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Exploring Configurations for Business Value from Event-Driven Architecture in Healthcare

Research-in-Progress

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Abstract

Event-driven architecture is one of IT architectures introduced to assist enterprises operate in a real-time environment such as healthcare. As IT business value generation is a complex process, we explore configurations of event-driven architecture and other organizational elements in achieving healthcare performance. We purpose an alternative non-regression-based way, configurational approach, to study such process. Drawing on the configuration view, we attempt to capture the complexity of interactions among EDA-enabled capability and organizational elements needed to achieve higher health care quality. We tested our model with both primary and secondary data. Results show three different configurations with high levels of responding capability, dynamic capability and physicians’ resistance to IT changes present in all three paths. Our findings advance understanding of a complex business value generation process and also provide practical guidance for healthcare managerial practices.

Keywords: Event-driven architecture; dynamic capability, business value, fsQCA, healthcare information technology; configuration theory

Introduction

Event-driven architecture (EDA) is one of the emerging IT architectures that have been introduced to assist enterprises operate in a real-time environment (Ranadivé 1999; Taylor, Yochem, Phillips, & Martinez, 2009). An EDA system is typically composed of messaging, adapters, message transformation, business flow coordination, event notification and monitoring functions (Ranadivé, 1999). It relies on the design principles of the publish/subscribe mechanism, the loose coupling principle and the asynchronous interaction function (Michelson, 2006; Taylor et al., 2009) to synchronize the analysis of multiple data streams in real time, which is particularly helpful for healthcare providers seeking to improve medical data integration (Taylor et al. 2009). Although the pace of Information Technology (IT) transformation in health care tends to trail behind the other industries (Lucas et al. 2013; Romanow, Cho & Straub, 2012),
the adoption of healthcare IT (HIT) has identified a number of benefits, including reductions in care delivery costs and medical errors and improvements on clinical outcomes (Agarwal et al., 2010; Bhattacherjee & Hikmet, 2007; Goh et al., 2011). Research has shown that IT architecture resources are crucial in achieving these benefits in healthcare organizations (e.g., Bradley et al. 2012; Goh et al. 2011; Leung, 2012; Singh, Mathiassen, Stachura, & Astapova, 2011). In particular, taking into account the suitability and capability of a firm's IT architecture can help healthcare organizations to identify market niches, respond to customer needs, integrate inter-organizational information and improve their operational flexibility to enable them to deal more effectively with the uneven workflows they typically experience due to emergencies and unexpected events (Lucas., Agarwal, Clemons., El Sawy, & Weber, 2013).

Research based on the logic of resource-based view (Barney, 1991; 2001) has suggested that EDA-based health information systems can generate EDA-specific capabilities as a unique, distinctive resource that reinforces existing organizational capabilities, thereby helping an organization gain superior healthcare performance (e.g., Chen, Brown, Hu, King, & Chen., 2011; Taylor et al., 2009). In this study, we seek to explore the role of EDA in achieving healthcare performance (i.e., quality of care) from the theoretical perspectives that IT business value generation is a complex process (Melville, Kraemer & Gurbaxani, 2004; Nevo & Wade, 2010) that cannot be fully explained using regression-based methods but rather by a systemic and simultaneous arrangement of multiple elements (Fichman, 2004; Fichman et al., 2014). As such, the complexity of the interactions between different EDA-related IT capabilities, and organizational capabilities and elements should be captured jointly to achieve higher health care quality.

To answer the research question of "How do other organizational elements combine with EDA capabilities to cause high quality of care in healthcare organizations", we first conceptualize the multi-dimensional role of EDA capabilities. Then we explore various combinations of interdependent and complementary elements that interact with EDA for better business value based on configuration theory.

