and 1d (Table 7) can be regarded as a detailed characterization of the major features of four key sub-groups of users as described by solution 1 in Table 6. Specifically, we can see that image is a sufficient condition for a male user group with high membership of both benevolence and long-term USE of adopting the technology (solution 1a). Also, image is a sufficient condition for another male user group with negative perceptions as to EOU, benevolence, and near-term and long-term USE of adopting the technology.

Therefore, based on both the core and peripheral conditions across all the configurations, practical suggestions can be made with relevance for different user groups. This offers practitioners a reference for adopting relevant strategies based on the particular features of the different user groups. Specifically, the peripheral conditions as well as the 'absent' core perceptions defined the features of the particular user groups. The 'present' core perceptions determined which strategies practitioners should improve with respect to the user groups in question.

For instance, for practitioners, the results suggest that it is important to enhance the perception of image for male users (solution 1). Specifically, image will be a sufficient condition for four particular male user groups. These four user groups are characterized by (i) positive perceptions of long-term USE and benevolence (solution 1a); (ii) positive perceptions of near-term USE, EOU, and benevolence (solution 1b); (iii) positive perceptions as to EOU and near-term and long-term USE (solution 1c); and (iv) negative perceptions of the perceived EOU, benevolence, and near-term and long-term USE (solution 1d). The peripheral conditions may be necessary for the core conditions to take effect. Therefore, with those males who report a high value for benevolence, it is necessary to increase the perceived long-term USE (solution 1a) or EOU and near-term USE (solution 1b), so that image can work as a sufficient condition. Solution 2 indicates the strategies for females: the practitioners need to improve the perceived EOU, benevolence and long-term USE in order for females to adopt their technology.

Furthermore, as is mentioned previously, the coverage value of a solution indicates the percentage of the aggregated membership values for the cases that take the given path specified by the solution to the outcome, enabling researchers to assess the importance of the individual causal paths. In terms of overall solution coverage, the combined models account for about 66% of membership in the outcome. No unique condition is found to be shared across all solutions, suggesting the lack of a unique necessary condition. This also suggests the existence of large deviations in the motivations for adopting the technology.

The theoretical implications of the results can be described in brief as (i) offering evidence that causal asymmetry exists in the context of mobile government services adoption; (ii) identifying two main configurations for the mobile government services adoption, along with their relative importance via unique coverage; (iii) discriminating the relative importance of a factor in a configuration through detection of core vs. peripheral factors; and (iv) specifying the relevance of a particular configuration to a specific gender group in mobile government services adoption.

Discussion

To contrast FsQCA with RBMs, duplication of the test with an RBM was performed. The results are provided in Appendix E. Specifically, the SEM test shows that perceived image, long-term USE, EOU, and benevolence have a significant influence on intention to use while gender[3] and near-term USE are insignificant determinants. The model explained 36.2% of the variance of intention to use. In other words, a high proportion of variance remains unexplained.

It is worth noting that RBMs and FsQCA differ in their assumptions and in how they interpret social phenomena, and subsequently the respective nature of both the knowledge and theory that they establish. More specifically, even though RBMs and FsQCA share the same target objective for study of IS user behaviour, the insight they offer differs substantially (c.f. Becker & Niehaves, 2007).

From an epistemological perspective, RBMs such as MRA and SEM are instruments for obtaining 'linear-style' knowledge of *an assumed* '*symmetric and linear*' *world*, and factors in this world compete in the explanation of outcomes – for example, through R^2. In other words, MRA and SEM are manipulated to reduce the complexity of human nature to a symmetric and linear world through looking separately at the effect of each individual factor in order to facilitate easier, intuitive but simplified interpretation of social phenomena.

We can take the result of SEM analysis as an example. Near-term USE in this study was reported to have no significant *linear* relationship with intention to use. Frequently, this kind of insignificant relationship is interpreted as confirming that there is no effect at all, because the matter of assuming of a symmetric relationship is often ignored. Meanwhile, the interpretation of each independent variable can (and should) be performed separately and individually. For instance, a one-unit increase in the value of image can, on its own, lead to an increase in intention to use amounting to 0.228 units (Appendix E), independently of the initial values of other variables. Therefore, suggestions from RBMs for practitioners can include adopting strategies to improve people's perceptions of image ($\beta = 0.228$), long-term USE ($\beta = 0.225$), EOU ($\beta = 0.178$), and benevolence ($\beta = 0.151$) and that they should not focus on near-term USE or gender issues.

