CONFIGURATIONAL APPROACH TO UNCOVERING THE EFFECT OF ENTERPRISE ARCHITECTURE DESIGN ON ORGANIZATIONAL PERFORMANCE

Emergent Research Forum paper

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Abstract
Despite this growing adoption of enterprise architecture (EA), there has been little research that provides compelling empirical evidence of the EA impact on organizational performance. We argue that the lack of strong empirical evidence is due to the complexity of EA configurations and the limitations of the traditional correlation-based methods for uncovering the complex relationships. This research intends to examine how EA elements are combined with organizational and environmental elements to produce high or low organizational performance. We identify four EA design factors including centralization, modularity, standardization, and open platforms. Then, we analyze empirical field data, using fuzzy-set qualitative comparative analysis (fsQCA), an emerging set-theoretic configurational methodology. We seek to explain that the way of configuring EA design factors matters for the EA impact on organizational performance and the multifaceted role of each factor over the equifinal configurations. We present our preliminary result and discuss its implications for EA design.

Keywords: Enterprise architecture, EA design factor, set-theoretic configurational approach, fsQCA, centralization, modularity, standardization, open platform

Introduction
Organizations have invested substantial resources in designing and implementing enterprise architecture (EA). EA refers to the definition and representation of a high-level view of an enterprise’s business processes and IT systems, their relationships, and the extent to which these processes and systems are shared by the entire enterprise (Tamm et al. 2011). One of the important benefits of EA is that it addresses the problem of IT silos that inhibit information flows and integration, thus improving organizational performance (Boh and Yellin 2006; Tamm et al. 2011). EA not only provides ways to identify and bridge existing silos of IT systems, but also prescribes directions for the deployment and integration of future technological and managerial developments (Richardson et al. 1990; Iyer and Gottlieb 2004). As digital technologies have become tightly interconnected with business processes and have triggered frequent and unpredictable changes in business environments (El Sawy et al. 2010), the role of EA appears increasingly more crucial to achieving competitive advantage. Despite a growing adoption of EA in practice (Ross et al. 2006), it is inconclusive if and how EA affects organizational performance as prior studies have shown mixed effects (Tamm et al. 2011). As a result, both scholars and practitioners are ill-informed about the business value of EA (Tamm et al. 2011). Further, there has been a lack of theories that guide effective EA
In this research, we argue that the lack of strong empirical evidence of the business value of EA is partly but importantly due to the complex interplay of EA with organizational and environmental factors and to the limitations of existing research methodologies in investigating the complex causal relationships between EA and organizational performance. We argue that it is not mere presence of EA, but how it is designed and configured that affects organizational performance. EA encompasses a broad range of organizational and technological elements including business process, business applications, data, and IT infrastructure. Organizations can design EA in many different ways, resulting in heterogeneity in EA configurations. In this research, we identify four important EA design factors (i.e., centralization, modularity, standardization, and platforms openness).

We propose that it is the holistic configuration of EA design factors, organizational and environmental factors that ultimately determines organizational performance. Although the typical correlation-based approaches such as regression and structural equation modeling are effective for finding a universal or average pattern in bivariate or multivariate relationships, they come short of capturing the nonlinear, complex effect of a configuration in which multiple elements are interconnected and combined to produce the outcome of interest (El Sawy et al. 2010; Fiss 2011; Meyer et al. 2005). In this research, we use fuzzy-set qualitative comparative analysis (fsQCA), which is an emerging methodology for building and testing a configurational theory (Ragin 2008; Rihoux and Ragin 2009; Park and El Sawy 2013; Fiss 2011).

This study aims to examine how EA design factors systemically combine with organizational and environmental factors to produce high organizational performance. We also seek to find multiple equifinal EA configurations that produce equally high performance with the assumption that no single configuration is universally optimal. Further, fsQCA enables us to show that the causal structures of EA configurations producing high performance can be different from those of EA configurations producing low performance. In other words, there might be two different sets of causal structures where one set of causal structures only explains high performance but not low performance and the other set only explains low performance but not high performance.

**EA Design Factors**

Based on the literature of organizational structure and typology (e.g., Miles and Snow 1978; Ethiraj and Levinthal 2004; Fiss 2011; Sabherwal and Chan 2001; Desarbo et al. 2005) and extant EA theories (e.g., Richardson et al. 1990; Ross et al. 2006; Boh and Yellin 2006; Tamm et al. 2011), we investigate how the four EA design factors, organization size and environmental turbulence are combined to affect organizational performance.

We briefly discuss each of the four EA design factors, which are the central foci of the current study. First, we define centralization as the extent to which EA elements (i.e., business process, applications, data, and IT infrastructure) are concentrated in one location and are managed by a single unit. Both enterprise computing and organizational structures require balancing and re-balancing of the contrasting forces of centralization and decentralization (Fiedler et al. 1996; Lawrence and Lorsch 1967; Nickerson and Zenger 2002).