**Research Model**

Our research model relies on configuration theory to disentangle the complex interactions among the elements leading to business value. Configuration theory is better suited for understanding patterns and combinations of factors and how they, as configurations, cause specific outcomes to occur in a certain context (Fiss, 2007; Meyer, Tsui & Hinings, 1993). Specifically, we examine the elements of EDA capabilities, organizational capability, and other organizational elements that can be combined into potential configurations to result in business value. This configurational perspective provides the basis for our analysis of the causal paths that explain how, in health care context, the combination of EDA capabilities and other organizational elements may lead to superior health care quality. Figure 1 illustrates the interactions among these elements as holistic confluence that subsequently contributes to enhance business value as quality of care in healthcare.
The Elements of EDA Capability

EDA capability definition is absent in most but one paper (Taylor et al, 2009). We define EDA capability in healthcare as the ability to propagate real-time medical events data across healthcare units automatically to support user evaluations of patients’ conditions and facilitate appropriate treatment decisions. In this context, EDA capability reflects the extent to which health service providers manage and control their healthcare relevant IT resources effectively to facilitate their operational processes and promote competitive strategies based on an event-driven architecture. We posit that EDA capability is a reflective construct with four dimensions: sensing capability, responding capability, interoperability capability, and flexibility capability (Table 1).

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Description</th>
<th>Supporting research</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensing Capability</td>
<td>The ability to recognize event-triggering information and to provide managerial overview of the relevant business processes in real time.</td>
<td>El Sawy &amp; Pavlou (2008); Houghton et al. (2004); Taylor et al. (2009)</td>
</tr>
<tr>
<td>Responding Capability</td>
<td>The ability of the IT architecture to support the manager’s decisions and actions at each organizational level.</td>
<td>El Sawy &amp; Pavlou (2008); Houghton et al. (2004); Taylor et al. (2009)</td>
</tr>
<tr>
<td>Interoperability</td>
<td>Provides a system platform which performs the exchanging and sharing of data on two or more software components</td>
<td>Spooner &amp; Classen (2009); Taylor et al. (2009)</td>
</tr>
<tr>
<td>Flexibility Capability</td>
<td>Enables an organization to speed up operational changes and promote a high degree of business agility via IT architecture modularity, compatibility and maintainability</td>
<td>Byrd &amp; Turner (2000); Duncan (1995); Ranadivé (1999); Taylor et al. (2009)</td>
</tr>
</tbody>
</table>

Table 1. EDA Capability Dimension/Source

Organizational Elements: Size, Top Management Support, and Physician Resistance to IT

Organizational size, including both the firm and IT department sizes have been widely acknowledged as important determinants of converting IT assets into business value (Lucas, 1993; Markus & Soh, 1993). In general, large organizations possess more organizational capabilities obtained from their more abundant resources (Damanpour & Schneider, 2006). Organizational size is considered as an important element of firm characteristics influencing IT capabilities (Park, Pavlou, & Saraf, 2014) and organizational innovation (Cobo-Benita, Rodriguez-Segura, Ortiz-Marcos, & Ballesteros-Sánchez, 2016; Ganter & Hecker, 2014).

Based on the institutional theory, top management is viewed as primary human agency that translates external influences (e.g., external knowledge) into managerial and strategic actions such as knowledge integration and technical and organizational changes (Liang, Saraf, Hu, & Xue, 2007). Top management acts as a powerful template that guides organizational behavior and is able to change the norms, values, culture as well as organizational regulations, routines, rules, and procedures in an organization (Purvis, Sambamurthy & Zmud, 2001). Past research indicates that support from top management such as formal monitoring of progress and incentives are critical to successful adoption and implementation of information systems (Chatterjee, Grewal, & Sambamurthy, 2002; Liang et al., 2007; Mitchell, 2006).

In the context of healthcare, physician resistance to change is one key barrier in adoption of IS since most physicians rely on their professional experiences in making clinical decisions instead on IS output that they might not be familiar with or have not been trained to use (LeTourneau, 2004; Paré, Raymond, de Guinea, et al., 2014). Prior research on healthcare IT adoption has highlighted that physicians or medical
staffs have strong influence on such adoption decisions and the performance of IS/IT usage (e.g., Boonstra & Broekhuis, 2010; Meinert, 2005). Thus, we consider physician resistance to IT as a potential organizational element for achieving care of quality in healthcare.