[3]Gender is set to be a numeric variable with a value of either 1 (male) and 2 (female) from the perspective of categorical regression analysis.

Epistemologically, FsQCA describes the world of IS user phenomena in a different manner. It assumes the existence of asymmetric relationships in this world, therefore necessary and/or sufficient conditions are needed if one is to capture a particular social phenomenon. Accordingly, in contrast to RBMs, the world of FsQCA is not necessarily linear and symmetric, though it does not object to the existence of symmetric relationships. For instance, whilst the results of SEM analysis reject the existence of significant (linear) impact of both near-term USE and gender on intention to use, FsQCA reports the two variables as either core or peripheral conditions in different solutions that trigger the intention to adopt. In other words, factors reported with no significant linear relationships may be reported as important conditions by FsQCA from an asymmetric relationship perspective. In addition, through configurations, FsQCA interprets the effect of an individual variable by considering the presence or absence of other variables, thereby resulting in an understanding of the effect of '*variable in context*'.

Moreover, when accounting for the features of RBMs, researchers have to make a symmetric hypothesis and build relevant theories that are based on symmetric relationships between variables (c.f. Davis, 1989). Frequent appearance of the same factor in different studies—as a significant and influential factor in the symmetric relationship in question – is widely understood as indicating accumulation of the *knowledge* that this factor is important, and the theory is thereby further confirmed. In our illustrative study, image is the most influential factor and if this finding is broadly confirmed by other studies of e-government, image would be likely utilized as a core factor in future model/theory-building linked to e-government services adoption.

In contrast, the knowledge accumulation or theory-building in FsQCA is grounded not in hypothesized symmetric relationships between individual factors, but in the existence and popularity of configurations portraying how individual factors function together in bringing about a given outcome. The frequent appearance of a particular configuration across different research contexts facilitates accumulating understanding of its importance or of knowledge of the configuration. For instance, the primacy of image among males in the solutions in the study described here highlights its importance in motivating their adoption of the technology. If substantially more studies report similar findings or configurations, this fact can be used as a theoretical basis for development of relevant adoption theories. From this perspective, we tentatively propose that the major difference in theory's building and testing between configurational analysis and RBMs may be that RBM theory is fundamentally based on testing of individual factors and individually hypothesized relationships while configurational analysis is based on testing the validity of particular configurations or added combinations of particular variables. From our review of FsQCA literature, it seems that configurational research today is still at the stage of tentatively implementing FsQCA in different contexts, on the basis of the hypothesized importance of individual factors. In this regard, we tend to believe that a long enough period for accumulating understanding of the importance of particular configurations is a necessary step in providing important materials for the building of a future, more sophisticated configuration-based theory. More detailed comparison between RBMs and FsQCA is provided in Appendix F.

To summarize, we argue that the main benefit of FsQCA lies in supplementing mainstream, symmetric-relationship-based RBMs by offering a more complete understanding of IS use phenomena from an asymmetric relationship perspective: enabling new insights, greater knowledge in the field, and new IS theory. Meanwhile, IS researchers should also be aware of FsQCA's potential drawbacks (Subsection 2.4): interpreting very complex results is highly labour-intensive, potentially resulting in a large amount of subjective bias. Finally, considering the features of both RBMs and FsQCA, we recommend the use of FsQCA as a supplement to mainstream RBMs in IS research when (i) the conventional symmetric approach cannot satisfactorily interpret the given IS phenomenon of interest, (ii) evidence suggesting asymmetric relationships becomes a prevalent issue (Figure 1),[4] or (iii) the primary task of the research is full interpretation of the given IS phenomenon of interest. Similar to SEM, construct validity is an important requirement when the relationships between latent variables can be studied for FsQCA.

