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Qualitative Comparative Analysis (QCA) In Information Systems Research: Status Quo, Guidelines, and Future Directions

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Abstract:

Qualitative comparative analysis (QCA) allows researchers to study how configurations of conditions lead to outcomes and, thereby, richly explain the dynamics of complex digital phenomena. To advance discussion on QCA in the information systems (IS) discipline, we introduce its fundamental concepts and offer guidelines for authors on how to apply QCA to advance IS research. We also provide checklists for reviewers of QCA papers. We illustrate how to apply our guidelines through two exemplar studies. In the first exemplar study, we focus on IT-business strategic alignment to study the influence that different forms of alignment have on firm performance. In the second exemplar study, we use the perspective of the integrated technology acceptance model to explain an individual's intention to use a digital assistant. The contrasting results from both studies highlight how to use QCA to derive robust and reproducible results. By doing so, we contribute to encouraging IS scholars to use QCA to develop sophisticated models that accurately depict real-world IS phenomena.

Keywords: Qualitative Comparative Analysis (QCA), Configurational Approach, IT-business Strategic Alignment, Integrated Technology Acceptance Model (TAM), Firm performance, Digital Assistant.

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1 Introduction

Qualitative comparative analysis (QCA) has become an increasingly prevalent method for configurational approaches across business and behavioral sciences (Misangyi et al., 2017; Mattke et al., 2021b). QCA draws on set-theory, using Boolean algebra, to explain the relationships between multiple conditions—or configurations thereof—and an outcome (Ragin, 2014). Consider how different forms of alignment (i.e., business, IT, intellectual, and operational alignment) relate to firm performance as Henderson and Venkatraman (1999) proposed. Following QCA terminology, the four forms of alignment represent conditions and firm performance represents the outcome; together, they allow one to study two types of relationships. On the one hand, QCA identifies whether specific conditions are necessary for an outcome to occur (i.e., whether any of the four forms of alignment always needs to exist for a firm to achieve high performance). For example, does intellectual alignment always need to exist for firms to have high firm performance? On the other hand, QCA identifies whether specific configurations of conditions prove sufficient to evoke an outcome. Put differently, QCA can identify whether different combinations of the four alignment types, such as intellectual and operational alignment, always lead to high firm performance regardless of the others.

Overall, QCA provides a promising way to unfold the complexity associated with the interplay between multiple conditions that influence an outcome and how these conditions can compensate for one another. Among its many benefits, QCA considers that the explanations that lead to an outcome's occurrence often differ from those that lead to its nonoccurrence and are not the inverse explanation. For example, to continue with our example above, one can use QCA to analyze what configurations evoke high firm performance separately from what configurations evoke low firm performance. Thus, it allows one to refine which configurations lead to a high-level outcome and differentiate them from other configurations that lead to low-level outcomes. In addition, one can apply QCA to understand how the interplay between multiple conditions influences an outcome. For example, QCA can identify several—and hypothetically quite different—explanations where high and low levels of a condition affect an outcome and depend on the interplay with other conditions. For example, QCA might show that low IT alignment might be associated with high firm performance in one configuration, while high IT alignment might also explain high firm performance in a different configuration. Thus, QCA can provide valuable insights when one expects non-linear influences.

In IS research, mainly relatively new studies have applied QCA. While some IS studies have used QCA at the individual (Mattke et al., 2020a) and organizational levels (Park et al., 2020), our discipline mostly lacks shared knowledge about how to conduct a QCA study, how to report validation criteria, and how to evaluate QCA results. To build a shared understanding, we introduce QCA's foundations, propose guidelines for applying QCA in IS research, illustrate the guidelines with two studies, and highlight QCA specific recommendations for IS research. We contribute to the IS discipline by guiding scholars on how to rigorously apply QCA in the IS field.

2 QCA Foundations

Charles Ragin established qualitative comparative analysis (QCA) in 1987 to analyze complex patterns in the social sciences, and researchers commonly applied it to studies with sample sizes too small for regression models but too large for cross-case analyses (Ragin, 2014). While researchers initially applied it to many macro-level topics, QCA has gained widespread application in management and organization research.

As its main benefit, QCA can create rich explanations for complex phenomena. QCA draws on set theory, using Boolean algebra, to empirically examine the relationship between multiple conditions and an outcome (see Table 1). In the QCA context, "condition" refers to a set membership in a variable, which QCA uses to explain the outcome. The "outcome" refers to a set membership in a variable that one or more conditions explain. QCA represents the outcome and the conditions as set memberships, and a condition or outcome may either fully or partially belong or not belong to a set. Thus, a condition's or outcome's value expresses the extent to which it belongs to a set (Mattke et al., 2021b).

To illustrate how to apply QCA, we continue the example relationship between IT strategy and firm performance. In a QCA study, one would represent the outcome "high firm performance" as a set. The representation as a set enables one to express a measurement of a firm's performance as the extent to which the measurement belongs to the set "high firm performance".

While QCA can analyze single conditions, it can also enable one to group multiple conditions together as a configuration (of conditions) that link to an outcome. In a configuration, each condition shows a certain membership in the set. QCA uses set theory to identify configurations that explain outcomes. Thus, to continue with our illustration, we can examine whether different alignment configurations lead to high or low firm performance, a well-studied topic in IS research (Henderson & Venkatraman, 1999; Chau et al., 2020). Thus, in QCA terms, the conditions include 1) business alignment, 2) IT alignment, 3) intellectual alignment, and 4) operational alignment, while form performance constitutes the outcome. QCA allows one to analyze what configurations among these four alignment forms evoke high firm performance. A configuration would refer to any combination of the four alignment forms linked to a firm performance, where each condition and the outcome can have a certain set membership.

Table 1. Definition for Central QCA Terms (Ragin, 2014; Schneider & Wagemann, 2012)

QCA terms	Definition
Condition	A condition refers to a set membership in a variable, which QCA uses to explain the outcome. A condition is expressed in a set membership where the value 0 indicates that a condition is fully out of a set and the value 1 indicates that a condition is fully in a set.
Outcome	An outcome refers to a set membership in a variable that the conditions explain. The outcome is expressed in terms of a set where 0 indicates that an outcome is fully out of a set and the value of 1 indicates that an outcome is fully in a set.
Configuration	A configuration refers to a specific group of conditions that links to a specific outcome. Thus, a configuration shows a group of conditions that may or may not exhibit the outcome.

Two major variants exist in representing conditions and outcomes in sets (Table 2). First, one can represent conditions and outcomes as binary (0 or 1), also known as crisp sets (cs), which means that an observation is either fully out of a set (which the value 0 represents) or fully in a set (which the value 1 represents) (Ragin, 2014). Crisp sets do not account for partial membership. For instance, we can represent intellectual alignment as a crisp set. We can either say that a firm has low intellectual alignment (crisp set value 0) or high intellectual alignment (crisp set value 1).

Second, conditions and outcomes can have any continuous value between 0 to 1, known as fuzzy sets (fs), and, thus, can represent membership in a set along a membership continuum (Ragin, 2000). By using fuzzy sets, one can represent the extent to which a firm has realized intellectual alignment in a more nuanced way (e.g., the fuzzy value 0.70 represents rather high intellectual alignment but not as high as the fuzzy value 1). Similarly, the fuzzy value 0.30 represents rather low alignment but not as low as the fuzzy value 0. The fuzzy value 0.50 indicates the point of maximum ambiguity, which means that one cannot classify a condition or outcome as more belonging to or not belonging to a set. We discuss the special role that 0.50 fuzzy values play in Section 3.3.

QCA explains the relationship between conditions and an outcome. To do so, QCA tests for sufficient configurations that explain an outcome and necessary conditions in sufficient configurations. Sufficient configurations imply that every time a particular configuration exists, a specific outcome exists as well. A sufficient configuration for the outcome exists if all observations of a particular configuration display the outcome as well (Ragin, 2014). In set theory terms, if the configuration results in a consistent subset of the outcome, it indicates a sufficient configuration (Schneider & Wagemann, 2012). In our running example, one configuration with high levels in all four forms of alignment might evoke a high firm performance. Another configuration might show high business alignment, high IT alignment, but low intellectual alignment and still evoke high firm performance.

One calls a condition necessary if all configurations that display the outcome also exhibit the condition. In set theory terms, if the condition constitutes a superset of the outcome, the condition constitutes a necessary condition for the outcome to occur (Schneider & Wagemann, 2012). In other words, a necessary condition needs to exist if the outcome exists as well. When speaking about alignment, we might see high intellectual alignment exists in all configurations that lead to a high firm performance; in this case, we would conclude that high intellectual alignment constitutes a necessary condition for high firm performance.

Table 2. Crisp and Fuzzy Sets (Ragin, 2014; Schneider and Wagemann, 2012)

<table>
<tr><th colspan="5">Crisp set (cs)</th></tr>
<tr><td>Fully out of a set</td><td>Rather out a set</td><td>Point of maximum ambiguity</td><td>Rather in a set</td><td>Fully in a set</td></tr>
<tr><td>The value 0 means that a condition or outcome does not belong to a set and refers to a low level of the condition or outcome.
Researchers often refer to such conditions and outcomes as absent.</td><td>Does not exist</td><td>Does not exist</td><td>Does not exist</td><td>The value 1 means that a condition or outcome belongs to a set and refers to a high level of the condition or outcome.
Researchers often refer to such conditions and outcomes as present</td></tr>
<tr><th colspan="5">Fuzzy set (fs)</th></tr>
<tr><td>Fully out of a set</td><td>Rather out a set</td><td>Point of maximum ambiguity</td><td>Rather in a set</td><td>Fully in a set</td></tr>
<tr><td>The value 0 means that a condition or outcome does not belong to a set.</td><td>Values lower than 0.50</td><td>The value 0.50 indicates the point of maximum ambiguity where the condition or outcome is neither in nor out of the set.</td><td>Values higher than 0.50</td><td>The value 1 means that a condition or outcome belongs to a set.</td></tr>
<tr><td colspan="2">All fs values smaller than 0.50 refer to a low level of the condition or outcome.
Researchers often refer to such conditions and outcomes as absent.</td><td></td><td colspan="2">All fs values larger than 0.50 refer to a high level of the condition or outcome. Researchers often refer to such conditions and outcomes as present.</td></tr>
</table>

3 Guidelines for Using QCA in IS Research

In the following, we provide a step-by-step framework to guide scholars seeking to use QCA. In each step, we explain the main tasks for the analysis and direction for scholars who author and review QCA papers (see Table 3 for an overview). Additionally, we illustrate each step with two exemplar studies. In the first exemplar study, we direct attention to the influence that different configurations of different forms of alignment have on firm performance (Gerow et al., 2015). In the second exemplar study, we build on the integrated technology acceptance model (Pavlou, 2003) to explain what configuration of trust, risk, usefulness, and ease of use lead to an individual's intention to use a digital assistant. We chose both studies because IS scholars know the underlying theories well the research shows that an interplay between the conditions exists (Table 4 third row). Furthermore, the two studies highlight how unique QCA aspects influence the analysis and the results.