**Dynamic Capability**

Dynamic capability is a firm’s ability to integrate, reconfigure, gain and renew resources to match rapidly-changing market environments (Eisenhardt & Martin, 2000; Helfat & Peteraf, 2003; Teece, Pisano & Shuen, 1997; Winter, 2003). It also enhances a firm’s agility (Roberts & Grover, 2012). Dynamic capability is conducive not only to reconfiguring a firm’s resources and routines (Zahra, Sapienza & Davidsson, 2006), but also to improving the effectiveness of its operating routines (Zollo & Winter 2002). Dynamic capability leads inherent operational capabilities into new fields by reconfiguring resources to suit changing business circumstances. Barreto (2010) and Teece (2007) both consider dynamic capability as the ability to sense and shape opportunities and threats, to seize market opportunities and to maintain competitiveness.

Several studies have explored the impact of dynamic capability on organizational performance in the healthcare industry. An early study by Pablo et al. (2007) examined how public healthcare organizations identify, enable and manage their dynamic capacities successfully, concluding that learning through experimenting is a key element of dynamic capability and that this enables healthcare organizations to pursue organizational improvement and performance. Ridder et al. (2007) addressed the issue of how dynamic capability contributed to the optimization of diagnosis-related groups (DRGs) in a German hospital. Singh et al. (2011) demonstrated that IT-enabled dynamic capability can help healthcare organizations maintain a competitive advantage by enhancing the organization’s ability to identify healthcare resources and respond to patient needs. We therefore include dynamic capability in our research model as it plays a critical enabler role in creating business value in healthcare.

**Outcome- Business Value**

There are many ways to measure healthcare organization performance such as cost reduction, quality of care, and patient satisfaction. Business value in this study is not defined in the traditional sense as in financial terms because most of healthcare organizations are not operating for profit and because their goals are to serve. Therefore, we did not choose a financial performance measure as the outcome. Instead, we propose to use a service quality measure as performance. We choose the Centers for Medicare & Medicaid Services’ (CMS) 30-day risk-standardized readmission rate among various quality measures for three reasons: 1) it is the most recent measure added to annual report; 2) availability, and 3) how it is measured and what it represents. The readmission rate measures assess a broad set of healthcare activities that affect patients’ well-being. Patients who receive high-quality care during their hospitalizations and their transition to the outpatient setting will likely have better outcomes, such as survival, functional ability, and quality of life.

**Research Method**

Extending the theoretical perspective from strategic alignment between IT and business to co-evolution, some IS strategy studies have suggested that the key to successful health information technologies (HIT) implementation is to orchestrate the complex and dynamic interactions between organizational capabilities and HIT during the business process (Agarwal et al., 2010; Goh, Gao, & Agarwal, 2011; Novak et al., 2012). Although these studies have noted the systemic notion of co-evolution among individual elements for IS success, examining the effect of co-evolution with conventional correlation-based linear methods (e.g., two-way correlations, testing moderator/mediator effect) does not allow for a holistic view and capturing non-linear interdependent interactions among these elements. To explore a more realistic view, we apply configurational approach (e.g., Fiss, 2011; Ragin, 2008a) and used fuzzy-set qualitative comparative analysis (fsQCA) to analyze cases.

**Data Collection and Matching**

We obtained both qualitative and quantitative data from HIMSS (Healthcare Information and Management Systems Society) database and a survey respectively. Our sample was acquired through a
systematic random sampling technique (Cochran, 2007). An initial population set of 4668 CIOs in health care was extracted from HIMSS database. After cleaning up incomplete information and duplicates, 3309 sets of data were available. We then systematically selected every third person from the list to generate our sample population of 1103 CIOs. Each organization was assigned a randomly generated case id to protect the privacy of the respondents and for matching qualitative data in the second stage of data collection using a web questionnaire.

The questionnaire was posted on the Qualtrics Survey platform. An invitation letter with description of research purpose and a participant-specific hyperlink were sent via this platform. A first round of 1103 questionnaires was sent in May, 2014, and immediately 183 emails bounced back due to their organizations’ firewall blocking policy. During a three month period, we received 75 complete responses after three-round reminders from 920 effective invitations, which results in an 8.15% response rate. We then use the case ids to match for outcome acquired from the HIMSS database. We chose to use excess readmission ratio as the proxy of our outcome, the higher the ratio the worse the quality. Initial matching and complete data yielded 25 cases.

