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Integrating QCA and HLM for Multilevel Research on Organizational Configurations

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Abstract

Mixed methods systematically combine multiple research approaches—either in basic parallel, sequential, or conversion designs or in more complex multilevel or integrated designs. Multilevel mixed designs are among the most valuable and dynamic. Yet current multilevel designs, which are rare in the mixed methods literature, do not strongly integrate qualitative and quantitative approaches for use in one study. This lack of integration is particularly problematic for research in the organization sciences because of the variety of multilevel concepts that researchers study. In this article, we develop a multilevel mixed methods technique that integrates qualitative comparative analysis (QCA) with hierarchical linear modeling (HLM). This technique is among the first of the multilevel ones to integrate qualitative and quantitative methods in a single research design. Using Miles and Snow's typology of generic strategies as an example of organizational configurations, we both illustrate how researchers may apply this technique and provide recommendations for its application and potential extensions. Our technique offers new opportunities for bridging macro and micro inquiries by developing strong inferences for testing, refining, and extending multilevel theories of organizational configurations.

Keywords

multilevel mixed methods research, qualitative comparative analysis, hierarchical linear modeling, organizational configuration

During the past three decades, mixed methods—combinations of quantitative and qualitative research approaches—have made important contributions to the organization sciences (Johnson, Onwuegbuzie, & Turner, 2007; Molina-Azorin, 2012). The central premise of mixed methods research is that the systematic use of two methods offers contributions beyond those that single

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methods alone may produce. More specifically, mixed methods designs provide results that allow researchers to draw stronger inferences and simultaneously build and test theory within one study (Molina-Azorin, 2012; Teddlie & Tashakkori, 2009). Given the variety of different mixed methods designs (Hesse-Biber & Johnson, 2015), Teddlie and Tashakkori (2009) developed a categorization ranging from relatively simple designs (e.g., parallel, sequential, or conversion) to more complex ones (e.g., multilevel or fully integrated).

Thus far, multilevel mixed methods designs primarily collect and analyze qualitative and quantitative data separately for each level. The integration of qualitative and quantitative methods occurs only later, during the interpretation stage, when researcher triangulate results to draw meta-inferences (Tashakkori & Teddlie, 2008). Yet the quality of inferences is inevitably linked to design questions so that—by not integrating qualitative and quantitative approaches at an earlier stage—the inference quality of current multilevel mixed methods designs is likewise affected. More integrated multilevel mixed methods designs promise stronger meta-inferences by, for example, using the strengths of one method to compensate for the weaknesses of the other or increasing the theoretical consistency of the individual and integrative efficacy of various components of the study.

In this article, we develop an integrated multilevel mixed methods technique that interactively mixes qualitative and quantitative approaches across all stages of the research process. Our technique sequentially combines qualitative comparative analysis (QCA), a qualitative case-oriented method, with hierarchical linear modeling (HLM), the standard method in quantitative multilevel studies. QCA uses Boolean algebra to systematically compare combinations of conditions with reference to a predefined outcome. QCA results are unique in revealing alternative configurations, providing in-depth insights into their causal nature, and measuring nuanced degrees of set memberships (or "fit") of cases in configurations.

Our technique allows researchers to test and refine theories of organizational configurations, such as strategic groups or generic strategies (Fiss, 2007; Short, Payne, & Ketchen, 2008). Organizational configurations—"multidimensional constellation of conceptually distinct characteristics that commonly occur together" (Meyer, Tsui, & Hinings, 1993, p. 1175)—have played an important role in the organization sciences. By combining QCA with HLM, we also provide new opportunities for extending configurational theories through examining alternative micro-level mechanisms. For example, while theories on effective workplace systems have primarily been concerned with understanding high-performing workplace systems, researchers have also asked to what extent these workplaces are associated with employee satisfaction (e.g., Batt & Colvin, 2011). By providing both insights into the causal structure of configurations and precise information about the dynamics between macro-level configurations and micro-level observations, the integrated multilevel mixed methods technique we develop in this article may help researchers answer such questions.

Using data from 1,201 firms, we illustrate the technique in three steps within the context of Miles and Snow's (1978) typology of generic strategies. First, we use QCA to define and describe generic strategies. Second, we illustrate how researchers may transfer the QCA results into a simple two-level HLM model. Third, we both categorize each firm as adopting one of the identified generic strategies and test whether adopting one of them explains how firms innovate—and, if so, how successfully they do so. Our illustration helps researchers to implement this technique and provides both information on software and references to sources for researchers seeking to gain a deeper understanding of the steps involved.

Combining QCA with HLM may facilitate multilevel studies and the bridging of macro and micro inquiries in diverse domains of organizational research. In so doing, we make three contributions to the mixed methods literature. First, we present one of the first multilevel mixed methods techniques that analytically integrates qualitative and quantitative approaches. Second, we reveal an important trade-off between the compatibility and the degree of the integration of two approaches, a trade-off likely inherent in other integrated mixed methods techniques. Third, we present a mixed methods technique capable of dealing with two important aspects of multilevel research, both of which challenge conventional multilevel methods: non-perfectly nested structures and the identification and validation of latent constructs (Aguinis & Molina-Azorín, 2015).

Multilevel Designs in the Mixed Methods Literature

In the past three decades, mixed methods research has grown rapidly in terms of its application, definition, and contribution to the organization sciences (Creswell & Plano Clark, 2010; Molina-Azorin, 2012). Mixed methods research systematically combines qualitative and quantitative research approaches (Johnson et al., 2007) in a way that offers researchers specific advantages and that helps them avoid the disadvantages associated with each individual approach (Molina-Azorin, 2012). Mixed methods research "capture[s] a more complete, holistic, and contextual portrayal of the phenomenon" (Jick, 1979, p. 603). It thus offers researchers unique opportunities for drawing stronger inferences, thereby providing the grounds not only for better understanding phenomena of interest but also for building and testing theory in one study.