Table 3. Seven Step Framework for QCA

Step	Description	Checklist for authors	Checklist for reviewer
Step 1: develop a configurational model	Ground the configurational research model and the selected conditions on theory and/or root it in specific knowledge of why the conditions relate to the outcome.	• Use theoretical and/or specific knowledge to justify selected conditions. • Explain why considering configurations can shed new light on a phenomenon.	• Did the authors justify the conditions they selected?
Step 2: collect and validate data	Collect and validate data.	• Consider the maximum number of conditions in the model. As a general rule of thumb, QCA can handle six conditions, and one should combine an increase in conditions with a significant increase in observations. • Use a sampling strategy that favors a high number of possible configurations (i.e., high variance in the observations). • Sample configurations that lead to a high outcome and to a low outcome. • Test the data for (content, discriminant) validity, (indicator, construct) reliability, and potential biases (especially common method bias).	• Did the authors consider an appropriate number of conditions for the sample size? • Did the authors collect appropriate data for the study? • Did the authors validate the data? • Did the authors test the data for bias?
Step 3: calibrate the data	Calibrate the collected data into crisp sets and/or fuzzy sets.	• Use fuzzy sets rather than crisp sets whenever possible. • Justify the calibration anchors (i.e., when values fully belong or do not belong to a set) based on theory, logic and/or good practices. • Report the anchor for calibration. • Deal with 0.50 fuzzy values.	• Did the authors justify why they used crisp sets justified (if applicable)? • Did the authors report calibration anchor? • Did the authors base calibration anchors on theory, logic, and/or best practices?
Step 4.1: analyze necessary conditions for the high level of the outcome	Test whether a high or a low single condition constitutes a necessary condition for high outcome.	• Use at least a 0.90 consistency threshold and 0.60 coverage threshold to identify necessary conditions. • Examine the high and low conditions for necessary conditions. • Report the consistency and coverage values for all tested conditions. • Discuss whether the necessary conditions make theoretical and practical sense. • Report the relevance of necessity (RoN) if a lack of variance could have caused a necessary condition (e.g., it remained nearly “constant” in the data set).	• Did the authors report the consistency threshold they used? • Did the authors report consistency and coverage values for all conditions? • Did the authors test the necessary condition for the high and the low outcomes?
Step 4.2: analyze necessary conditions for the low level of the outcome	Test the necessary conditions for the low outcome.		
Step 5.1: analyze sufficient configurations for the high level of the outcome	Construct the truth table and incorporate the calibrated data. Analyze sufficient configurations for the high outcome by applying thresholds. Performing the logical minimization to the sufficient configurations.	• Report the number of possible configurations • Report the logical remainder index, which reports the proportion of truth table rows with no observations (logical remainders). • Report the distribution of the configurations in the data set. • Report the distribution of observations with a high and low outcome. • Chose the frequency threshold so that the significant part (~70 to 80 percent) of the observations remain after applying the threshold.	• Did the authors report the number of observations with a high and low outcome? • Did the authors report how the observations are distributed among the different configurations? • Did the authors discuss how much of the data set the configurations with the highest number of observations cover?

Step 5.2: analyze sufficient configurations for the low level of the outcome	Repeating the procedure in Step 5.1 for sufficient configurations for the low outcome.	• Set the frequency threshold so that each configuration comprises a big enough number (around five percent) of observations to identify common configurations in the data set. • Use a raw consistency threshold of at least 0.75, though one can also use higher thresholds, such as 0.80, 0.85, or 0.90. • Apply a proportional reduction in inconsistency (PRI) threshold (higher than 0.50) when using fuzzy sets to determine sufficient configurations. • Justify the threshold levels. • Report the entire truth table or reduced truth table.	• Did the authors report the logical reminder index? • Did the authors discuss whether the logical reminders compromise QCA results? • Did the authors report and justify the frequency threshold, raw consistency, and PRI consistency? • Did the authors report the (reduced) truth tables?
Step 6: report the findings	Display the solution graphically.	• Graphically report the minimized sufficient configurations. • Include the necessary conditions in the graphical solution. • Include relevant key figures in the graphical solution to judge the data's quality and findings' robustness.	• Did the authors graphically report the solution?
Step 7: validate the findings	Validate and report on the results' robustness.	• Report the robustness to thresholds. • Report the robustness to calibration.	• Did the results remain stable to different thresholds? • Did the results remain stable to different calibration processes?

3.1 Step 1: Develop a Configurational Model

To conduct a QCA, one first needs to develop a configurational research model. To do so, one needs to determine relevant conditions based on theory and/or specific domain knowledge (Ragin, 2014). While some theories explicitly state an underlying mechanism that comprises a complex interplay between multiple conditions (Greckhamer et al., 2013), researchers can find it difficult to determine why configurations need to be considered because most theories do not offer arguments about why an outcome results from a configuration (Delbridge & Fiss, 2013). As a result, the initial model development often requires one to explain why considering configurations can shed new light on a phenomenon (Greckhamer et al., 2018).

Table 4. Step One Illustration

	First exemplar study (firm performance)	Second exemplar study (digital assistant use)
Conditions	Business alignment, IT alignment, intellectual alignment and operational alignment	Trust, risk, usefulness and ease of use
Outcome	Firm performance	Intention to use a digital assistant
Theoretical foundation	Based on alignment research, different forms of alignment commonly coexist (in configurations) and that firms can have them at high and low levels (Gerow et al., 2015; Henderson & Venkatraman, 1999).	Based on the integrated technology acceptance model (Pavlou, 2003) and research showing the complex interplay between multiple conditions forming an individual's behavior (Straatmann et al., 2018).

In the first exemplar study, we focus on the running example from above to analyze how different configurations of different forms of alignment influence firm performance. In the second exemplar study, we direct attention to the trend to use digital assistants, such as Apple's Siri and Amazon's Alexa, on mobile or smart home devices (Table 4).

3.2 Step 2: Collect and Validate Data

In the second step, one collects data that satisfy the requirements to use QCA. Even though the letter "Q" in QCA stands for "qualitative", QCA can handle both qualitative and quantitative data since it uses set theory. The only prerequisite to use data in QCA concerns the need to express the conditions and the outcome in sets (see Table 2). Thus, one can transform qualitative data, such as interview or report data, and quantitative data, such as survey data or behavior data, into crisp sets or fuzzy sets (we provide more details in the third step).

The number of conditions in a configurational model determines the minimum sample size that one needs to avoid finding sufficient configurations in random data. Initial guidelines suggest that one needs at least five observations for every condition (Marx & Dusa, 2011; Thomann & Maggetti, 2017). For instance, when examining the four different forms of alignment (and, thus, four different conditions), one would need at least 20 observations. Simulations show that exceeding this threshold (i.e., less than five observations per condition) will increase the likelihood that one will find a sufficient configuration in random simulated data (Marx & Dusa, 2011). Since QCA can work with small data sets, QCA enables researchers to study data sets about a limited overall population. Using the running example, one could not use a cross-case analysis or a linear analysis to learn about which forms of alignment lead to different performance levels for companies in the Dow Jones 30 since the former cannot handle such a big data set, and the latter cannot handle such a small data set.

However, note that sample size alone does not indicate data quality well when the research setting does not allow one to sample a well-defined population or at least an adequate portion of the population. To continue the running example, in case we wanted to examine not only Dow Jones 30 companies but also companies in general with a much larger population, one needs to look beyond the sample size and ensure the data set also includes a high number of possible configurations. That means it must include many possible permutations of conditions with low or high levels. For instance, a configurational model with four conditions has 16 possible configurations (2^k with k being the number of conditions). If, in this example, a data set comprised 30 observations with four different configurations, one would have obtained the minimum required sample size. But one would also find 12 unobserved configurations in the data set (or logical remainders in QCA terminology) that might exist in reality. Hence, the data set only represents 25 percent of the overall possible configurations without any insights on how the other 12 logical remainders relate to the outcome. In this example, the 12 logical remainders might exist in reality but not appear in the data sample. Therefore, researchers should focus on drawing a sample with a high number of possible configurations that lead to a high or low outcome (Greckhamer et al., 2018; Thomann & Maggetti, 2017). A high ratio of observed to possible configurations in the data set better reflects the population so that the higher the ratio, the stronger the analysis's empirical foundation.

Having a high number of logical remainders when these unobserved configurations certainly exist in reality can yield problematic, idiosyncratic results because the data may not contain sufficient configurations to accurately generalize results to reality. Data sets with little variability in the configurations limit the proportion of covered configurations (Wagemann et al., 2016). Such a limitation can lead to biased results because the data set may not reveal basic configurations that exist in reality, which will limit QCA's explanatory power. For example, using logical minimization to reduce the number of sufficient configurations (see Section 3.5) might only reveal a limited number of conditions that do not have an influence (a "don't care situation" in QCA terminology; see Section 3.5). A high number of logical remainders often becomes an even worse problem with a high number of conditions (Wagemann et al., 2016). For instance, a configurational model with ten conditions has 1,024 (2^{10}) possible configurations. Even with 500 observations where each observation represented one configuration, one would find 524 logical remainders.

Note that rare or impossible and nonexistent configurations can also influence how many logical remainders the data set contains (Ragin, 2014). To use the running example, if we sample the Dow Jones 30 companies, 75 percent of the possible configurations might not exist in the data set, which would not be problematic because one can easily argue that these configurations do not exist in reality. For instance, all Dow Jones 30 companies have good intellectual alignment, so one can argue that configurations with low intellectual alignment do not exist in reality when only considering the Dow Jones 30 companies. However, if we analyze companies in general and the data set does not contain 75 percent of the possible configurations, it becomes much harder to argue that these configurations do not exist in reality. For instance, when considering companies in general, configurations with low intellectual alignment likely exist, so these missing configurations would have a higher chance to distort the results.

We outline how to report the number of logical reminders and the implications for the data set in Section 3.5.

Besides drawing a high number of possible configurations (i.e., permutations of conditions with a low or high level), one should adopt a sampling strategy that draws a nearly equal number of configurations that lead to a high and a low outcome (Greckhamer et al., 2013, 2018). One needs to ensure they do so because, when analyzing whether a specific configuration leads to a high outcome, QCA also considers the observations in this configuration that lead to a low level. For this analysis, the data set must have variance not only in the conditions but also in the outcomes. One can ensure it does so by purposefully sampling observations with a high outcome and observations with a low outcome (Greckhamer et al., 2018). We outline how to report the number of configurations that lead to a high and low outcome in Section 3.5.