Conclusions and limitations

The paper has described our endeavor to introduce FsQCA to the IS behavioural research community in terms of its capacity to model asymmetric relationships among IS behaviour determinants. We believe that introducing the FsQCA to the IS user behaviour research community enables new insights into IS user behaviour, in line with similar processes in other social science disciplines. It is an in-depth guide to the use of the method and an example showcasing the differences and benefits of the methodology brought by the method relative to RBMs. We hope it speeds up the IS community's adoption of FsQCA.

Here, we have offered evidence of the asymmetric effects of IS behavioural determinants on IS behaviour. This result is not astonishing, given that pure symmetrical relationships are rare in practice (Woodside, 2013). This lays a fundamental and concrete foundation for future incorporation of FsQCA into IS behaviour research. We have also demonstrated how FsQCA aids in detecting and uncovering asymmetric relationships in explanations of IS behaviour phenomena, by such means as tailoring the data calibration technique related to full membership for the uniqueness of IS user perception variables. The identification of configurations contributes to a new basis of understanding IS user phenomena and for future development of both knowledge and theory.

Furthermore, this work has provided detailed guidance on how to use FsQCA in IS behaviour research. Various features of FsQCA have been discussed and advanced functions described, offering a possibility for IS scholars to tailor the method to the contexts of their own research. In addition, proceeding from the work of Fiss (2011), we have incorporated the concept of core and peripheral conditions into our understanding, to differentiate the effects of different conditions in a configuration.

Through the study, we offer evidence that different configurations leading to the same behavioural outcomes do exist. Our results show that FsQCA is applicable to IS behaviour research and can offer new insights in understanding IS phenomena. In particular, the configurations assist in confirming and quantifying how (i) different configurations of determinants lead to the same IS behaviour and that (ii) users who have negative perceptions of a certain attribute of

[4]The correlation value may not necessarily be a good indicator of a symmetric/asymmetric relationship, if the correlation is established primarily by the data points in one or two quadrants. Therefore, we recommend a direct examination of distribution to detect the extent of counter-hypothesis observations in the dataset, as with people who perceive the technology useful but do not adopt it and vice versa (Figure 1). Accordingly, an important benefit of this analysis is that perfect set-theoretic relationships can be present even in the absence of strong correlations.

IS will still adopt the IS on account of the positive value they attribute to some other features of the IS. Understanding the trade-offs between individual attributes and identifying different paths to the behavioural outcome are important for researchers and practitioners alike.

The knowledge obtained from FsQCA and from RBMs are of epistemologically different nature. Harmoniously integrating knowledge gained from the use of FsQCA and RBMs into a unified theory is a challenge that our study cannot address. Given the limits of our experience and knowledge, some unknown benefits and problems of applying FsQCA within IS behavioural research may exist. Furthermore, the rapid advancing of FsQCA and its broad usage may well mean that some innovative implementation of the method has appeared during our writing process. We call for further independent and innovative research to ascertain the full potential of FsQCA for IS research.

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APPENDIX A.

PERCEIVED EASE OF USE

EOU1: I think it is easy to access San-nong-related government information through a mobile phone.

EOU2: For me, it is easy to access San-nong-related government information through a mobile phone.

EOU3: Learning to use a mobile government for San-nong-related government information is easy.

EOU4: Overall, mobile government is easy to use.

Perceived near-term usefulness

PU1: Mobile government improves my efficiency in accessing San-nong-related government information.

PU2: Mobile government makes it easier to access San-nong-related government information.

PU3: Mobile government saves my time and effort to access San-nong-related government information.

PU4: Mobile government improves my performance to access San-nong-related government information.

Perceived long-term usefulness

VA1: Using mobile government helps improve my family income.
VA2: Mobile government improves my production efficiency.
VA3: Using mobile government helps improve the quality of my life.

Benevolence

BE1: Mobile government puts peasants' interests first.
BE2: Mobile government keeps peasants' interests in mind.
BE3: Mobile government understands peasants' needs and preferences.

Image

IM1: People who adopt mobile government have a better reputation.
IM2: People who adopt mobile government have high prestige.
IM3: People who adopt mobile government have a better social status.