Teddlie and Tashakkori (2009) distinguish among five types of mixed methods designs. The three simple designs are the *parallel* mixed design, in which integration occurs in parallel fashion; the *sequential* mixed design, in which integration occurs chronologically; and the *conversion* mixed design, in which data are transformed (e.g., interview data are transformed into numerical data). The two more complex designs are the *multilevel* mixed design, in which integration occurs across levels of analysis, and the *fully integrated* mixed design, in which integration occurs interactively across all stages of the study.

These mixed methods design types differ in how they integrate approaches across the different stages—such as data collection, analysis, and interpretation. The three simple designs are mutually exclusive as they integrate the qualitative and quantitative approach in one study for only one stage. In contrast, in the fully integrated mixed design, integration occurs interactively during all stages. The multilevel mixed design differs from all other designs in that it uses the qualitative and quantitative approaches at different *levels* of a study (e.g., employee, team, firm, industry). Thus in theory, multilevel mixed designs may appear as either simple (i.e., parallel, sequential, conversion) or fully integrated mixed designs.

Current multilevel mixed methods designs collect and analyze multiple sets of data from different levels in a study, combining qualitative and quantitative strands either in parallel or sequentially. For example, a parallel multilevel mixed methods study may implement two parallel strands of research: at the macro level, a qualitative one including interview data; at the micro level, a quantitative one including statistical analysis. In this example, integration occurs during the interpretation stage by triangulating the findings from both strands to draw meta-inferences—overarching conclusions about their phenomena of interest.

In contrast, sequential multilevel mixed methods studies may first use a quantitative study using conventional multilevel analysis (e.g., HLM) at the macro level. Drawing on the findings of the quantitative study, researchers may select specific cases at the micro level and use qualitative methods (e.g., grounded theory) to provide deeper insights into the mechanisms explaining the phenomena under investigation. In this example, integration occurs during the interpretation stage when the results from one strand inform the other one.

Although multilevel mixed designs are some of the most valuable, dynamic, and innovative (Teddlie & Tashakkori, 2009), researchers interested in examining multilevel phenomena currently have only limited opportunities to benefit from the advantages of mixed methods research. First, multilevel mixed methods are rare "because only certain types of data are structured in a nested manner with the different levels of analysis" (Teddlie & Tashakkori, 2009, p. 156). The scarcity of multilevel mixed designs is particularly problematic for research in the organization sciences because of the field's interdisciplinary nature and the variety of multilevel concepts that organizational researchers study (Rousseau, 2011). Thus, new multilevel mixed designs would aid organizational research in better understanding multilevel phenomena.

Second, current multilevel mixed designs do not strongly integrate qualitative and quantitative approaches for use in one study. Yet design questions, especially in the context of integrated models, are importantly related to the inference quality of a study (Nastasi, Hitchcock, & Brown, 2010). For example, through more strongly integrating methods, researchers may increase design suitability, within-design consistency between a study's methodological components, and interpretive and theoretical consistency (Teddlie & Tashakkori, 2009). Thus, in addition to developing more multilevel mixed designs, organizational research would benefit from designs that improve the quality of inference by more strongly and interactively integrating qualitative and quantitative approaches.

Combining QCA and HLM

In this article, we develop a multilevel mixed methods technique that sequentially combines QCA and HLM to increase the depth and breadth of multilevel research on organizational configurations. Both components are equally important; yet, because QCA is relatively new and HLM more commonly applied, we focus in this section on introducing QCA in more detail.

QCA was developed in the 1980s by Charles Ragin as a formal methodology for small-*N*, comparative research. In contrast to quantitative methods, which are predominantly variable-oriented, QCA is case-oriented and uses set theory to conceptualize relationships among attributes within cases (Ragin, 1987). QCA analyzes set-theoretic relationships with a minimization procedure based on Boolean algebra rather than on correlational analysis. Therefore, QCA enables researchers to implement empirical analyses that closely reflect verbally formulated theories and offers substantial opportunities for both in-depth descriptive contributions and explanations of more complex causal mechanisms (Fiss, 2011; Ragin, 2008b).

QCA is especially suited for analyzing complex cause-and-effect relationships because it allows researchers to incorporate three important features of configurational theory: equifinality, conjunctural causation, and causal core and periphery. *Equifinality* refers to situations in which different combinations of causal conditions trigger the same outcome. *Conjunctural causation* goes beyond the analysis of single effects by stipulating that combinations of causal conditions are jointly sufficient for producing a given outcome. The concepts of *causal core and periphery* allow researchers to separate essential conditions from those less important or even irrelevant (Fiss, 2011). QCA therefore offers opportunities for in-depth empirical and theoretical research of alternative combinations of causal conditions that jointly affect an outcome of interest.

During the past decade, QCA has rapidly gained popularity, frequently drawing on typology theories prevalent across many fields in the organization sciences (e.g., Meyer et al., 1993; Short et al., 2008; Meuer & Rupietta, forthcoming). Equifinality is an element central to typologies because they specify alternative ideal types associated with a given outcome (Doty & Glick, 1994; Fiss, 2007). Additionally, typologies not only describe ideal types but also explain how combinations of different conditions cause an outcome. Typology theorizing is thus inherently configurational. Analyzing such complex cause and effects requires a method capable of accounting for conjunctural causes. Organizational researchers have already applied QCA for analyzing a variety of phenomena of relevance to organizations, such as generic strategies (e.g., Fiss, 2011), corporate governance mechanisms (e.g., Bell, Filatotchev, & Aguilera, 2014), and stakeholder management (e.g., Garcia-Castro & Francoeur, 2016).