The survey consists seven sections: EDA capability, dynamic capability, competitive advantages, physician’s resistance to IT, top management support, demographic data, and comment. For EDA capability, we used 5 items (questions) for sensing capability, 4 for responding, 4 for interoperability, and 5 for flexibility. Please see the descriptions of these four capabilities in Table 1. We asked participants to rate their dynamic capabilities based on the past five years experience using 12 items. We collected data from 12 questions on IT service quality and speed to market using as competitive advantage. These data are designed to triangulate the secondary data. Then the participants are asked to evaluate the degree of physicians’ resistance to IT in their organization for the past five years by answering four questions. Top management attitude toward IT is measured by four items. Demographic data include age, gender, years in IS/IT field.

**Case Data Analysis**

Because our data are both qualitative and quantitative in nature and we wanted to explore non-linear interactions, we need an analysis method that could handle such combination and examine cases which lead us to Qualitative Comparative Analysis (QCA). QCA was developed in political science to evaluate case studies with too few cases for standard statistical analysis and where the available data are often qualitative or a combination of qualitative and quantitative (Ragin, 1987; Rihoux & Ragin, 2009). Simply put by Cress and Snow (2000, p.1079) that “QCA, ... is conjunctural in its logic, examining the various ways in which specified factors interact and combine with one another to yield particular outcomes.” In contrast to statistical regression-based methods, QCA is based on set theory and logic and is designed to evaluate social systems characterized by causal complexity. QCA investigates the specific conditions under which an outcome occurs while statistical regression estimates the “average effects of independent variables” (Mahoney, 2010, p.132). This view of causation has gained increased attention in the social sciences (Brady & Collier, 2010; Collier & Gerring, 2009). QCA assumes each causal pathway can contain different combinations of explanatory characteristics. This method looks for the effect of combinations—configurations—of necessary and sufficient explanatory characteristics, rather than for the effect of each individual characteristic while holding the other characteristics constant (equal).

QCA belongs to a class of analytic techniques based on set theory called Configurational Comparative Methods (CCMs). QCA is configurational because it allows investigators to identify combinations of configurations associated with an outcome of interest. There are three types of QCA: (1) crisp-set QCA (csQCA), (2) multi-valued QCA (mvQCA), and (3) fuzzy-set QCA (fsQCA). These types differ in how the characteristics are coded. csQCA codes characteristics in binary (0 and 1). mvQCA require characteristics to be coded as multi-valued (more than two discrete values, usually three) variables. fsQCA allows a characteristic to have any continuous value from 0 to 1. We use fuzzy set QCA for the advantage of being able to show the degree of membership (Ragin, 2008) versus simply 0 and 1.

In essence, fsQCA takes the perspective that cases are constituted by combinations of theoretically relevant attributes and that the relationships between these attributes and the outcome of interest can be understood through the examination of subset relations (Ragin, 2000, 2008a,b). The attributes and the outcome are “best understood in terms of set membership” (Fiss, 2007, p.1183). For example, in this study, we proposed that different combinations of EDA capability and organization characteristics could
explain some portions of the outcome, hospital service quality. In particular, our exploratory analyses investigate what, if any, combinations of EDA capability and hospital characteristics are sufficient for obtaining high hospital quality.

**Step 1. Calibration.** After case selection, a critical requirement in QCA analysis is to carefully convert data into measures of set membership using theoretical or substantive knowledge external to the empirical data—a process called calibration. It is a process of transforming interval scale values to fuzzy set membership scores based on three qualitative anchors: full membership, full non-membership, and the crossover point of maximum ambiguity regarding membership in the set of interest. The set membership score represents the extent to which each case is a member of, for example, high level of responding capability. We followed Ragin (2008) in calibrating fuzzy-set memberships. For each calibration, we set thresholds based on industry common standards when available, extant theory or substantive knowledge. We used the direct method of calibration in the fsQCA software to transform the measures into set memberships (e.g., Fiss, 2011; Ragin, 2008a). Survey items that are on Likert scale have built-in membership scores.