Returning to our illustration, assume that we want to learn which forms of alignment lead to different performance levels and sample only high-performing firms. Consequently, nearly all configurations in the data will be a sufficient configuration that leads to high firm performance. However, one would not account for configurations that might be irrelevant because they also lead to low firm performance unless one also adopts a sampling strategy that draws observations with low firm performance. Thus, one should take care to use the full sample frame of firms (e.g., those that have both high and low performance). With such a sample, one can examine whether a configuration truly constitutes a sufficient configuration or whether it does only due to an insufficient number of configurations that lead to the low outcome.

Table 5. Step Two Illustration

	Exemplar study 1 (firm performance)	Exemplar study 2 (use of digital assistant)
Data	Existing and pre-validated data (N = 138) that Gerow et al. (2015) collected and published	Purposefully sampled data (N = 232) (for more details about sampling strategy, the validation, and a raw data extract, see Appendix)
Exceeding the minimum number of observations	With four conditions: exceeding the minimum of 20 observations	With four conditions: exceeding the minimum of 20 observations

Both studies used validated data and a large enough sample size to conduct a QCA study since both contained more than 20 observations (see Table 5).

3.3 Step 3: Calibrate the Data

In the third step, one transfers data on conditions and the outcome into crisp sets or fuzzy sets (see Table 2)—a process called calibration.

First, creating crisp sets requires authors to justify why they classify certain condition or outcome values as low (or, in set theoretical terms, as fully out of a set) and as high (or, in set theoretical terms, as fully in a set). To put it in QCA terms, we need to set an anchor that determines which values one classifies as low or high. Thus, transferring data into crisp sets requires one to reduce data to binary values, such as a simple “yes or no”. Consequently, using crisp sets for non-binary data is associated with information loss because conditions and outcomes can only be binary.

To continue our illustration, we can represent intellectual alignment as a crisp set so we can either say that a firm has low intellectual alignment (crisp set value 0) or high intellectual alignment (crisp set value 1). When one measures a firm’s intellectual alignment with eight items using a five-point Likert scale (e.g. Gerow et al., 2015), one can use various dichotomization methods, such as mean split, median split, or the extreme group approach (Butts & Ng, 2009). Researchers most commonly use the mean split as their dichotomization method. To do this dichotomization, one calculates the items’ mean value. One can then represent all mean values that range the value 1 to 4 (exclusive) as the crisp value 0 and all mean values above 4 to 7 as the crisp value 1. In case the value equals 4, one can neither associate it with high or low intellectual alignment. However, we discuss how to deal with this situation (point of maximum ambiguity) later in this section.

Similarly, rather than using quantitative data and calibrating it into crisp sets, one can use qualitative data and calibrate it into crisp sets. For instance, when conducting interviews at firms to assess intellectual alignment, we can classify alignment as having a high level (crisp set value 1) when the interviewees reveal high intellectual alignment. One also uses crisp sets to represent binary data, such as whether a firm belongs to the financial sector.

Alternatively, conditions and outcomes can take on any continuous value between 0 to 1 in fuzzy sets, which can represent any membership between low membership (or, in set theoretical terms, as fully out of a set) and high membership (or, in set theoretical terms, as fully in a set) (Ragin, 2000). When compared to crisp sets, fuzzy sets capture membership more precisely, which make them the preferred solution (Ragin, 2000). For instance, using fuzzy sets, one can represent a firm's intellectual alignment level in a more nuanced way. To continue the example from above, the fuzzy value 0.70 represents rather high intellectual alignment but not as high as the fuzzy value 1. Similarly, the fuzzy value 0.30 represents rather low alignment but not as low as the fuzzy value 0.

One transfers data into fuzzy sets through "direct calibration". The Direct calibration commonly uses a logistic function to calculate the membership and to fit the data in between the three chosen anchors (Schneider & Wagemann, 2012): similar to above, one would define an anchor to classify values as low (or, in set theoretical terms, as fully out of a set), an anchor to classify values as high (or, in set theoretical terms, fully in the set) and additionally a point of maximum ambiguity, which means that one cannot classify values as high or low. Observations between the point of maximum ambiguity and the anchor for fully in a set would receive a fuzzy value between 0.50 and 1. Observations between the set anchor for fully out of a set and the point of maximum ambiguity would receive a fuzzy value between 0 and 0.50 (Ragin, 2008). Thus, taking the same data example with firm's intellectual alignment measured on a five-point Likert scale, one would calibrate the mean value 1 for intellectual alignment to the fuzzy value 0, the mean value 2.50 to the fuzzy value 0.50 and the mean value 5 to the fuzzy value 1. Mean values between 0 and 2.50 will receive fuzzy values between 0 and 0.50, and mean values between 2.50 and 5 will receive a fuzzy value between 0.50 and 1.

In most situations, good practice dictates that one use the minimum value on the Likert scale for the set anchor for fully out of a set, the median value for the point of maximum ambiguity, and the maximum Likert value for the set anchor for fully in a set (Misangyi et al., 2017). On a five-point-Likert scale, some authors just assign the anchors to the values 1, 3 and 5, while others assign the set anchor for fully out of a set to the observed minimum value (or a low-value percentile), the point of maximum ambiguity to the observed mean value (or median value), and the set anchor for fully in a set to the observed maximum value (or a high-value percentile). Assigning values in this way "completely obscures" what the anchor points mean (Wagemann et al., 2016, p. 2534), binds them to the data set, and ignores the substantive meaning of the data that one gathered from a Likert scale (Fiss, 2007).

Note that, rather than high or low values, one specific data set's relative value distinguishes fuzzy sets. Thus, repeating the analysis with a different sample with different data distributions and different mean values would result in substantially different sufficient configurations. For instance, when conducting two different studies that examine a firm's alignment, assume the mean value for intellectual alignment equals 5.50 in study A and 3.50 in study B. When using a mean calibration, we assume that the mean value differentiates a condition's high and low levels. Using such a mean calibration, one would classify values as low in study A but high in study B (see bolded rows in Table 6). Thus, each study would reveal substantially different configurations because one classified the Likert scale data differently.

Table 6. Example for Using Mean Values for Calibration with Different Results

Study A with the mean value 5.5 for a firm's intellectual alignment		**Study B with the mean value 3.5 for a firm's intellectual alignment**	
Likert scale data	Mean calibrated data	Likert scale data	Mean calibrated data
1	0.00	1	0.00
2	0.05	2	0.05
3	0.11	3	0.27
4	**0.22**	**4**	**0.64**
5	**0.40**	**5**	**0.85**
6	0.95	6	0.95
7	1.00	7	1.00

While one might have reasons to depart from using the recommended Likert-type anchors (e.g., dominant high conditions in the population), one needs to justify the calibration anchors based on logic, good practices, or theory (Ragin, 2014; Schneider & Wagemann, 2012). Similarly, when calibrating data that one did not measure on a Likert scale (e.g., a firm's revenue), one needs to justify the logic behind the calibration.

One can use fuzzy sets not only with quantitative data but also with qualitative data by calibrating it into fuzzy sets via the calibration process. To continue our running example, when conducting interviews at firms to assess their firm performance, one can develop an interview guideline to ask specific topics related to firm performance's dimensions (e.g., return on sales, sales growth). For each dimension, one can then define anchor points and assign fuzzy set memberships. For instance, when the interviewees reveal that the firm has an average return on sales, one would assign the fuzzy set value 0.50 to it (Table 7). Based on such defined anchors, one can calibrate the qualitative data into fuzzy sets.

Table 7. Example for Calibrating Qualitative Data

Measure for firm performance	Anchor	Fuzzy set value
Interviewee's assessment of the return on sales.	When stating that the return on sales is very low	0
	When stating that the return on sales is rather low	0.25
	When stating that the return on sales is average	0.50
	When stating that the return on sales is rather high	0.75
	When stating that the return on sales is very high	1

Empirically, the fuzzy value 0.50 represents the point of maximum ambiguity (see Table 2), which means one does not know whether the observation is classified as closer to be in the set or out of the set. QCA algorithm cannot work with configurations that have at least one 0.50 fuzzy set value, resulting in dropping the configuration from analysis (Wagemann et al., 2016). One can use two methods to avoid 0.50 fuzzy set values and, thus, the need to remove configurations: one can either 1). add a small constant (often 0.001) to 0.50 fuzzy values (Mattke et al., 2020a; Maier et al., 2021a) or 2) subtract a small constant from them (Crilly et al., 2012; Maier et al., 2021a) to retain them in future analyses. In Section 3.7, we explain why one needs to test whether the results remain robust to adding or subtracting a small constant.

Table 8. Step Three Illustration

	First exemplar study (firm performance)	Second exemplar study (digital assistant use)
Calibrated into	Fuzzy sets	Fuzzy sets
Likert scale	Five-point Likert scale	Seven-point Likert scale
Anchors for calibration	Value 1 as the anchor for being fully out of the set (resulting in the fuzzy value 0.05), the value 3 as the point of maximum ambiguity (resulting in the fuzzy value 0.50), and the value 5 as the anchor for being fully in the set (resulting in the fuzzy value 0.95)	Value 1 as the anchor for being fully out of the set (resulting in the fuzzy value 0.01), the value 4 as the point of maximum ambiguity (resulting in the fuzzy value the 0.50), and the value 7 as the anchor for fully in the set (resulting in the fuzzy value 0.99)
Dealing with 0.50 fuzzy set values	Added a constant 0.001 to all 0.50 fuzzy values	Added a constant 0.001 to all 0.50 fuzzy values

In the first exemplar study, we calibrated the constructs measured on a five-point Likert scale into fuzzy sets. In the second exemplar study, we transformed the constructs measured on a seven-point Likert scale into fuzzy sets. In both studies, we added a small constant to avoid 0.50 fuzzy set values (see Table 8).

3.4 Step 4: Analyze Necessary Conditions

In step four, one assesses whether each condition needs to exist for the outcome to occur. A necessary condition appears in all observations that have the outcome of interest. As QCA represents outcomes in sets, one can analyze necessary conditions for the high outcome and necessary conditions for the low condition separately (Ragin, 2014).

In order to account for noise in the data and measurement inaccuracies, QCA uses consistency as a tool to measure necessity. In the necessary condition context, consistency refers to the degree to which a condition is a necessary condition, and the consistency value 1 represents a perfect necessary condition (Ragin, 2006). To account for noise in the data, randomness, measurement inaccuracies (Ragin, 2000), a condition's high or low level needs to exceed the consistency threshold 0.90 (Schneider & Wagemann, 2012). One can label any condition that meets or exceeds this threshold a necessary condition. For instance, if one finds a high condition necessary for a high outcome, the high condition appears in at least 90 percent[1] of the observations that lead to the high outcome. For instance, every firm that shows high firm performance might also have high operational alignment. Thus, one would conclude that high operational alignment constitutes a necessary condition for high firm performance.