Modularity decreases interdependence among the subsystems of a complex system (Sanchez and Mahoney 1996). As a result, the subsystems are loosely coupled rather than tightly knitted. Modularity can be found in both technical and organizational structures (Tiwana and Konsynski 2010; Langlois 2002; Ethiraj and Levinthal 2004). While greater modularity can facilitate organizational agility and lower coordination cost, it requires intentional design efforts to structure a complex system in a way that interdependent components are enclosed in the same subsystem.

EA standards are a set of policies, rules, and guidelines that form unifying principles and practices across business units. Due to the increasing proliferation and complexity of IT products, organizations often implement different types of technologies, resulting in a high degree of heterogeneity and thus a low degree of standardization (Benamati and Lederer 2001).

Managers continuously face choices between open platforms (e.g., Linux, Android, XML) and proprietary platforms (e.g., Microsoft Windows, iOS, EDI) (Tafti et al. 2013). Open platforms allow any vendors to
develop applications, technology, and data formats that are interoperable with others that are also based on the same open platforms. On the other hand, proprietary platforms provide vendors and developers with limited access to the inner workings of the platforms, thus limiting interoperability.

Research Methods

Data Collection

We use a field survey method to collect data from multiple industries. We collected data from senior managers who are knowledgeable about their organization’s structure and enterprise architecture. We distributed survey questionnaires to the participants of a conference on big data and analytics, hosted by IBM in 2014. 500 survey questionnaires were distributed and 129 were returned. We excluded 25 responses because they are incomplete or answered by low-level employees. Our final data set retains 104 responses.

Measurement of Constructs

We measure four EA design factors by adapting existing measures from prior research (Tafti et al. 2013; Boh and Yellin 2006; Iyer and Gottlieb 2004; Ethiraj and Leventhal 2004). Organizational performance is measured by perceived performance (Sabherwal and Chan 2001). Environmental turbulence is measured by clockspeed of industry (Nadkarni and Narayanan 2007) and industry uncertainty (McCarthy et al. 2010). Organization size is measured by the number of employees (Fiss 2011; Sabherwal and Chan 2001).

Data Analysis Methods: fuzzy-set Qualitative Comparative Analysis (fsQCA)

In this research, we use fsQCA to examine the non-linear, complex effects of EA configurations on organizational performance. Unlike traditional correlation-based methods such as regression analysis, fsQCA does not seek to discover linear, additive relationships in which an incremental change in an independent variable leads to an incremental change in a dependent variable. Instead, fsQCA assumes that the variables of cases are frequently interdependent and may jointly bring about an outcome. Thus, fsQCA is best suited for investigating an interconnected dynamics of a complex system like EA in which the impact of one element on the outcome of interest is dependent on many other elements above and beyond two-way or three-way interactions. As shown in Figure 1, fsQCA treats a configuration of variables as a single predictor for the outcome.

Figure 1. Comparison between General Liner Model (GLM) and QCA Model
First, we calibrate the fuzzy membership of a case (i.e., organization) for each variable, where the membership score ranges between 0 (full non-membership) and 1 (full membership). For all variables measured by a 7-point Likert scale (1 = lowest, 7 = highest, 4 = neutral), we calibrate a fuzzy membership by setting 6 as the full membership anchor for a given variable, 2 as the anchor for full non-membership, and 4 as the crossover point. For organization size, we set 500 as the threshold for full membership for large organizations, 20 as full non-membership, and 100 as a crossover. Once the fuzzy memberships of all variables are calibrated, each case is assigned to one of the possible combinations of all variables using a truth-table algorithm in fsQCA software (available at www.fsqca.com). The truth-table algorithm uses Boolean algebra and counterfactual analysis to identify a parsimonious number of succinct configurations that produce high or low organizational performance, where each configuration consists of most important variables affecting the outcome. Space limitation does not allow us to explain the details of the fsQCA procedures. For the details, refer to Ragin (2008) or Rihoux and Ragin (2009).

**Preliminary Analysis Results**

Figure 2 shows our preliminary fsQCA results. We find five distinct configurations that produce high organizational performance and four distinct configurations producing low organizational performance. The configurations are presented using the notation system introduced by Ragin and Fiss (2008). Large circles indicate “core” elements that have a strong relationship with the outcome, and small circles indicate peripheral elements that have a rather weaker relationship with the outcome. Darksly shaded circles indicate that an element must be present, while crossed-out circles indicate that an element must be absent. Blank spaces indicate a “don’t-care situation,” meaning the causal element may be either present or absent. Thus, unlike a conventional configurational method such as cluster analysis, fsQCA teases out the detailed causal role of individual elements.

Overall solution consistency for high performance is 0.91, the degree to which the configurations consistently produce the outcome (Ragin 2008), a similar concept with a significance level in regression analysis. Overall solution coverage is 0.74, meaning the 74 percent of high performing organizations are covered (accounted for) by the five configurations, similar with \( R^2 \) in regression. Raw coverage refers to the extent to which each configuration covers the cases of the outcome, showing a relative importance of the configuration for the outcome (Ragin 2008). In our results, H1 is the most widely observed configuration that leads to high organizational performance.