As aforementioned, we use excess readmission ratio as the proxy for our outcome, service quality. We first averaged the available readmission rates to get the raw score for the outcome. Then we set up a “high service quality” (which equates low readmission rate) set by calibrating the raw scores. To be fully in the high service quality set, the averaged readmission ratio has to be low comparatively, hence the cutoff point for fully in this low readmission set is .92, .99 for the cross-over point, and 1.1 for fully not-in-the-set (i.e., full non-membership) anchor point.

The configuration situations (constructs, or independent variables might be more familiar terms but not used in configurations) selected for this study are: the four EDA capabilities, three organizational characteristics (top management support for IT, physicians’ resistance of IT, and organization size), and an organization’s overall dynamic capability. All the items for the variables except the EDA capability dimensions are extracted from literature and validated. This study uses a 5-point Likert scale for construct survey items: 1 = lowest, 3 = ambiguous, 5 = highest level. We therefore set up the high level membership sets using 5 as the fully in the set cutoff point, 3 as the cross over point, and 1 as fully not in the set point. We calibrate the large firm size set according to an external industry common practice of categorizing hospital sizes – a hospital is considered large if its bed size is greater than 500. We thus calibrated the large firm size set using 500, 301, and 100 as the cutoff points for full membership, cross over, and full non-membership.

We developed the scales of EDA capability/dimensions incorporating scale development procedures and recommendations Mackenzie et al. (2011). Construct validity and reliability are tested in pre-test and pilot test. Exploratory factor analysis and confirmatory factor analysis were conducted. Number of items (from 17 to 15) and wording were modified accordingly. The Cronbach’s alpha for each EDA capability ranges from 0.709 to 0.849, which indicate a satisfactory degree of internal consistency reliability of the measures (Bollen & Lennox, 1991). Composite reliabilities were 0.97, 0.93, 0.94, and 0.93 for flexibility capability, sensing capability, interoperability and responding capability respectively. The final scale has satisfactory levels of convergent (AVEs 0.89, 0.77, 0.80, and 0.81), discriminantat (all factor correlations < .7) and criterion validities. Items and details are available upon request due to page limitation.

**Step 2. Main analysis.** After calibration, sets are ready for the fuzzy truth table analysis in relations of the configuration conditions and the outcome. Scholars suggest to test what conditions might be necessary for the outcome before analyzing sufficiency (e.g., Legewie, 2013). A “necessary” condition is defined as that the outcome would not have happened without it. The test shows that responding capability, dynamic capability and physicians’ resistance to changes IT are necessary conditions with consistency score of 0.941, 0.980, and 0.937 respectively which all exceed the suggested level of 0.9 to be considered “necessary”.

After the necessary conditions analysis, we then run the truth table algorithm for the sufficient conditions. This process clarifies any relationships between combinations of potentially causal or descriptive characteristics and the outcome of interest. The output of fuzzy-set truth table analysis is one or more combinations of characteristics associated with an outcome. We choose 1 as the frequency cut-off point.
and 0.75 as the consistency cut-off point. Results presented next show three possible solutions (or "recipes", or "configurations").

**Initial Results**

**Model Fit Measures**

Three different solutions (or configurations or paths) were found (Table 2). In QCA, two central measurements provide parameters of fit: consistency and coverage (Ragin, 2008). Consistency measures the degree to which a relation of necessity or sufficiency between a causal condition (or combination of conditions) and an outcome is met within a given data set (Ragin, Drass, & Davey, 2006). It resembles the notion of significance in statistical models (Thiem, 2010). Consistency values range from "0" to "1," with "0" indicating no consistency and "1" indicating perfect consistency. The consistency scores of the three solutions are 0.885, 0.759, and 0.883, all above the suggested cutoff value of .75 (Legewie, 2013) which suggests that these three models (solutions/recipes/configurations) are adequately specified. Once consistency has been established, coverage provides a measure of empirical relevance (Legewie, 2013). The analogous measure in statistical models would be R², the explained variance contribution of a variable (Thiem, 2010, p.6). Coverage values also range between "0" and "1". fsQCA analysis presents two types of coverage, the raw coverage and the unique coverage. Raw coverage measures the proportion of memberships in the outcome explained by each term of the solution. Solutions 1, 2 and 3 explains 43.6%, 29% and 37.6% of high service quality respectively. Table 2 shows that solution 1 (S1) has the highest raw coverage score of .436, indicating that the recipe 2 covers more cases in the outcome data set.