The QCA Approach

QCA involves four steps that require theoretical, substantive, and contextual understanding of the investigated phenomena. In the first step, the researcher uses *theoretical* or *substantive* knowledge to identify causal conditions[1] relevant for explaining the phenomenon of interest. For example, Crilly (2011) uses QCA to predict the stakeholder orientation of subsidiaries, building on substantive knowledge inductively derived from interviews to "identify features associated with subsidiaries' prioritizing of shareholders over non-shareholders" (p. 697). Fiss (2011) draws on theoretical knowledge about Miles and Snow's (1978) typology to identify structural and environmental attributes of generic strategies. QCA requires substantive and theoretical familiarity with the research context for identifying the constitutive elements of an organizational configuration as causal conditions in a QCA.[2]

In the second step, QCA transforms data to sets for each causal condition. To do so, QCA requires researchers to "calibrate" the data (Ragin, 2008a). Preceding the analysis, researchers define sets by using qualitatively meaningful thresholds for "fully in" or "fully out" of any set. To define these thresholds, researchers draw on their theoretical and substantive understanding of the cases and their context. For example, Bell et al. (2014), in developing the set of board independence, point out that "boards of the largest and best-established US firms had on average 70 percent independent members" (p. 309) during the same sample period. Using this information, they consider a board "independent" (i.e., coded as 1 and thus fully in the set of board-independent IPOs) if at least 70% of board members were independent. Thus, QCA allows researchers to embed their models in the research context by drawing on theoretical and substantive insights about the phenomenon under investigation.

In the third step, QCA organizes all logically possible configurations of absent and present conditions in a truth table—an instrument of formal logic that relies on Boolean algebra. The number of rows in a truth table is calculated as 2^k, where k denotes the number of causal conditions included in the analysis. The greater the number of causal conditions, the greater the number of logically possible configurations.[3] The truth table "maps" all cases to the conceptual property space underlying the analysis. Additionally, the truth table provides information about the number of observations (e.g., employees, firms) that share a combination of causal conditions. The truth table also gives information about the degree to which such a combination of causal conditions is consistent with an outcome.

To prepare the truth table for the Boolean minimization, researchers use this information to specify two criteria: the frequency cut-off and the consistency cut-off. The frequency cut-off defines the minimum number of cases necessary for including a configuration in the analysis. Because typologies in the organization sciences define causal conditions common to sets of firms, the frequency cut-off is an important analytical instrument for empirical analyses based on typologies. The consistency cut-off defines the minimum degree of consistency of a configuration with the outcome of interest. A consistency of 1 indicates that all observations with a specific configuration display the outcome, whereas a consistency of 0 indicates that no observation with this configuration displays the outcome. By defining both the frequency and the consistency cut-offs, researchers determine those configurations that provide sufficient evidence for inclusion in the minimization process.

In the fourth step, QCA uses Boolean algebra to minimize the truth table by systematically comparing all selected configurations.[4] To this end, QCA draws on Mill's method of difference: If two cases differ only in a single condition but both lead to the outcome of interest, this distinguishing condition is irrelevant for explaining the outcome and can thus be eliminated. For example, comparing two equally successful scholars similar in all attributes (e.g., affiliation, position, age) except one (e.g., gender), QCA would eliminate gender as an attribute relevant for explaining the scholars' success. By formally and systematically analyzing set-theoretic relationships, QCA reduces the complexity of configuration to a minimum set of essential, peripheral, and irrelevant attributes. Through this procedure, QCA allows researchers to identify complex (e.g., more than three-way) associations among attributes that jointly explain an outcome of interest.

Unique Features of QCA Results

QCA results have three unique features. First, QCA identifies alternative configurations that are equally valid for explaining an outcome of interest (equifinality). Researchers are increasingly building on this advantage. For example, Fiss (2011) uses QCA to identify four generic strategies associated with high financial performance. Crilly, Zollo, and Hansen (2014), analyzing interview data from 17 multinational firms facing identical pressures, identify evasive and emergent decoupling responses as equally effective responses to external pressures. Thus, QCA results yield more nuanced insights into alternative solutions than conventional techniques.

Second, QCA identifies theoretically driven combinations of causal conditions with respect to a specific outcome. Obtaining this result requires researchers to explicitly theorize about how causal conditions are associated with the outcome of interest. Through minimization, QCA displays only those specific combinations of causal conditions sufficient for the outcome. The results thus provide insights into which causal conditions work in concert to explain the outcome (conjunctural causation). This feature, unique to QCA, is unavailable in other common methods for identifying multidimensional dynamics, such as cluster or factor analysis (DeSarbo & Grewal, 2008; Ketchen & Shook, 1996).

Third, QCA results provide rich insights into the internal causal structures of different configurations. Specifically, using "easy" and "difficult" counterfactual analysis,[5] QCA can distinguish core conditions from peripheral and irrelevant ones, where the difference is determined by the "strength of the evidence relative to the outcome" (Fiss, 2011, p. 403). Researchers benefit from the unique features of QCA results because the results allow them to test existing theories (Fiss, 2011), understand alternative mechanisms leading to an outcome of interest (Bell et al., 2014), or develop theories about how alternative configurations relate to one another (Meuer, Rupietta, & Backes-Gellner, 2015).

Transferring QCA Results to HLM

QCA essentially develops a multilevel data structure in which cases (e.g., individuals, firms) are observable micro-level units and the configurations (e.g., generic strategies, innovation systems) are initially unobservable, theoretically informed, latent, macro-level classes. The multilevel mixed methods technique we develop here takes advantage of this multilevel structure by integrating the results of the QCA in HLM through a two-step process.

First, we calculate the set-membership scores for each micro-level unit in each macro-level configuration. QCA, as a set-theoretic method, measures causal conditions and outcomes as degrees of memberships in predefined sets. Thus, for every causal condition in the analysis, every case has a membership score ranging between 0 and 1. The configurations identified through the QCA represent specific combinations of conditions, allowing us to calculate the set-membership score of each case in all configurations. To measure set-memberships, we identify the set-intersections by using the following Boolean algebraic equation:

$$ms_i = \min(x_1, \ldots, x_j) \tag{1}$$

The membership score of a case in configuration i is the minimum of all conditions x that define a configuration. These conditions can be present, absent, or irrelevant. A present condition can be used directly for calculating the degree of membership. An irrelevant condition is ignored. An absent condition requires transformation if it is to represent the negation of a condition:

$$\textit{negation of } x_i = 1 - x_i \tag{2}$$

After one calculates all set-membership scores for each case in each configuration, the second step in integrating QCA with HLM involves meaningfully classifying cases. The criterion for allocating cases is the case's degree of membership in a configuration. If the set-membership score of a case in a configuration exceeds 0.5, the case is considered a member of this configuration. The set-membership scores thus allow researchers to allocate cases to meaningful classes. The most basic approach is to generate discrete classes of cases with a set-membership score higher than 0.5. Because configurations are mutually exclusive, all cases can be uniquely categorized in classes, and the number of classes corresponds to the number of configurations plus one residual class. The residual class contains all cases with no membership score higher than 0.5 in any configuration.