Intention

INT1: I plan to use mobile government in the future.
INT2: I predict that I will use mobile government in the future.

APPENDIX B.

Rotated component matrix

	Component					
	1	2	3	4	5	6
Long-term usefulness1	.202	.226	.137	.132	.827	.209
Long-term usefulness2	.152	.259	.198	.109	.840	.088
Long-term usefulness3	.185	.289	.204	.171	.785	.142
Near-term usefulness1	.139	.842	.019	.205	.186	.129
Near-term usefulness2	.192	.846	.006	.155	.191	.124
Near-term usefulness3	.246	.794	.108	.156	.221	.062
Near-term usefulness4	.259	.614	.289	.222	.349	.005
Benevolence1	.138	.198	.132	.881	.103	.148
Benevolence2	.124	.223	.178	.872	.103	.109
Benevolence3	.149	.160	.218	.816	.175	.093
Ease of Use1	.823	.205	.109	.154	.151	.056
Ease of Use2	.848	.135	.170	.078	.226	.053
Ease of Use3	.783	.242	.164	.113	.049	.189

(Continues)

APPENDIX B. (Continued)

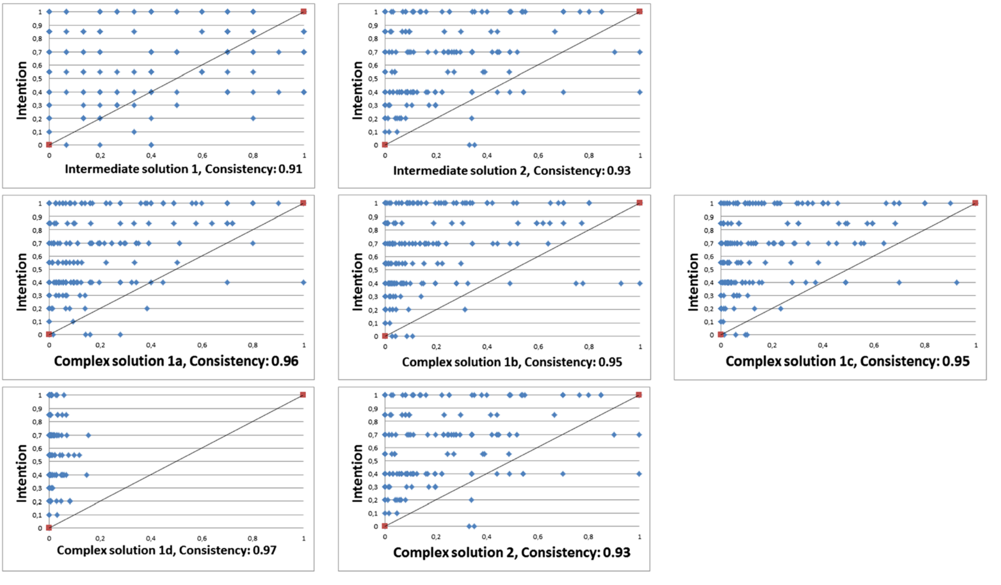
Ease of Use4	.821	.148	.184	.127	.145	.190
Image1	.173	.108	.893	.176	.154	.148
Image2	.199	.093	.871	.197	.201	.145
Image3	.197	.035	.891	.167	.155	.166
Behavioural Intention1	.184	.123	.234	.168	.191	.862
Behavioural Intention2	.190	.131	.175	.147	.159	.884