Unique coverage measures the proportion of memberships in the outcome explained solely by each individual solution term (memberships that are not covered by other solution terms). Solutions with higher unique coverage thus gain relevance because without them more cases would be beyond the explanatory reach of the model (Legewie, 2013). S1 uniquely explains 15.6% of the variances of high service quality; S2 8.2% and S3 uniquely explains 17.6%.

<table>
<thead>
<tr>
<th>Outcome: High Healthcare Quality</th>
<th>Solution</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Casual conditions</strong></td>
<td>1</td>
</tr>
<tr>
<td>EDA Capability</td>
<td></td>
</tr>
<tr>
<td>Flexibility</td>
<td>☒</td>
</tr>
<tr>
<td>Sensing</td>
<td>☒</td>
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<tr>
<td>Interoperability</td>
<td>☒</td>
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<tr>
<td>Responding</td>
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<tr>
<td>Organizational Capability</td>
<td>☒</td>
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<tr>
<td>Dynamic Capability</td>
<td></td>
</tr>
<tr>
<td>Organizational Elements</td>
<td></td>
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<tr>
<td>Org. size (Large firm)</td>
<td>☒</td>
</tr>
<tr>
<td>Top Management Support</td>
<td>☒</td>
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<tr>
<td>Physician resistance to IT</td>
<td>☒</td>
</tr>
<tr>
<td>Consistency</td>
<td>0.885</td>
</tr>
<tr>
<td>Raw Coverage</td>
<td>0.436</td>
</tr>
<tr>
<td>Unique Coverage</td>
<td>0.156</td>
</tr>
<tr>
<td><strong>Overall Solution Consistency</strong></td>
<td><strong>0.827</strong></td>
</tr>
<tr>
<td><strong>Overall Solution Coverage</strong></td>
<td><strong>0.703</strong></td>
</tr>
</tbody>
</table>

Note: ☒: core element; ☒: the presence of an element; ☒: absence of an element; Blank space indicates a "don't care" situation (element either present or absent) (notations are adapted from Ragin & Fiss, 2008).

Table 2. The Result -Solutions

fsQCA also presents overall solution coverage and solution consistency. Solution coverage measures the proportion of memberships in the outcome that is explained by the complete solution. Overall solution consistency roughly means that the degree to which these configurations consistently result in high service quality. Therefore, we can roughly say that these three solutions can consistently explain 83 percent of high service quality. Overall solution coverage roughly means that the extent to which these solutions cover high service quality. In a fuzzy set relation, it explains what percent of membership for the
outcome set can be captured by the configurations. The complete solution can capture 70 percent of high service quality.

Core elements are defined as "causal conditions for which the evidence indicates a strong causal relationship with the outcome of interest." (Fiss, 2011, p. 398). Responding and dynamic capabilities are two core elements in all three solutions, which indicates that healthcare organizations need to build up these two capabilities to gain high quality. In contrast, peripheral elements are those "... a causal relationship with the outcome is weaker [than core elements]" but nonetheless contributing to the outcome (Fiss, 2011, p. 398).

Solution Interpretation

Solution 1 indicates that combining responding capability and dynamic capability as the core elements with sensing and interoperability as peripheral elements is sufficient for either large or small size healthcare organizations to achieve high quality in the presence of top management support of IT and physician resistance to IT. Flexibility does not contribute to this configuration.