**Figure 2. fsQCA Results – EA Configurations of High Performance**
<table>
<thead>
<tr>
<th>Configuration Element</th>
<th>EA Configurations of High Performance</th>
<th>EA Configurations of Low Performance</th>
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<tr>
<td><strong>EA Design Factors</strong></td>
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<td>Centralization</td>
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<td>Open Platform</td>
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<td><strong>Size (Large Organization)</strong></td>
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<td><strong>Environment Turbulence</strong></td>
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<td>(Speed &amp; Uncertainty of Change)</td>
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<td>Consistency</td>
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<td>0.94</td>
<td>0.92</td>
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<td>0.09</td>
<td>0.04</td>
<td>0.08</td>
<td>0.09</td>
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**Overall Solution Consistency**

H1: 0.91
L1: 0.85

**Overall Solution Coverage**

H1: 0.74
L1: 0.70
The fsQCA results show that there are multiple ways to configure enterprise architecture to achieve the same level of organization performance with different causal structures, known as equifinality. By comparing the similarities and differences between such multiple equifinal configurations, we can extract patterns to produce the certain level of performance.

First, we find that five configurations (H1–H5) produce a high level of organizational performance. For H1, H2, and H3, EA standardization plays a core role in achieving high performance when environments are turbulent. H4 represents organizations that achieve high performance with use of open platform in turbulent environment. By comparing these four configuration, we find the following patterns: in turbulent environments, organizations can achieve high performance either by configuring enterprise architecture either by increasing standardization or by increasing the adoption of open platforms. Further, a high level of open platform should not be combined with a high level of centralization, modularity, or standardization in order to produce high organizational performance. H5 configuration represents a high performing configuration in stable environments, in which modularity plays a core role with support of centralization and absence of standardization and open platform.

Second, we find that four configurations (L1–L4) result in low performance. L1, L2, and L3 configurations represent low performing organizations with absence of a high level of modularity and standardization. L4 shows a more interesting pattern that, in stable environments, small or medium-sized organizations with highly standardized EA with support of centralization and modularity and absence of open platform are likely to produce low performance.

Third, the results show that low performing configurations are not the exact opposite to high performing ones. This is known as causal asymmetry, meaning that organizations cannot achieve high performance simply by increasing the level of EA factors that produce low performance because the casual structure for high performance is not the same as the casual structure for low performance.

Standardized EA may increase efficiency and decrease coordination costs across business units (Ross 2006). We find that a high level of standardization increases organizational performance when organization size is large (H2 and H3). Interestingly, we find that when centralization and modularity accompany standardization, a high organizational performance is achieved regardless of organization size. While decentralized EA may have advantages in local adaptation, centralized EA would facilitate integration and enable exercising a strong control over technological resources (Fiedler et al. 1996). Thus, centralization needs to be present for a large organization who wants to have a strong control to achieve cost efficiency (H2).

Open platform can increase flexibility in connecting to new business partners, whereas closed proprietary technologies can lead to inflexibility in doing so (Gosain et al. 2005; McAfee 2005). Open platform also makes it easier to establish automated communications and transactions between firms (Chatterjee et al. 2006, Moore 2001). On the other hand, advanced proprietary technologies can provide an organization with competitive advantages that other organizations may not be able to easily imitate. The degree of openness in EA would affect an organization’s ability to integrate its systems and processes with those of its business alliances and to assimilate emerging technologies. Thus, open platform can play a core role for organizations in turbulent environments (H4), while proprietary platform may be a core element for organizations in stable environments (H5).

Modularity makes it easier to change individual subsystems by lowering coordination costs in the entire system as interactions among the subsystems of a modular system are less frequent than those within them (Ethiraj and Levinthal 2004; Schilling 2000). It can increase organizational agility and enhance business-IT alignment by fostering adaptations to changing business requirements (Tiwana and Konsynski 2010) as seen in H1. Further, H5 shows that in stable environments EA configurations with a high level of modularity combined with a high level of centralization lead to high organizational performance.

**Conclusion and Future Study**

In this paper, we identify multiple equifinal EA configurations that produce high or low organizational performance. fsQCA enabled us to show how each EA design factor plays different roles over these
configurations in achieving high or low organizational performance. The role of each EA design factor changes depending on its interaction with other elements. Thus, we demonstrated that how EA design factors are configured matters and that the multiple distinct EA configurations, rather than a single one, can achieve high organizational performance.

The present paper shows only the preliminary analysis results. We plan to complete this research by incorporating firm strategy type (e.g., Miles and Snow 1978) as an additional critical element of EA configuration. By doing so, we seek to understand how EA design factors interact not only with organization size and environmental turbulence but also with firm strategy type in affecting organizational performance. Based on the patterns extracted from similarity and difference comparison among multiple equifinal EA configurations, we hope to identify EA design principles that guide organizations to build effective EA configurations under their unique idiosyncratic context.

References