Even if the analysis reveals a necessary condition, one needs to keep in mind that, depending on the data, QCA can generate necessary conditions that are actually not necessary (Type 1 error), which researchers also call trivial necessary conditions (Ragin, 2006). First, a trivial necessary condition can arise when it constitutes a much bigger superset than the outcome. In this case, a low coverage score can indicate a trivial necessary condition (Schneider, 2018). Most QCA software also reports the coverage score of the tested conditions; or, in crisp set terms, it reports the proportion of observations that exhibit both the condition and the outcome[2]. Therefore, as a rule of thumb, a necessary condition needs to exceed the 0.60 coverage threshold (Maier et al., 2020; Mattke et al., 2020a). Second, a trivial necessary condition can arise if a condition remains mostly constant (i.e., varies little) in the entire data set. In this case, one should calculate the relevance of necessity (RoN) score (Ragin, 2006). Again, as a rule of thumb, a necessary condition should exceed the RoN score 0.60 (Mattke et al., 2020a; Maier et al., 2020). Third, if a condition constitutes a necessary one for both a high and low outcome, it probably constitutes a trivial necessary condition. Good practice dictates that researchers report the consistency, coverage and RoN, values of all tested conditions and discuss whether the revealed necessary condition (with consistency > 0.90, coverage > 0.60 and RoN > 0.60) has not only empirical but also practical relevance.

The analysis for the first exemplar study identified trivial necessary conditions (Table 10), which conditions that remain mostly constant in the entire data set can cause. We show that, by additionally testing the coverage and RoN, one can avoid type 1 errors. The analysis for the second exemplar study identified no complications with trivial necessary conditions (see Table 11). We summarize this step in Table 9.

Table 9. Step Four Illustration

	First exemplar study (firm performance)	Second exemplar study (digital assistant use)
Necessary conditions for high level of the outcome	High business alignment, high IT alignment, high intellectual alignment, and high operational alignment constitute necessary conditions for high firm performance while low alignment does not exceed the consistency threshold (Table 10).	High usefulness constitutes a necessary condition for an individual's high intention (Table 11).
Necessary conditions for low level of the outcome	Low business alignment, low IT alignment, low intellectual alignment, and low operational alignment constitute necessary conditions for low firm performance, which indicates possible trivial necessary conditions (Table 10).	For an individual's low intention to use digital assistant, the analysis did not reveal any necessary condition (see Table 11).
Test for trivial necessary conditions	Low business alignment, low IT alignment, low intellectual alignment, and low operational alignment for low firm performance do not exceed the coverage and RoN thresholds (i.e., 0.60). Thus, they constitute trivial necessary conditions for low firm performance.	High usefulness exceeds the coverage and the RoN threshold, which shows that high usefulness constitutes a non-trivial necessary condition for high intention to use a digital assistant.

[1] We define consistency here following how one calculates consistency for crisp sets. Fuzzy sets follow nearly the same principle.
[2] For a simpler explanation, we refer to the coverage definition for crisp sets. Fuzzy sets follow a similar principle but involves a slightly more complicated formula (see Ragin, 2006)

Table 10. Results Necessary Condition for High and Low Firm Performance (First Example Study)

	High firm performance			Low firm performance		
	Consistency	Coverage	RoN	Consistency	Coverage	RoN
Business alignment	**0.94**	**0.89**	**0.74**	0.94	0.34	0.32
~Business alignment	0.31	0.93	0.98	0.69	0.80	0.94
IT alignment	**0.93**	**0.85**	**0.65**	0.98	0.35	0.30
~IT alignment	0.29	0.98	0.99	0.59	0.75	0.94
Intellectual alignment	**0.93**	**0.87**	**0.69**	0.97	0.35	0.31
~Intellectual alignment	0.30	0.97	0.99	0.62	0.76	0.94
Operational alignment	**0.93**	**0.87**	**0.69**	0.98	0.35	0.31
~Operational alignment	0.30	0.97	0.99	0.64	0.78	0.94
Note: conditions with a tilde (~) represent the low condition. Numbers in bold indicate necessary conditions.						

Table 11. Results Necessary Condition for High and Low Intention (Second Example Study)

	High intention to use a digital assistant			Low intention to use a digital assistant		
	Consistency	Coverage	RoN	Consistency	Coverage	RoN
Usefulness	**0.92**	**0.84**	**0.75**	0.44	0.25	0.40
~Usefulness	0.18	0.34	0.75	0.72	0.85	0.93
Ease of use	0.87	0.70	0.52	0.72	0.37	0.34
~Ease of use	0.22	0.55	0.87	0.42	0.68	0.91
Risk	0.44	0.57	0.73	0.66	0.56	0.72
~Risk	0.66	0.75	0.78	0.49	0.36	0.58
Trust	0.77	0.74	0.69	0.59	0.36	0.47
~Trust	0.33	0.56	0.80	0.57	0.61	0.82
Note: conditions with a tilde (~) represent the low condition. Numbers in bold indicate necessary conditions.						

3.5 Step 5: Analyze Sufficient Configurations

In this step, one considers whether the QCA yielded sufficient configurations. To do so, one needs to incorporate the calibrated data into a truth table. The truth table lists all possible configurations of the conditions. As Table 2 shows, one can classify each condition as either having a high level (crisp set value of 1 or fuzzy set value > 0.50) or a low level (crisp set of 0 or fuzzy set value < 0.50). Therefore, the truth table comprises 2^k rows with k being the number of conditions. A truth table only represents conditions as values 0 and 1. To consolidate the truth table, one maps each observation in the data set to one of the 2^k rows (Ragin, 2014). In this way, for each row and, thus, for each possible configuration of conditions, one calculates the total number of observations (Schneider & Wagemann, 2012). The consolidated truth table provides valuable information to evaluate the data set (e.g., it shows the observations' distribution among the different configurations).

As we outline above, to obtain reliable and valid QCA results, one needs a high number of possible configurations in the data set. Therefore, we recommend that one discuss how much of the data set the configurations with the highest number of observations cover. Additionally, we recommend that one report the number of possible configurations and the proportion of unobserved configurations (in QCA terminology, logical remainders). The lower the number of logical remainders, the stronger the data set's empirical basis for the QCA and the more the results will generalize to the population. Thus, one should calculate and report the proportion of unobserved configurations (logical remainder index). More than just the number of logical remainders, one needs to consider whether the logical reminders compromise QCA results (Thomann & Maggetti, 2017). Theoretically and practically, if a priori knowledge suggests that one needs to consider logical remainders to understand the phenomena of interest, then the QCA results may be compromised.

After consolidating the truth table, one must consider whether the truth table contains sufficient configurations. As one will rarely observe perfectly sufficient configurations due to noise in the data, randomness, measurement inaccuracies (Ragin, 2000), QCA employs established thresholds that a configuration needs to exceed for one to name it sufficient. A sufficient configuration must meet a certain frequency threshold, a certain raw consistency threshold, and a certain proportional reduction in inconsistency (PRI) threshold, which we discuss below and summarize in Table 12. QCA allows one to separately analyze sufficient configurations for the high outcome and the low outcome. Therefore, we recommend that one first analyze sufficient configurations for the high outcome before analyzing the sufficient configurations for the low outcome.

First, the frequency threshold reduces the truth table to configurations that have a minimum number of observations; thus, one can consider only configurations that exceed this threshold as sufficient configurations. For instance, if one set the frequency threshold to three, one would consider only configurations that had at least three observations for further analysis. By setting a frequency threshold, one can filter out idiosyncratic configurations based on the assumption that they show a low number of observations. Selecting the frequency threshold balances the desire to identify common configurations with a high frequency threshold and niche configurations with selecting a lower frequency threshold. A low frequency threshold will likely result in sufficient configurations that apply only to the data set and that lack robustness to changes in the calibration or in how one analyzes sufficient configurations. Accordingly, applying a low frequency threshold would lead to irreproducible QCA results.

Two rules of thumb can help researchers when selecting a frequency threshold. First, one needs a higher frequency threshold with a larger data set. Researchers initially applied QCA for small-N studies and chose a relatively small frequency threshold (i.e., 1 or 2). However, for larger-N studies (>100 observations), which appear commonly in the IS discipline, we would advise researchers to set a higher frequency threshold (Maggeti & Levi-Faur, 2013). Second, one should choose the frequency threshold so that at least 70 to 80 percent of the observations remain in the analysis (Greckhamer et al., 2018).

Second, one can use a specific configuration's raw consistency, which indicates the proportion of configurations that show the outcome[3], as a tool to measure consistency. For instance, the raw consistency 1 would indicate a perfect sufficient configuration and, thus, that all configurations in the row show the outcome. In contrast, the raw consistency 0.50 would indicate that 50 percent of the configurations show the outcome. Therefore, a high raw consistency score indicates that the configuration leads to the outcome and that measure is comparable to the significance level (i.e., the p-value commonly used in null-hypotheses testing) (Greckhamer et al., 2018). In general, 0.75 constitutes the minimum raw consistency threshold (Ragin, 2006), but researchers have often used higher raw consistency thresholds such as 0.85 (Ragin, 2009) are to increase the configurations' reliability. Therefore, one can consider configurations that exceed the raw consistency threshold sufficient.

Third, as a common challenge in QCA studies in which one measures the outcome as a fuzzy set, one may find a configuration sufficient for the same outcome at both the high and low levels. PRI consistency indicates the degree to which a configuration does *not* simultaneously constitute a sufficient configuration for the same outcome at both the high and low levels. One cannot predict out the outcome of configurations that one finds sufficient for the same outcome at both the high and low levels due to their inconclusive nature. Therefore, by setting a PRI consistency threshold, one eliminates configurations that are sufficient for the same outcome at both the high and low levels (Mattke et al., 2020b). Configurations with a PRI consistency score below 0.50 indicate inconclusive configurations; as a result of thumb, the PRI consistency threshold should be around 0.75 to produce meaningful configurations (Greckhamer et al., 2018; Mattke et al., 2020b).

In summary, to reduce observations in a truth table to sufficient configurations, researchers need to consider whether configurations exceed a frequency threshold, a raw consistency threshold, and a PRI consistency threshold. Researchers can consider configurations that exceed all thresholds sufficient in the truth table. As researchers can seldom report an entire truth table due to limited space in a research paper, we recommend that they publish entire truth tables in online appendices or at least report the reduced truth table in their research papers (i.e., the truth table that, after applying the thresholds, additionally include the number of observations for each row, the raw consistency, and PRI consistency values for each row). By reporting these values, researchers ensure that the final QCA solution becomes more transparent and that they report the results' robustness to changes in the threshold.