HLM

Categorizing micro-level units to mutually exclusive latent classes develops a perfectly nested multilevel data structure: Each micro-level unit can be classified unambiguously into macro-level classes (e.g., membership, non-membership, or hybrid membership in generic strategies). This categorization allows the analysis of the multilevel data structure in HLM. For illustrative purposes, we describe the analysis in a simple two-level HLM, in which we model the latent classes identified through QCA as macro-level classes. The model consists of a micro-level equation, Equation 3, which contains different intercepts and slopes:

$$y_{ij} = \beta_{0j} + \beta_{1j}x_{ij} + e_{ij} \tag{3}$$

in which y_{ij} denotes the outcome y of case i in configuration j. The two macro-level equations are defined as follows:

$$\beta_{0j} = \gamma_{oo} + r_{oj}\,, \tag{4}$$

$$\beta_{1j} = \gamma_{1o} + r_{1j} \tag{5}$$

The intercept β_{0j} and the slope β_{1j} vary with the macro-level class. The intercept β_{0j} has a fixed part γ_{oo} and varies around a random part r_{0j}. The equation for the slope β_{1j} has a similar structure. The fixed part is the average intercept from the entire sample. The random parts are random draws from a distribution.

Substituting the equations for the random coefficients β_{0j} and β_{1j} into the micro-level equation yields the estimation equation for the HLM:

$$y_{ij} = \gamma_{00} + \gamma_{10}x_{ij} + r_{oj} + r_{1j}x_{ij} + e_{ij} \tag{6}$$

in which the first two components ($\gamma_{00} + \gamma_{10}x_{ij}$) denote the fixed effects, and the third and the fourth components ($r_{oj} + r_{1j}x_{ij}$) denote random effects. e_{ij} is an independent and identically distributed error term that follows a normal distribution. The two-level HLM estimates effects between an observable micro level and latent macro level identified through QCA.

Interpreting HLM Results

As in a conventional HLM, the results allow researchers to draw inferences about within-level and cross-level effects. Yet the specificity of our technique allows for the inclusion of latent classes as macro-level units with a strong theoretical foundation. These latent classes are themselves linked to a certain outcome. Based on strong and often well-explained internal mechanisms, the latent classes in our technique may offer new insights into theoretically important mechanisms of the micro-level units. Additionally, triangulating the HLM results with the additional insights into the internal nature of the configurations identified through QCA provides a strong basis for corroborating and converging findings on the multilevel dynamics of latent classes. Thus, unique to our technique is the possibility of examining both theoretically motivated macro-level classes and their cross-level interactions in a broader setting.

Illustrating the Technique

We demonstrate our multilevel mixed methods technique with an illustration that uses Miles and Snow‘s (1978) typology of generic strategies. Miles and Snow define three generic strategies—conceptualized as unique combinations of structural and environmental conditions—for firms to outperform competitors: the "Prospector," a strategy for small and decentralized firms with low degrees of hierarchy; the "Defender," a strategy for large, centralized, and hierarchical firms; and the "Analyzer," a more complex strategy for firms with structural characteristics between those of the Prospector and the Defender. A fourth generic strategy, the "Reactor," is an inefficient type associated with low performance (Doty & Glick, 1994; Fiss, 2011).

Our illustration draws on an important corollary of Miles and Snow's (1978) typology. The typology proposes that all strategies be associated with comparably high levels of performance. It also stipulates that firms will differ in *how* and *how successfully* they innovate, depending on how consistently they adopt one of the generic strategies. Thus, the typology suggests that embedded *within* each of the generic strategies are organizational mechanisms that allow firms not only to outperform competitors but also to successfully develop new or improve existing products or services. Our technique is useful for testing this corollary because it separates the identification of firms' adoption of a generic strategy from the analysis of organizational mechanisms associated with innovation.

Our technique closely follows Rouse and Daellenbach's (1999) framework for isolating sources of sustainable competitive advantages. Rouse and Daellenbach argue that conventional strategy research, by relying on large samples, indiscriminately includes low- and average-performing firms. Because these firms by definition do not have any sustainable competitive advantage, such research is unlikely to uncover mechanisms of sustained competitive advantage. Instead, Rouse and Daellenbach recommend that researchers seeking to understand the sources of sustainable competitive advantage focus on firms with above-average performance because "only firms with unique resources and competencies ... have the potential for competitive advantage" (p. 488). Doing so yields a much clearer comparison of firms' differences. More specifically, their framework requires researchers to use multiple variables to cluster firms into groups for both examining firms' performance differences *within* groups and comparing high-performing firms *between* groups. By systematically reducing the sample size, Rouse and Daellenbach's framework allows researchers to focus on only those firms whose underlying organizational mechanisms lead to sustained competitive advantage.

Our technique corresponds to Rouse and Daellenbach's (1999) framework in offering researchers the opportunity to focus on a specific subpopulation of firms, one that is theoretically important for understanding organizational mechanisms. In essence, the use of QCA allows researchers to gain insights into the structure of generic strategies and categorize those strategies "using more than one variable" (Rouse & Daellenbach, 1999, p. 489). After having identified generic strategies, our technique then uses HLM to examine variations among this selected subpopulation of firms. These firms are theoretically important because their strategies will help researchers better understand organizational mechanisms for innovation. Thus, the results allow researchers to draw inferences about a smaller but theoretically important subpopulation. In our illustration, we use our technique to both test Miles and Snow's (1978) typology and extend it by revealing different innovation mechanisms *within* each of the generic strategies.