APPENDIX C.

```
#The following is the R code developed to facilitate data calibration.
#First we calibrate binary variables using the following function.
#The original variable has values 1 and 2 (if it is 0 and 1, there is no need for calibration)

bin <- function(x) x-1

# We can calibrate every binary, Var.b.i variable as follows

Var.b.1.f <- bin(Var.b.1)
…
Var.b.n.f <- bin(Var.b.n)

# Here is a general function to calibrate a variable by using an ordinal scale with k items into fuzzy memberships
# First, we define the linear membership function on a subinterval of the domain
# Later, x will be the scale item to be recalibrated, a and b two
# consecutive scale items with corresponding associated fuzzy membership values m and n

bas <- function(x,a,b,m,n) m+(n-m)*((x-a)/(b-a))

# Using this function we can create a general calibration function
# The m_i values are all the membership values associated to the scale
# and are to be defined in the next step
# The calibration will result in a piecewise linear function

likert <- function(x,m_1,m_2,…,m_k) ifelse(x < 2, bas(x,1,2,m_1,m_2),

ifelse(x >= 2 & x < 3,bas(x,2,3,m_2,m_3),…
ifelse(x >= k – 1 & x <= k, bas(x,k-1,k,m_k-1,m_k),0 ))))

#Here we define the breaking point for the membership function
n_1 < –0
n_2 < –0.2
n_3< –0.4
```

```
…n_k <- 1
# Finally we calibrate the ordinal variables Var.o.i
Var.o.1.f <- likert(Var.o.1,n_1,n_2,…,n_k)
…
Var.o.m.f <- likert(Var.o.m,n_1,n_2,…,n_k)
```

APPENDIX D.



APPENDIX E.

Hypothesized relationship	Path coefficient	*p*-value
Gender → Intention	0.009	Not significant
Near-term usefulness → Intention	−0.009	Not significant
Ease of use → Intention	0.178	$p < 0.01$
Long-term usefulness → Intention	0.225	$p < 0.01$
Benevolence → Intention	0.151	$p < 0.01$
Image → Intention	0.228	$p < 0.001$

- In RBMs, coding of gender as a numeric variable (1 or 2 for male or female respectively).
- R^2 explained: 36.2%.
- Model fit index: CMIN/DF = 3.17; $p < 0.001$; AGFI = 0.850; NFI = 0.929; IFI = 0.950; TLI = 0.936; CFI = 0.950; RMSEA = 0.073.
- Correlation between gender and intention (correlation = - 0.032, $p = 0.524$).

APPENDIX F.

	RBMs	FsQCA
Key assumptions	• The relationships between variables are assumed to be symmetric and linear in MRA and SEM. - The five precursors are *symmetrically* related to the intention to use.	• The relationships between variables can be either asymmetric or symmetric. - The precursors are identified as sufficient and/or necessary conditions for the intention to use.
Hypothesized direction of relationship (HDR)	• HDR affects the acceptance or rejection of a hypothesis. - The precursors positively relate to intention to use.	• HDR affects the results of intermediate solutions, but not complex solutions - The presence of each of five predictors is assumed to be associated with the presence of the intention to use in intermediate solutions.
Relationships between precursors	• Precursors compete to explain the phenomena through R^2. - Adding a new precursor tends to reduce the predictive power of other variables, even though it may increase the total R^2.	• Precursors cooperate to explain the phenomena by means of configurations. - Adding a new variable probably enriches the configurations. However, it may make interpretation of the result more difficult.
Examination of relationship	• The *p*-value is used: - For example: image significantly affects the intention to use at the level of p-value < 0.001.	• Consistency is used to measure the sufficiency of a combination - For example: a consistency 0.91 for Intermediate solution 1 means that 91% of the membership of intention to use is accounted for in the cases wherein the configuration male and image is present.
Interpretation of counter-hypothesized relationship (CHR)	• A CHR cannot be well explained, as it conflicts with prior knowledge. - An example is found in the samples in the red region of Figure 1.	• A CHR can be properly explained. - For example: people who have a negative perception of near-term usefulness may also exhibit adoption when particular conditions are satisfied.
Estimation for individual factor	• The effect of an individual factor can and should be interpreted individually. - For example: A one-unit increase in the value for image can lead to a 0.228-unit increase in intention to use. - Explaining the effect of individual variables is easy.	• Usually, the effect of a factor cannot be interpreted on its own without consideration of other factors. - An example is solution 1 in Table 6. - Explaining the effect of an individual variable is difficult.
Knowledge accumulation	• Acceptance or rejection of a hypothesis is based on the strength of its effect.	• Detection of a configuration is related to its existence and coverage value.
Theory-building	• The generalization of hypotheses is handled by application of the assumption of a symmetric relationship.	• The generalization of a configuration is based on the assumption that asymmetric relationships can exist.