[3] To help readers easily understand what we mean here, we refer to the consistency definition for crisp sets. Fuzzy sets follow a principle but use a slightly more complicated formula (see Ragin, 2006)

Table 12. Thresholds for Sufficient Configurations

Thresholds	Explanation	Recommendations
Frequency threshold	One can consider only configurations that exceed the frequency threshold sufficient.	• Larger data sets require a higher frequency threshold • At least 70 to 80 percent of the configurations should exceed the frequency threshold
Raw consistency threshold	One can consider only configurations that exceed the raw consistency threshold (i.e., that consistently lead to the outcome) sufficient.	• Set the minimum raw consistency threshold to 0.75, though higher thresholds (e.g., 0.85) show more reliable results
Proportional reduction in inconsistency (PRI) threshold	One can consider only configurations that exceed the PRI consistency threshold (i.e., that simultaneously do not lead to the same outcome at both the high and low levels) sufficient.	• Set the PRI threshold to around 0.75 or higher

When researchers find many sufficient configurations, they will usually need to use logical minimization to reduce their number since reporting so many provides few insights and lacks practical relevance. Logical minimization reformulates all identified sufficient configurations in a less complex, more interpretable manner without losing any information (Ragin, 2014). Most often, researchers use the Quine-McCluskey algorithm to minimize the configurations. This approach suggests that a condition is logically redundant and does not play a role in explaining the outcome ("don't care situation") if it appears at a high level in one configuration and at a low level in another. In this situation, one can omit the logically redundant condition and merge the two configurations into one.

Note that researchers can integrate counterfactual analysis into QCA analyses (Ragin & Fiss, 2008) as a way to deal with the logical remainders in a dataset and, thus, make assumptions about unobserved configurations in a data set (Misangyi et al., 2017). More precisely, counterfactuals constitute assumptions about whether a high or low condition leads to an outcome: in this way, a counterfactual analysis considers these assumptions even if the data set lacks empirical data about them. One can use either "easy" or "difficult" counterfactuals. Easy counterfactuals are assumptions, backed up by existing theory or empirical evidence despite no observations being present, that the presence of a condition leads to the outcome. Difficult counterfactuals are assumptions about what would have happened if a condition were absent (Ragin & Fiss, 2008).

While a counterfactual analysis can improve the QCA results, especially in situations with many logical remainders (Thomann & Maggetti, 2020; Wagemann et al., 2016), we do not focus on this additional option in QCA. Moreover, authors should err towards adopting a more conservative approach to QCA and focus on reducing the number of logical remainders through strategic or purposive sampling (Greckhamer et al., 2013). In any case, if authors using QCA decide to make assumptions on logical remainders and use counterfactual analysis, they must explain the theoretical reasons behind the assumption and discuss why their data set does not observe the configurations.

In Table 13, we summarize the steps that researchers need to follow to analyze sufficient configurations. We see that the first exemplar study had several issues, such as many logical reminders, low variance in the observations, and an unbalanced data set, which all could weaken its empirical results. In particular, we needed to apply a relatively low frequency threshold because, otherwise, the analysis would result in only one sufficient configuration. In contrast, the second exemplar study exhibited an ideal situation, and we can see that the purposeful sampling improved QCA's analytic power.

Table 13. Step Five Illustration

	First exemplar study (firm performance)	Second exemplar study (digital assistant use)
Number of possible configurations	Sixteen possible configurations. See Table A5 in the Appendix for the truth table for high form performance and Table A6 for the truth table for low firm performance.	Sixteen possible configurations. See Table A7 in the appendix for the truth table for high intention and Table A8 for the truth table for low intention.
Logical remainders	Six logical remainders, which means that not all possible configurations exist in the data sample. Therefore, we covered only 62.50 percent (logical reminder index of 37.50 percent) of all possible configurations.	No logical remainder. This means that all possible configurations exist in the data sample and we cover 100 percent of all possible configurations (logical reminder index of 0 percent).
Implication of logical remainders	The logical remainders may limit the QCA results' meaningfulness because the data set does not cover some practically relevant configurations. For instance, we cannot make any statements about how firms perform that show only high business alignment and high operational alignment.	No negative implications.
Highest number of observations for a single configuration	Highest: 124 (one configuration represented 89.86 percent of the entire data set) Second highest: 5 (the second-largest configuration represented 3.62 percent of the data set) These results show that the data set has a low variance in the observations so that one configuration covered a large extent of the entire data set and, thus, evidenced a weak empirical basis for reliable QCA results.	Highest: 72 (one configuration represented 31.03 percent of the entire data set) Second highest: 52 observations (the second-largest configuration represented 22.41 percent of the data set) These results shows that the data set had a high variance in the observations so that it equally covered many possible configurations and, thus evidenced a strong empirical basis for reliable QCA results.
High vs. low outcome	Only 10.87 percent of the observations showed low firm performance. Thus, the data set lacked balance, which could cause several issues. We may have found some sufficient configurations that led to high firm performance because the sample did not include configurations that led to low firm performance. Additionally, we might not have found sufficient configurations for low firm performance because we did not have enough observations with low firm performance.	The data set exhibited balance because 62.93 percent of the observations showed high intention and 37.07 percent of the observations showed low intention.
Used thresholds	We set the raw consistency threshold to 0.85, the PRI consistency threshold to 0.75, and the frequency threshold to 2. We did not set the frequency threshold to around five percent because it would have only resulted in one remaining configuration. To illustrate how a small frequency threshold influences a QCA analysis, we used two observations as a frequency threshold. With this frequency threshold, we still considered 94.24 percent of the observations in the data set and, thus, ensured that we included most of the data set when analyzing sufficient configurations.	We set the raw consistency threshold to 0.85, the PRI consistency threshold to 0.75, and the frequency threshold to 11. We found this frequency threshold appropriate because we still considered 83 percent of the observations in the data set and, thus, ensured that we included most of the data set when analyzing sufficient configurations.

3.6 Step 6: Report the Findings

In this step, one reports the solution. For each minimized sufficient configuration, one calculates a raw coverage, unique coverage, and consistency score. The unique coverage scores allow one to assess the sufficient configuration's unique relevance, while the raw coverage assesses the overall relevance. Furthermore, one calculates a solution coverage and solution consistency score for all configurations together (see Table 14).

Table 14. Essential Definitions for QCA Solutions (Ragin, 2006)

Measure	Explanation
Raw coverage	Quantifies the extent to which one configuration explains the data set.
Unique coverage	Quantifies the extent to which one configuration solely explains the data set (i.e., it excludes the extent to which other configurations explain it).
Consistency	Quantifies the extent to which the configuration exhibits the outcome.
Solution coverage	Quantifies the extent to which the observations in the data set fit to at least one configuration in the solution.
Solution consistency	Quantifies the extent to which the observations in the data set correspond to the solution.

Most software packages present the results in terms of a solution formula, which uses Boolean expressions to describe the sufficient configurations. We recommend that one graphically display the solution as Ragin and Fiss (2008) note because one can more interpret a graphic solution than a Boolean expression. Researchers often use black circles to indicate a low condition and crossed-out white circles to indicate a high condition. Since one has logically minimized these configurations, "don't care" situations will have emerged, which one indicates with a blank space. In a "don't care" situation, the condition can either be present or absent and thus does not have an influence. In the picture of the solution, one should mark the necessary conditions.

Table 15. Step Six Illustration

	First exemplar study (firm performance)	Second exemplar study (digital assistant use)
Conflict with necessary condition	The results show two "don't care" situations for IT alignment in configuration 1 (C1) and business alignment in C2, which conflicts with necessary condition results. Therefore, high IT alignment and high business alignment do not constitute necessary conditions.	No conflict.
Summary results for high level of the outcome	Two configurations among the four forms of alignment lead to high firm performance. In both configurations, a firm needs to have high intellectual and high operational alignment. C1 shows that firms can achieve high firm performance when business alignment is high; it does not matter whether IT alignment is high or low. In contrast, C2 shows a second way in which firms can achieve high firm performance by focusing on IT alignment. In this condition, IT alignment must be high, while it does not matter whether the business alignment is high or low (see Figure 1).	For individuals' high intention to use a digital assistant, they need to perceive the digital assistant as highly useful and easy to use. C1 shows that, when individuals perceive the risk of using a digital assistant as low then it does not matter whether they have high or low trust but still intend to use the digital assistant. C2, in contrast, shows that, when individuals have high trust, they intend to use the digital assistant despite whether they perceive it as high or low risk (see Figure 2).
Summary results for low level of the outcome	No sufficient configuration identified.	Two sufficient configurations can explain individuals' low intention to use a digital assistant. In both sufficient configurations, the individuals perceive low usefulness and high risk. C3 shows that individuals have a low intention to use a digital assistant if they have low trust, while the digital assistant's ease of use can be high or low. C4 shows that individuals do not intend to use a digital assistant even if they perceive the digital assistant as easy to use (see Figure 2).

With the results for the first exemplar study, we see that two necessary conditions constitute a “don’t care” situation. As we mention above, the data set has low variance in the observations, which means that one configuration where all conditions have a high level reflects 89.13 percent of the data set. The low variance in the observations causes that the conditions are nearly constant in the data set through which QCA identified those conditions as necessary. Additionally, applying a frequency threshold of two leads to the identification of niche configurations, which might go against the common and dominant configurations in the data set. Therefore, we do not consider high IT alignment and high business alignment as necessary conditions. Again, the second exemplar study shows no conflicting results, and we identified two sufficient configurations for high intention to use a digital assistant and two sufficient configurations for low intention to use a digital assistant (see Table 15).