For the illustration, we use data from the "Innovation Survey" of the Swiss Economic Institute. Our sample consists of 1,201 firms from the 2005 wave. To calibrate the causal conditions, we complement these data with qualitative information. Our illustration follows Table 1, which mirrors the structure of the previous section and includes both additional information about software and references to the literature. For our illustration, we use Fs/QCA, Version 2.5—a freeware developed by Ragin and Davey (2014). Available R packages for QCA, such as QCAGUI (Dusa, 2016), QCApro (Thiem, 2016), or QCA3 (Huang, 2014), provide alternative software for the calibration, the truth table analysis, and the Boolean minimization.

Identifying Generic Strategies Using QCA

Identifying generic strategies using QCA involves four steps. The first step in a QCA requires researchers to use their theoretical and substantive knowledge to define the outcome and identify causal conditions. In our illustration, we draw on the extensive body of literature on Miles and Snow's (1978) typology to identify those conditions that researchers consider constitutive elements of generic strategies (e.g., DeSarbo & Grewal, 2008; Shortell & Zajac, 1990). We use financial performance as the outcome, measured as return on assets (i.e., revenues minus overhead—such as salaries or expenditures on goods and services—and divided by revenue). Moreover, we define six causal conditions: four structural (size, centralization, hierarchy, and specialization) and two environmental (rate of environmental change and intensity of competition). Together, these causal conditions constitute the dimensions we use for identifying and constructing generic strategies. The selection of causal conditions in our illustration closely follows Fiss (2011), who uses QCA for advancing Miles and Snow's typology.

The second step in a QCA involves calibrating the sets for the outcome and causal conditions. Calibration assigns each case a certain degree of set-membership "relative to substantive knowledge rather than the sample mean" (Fiss, 2011, p. 402). Membership scores range from 0 to 1, where 1 indicates full membership; 0, full non-membership; and 0.5, the point of maximum ambiguity between membership and non-membership. For example, in our illustration we draw on the size classification of the Swiss Federal Statistical Office to calibrate the set of *large firms*. This classification defines small firms as those with more than 9 but fewer than 50 employees; medium-sized firms, with more than 49 but fewer than 250; and large firms, with more than 249. To calibrate the set of large firms based on theoretically meaningful points, we set full membership at 249 employees, full non-membership at 9, and the crossover point at 50 (i.e., the number of employees distinguishing small from medium-sized firms).[6]

Table 2 provides descriptive statistics for all calibrated and uncalibrated measures. One notable difference between the calibrated and uncalibrated measures is that the calibrated ones range from 0 to 1, whereas the uncalibrated ones follow their original range. Table 2 also includes the two variables, patenting and R&D intensity, that we use later in the HLM for examining to what extent the adoption of a generic strategy is associated with innovation. Because of missing data, information on R&D intensity is available for only 709 firms.

The third step in a QCA involves the truth table analysis. The truth table lists all possible combinations of conditions (i.e., configurations). The number of configurations is 2^k (k is the number of conditions in the analysis), and each row in the truth table corresponds to one hypothetically possible configuration. In our illustration, with six conditions, there are 64 (2^6) logically possible combinations of structural and environmental conditions. Depending on the size of the data set, researchers may manually write out the truth table or may automatically develop the truth table using the QCA software packages listed in Table 1.

Table 1. Overview of the Steps Involved in the Integrated Multilevel Mixed Methods Technique.

Analytic Steps		Intermediate Steps	Software Packages	Analytical Logic and Purpose (see also, Rouse & Daellenbach, 1999)
Step 1	QCA	1. Selection of conditions 2. Calibration 3. Truth table analysis 4. Boolean minimization *Result*: Configuration chart	• Fs/QCA (Ragin & Davey, 2014) • R package: QCAGUI (Dusa, 2016) • R package: QCApro (Thiem, 2016) • R package: QCA3 (Huang, 2014)	Use QCA as approach for multidimensional construction of organizational configurations (e.g., strategic groups, generic strategies). Intermediate steps embedded in QCA, especially the informed selection of conditions and their calibration, help researchers identify *theoretically informed* groups. Using more than one variable serves researchers to validate the group construction.
Step 2	Transfer QCA results to HLM	1. Measuring membership scores of firms in latent classes 2. Classifying firms as a member of a latent class *Result*: Hierarchical multilevel data structure	• Standard statistics software (e.g., R or Stata)	Assign micro-level observations (e.g., firms, individuals) into multidimensional, macro-level classes (i.e., organizational configurations).
Step 3	HLM	1. HLM with latent class at the macro level and observations at the micro level *Result*: Nuanced insights into causal structure of configurations, combined with precise information about multilevel between macro-level configurations and micro-level observations.	• HLM or mixed effects models (e.g., HLM, R, STATA).	Analyze and compare performance variation between high- and low-performing micro-level observations (e.g., firms, individuals) within macro-level classes (i.e., organizational configurations). Researchers may compare various performance indices.

Note. QCA = qualitative comparative analysis; HLM = hierarchical linear modeling.

Table 2. Descriptive Statistics of Variables Included in the QCA and HLM.

		Uncalibrated Variables				Calibrated Conditions			
	Observations	Mean	*SD*	Min	Max	Mean	*SD*	Min	Max
Variables/conditions for QCA									
Financial performance (high)	1,201	0.22	0.16	0.00	0.98	0.46	0.34	0.01	1.00
Specialization (high)	1,201	0.54	0.13	0.00	0.80	0.53	0.33	0.00	1.00
Hierarchy (large)	1,201	2.49	1.20	0.00	15.00	0.46	0.33	0.01	1.00
Centralization (high)	1,201	3.61	0.58	1.71	5.00	0.69	0.17	0.13	0.95
Number of employees (large firm)	1,201	275.83	1,474.06	3.00	39,129	0.62	0.29	0.03	1.00
Environmental change (high)	1,201	1.34	1.17	0.00	4.00	0.35	0.26	0.05	0.95
Competition intensity (high)	1,201	2.49	1.41	1.00	5.00	0.37	0.34	0.05	0.95
Variables for HLM									
Patenting	1,195	0.17	0.38	0.00	1.00				
R&D intensity (expenditures/ turnover)	709	0.02	0.05	0.00	0.67				

Note. QCA = qualitative comparative analysis; HLM = hierarchical linear modeling.