Solution 2 shows that the combination of the two core elements, responding and dynamic capabilities, with two peripheral elements, flexibility and sensing, is sufficient for small to medium firms to accomplish high quality.

Solution 3 is for large healthcare organizations in which their top management supports IT but their physician's resistance to IT is high. Under these situations, high quality is achievable by joining flexibility to responding and dynamic capabilities. Unlike solutions 1 and 2, sensing capability is absent for this configuration.

We chose three elements (firm size, top management support and physician resistance to IT) for organizations to identify which solution they should follow. High level of physician resistance to IT and top management support are two organizational characteristics present in all cases that have high quality of care, which left the firm size as the determinant of which solution path a healthcare organization should follow. These organizational characteristics are not "causal" factors per se. They are included in the model as specific conditions organizations check against in order to choose the configuration they could/should use.

Discussion

We applied configurational approach to explore the complex relationships and used fuzzy-set qualitative comparative analysis (fsQCA) to analyze cases. Unlike traditional correlation-based methods, fsQCA does not seek to discover relationships in which an incremental change in an independent variable (condition) leads to an incremental change in a dependent variable (outcome). Instead, this method is better suited for investigating an interconnected dynamics of a complex system in which the impact of one element on the outcome of interest is dependent on other elements and a little change in one element can trigger changes in other elements and eventually change the whole organizational and technological structures and thus performance.

Configurational approach was introduced as a novel and appropriate analytic approach to examine a complex system of combinations of elements to create business value. Our findings reveal the applicability of configurational approach to overcome limitations of conventional statistical methods and provide new insights to IS research, especially in explaining the complex interactions between IT capabilities and organizational capabilities (El Sawy et al., 2010). By comparing the similarities and differences between multiple equifinal configurations, healthcare practitioners can follow pathways (i.e., the recipes/solutions) according to their unique organizational size, culture, structure, and business process.

One interesting result is that each solution is for different organization size: S1 is for any size (a "don't care" situation of the organization size); S2 is for small to medium (not large) organization; and S3 happens to be for large organizations. Managers in different size organizations can just follow the specific recipe combination of elements to achieve high performance. This is a very useful practical contribution.

Similarities among these three configurations are 1) the presence of the three necessary conditions, high level of responding capability, dynamic capability and physician resistance to IT. It seems that,
Currently in healthcare, there is a presence of physician resistance to IT regardless of the organization size; and 2) the presence of top management support as a common contributing element.

**Differences among solutions:** Interoperability capability only appears in solution 1 as a causal element. This capability represents how well an organization’s IT platform accommodates different softwares. We will include more IT flexibility element to further test the relationship.

Sensing capability and flexibility contributes to high quality under different situations. Flexibility is needed with either high or low interoperability (solutions 2 and 3). Sensing capability is not needed for large firms to achieve high quality as long as they have high level flexibility (solution 3) combined with the same core and peripheral elements as solution 2.

From the traditional regression-type of analysis, one limitation of this study is obviously the sample size. One advantage of applying QCA is that it allows analyzing small to medium of cases (e.g., 10 to 50) and still shows the validity of the results.

**Conclusion and Future Study**

In conclusion, the findings of this study advance our understanding of how EDA-enabled IT capabilities combine with dynamic capabilities and other organizational elements to achieve higher quality of care in health care. Most importantly, we offer evidence that different solutions leading to the same outcome from the effective use of EDA and other organizational elements do exist. We thus posit that configurational approach is a good contender for IS research when the goal is to explore different pathways to outcome. fsQCA is a good analysis tool for business value of IT research that can offer new insights in understanding the complex interactions between IT and organizational factors. To reduce bias, we also provide better reliability and validity of our results by using actual measures (secondary data of our outcome) rather than relying on self-reported responses. Doing so has the benefit of making more accurate interpretation for each configuration.

For our future study, we will try to identify other prudent conditions such as various IT infrastructure capabilities to include in our research model. A mixed method research design (e.g., qualitative Delphi approach and content analysis) will be carried out. Although we applied a method that accommodates small sample size, we will continue to collect more cases to mitigate this shortcoming and for richer information sources.

**References**