	High firm performance		Low firm performance
	C1	C2	
Business alignment	●		*No sufficient configurations identified*
IT alignment		●	
Intellectual alignment	★	★	
Operational alignment	★	★	
Raw coverage	0.88	0.88	
Unique coverage	0.01	0.01	
Consistency	0.91	0.89	
Solution coverage	0. 79		
Solution consistency	0.86		

Note:
Observations high firm performance: N = 123 (equals 89.13 percent of sample size)
Observations low firm performance: N = 15 (equals 10.87 percent of sample size)
Logical reminder index: 37.50 percent
Frequency threshold: 2 (equals 1 percent of sample size)
Raw consistency threshold: 0.85
PRI consistency: 0.75
Remaining configurations after threshold: 94.24 percent (131 out of 138)

Key:
● *High level of a condition* ★ *Necessary condition (high level)*
⊗ *Low level of a condition*
‘Don’t care situation‘

Figure 1. The Findings in Graphical Form (First Example Study)

	High intention to use digital assistants		Low intention to use digital assistants	
	C1	C2	C3	C4
Usefulness	★	★	⊗	⊗
Ease of use	●	●		●
Risk	⊗		●	●
Trust		●	⊗	
Raw coverage	0.59	0.70	0.42	0.44
Unique coverage	0.08	0.20	0.09	0.11
Consistency	0.86	0.85	0.89	0.89
Solution coverage	0. 79		0.52	
Solution consistency	0.86		0.90	

Note:
Observations high intention: N = 146 (equals 62.93 percent of sample size)
Observations low intention: N = 86 (equals 37.07 percent of sample size)
Logical reminder index: 0 percent
Frequency threshold: 11 (equals 4.7 percent of sample size)
Consitency threshold: 0.85
PRI consistency: 0.75
Remaining configurations after theshold: 83 percent (192 out of 232)

Key:
● *High level of a condition* ★ *Necessary condition (high level)*
⊗ *Low level of a condition*
'Don't care situation'

Figure 2. The Findings in Graphical Form (Second Example Study)

3.7 Step 7: Validate the Findings

QCA results are sensitive to method decisions. Thus, to estimate the impact that method decisions have on results, one needs to check whether QCA's thresholds and calibration exhibit robustness (Maggetti & Levi-Faur, 2013; Mattke et al., 2020a; Maier et al., 2021a).

3.7.1 Robustness to Thresholds

We note that QCA results can already change significantly if one drops or includes a sufficient configuration, such as if one increases or decreases the frequency, raw consistency, or PRI consistency threshold. Thus, we recommend reporting in which ranges of the threshold the solution remains unchanged. When reporting the entire truth table, one can clearly see the robustness regarding frequency, raw consistency, and PRI consistency threshold. However, reduced truth tables do not provide any information about observations below the frequency threshold. Thus, one should extend the reduced truth table with those observations closest to the frequency threshold. Alternatively, one should replicate the analysis with a lower frequency threshold and reported whether the result changed significantly.

3.7.2 Robustness to Calibration

Furthermore, the QCA results can also be sensitive to the calibration anchors one chooses—especially when one uses non-regular calibration thresholds. Therefore, researchers should replicate their analysis with different calibration anchors (primarily when they use non-standardized data and thresholds). Furthermore, when adding a small constant to 0.50 fuzzy values, we recommend that researchers repeat the analysis first by subtracting a small constant and then by adding a small constant.

We see in the first exemplar study that C2 remains robust to changes in thresholds and changes in calibration. Because C1 has only two observations, we see that changes in threshold or changes in the fuzzy value 0.50 can remove the C1 from the results. As such, future research would need to further consider C1’s robustness. The second exemplar study illustrates results that remain stable to changes in thresholds and calibration (see Table 16).

Table 16. Step Seven Illustration

	First exemplar study (firm performance)	Second exemplar study (digital assistant use)
Robustness to thresholds	• Report robustness to the frequency threshold: C1 is not stable to changes • Report robustness to the raw consistency threshold: robust up to the raw consistency 0.92 • Report robustness to the PRI threshold: robust up to the PRI 0.77	• Report robustness to the frequency threshold ○ High intention: stable from 1 up to 13 ○ Low intention: stable from 1 up to 11 • Report robustness to the raw consistency threshold ○ High intention: robust up to the raw consistency 0.85 ○ Low intention: robust up to the raw consistency 0.86 • Report robustness to the PRI threshold ○ High intention: robust up to 0.79 ○ Low intention: robust up to 0.75
Robustness to calibration	• Configurations remain robust to other calibration anchors • C1 is sensitive to subtracting 0.001 from 0.50 fuzzy values rather than adding 0.001	• Robust to other calibration ○ 1 as the anchor for being fully out of the set (resulting in fuzzy value 0.05), ○ 4 as the point of maximum ambiguity (resulting in the fuzzy set value 0.50) ○ 7 as the anchor for being fully in the set (resulting in the fuzzy set value 0.95) • Robust when adding 0.001 or when subtracting 0.001 from 0.50 fuzzy values

4 Critical Evaluation of the Two Studies and Recommendations for IS Research

In this paper, we illustrate how to apply QCA with two illustrative studies. In doing so, we highlight its unique aspects and outline recommendations for IS research.

As for how the sampling strategy in the studies affected the collected data, the first exemplar study relied on a commercial data-collection company to draw a sample from a CIO panel with a focus on getting responses from a notoriously difficult to sample population. While this focus on gathering data from a population conforms with norms for variance-based studies (see Gerow et al., 2015), it did not focus on gathering data from high and low-performing firms. In the second exemplar study, we used purposive sampling to ensure sufficient variance in the observations and in the outcome. We can see that the sampling technique one adopts has profound implications for how one applies QCA.

Looking at the first exemplar study, we see that 89.13 percent of the observations reported a high firm performance, which limits QCA results’ power in several ways. Among others, we do not find any sufficient configurations that lead to low firm performance due to the unbalanced data set. Additionally, one might identify an identified sufficient configuration as sufficient only because the data set only contains this configuration with high firm performance. The same configuration might also lead to low firm performance, which would show that this configuration is not sufficient. Absent data on many configurations that lead to low performance, we cannot easily evaluate the results’ quality. This issue does not pertain only to this study but demonstrates that QCA results can suffer from an unbalanced data set, which, for example, dominantly shows a high outcome. As for one, one reason concerns non-response bias (e.g., only firms with high firm performance participate in such studies). To overcome this issue, QCA results would benefit from additionally sampling to reduce non-response bias.

As another possible solution, one could also redefine the outcome and focus on an adjusted outcome, such as “very high performance”. To calibrate the data into the set “very high performance”, the point of maximum ambiguity should be moved to the value 5 (rather than 4). When using a different calibration, one needs to highlight that one considered a non-standard set (here: “very high” rather than “high”) and rename the set accordantly (e.g., “very high alignment” rather than “high alignment” for fully belonging to the set) as, otherwise, one threatens the results’ reproducibility.

The issues that we note with the first exemplar study stand in contrast to the second exemplar study since we explicitly sampled participants with and without an interest in using a digital assistant. Additionally, we sampled data for five digital assistants (Alexa, Cortana, Siri, Google, Bixby; see Appendix), which led to high variance in observations, a balanced distribution of configurations, and a balanced distribution of observations with a high and low outcome level. With this data set, we did not face any problems in analyzing necessary conditions, sufficient configurations, or robustness. Accordingly, to avoid idiosyncratic results in IS research, we recommend:

Recommendation 1: Whenever possible, use data sets for QCA with a balanced distribution of observations with high and low outcome.

Regarding the sampling strategy, we see that the data set in the first exemplar study has 37.50 percent logical remainders, and a single configuration represents 89.86 percent of the entire data set. Therefore, the QCA results might have limitations because the data set does not reflect a well-defined population or an adequate proportion of it. Thus, the data set might not capture other sufficient configurations. The preferred solution would be to sample additional data to reduce the number of logical remainders followed by conducting the solution to adjust the calibration and, for example, focus on “very high” forms of alignment. In contrast, the second exemplar study provides a strong empirical foundation for the QCA because all possible configurations exist in the data set and the highest number of a single configuration only reflects 31.03 percent of the entire data set. Accordingly, we recommend that researchers:

Recommendation 2: Use data sets for QCA that represent many possible configurations and discuss how logical remainders might impact the QCA study’s results.

As for analyzing necessary conditions, in the first exemplar study, we can see that only considering the consistency score for necessary conditions yields the same necessary conditions for high and low firm performance. This counterintuitive finding can arise due to data sets with some conditions that do not vary much throughout all observations. For instance, the first exemplar study shows that one configuration, which comprised only high-level conditions (i.e., all four alignments at a high level), represented 89.86 percent of the data set. The little variance in the conditions explains why we identified trivial necessary conditions. By additionally considering the coverage and relevance of necessity (RoN) scores, we find trivial necessary conditions for low firm performance. Accordingly, we recommend that researchers:

Recommendation 3: Consider the coverage scores and the RoN scores to avoid identifying trivial necessary conditions.

As for analyzing sufficient configurations, the frequency threshold one chooses influences the QCA results. Researchers originally used QCA for small sample size studies with a small population. Consequently, early QCA studies used small frequency thresholds (e.g., 1 or 2) (Misangyi et al., 2017) since QCA can work well with small data sets on a well-defined population.

However, using the same low frequency thresholds in research settings where one cannot sample a well-defined population or at least an adequate portion of the population threatens QCA results’ validity. For instance, both exemplar studies that we report on in this paper could not sample an adequate portion of the population. Using low frequency thresholds for such data sets could result in false sufficient configurations, which QCA only identifies as sufficient because the data set contains a limited number of observations.

In the first exemplar study, we choose a low frequency threshold (i.e., 2, which represented around one percent of the sample size) to understand the complex interplay between different forms of alignment as, otherwise, the results would show only one sufficient configuration with all high conditions. The low frequency threshold can cause several issues when the data set does not reflect a well-defined population, which we can see in the first exemplar study (see Section 3.5). For instance, through the low frequency threshold 2 (one percent of the sample size), we identified a sufficient configuration with only two observations in the data set and one sufficient configuration with only five observations. Using this low frequency threshold in the QCA analysis leads to minimized sufficient configurations where IT alignment and business alignment are “don’t care situations”. These conflict with the results of the necessary conditions, which revealed that high level of IT alignment and high level of business alignment are necessary conditions. Furthermore, in validating the results in the first exemplar study, we show that, due to the low frequency threshold configuration, C1 lacked robustness to changes in the calibration process and changes to the thresholds. Looking at the second exemplar study in which we set the frequency threshold to around five percent of the sample size, we see no conflicting findings for necessary conditions and robust sufficient configurations. Accordingly, to produce robust and reproducible QCA results in IS research, we recommend that researchers:

Recommendation 4: Use an appropriate frequency threshold according to the research setting and the sample size.

As for the decisions researchers need to make in the calibration and the analysis, we show they can evaluate QCA results' robustness. While only some QCA studies in IS research have verified their QCA results (Park & Mithas, 2020; Park et al., 2017; Mattke et al., 2020a, 2020b), we show how researchers can evaluate robustness for sufficient configurations. Among other things, we see in the first exemplar study that C1 reacts sensitively to changes in the threshold and calibration. Accordingly, we recommend that researchers:

Recommendation 5: Test and report the robustness against the calibration and the selected threshold values.