Preparing the truth table for the minimizations requires researchers to select those configurations (i.e., rows) to be included in the analysis. These configurations must meet the *consistency cut-off* and the *frequency cut-off*. Consistency measures how often cases in a single truth table row show the outcome of interest—a consistency of 1, indicating that all cases exhibit the outcome. In our illustration, a high consistency indicates that a certain combination of structural and environmental conditions is strongly associated with high performance. In turn, a low consistency indicates that among cases with the same configuration, some are high performing and some are low performing.

Because there are no universal cut-offs for consistency, researchers need to justify their consistency cut-off (Schneider & Wagemann, 2013). Greckhamer, Misangyi, Elms, and Lacey (2008) distinguish between three benchmarks: Solutions that pass the benchmark of 0.8 are called "almost always sufficient"; those that pass the benchmark of 0.65, "usually sufficient"; and those that pass the benchmark of 0.5, "sufficient more often than not." For our illustration, we select only those configurations with a consistency of at least 0.70.[7]

The frequency cut-off determines the number of cases a configuration must cover for inclusion in the analysis. This choice depends on the research question and the size of the data set (Greckhamer, Misangyi, & Fiss, 2013). In small-*N* studies, truth table rows frequently contain only a single case, demanding a frequency cut-off of 1. In large-*N* studies, truth table rows may contain more cases. In our large data set illustration, we choose a high frequency cut-off of 10 (cases) because we are interested in identifying *generic* strategies.

The fourth step in a QCA is Boolean minimization. During Boolean minimization, QCA systematically compares all configurations that are frequently and consistently associated with the outcome. For example, two configurations of structural and environmental conditions may be frequently adopted by many firms and consistently associated with high performance. If these two configurations differ by only one condition, such as high centralization, this difference indicates that a firm's degree of centralization is irrelevant for explaining why its configuration is associated with high performance. QCA systematically applies Boolean minimization to all configurations and, through this process, reduces the complexity of configurations. As a result, QCA reveals the most parsimonious combination of explanatory conditions. In small-*N* crisp-set settings, researchers may

	Solution								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Large Firm	●		●	⬤		●	●	●	
High Centralization	●	●		●	●			⨂	⨂
Large Hierarchy	⬤	⬤	⬤				⊗		⊗
Large Educ Specialization	⊗				⬤	⬤			
High Competition Intensity	⊗	⊗	⊗	⬤		⊗	⊗	⊗	⊗
High Competition Change		⊗	⊗	⊗	⊗	⊗	⊗	⊗	⊗
Consistency	0.72	0.70	0.69	0.69	0.66	0.69	0.71	0.74	0.74
Raw Coverage	0.30	0.40	0.39	0.33	0.53	0.40	0.33	0.36	0.31
Unique Coverage	0.02	0.01	0.00	0.01	0.04	0.00	0.00	0.00	0.01
Overall Solution Consistency	**0.62**								
Overall Solution Coverage	**0.69**								

Figure 1. Configuration chart of generic strategies identified through qualitative comparative analysis (QCA).

minimize the truth table manually. In large-N settings, we recommend the use of available software packages.

QCA Results

Figure 1 shows the results in a configuration chart that vertically organizes the identified generic strategies. Full circles indicate the presence of a condition; crossed-out circles, the absence of a condition; and empty cells, an irrelevant condition (i.e., neither its presence nor its absence matters for explaining the outcome of interest). Large circles indicate the core conditions of a configuration; small circles, the peripheral conditions.

Our results identify nine generic strategies associated with high financial performance, differing in their internal nature. For example, Configuration 1 features the presence of hierarchy as a core condition and the presence of large size and high centralization and the absence of high educational specialization as peripheral conditions. Thus, Configuration 1 closely resembles Miles and Snow's (1978) Defender strategy. In contrast, Configuration 9 features the absence of centralization as a core condition and the absence of hierarchy, competition intensity, and environmental change as peripheral conditions. Configuration 9 thus more closely resembles their Prospector strategy. Other configurations identified through QCA lie between these two poles. For brevity, we refrain from describing the remaining strategies in detail. Ultimately, the QCA results identify alternative generic strategies, reveal their internal structure, and provide researchers an approach to meaningfully assigning firms to groupings of generic strategies. Rouse and Daellenbach (1999) emphasize the importance of employing a multidimensional approach to group construction. QCA does precisely that, allowing researchers to construct groups and validate measures with substantive and theoretical knowledge (Zahra & Pearce, 1990).

Transferring QCA Results to HLM

To prepare the QCA results for use in HLM, we categorize each firm as a member of one of the identified generic strategies. We perform this categorization procedure in STATA. First, following Equation 1, we calculate the set-membership scores of each firm in all generic strategies. For example, for measuring the set-membership scores of all firms in the Defender strategy (Configuration 1), we specify in Equation 1 the presence of large size, high centralization, and large hierarchy and the absence of high specialization and high competition intensity. For the negation

Table 3. Hierarchical Linear Modeling Results.

Variable	Patenting	
	b	*SE*
R&D intensity	2.71	0.87
Intercept	0.17	0.03
var(slope)	4.55	3.33
var(intercept)	0.01	0.00
Observations	705	
Chi-square (*p* value)	62.27 (.00)	

of the conditions of high specialization and high competition intensity, we follow Equation 2. We repeat this procedure to obtain set-membership scores for all firms in all other generic strategies.

Second, we categorize firms according to their membership score. The criterion for allocating firms to a class (i.e., generic strategy) is a firm's membership score above 0.5 (i.e., above the cross-over point that separates membership from non-membership). We define nine classes (one for each generic strategy) that contain only those firms that are members of a configuration. We also define a residual class containing those firms not belonging to any configuration (i.e., without membership scores above 0.5 in any of the configurations). The categorization procedure groups firms into generic strategies. At the same time, the procedure organizes the data in a hierarchical multilevel structure with firms (at the micro level) allocated into mutually exclusive latent classes that correspond to generic strategies (at the macro level).