In summary, we see that, even if a data set is large enough and valid for other analysis types, such as linear regression (Gerow et al., 2015), it might not be an optimal choice for QCA studies. To reveal robust and reliable results from QCA studies in IS research, one needs to use a data set with high variance in the observations and with balanced distributions of observations with a high and low outcome, which one can achieve via strategic or purposive sampling.

5 Contributions and Research Opportunities in IS Research

While IS researchers have acknowledged QCA's power for almost two decades (Fichman, 2004), QCA applications remain relatively rare in our literature (Mattke et al., 2021b). As for why, IS researchers may still poorly understand QCA. To build knowledge in the IS community, we provide a primer on QCA, illustrate QCA analyses, and propose guidelines for how IS researchers can effectively conduct a QCA.

This study contributes to the IS discipline by providing a state-of-the-art seven-step framework for using QCA in IS research. For each step, we provide checklists to ensure they apply QCA in a valid, consistent, and reliable manner. Furthermore, because many IS reviewers may find QCA unfamiliar, we provide guidance and checklists for evaluating QCA analyses in manuscripts (see Table 3). Finally, we illustrate the guidelines with two exemplar studies (one on how alignment influences firm performance and one on how individuals' perceptions influence their intention to use digital assistants). In doing so, we show how researchers can apply QCA for specific IS topics on the organizational and individual levels.

By illustrating how to use our seven-step framework through two exemplar studies, we provide an opportunity for IS researchers to better methodologically understand QCA. We demonstrate how the sample characteristics may distort QCA results' validity and recommend to purposely sample populations to gather data sets with a high variance in observations and with balanced distributions of observations that show the same outcome at both high and low levels. To calibrate Likert-scale data into fuzzy sets for QCA studies, we show that using the mean value for calibration leads to non-reproducible QCA results. As for analyzing necessary conditions, this study constitutes the first in IS research to introduce and demonstrate two additional quality criteria for assessing necessary conditions. Future QCA research should use the coverage and the relevance of necessity (RoN) scores as new criteria to assess necessary conditions in IS research and, thereby, avoid trivial necessary conditions. By explaining QCA's foundations, we show that it has its roots in small sample studies and that one should not transfer the frequency thresholds that such studies use to large sample studies. Besides that, we empirically show in the first exemplar study that a low frequency threshold for sufficient configurations threatens QCA results' validity. Most important, while only some QCA studies in IS research have validated their QCA results (Park & Mithas, 2020; Park et al., 2017; Mattke et al., 2020a, 2020b), we summarize existing validation criteria from QCA research from related research fields. Finally, we propose a new validation criterion that enables researchers to test how robust 0.50 fuzzy set values remain after making necessary adjustments. In summary, we provide state-of-the-art good practices for conducting and reporting QCA, which can help IS researchers publish high-quality QCA studies. We suggest a path for applying QCA in IS research.

Our work creates many opportunities for applying QCA in IS research. First, many IS specific theoretical constructs require a multi-dimensional perspective. However, thus far, researchers have largely treated them as multi-dimensional second-order constructs while assuming that the underlying first-order constructs influence the second-order construct linearly and symmetrically (Polites et al., 2012; Wright et al., 2012). For instance, in technostress research, researchers often treat technostress as a superordinate second-order construct of five first-order constructs, which, for instance, influence job burnout (Maier et al., 2019). Treating technostress as a superordinate second-order construct implies that one assumes that the five first-order constructs have equal importance in explaining the second-order construct. Treating technostress as second-order construct means that a high level of a first-order construct leads to a high level of the second-order construct. Therefore, individuals only perceive high technostress if all five first-order constructs are also high (Polites et al., 2012). However, technostress could be an aggregate second-order construct (its dimensions may not covary), a dimension set (its dimensions may not covary and have separate effects), or even an index variable (one might need to weigh and sum its dimensions' value) because for burnout to occur, not all five first-order constructs need to be high and burnout might even occur if some of the first-order constructs are low.

Applying QCA could shed new light on the technostress concept's nature and form and explain how the different configurations of first-order constructs lead to job burnout. By shedding light on the interplay between first-order dimensions, QCA would help one model the technostress concept in a manner closer to how it impacts people in different settings. One cannot easily do so with contemporary quantitative techniques because they make it difficult to interpret interactions with more than two concepts. QCA could shed light on additional configurational IS constructs. For instance, how an individual perceives trust and distrust (McKnight et al., 2017) or individuals traits (Pflügner et al., 2021), such as dispositional resistance to change (Oreg, 2003), and IT mindfulness (Thatcher et al., 2018) have a configurational nature. Hence, as a first path for future IS research, we recommend that researchers use QCA to investigate multi-dimensional constructs as a means to shed light on how different ways to conceptualize how first-order dimensions interact to shape how we understand higher-order constructs.

Second, IS research (Cenfetelli, 2004; Cenfetelli & Schwarz, 2011; Polites et al., 2017) and some management research (e.g., motivator and hygiene factors; Herzberg et al., 1993), theorize or show empirically that the conditions that cause a behavior to occur differ from the conditions that cause the behavior not to occur (causal asymmetry). However, most research implicitly assumes causal symmetry among the outcomes (Polites et al., 2017). For instance, it is often assumed that perceiving something at a high level leads users to adopt a system). However, the same perceptions at a low level do not lead users to reject a system (Cenfetelli & Schwarz, 2011; Cenfetelli, 2004). As we demonstrate in the second exemplar study, QCA enables researchers to refine how they understand the conditions that lead to a high-level outcome and distinguish them from the conditions that lead only the same outcome at a low level. Thus, we recommend that researchers differentiate between configurations that lead to a high-level and a low-level outcome because the configurations might not be the inverse form.

Third, IS strategy research could benefit from applying QCA. IS strategy research has long drawn on work that sees organization strategy as a configuration of distinct interconnected characteristics (Chan et al., 2006; Meyer et al., 1993). For instance, IS research frequently draws on the strategy typology for organizations into prospectors, analyzers, and defenders (Miles et al., 1978). Generally, we can describe organizations with configurations, but research has also revealed that the simultaneous existence of and interplay between organizational attributes also influence organizational outcomes (Siggelkow, 2002). Thus, future studies could examine how different organizational responses and organizational IS capabilities lead to positive outcomes. A recent study (Park et al., 2017) focused on how the configurational interplay between communication and business-intelligence systems helps firms achieve organizational agility in different markets. IS research could address digital transformation's institutional complexity and examine which configurations yield a successful digital transformation. Researchers could also use QCA to reveal prescriptive configurations that can guide managers on what path to take to achieve high outcomes by aligning IS and firm strategies.

Fourth, the analytic tools of a scientist are not neutral so they influence the way we theorize (Gigerenzer, 1991), and the dominant place that linear analysis methods have in IS research has led to a current theoretical understanding characterized by a "general linear reality" (Abbott, 1988) and net-effect thinking, which limits research to understanding phenomena in a linear way. Therefore, we need to enhance IS theory development beyond the traditional linear paradigm and take up examining complex and asymmetric relationships.

QCA can help scientists explain IS-related phenomena. While traditional analysis approaches, such as linear regressions and SEM, and QCA follow different paths to approach associations, we argue that both analyses combined can reveal richer insights. For instance, QCA can complement findings from linear regression or SEM studies to uncover hidden patterns in data. In a linear regression model, researchers focus on showing that a condition (e.g., intellectual alignment) has a positive net influence on the outcome (e.g., high firm performance). However, in larger data sets, one can commonly find a substantial number of observations that run counter the positive influence (Maier et al., 2021b). For instance, even if one finds that intellectual alignment has a significant relationship with high firm performance, the data set may contain contrary observations, which would result in difficulties isolating the effect that intellectual alignment has on firm performance (Gerow et al., 2014). Therefore, as not all observations support the relationship, researchers could additionally use QCA for the same data set and contribute by showing how configurations lead to high firm performance. Therefore, in some cases, it might be helpful to combine QCA with traditional analysis approaches because it would shed light on observations that run counter to or complement the linear influence.

Finally, QCA creates new research opportunities. While we update researchers on QCA's foundations and offer guidance on how to apply QCA in this paper, we acknowledge that, as a young method, QCA continues to grow into a more nuanced and sophisticated research method. For instance, researchers have advanced QCA with a two-step approach in which one combines two sequential QCAs (Schneider & Wagemann, 2012). Among its benefits, the two-step approach reduces the number of logical reminders. Furthermore, the approach enables researchers to analyze mediating relationships (Maier et al., 2021b; Mattke et al., 2021a). Additionally, researchers have advanced QCA by incorporating time into it, an approach they refer to as temporal QCA (TQCA). TQCA enables one to identify sufficient configuration sequences at different times that lead to an outcome. With such an approach, we can identify what configuration sequences lead to an outcome and, at the same time, what configuration sequences in another temporal order will not lead to an outcome. This approach could provide new opportunities for employing QCA to understand the findings from longitudinal studies. Therefore, future research should not only limit the analysis to classical QCA. Instead, we need more research and guidance to advance QCA and to better understand how to apply those advanced QCA techniques.

6 Conclusion

This paper shows that employing QCA offers new opportunities for the IS discipline. We review how one can apply QCA in IS research and provide a comprehensive seven-step framework for using QCA. By enabling a shift to a broader neo-configurational perspective (Misangyi et al., 2017), our work reveals opportunities for researchers to revisit established higher-order concepts such as trust in technology and probe contradictory findings in areas such as IT strategy and reap greater conceptual clarity in the established IS literature. We offer guidance to authors and reviewers on how to apply and evaluate research that employs QCA. As a final thought, authors and reviewers applying our framework to organize or evaluate QCA analysis should remain open to advances in the method because, as QCA evolves, we anticipate that how researchers execute the steps detailed in our framework will also evolve.

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Appendix A: Additional Information for the Second Exemplar Study

As our sampling strategy, we sought individuals who had a digital assistant-enabled device and, thus, at least the opportunity to use a digital assistant. We explicitly asked for participants who had an interest in using a digital assistant and participants who did not to sample both the high and low outcome. We followed recommendations (Lowry et al., 2016) and included two screening questions, ("I am familiar with a digital assistant, such as Alexa, Siri or Bixby" and a reverse coded screening question "I am not aware of digital assistant") to sample only participants that fit the sampling strategy. We removed 94 participants who did not answer consistently that they were familiar with digital assistants. Additionally, we implemented one attention test ("This is an attention test: please select "agree" to continue.") in the survey to filter out participants who do not carefully read the questions based on which we removed 13 participants. We asked the participants what digital assistant (e.g., Siri, Alexa, Google Assistant, Cortana, Bixby) they owned and were most familiar with. We then customized the survey questions about digital assistants based on the participant's answer. In doing so, we focused on obtaining as many different configurations as possible. The final data sample comprised 232 participants whose demographic information we display in Table 1.

Table A1. Demographics (in Percent) of 232 Participants

Country of origin		**Gender**		**Age** (M: 32.4; SD: 10.63)	
Canada	3.4	Male	43.1	18-20	11.2
United Kingdom	6.0	Female	54.7	21-30	45.7
United States	63.4	Other	2.2	31-40	25.4
India	7.3			41-51	9.5
Italy	4.3			51 - 60	6.5
Other	15.5			61 - 70	1.7
Highest education level		**Number of times using a digital assistant a week**		**Digital assistant used by participants**	
High school / GED	10.8	0	26.3	Alexa	31.5
Some college	22.4	1	10.3	Cortana	5.6
Two-year college degree	11.2	2-7	37.1	Siri	37.9
Four-year college degree	35.8	7-14	9.5	Google	21.1
Master's degree or higher	19.8	>14	16.8	Bixby	3.9

As we used self-reported data, we additionally tested for common method bias (CMB). To test whether CMB posed an issue in this study, we conducted different tests, which all attested that CMB did not pose an issue. First, we conducted Harman's single factor test, which indicated that one factor explained less than 48 percent of the variance and, thus, indicates that CMB did not pose an issue. Second, we followed Pavlou et al.'s (2007) procedure to examine the correlation matrix (see Table 2) for extremely high correlations ($r > 0.9$). We found no such extremely high correlations. Third, we conducted a CMB test using PLS (Williams et al., 2003). To do so, we determined the extent to which CMB as a factor in the model influenced the R^2. Specifically, we transformed all items into single-item constructs and compared the model's R^2 with the CMB factor to the R^2 without a CMB factor. The CMB factor explained an average delta R^2 of 0.005, which indicates that no CMB distorted the results (Liang et al., 2007). In summary, all three tests attested that CMB did not pose an issue in this study.

To ensure content validity, we based all measures that we used in this study on existing measures from previous research and adapted them to the digital assistant context. We overview the measures in detail in Table 5. To use the collected data for the QCA analysis, we first needed to determine the measurement model's indicator validity, construct validity, and discriminant validity (Bagozzi, 1979). Since the results evidenced the measurement model's validity (see Table 3), we could perform the QCA.

Table A2. Descriptive Statistics and Discriminant Validity

		M	SD	α	CR	AVE	(1)	(2)	(3)	(4)	(5)
(1)	Intention to use	4.54	2.26	0.99	1.00	0.99	0.993				
(2)	Trust	4.53	1.21	0.91	0.95	0.85	0.299	0.923			
(3)	Risk	3.85	1.58	0.95	0.96	0.86	-0.314	-0.037	0.929		
(4)	Usefulness	4.78	1.70	0.86	0.90	0.71	0.695	0.396	-0.317	0.840	
(5)	Ease of use	5.15	1.29	0.94	0.95	0.64	0.311	0.373	-0.017	0.577	0.799

Note: square root of appears on the diagonal of bivariate correlations; M = mean; SD = standard distribution; CR = composite reliability; AVE = average variance extracted.

Table A3. Validation of the Measurement Model

Validation	Test and explanation of validation
Content validity	We only used items from previous research (see Table 4)
Indicator validity	All items had at least a 0.707 loading (Carmines & Zeller, 2008) (see Table 4)
Construct validity	The average variance extracted (AVE) exceeded 0.50 and the composite reliability exceeded 0.7 (Fornell & Larcker, 1981) (see Table 2).
Discriminant validity	The square root of the AVE exceeded the corresponding bivariate correlations of the constructs (Fornell & Larcker, 1981; Hulland, 1999) (see Table 2). Additionally, we used the heterotrait-monotrait (HTMT) ratio to calculate 0.83 as the highest value for intention to use and usefulness was lower than the absolute $HTMT_{0.85}$ criterion (Henseler et al., 2014).

With a valid measurement model, we could use the survey data for the QCA. To do so, we calculated the mean for each construct, which serves as the foundation for the calibration info fuzzy sets. We show a raw data extract in Table 4.

Table A4. Extract of the Raw Data

id	Intention to use	Trust	Risk	Usefulness	Ease of use
1	6.00	6.00	2.00	6.00	6.00
2	5.50	5.27	1.00	6.00	6.25
3	5.50	3.45	2.00	5.25	1.75
4	7.00	7.00	4.00	7.00	7.00
5	6.25	5.64	4.67	6.25	6.25
6	6.00	4.64	2.00	5.75	5.50
7	5.00	4.91	3.67	5.50	5.75
8	6.00	2.91	6.00	4.25	6.00
9	5.00	2.91	4.00	6.75	6.50

Table A5. Construct Measures

Construct	Based on	Question	Loadings
[Digital assistant]	Self-developed	Please specify which digital assistant you own, and you are familiar with.	
Intention to use	Agarwal & Karahanna (2000)	I plan to continue to use [*digital assistant*] in the future.	0.993
		I intend to continue using [*digital assistant*] in the future.	0.940
		I expect my use of [*digital assistant*] to continue in the future.	0.920
Risk	Pavlou (2003)	How would you characterize the decision to use [*digital assistant*]? (Insignificant risk / significant risk)	0.913
		How would you characterize the decision to use [*digital assistant*]? (Very positive situation / very negative situation)	0.940
		How would you characterize the decision to use [*digital assistant*]? (High potential for gain / high potential for loss)	0.915
Usefulness	Pavlou (2003)	Overall, I find [*digital assistant*] useful.	0.942
		I think [*digital assistant*] is valuable to me.	0.955
		The functions of [*digital assistant*] are useful to me.	0.954
		[*Digital assistant*] is functional.	0.861
Ease of use	Venkatesh & Morris (2000)	My intention with the [*digital assistant*] is clear and understandable.	0.719
		Interacting with [*digital assistant*] does not require a lot of my mental effort.	0.852
		I find [*digital assistant*] to be easy to use.	0.932
		I find it easy to get [*digital assistant*] to do what I want.	0.919
Trust [benevolence]	McKnight et al. (2002)	I believe that the company behind [*digital assistant*] would act in my best interest.	0.950
		If I required help, the company behind [*digital assistant*] would do its best to help me.	0.906
		The company behind [*digital assistant*] is interested in my wellbeing, not just its own.	0.926
Trust [integrity]		The company behind [*digital assistant*] is truthful in its dealings with me.	0.913
		I would characterize the company behind [*digital assistant*] as honest.	0.933
		The company behind [*digital assistant*] would keep its commitments.	0.903
		The company behind [*digital assistant*] is sincere and genuine.	0.921
Trust [competence]		The company behind [*digital assistant*] is competent and effective in providing a digital assistant.	0.899
		The company behind [*digital assistant*] performs its role of providing a digital assistant for me very well.	0.916
		Overall, the company behind [*digital assistant*] is a capable and proficient provider.	0.895
		In general, the company behind [*digital assistant*] is very knowledgeable about digital assistant.	0.783

Note: we measured all items with a seven-point Likert-type agreement scale that ranged from completely disagree (1) to completely agree (7) if not indicated otherwise.

Appendix B: Truth Tables

Table A6. The Truth Table for High Firm Performance

Business alignment	IT alignment	Strategic alignment	Operational alignment	Number of observations	High firm performance	Raw consistency	PRI consistency
1	1	1	1	124	1	0.92	0.88
0	1	1	1	5	1	0.95	0.77
1	0	1	1	2	1	0.99	0.94
0	0	1	1	1	0	0.99	0.96
1	1	0	1	1	0	0.99	0.96
1	1	0	0	1	0	0.99	0.95
0	0	0	0	1	0	0.99	0.94
1	1	1	0	1	0	0.99	0.93
0	0	1	0	1	0	0.99	0.92
0	1	0	1	1	0	0.98	0.83
1	0	0	0	0			
0	1	0	0	0			
1	0	1	0	0			
0	1	1	0	0			
0	0	0	1	0			
1	0	0	1	0			

Table A7. The Truth Table for Low Firm Performance

Business alignment	IT alignment	Strategic alignment	Operational alignment	Number of observations	Low firm performance	Raw consistency	PRI consistency
1	1	1	1	124	0	0.37	0.04
0	1	1	1	5	0	0.83	0.21
1	0	1	1	2	0	0.80	0.06
0	0	0	0	1	0	0.89	0.06
1	1	0	0	1	0	0.84	0.05
0	0	1	0	1	0	0.89	0.05
1	1	1	0	1	0	0.80	0.07
0	1	0	1	1	0	0.88	0.17
1	1	0	1	1	0	0.79	0.04
0	0	1	1	1	0	0.86	0.04
1	0	0	0	0			
0	1	0	0	0			
1	0	1	0	0			
0	1	1	0	0			
0	0	0	1	0			
1	0	0	1	0			

Table A8. The Truth Table for High Intention to Use a Digital Assistant

Usefulness	Ease of use	Risk	Trust	Number of observations	High intention to use a digital assistant	Raw consistency	PRI consistency
1	1	0	1	72	1	0.85	0.82
1	1	1	1	51	1	0.85	0.81
1	1	0	0	13	1	0.85	0.79
1	0	1	1	9	0	0.80	0.59
1	0	0	1	2	0	0.80	0.61
1	0	1	0	2	0	0.80	0.53
1	0	0	0	1	0	0.80	0.56
1	1	1	0	16	0	0.74	0.60
0	0	1	1	4	0	0.65	0.31
0	0	0	0	8	0	0.63	0.36
0	0	0	1	4	0	0.63	0.33
0	1	0	1	6	0	0.60	0.31
0	1	0	0	4	0	0.58	0.25
0	0	1	0	11	0	0.50	0.18
0	1	1	1	16	0	0.49	0.19
0	1	1	0	13	0	0.48	0.19

Table A9. The Truth Table for Low Intention to Use a Digital Assistant

Usefulness	Ease of use	Risk	Trust	Number of observations	Low intention to use a digital assistant	Raw consistency	PRI consistency
0	0	1	0	11	1	0.89	0.82
0	1	1	1	16	1	0.88	0.81
0	1	1	0	13	1	0.88	0.81
0	1	0	0	4	0	0.86	0.75
0	0	1	1	4	0	0.84	0.69
0	1	0	1	6	0	0.82	0.69
0	0	0	1	4	0	0.82	0.67
0	0	0	0	8	0	0.79	0.64
1	0	1	0	2	0	0.77	0.47
1	0	0	0	1	0	0.75	0.44
1	1	0	1	9	0	0.70	0.41
0	1	0	1	2	0	0.69	0.39
1	1	1	0	16	0	0.61	0.40
0	1	1	0	13	0	0.45	0.21
1	1	1	1	51	0	0.38	0.19
0	1	1	1	72	0	0.31	0.18

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