HLM

To explore organizational mechanisms suited for innovation within the generic strategies, we estimate a two-level HLM with the configurations—which resemble generic strategies—as latent classes at the macro level. At the micro level, we include patenting as the dependent variable and R&D intensity as the explanatory variable. The intercept and the slope vary by generic strategies. While variance in the intercept indicates that a firm's patenting differs according to the generic strategy (i.e., how innovative the firm is), variance in the slope indicates that the effect of a firm's R&D intensity on patenting differs by generic strategy (i.e., how the firm innovates).

Table 3 reports the results of the HLM. R&D intensity has a positive effect on patenting. The low variance in the intercept, reported at the bottom of Table 3, indicates that how innovative firms are does not depend on the generic strategy they adopt. However, the sizable variance in the slope indicates that how firms innovate differs according to the strategy they adopt. Thus, the results suggest that while adoption of a generic strategy does not affect how innovative firms are, it does affect the internal mechanisms through which firms innovate.

The results show two effects of interest to both the literature on strategic management and that on innovation. First, in contrast to suggestions that the Prospector strategic is the most innovative (e.g., DeSarbo, Benedetto, Song, & Sinha, 2005), our findings suggest that while generic strategies explain high performance among firms, they do not explain differences in how innovative firms are. Nonetheless, the findings indicate that understanding the internal mechanisms underlying the generic strategies is important because the adoption of a generic strategy may provide insights into how firms innovate. While some generic strategies leverage the effects of R&D intensity on patenting, others hamper them. In sum, the results provide nuanced insights into the organizational mechanisms for innovation, mechanisms that are embedded in generic strategies. In line with Rouse and

Daellenbach's (1999) logic, the multilevel mixed methods technique enables researchers to examine alternative micro-level mechanisms.

Interpretation and Extensions

With such findings, researchers may return to the QCA results to perform additional analyses for exploring in depth why, for example, generic strategies lead to similar levels of innovation yet do so through different innovation mechanisms. The distinction between the core and peripheral conditions provides both important guidance for ex post analyses and valuable opportunities for additional theory building through triangulating results. For example, researchers may analyze whether differences within configurations (i.e., those with the same core condition but different peripheral conditions) or differences between configurations (i.e., those with different core conditions) are driving the results.

In our illustration, Configurations 1 to 3 in Figure 1 closely resemble Miles and Snow's (1978) Defender. These configurations share the same core condition (presence of hierarchy) yet differ in the peripheral conditions. Analyzing the variance of innovation within a generic strategy (e.g., through F tests or regression analysis) would provide insights into how strongly changes in the peripheral conditions affect the way firms innovate. One might expect, for example, a small variation *within* generic strategies but a large one *between* them. The triangulation of the HLM results, the results of the ex post analysis, and the rich qualitative insights into the causal structure of configurations from the QCA provide a robust foundation for testing, refining, and extending multilevel theories of organizational configurations

While our illustration shows only the very core of the technique, researchers can extend it in at least two directions. First, the richness of the QCA results offers opportunities for a more nuanced classification of cases. Researchers may, for example, distinguish observations with a very high fit (a membership score close to 1) from those with a moderately high fit (a membership score between, say, 0.5 and 0.6). Similarly, researchers may classify observations with multiple class membership. These alternative classifications generate a non-perfectly nested data structure—one that is theoretically important, for example, for classifying hybrid memberships (e.g., DeSarbo & Grewal, 2008).

Second, researchers may extend the technique to analyze more complex multilevel structures by adding additional macro levels (e.g., industry or region). The addition of a third level leads to a structure in which the latent level identified through QCA (e.g., generic strategy) overlaps with a second, observable macro level (e.g., industry or region). Such "cross-classified" models, which can be estimated by standard extensions to the HLM, allow researchers to expand their analysis of multilevel effects (Raudenbush & Bryk, 2002).

While this technique offers a new way of tackling two important challenges in multilevel research (non-perfectly nested structures and latent class), it cannot deal with other important challenges. For example, the process character of many organizational phenomena demands that researchers explicitly include time considerations in developing and testing theories. However, as longitudinal approaches for QCA are only now emerging,[8] they require further development before researchers can use our technique for conducting longitudinal multilevel research on organizational configurations. Furthermore, some organizational theories conceptualize phenomena at multiple latent levels. Identity, for example, exists at the level of both the organization and the field (e.g., Ashforth, Rogers, & Corley, 2011). To handle research questions involving a latent class at the micro level and another latent class at the macro level, our technique needs further methodological development.

Discussion

In this article, we develop an integrated multilevel mixed methods technique that sequentially combines QCA and HLM to advance multilevel research on organizational configurations. Because

QCA and HLM are interactively integrated across all stages, the technique builds strongly on the advantages of both approaches. We illustrate the technique with a simple example set in the context of Miles and Snow's (1978) typology of generic strategies. Our illustration shows how QCA identifies configurations, how the unique QCA results may be transformed for use in HLM, and how a two-level HLM provides results on both within-level and cross-level effects. The illustration explains in a stepwise fashion how our technique works in practice and provides researchers with information about software and illustrative studies.

Current multilevel mixed designs, which are rare in the mixed methods literature, do not strongly integrate qualitative and quantitative approaches. Ours is among the first more integrated multilevel mixed methods techniques to analytically integrate qualitative and quantitative methods for use in a single study. We contribute to the mixed methods literature by developing a novel technique for use in multilevel research on organizational configurations.

We also identify an important trade-off related to the quality and rigor of implementing the design components of this technique. The QCA objective of complexity reduction leads to the identification of a few configurations at the macro level. Yet reducing the number of configurations has implications for implementation of the HLM in that it leads to fewer classes at the macro level but increases the number of micro-level observations within classes. In contrast, increasing the number of configurations by adjusting the QCA would increase the number of classes at the macro level but decrease micro-level observations per class. The number of classes and number of observations within a class greatly influence the statistical power in the multilevel model (Scherbaum & Ferreter, 2009) and determine the identification of statistically significant effects. Therefore, researchers sequentially combining QCA and HLM need to find an equilibrium that provides sufficient observations at both levels.

This trade-off between different components may also be inherent in other mixed designs that integrate approaches during the data analysis stage. We speculate that the value such designs may add to a study will depend on two factors: the extent to which two methods are integrated and the degree of compatibility of their underlying assumptions. In that case, integrated mixed methods will add explanatory value, particularly to those studies that strongly integrate highly compatible methods. However, those studies in which researchers integrate two less compatible methods may instead benefit from reducing the extent to which the methods are integrated. Future mixed methods research may gain a deeper understanding of integrated designs by exploring the extent to which the value of these designs depends on these two factors.

Our technique also offers researchers new opportunities for refining and extending theories of organizational configurations. It allows researchers to simultaneously reveal the causal structure of organizational configurations and examine them in their multilevel environment. Moreover, as our illustration has shown, the combination of QCA and HLM offers researchers opportunities for extending typologies by exploring the alternative micro-level mechanisms of organizational configurations. Configurational logic has been used for understanding strategic groups (e.g., DeSarbo & Grewal, 2008) and employment modes (e.g., Kang, Morris, & Snell, 2007) and may in the future valuably contribute to research in organizational behavior (Short et al., 2008). Because configurational phenomena are central to organization research, we argue that the new opportunities allow a greater in-depth study of how alternative causal structures of configurations at the macro level are linked to specific mechanisms at the micro level.

We also offer an alternative technique for multilevel analyses that allows researchers to address two particular aspects of multilevel phenomena that challenge conventional multilevel methods: non-perfectly nested structures and latent constructs. Ketchen, Boyd, and Bergh (2008), for example, point out that while management deals with multiple levels of analysis, the methods they use for examining multilevel phenomena are "relatively unsophisticated" (p. 10). Because QCA recognizes the complex causal nature of organizational configurations, the combination of QCA with HLM improves the analytical adequacy of multilevel research on latent, configurational constructs. Moreover, researchers can flexibly extend the basic two-level HLM model to account for hybrid memberships and cross-nested multilevel structures. Thus, our integrated multilevel mixed methods technique helps overcome some of the current challenges of multilevel research.

Conclusion

Our multilevel mixed methods technique responds to recent calls in the organization science literature for researchers to find solutions for dealing with non-perfectly nested multilevel data structures (e.g., Aguinis, Boyd, Pierce, & Short, 2011; Hitt, Beamish, Jackson, & Mathieu, 2007) and to take advantage of the benefits of QCA for deriving configurational constructs (e.g., Boyd, Haynes, Hitt, Bergh, & Ketchen, 2012). During the past 10 years, researchers have made important advancements in theories and methods for research on organizational configurations (Boyd et al., 2012). We present a technique that, by interactively combining QCA and HLM across the research process, promises strong inferences for multilevel research on organizational configurations. We thus offer a technique that contributes to the literature on organizational configurations by offering researchers new opportunities for advancing multilevel theories of organizational configurations.

Authors' Note

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Notes

1. Because qualitative comparative analysis (QCA) adopts a deterministic understanding of causality, most researchers use the terms *condition* and *outcome* rather than *independent variable* or *dependent variable* (as used in statistical, variance-based analyses). We apply the terminologies of both QCA and statistical analysis for clarity, as well as to underscore their different ontological foundations (Ragin, 2008a; Schneider & Wagemann, 2013).
2. McKelvey (1982) contrasts two kinds of typologies. Monothetic typologies discretely classify entities so that the entities' unique set of features is both sufficient and necessary for membership in the group. In contrast, polythetic typologies allow for variation in the classifying attributes of entities, so that units may vary in their degrees of membership. The technique we present here is applicable to both interpretations of a typology. The crisp-set variant of QCA (csQCA), in which every attribute defines a unit as being either in or out of a set, is suited for monothetic typologies. The fuzzy-set variant of QCA (fsQCA) allows

membership scores to range from 0 to 1 and is thus better suited for situations in which researchers adopt a polythetic interpretation of a typology.

3. Whereas the truth table of a QCA analysis with three attributes contains eight rows (2^3), one with five causal conditions contains 32 rows (2^5). Truth tables thus display all logically possible configurations: those for which empirical evidence exists and those hypothetical ones for which no empirical evidence exists. The combination of both observable and hypothetical configurations highlights the notion of limited diversity, which stipulates that combinations of conditions occur in coherent patterns (Meyer, Tsui, & Hinnings, 1993; Ragin, 2008a).
4. Whereas most QCA software packages, such as Fs/QCA, use the Quine-McCluskey algorithm (an optimization algorithm for minimization), the QCA packages available for the R environment do not use this algorithm (Baumgartner & Thiem, 2015). Instead of optimizing the results, these packages provide all possible single-outcome models, one of them identical to the results provided by other software packages. The results thus do not differ significantly.
5. Counterfactuals are thought experiments that differ in their plausibility (Ragin, 2008a). Counterfactuals are "easy" when, in the absence of observation, the researcher has robust theoretical and substantive knowledge about a certain relationship between an explanatory and an outcome variable. In contrast, counterfactuals are "difficult" when researchers instead need to rely solely on sound argumentation or empirical results to specify the relationship.
6. For brevity, we do not give detailed descriptions of the calibration of the remaining sets.
7. This benchmark is in line with those of other illustrations of QCA (e.g., Greckhamer, Misangyi, Elms, & Lacey, 2008). However, because QCA is a relatively young method, it has fewer standards compared to other methods (e.g., no significance tests), and the debate about the appropriate consistency level of QCA solutions is ongoing. A benchmark consistency of $\geq$0.80 is desirable and is often reported in applied QCA studies involving small to medium-sized samples. Yet, as Greckhamer, Misangyi, and Fiss (2013) argue, the application of QCA to large-*N* data sets "inevitably involves a departure from some of the underlying ideas" (p. 50).
8. For researchers interested in QCA developments, we recommend the COMPASSS webpage (www.compasss.org), which publishes methodological advancements in QCA in a peer-reviewed working paper series.

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