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Researchers suggest that data analytics (DA) enhance decisions related to interorganizational relationships (IOR) and lead to reduced risk and improved performance. However, and despite this potential, firms face challenges regarding effective use of their DA capabilities to enhance their IORs. The massive investment in DA, as well as the need for an efficient use of DA in IOR settings, create the potential opportunities for two streams of research: a deeper understanding of business value of DA in IOR; and a systematic examination of DA's strategy for an enhanced alignment with IORs. Despite the published scholarly works in these two research streams, the complexity, diversity, and newness associated with DA technologies make our understanding of the business value of DA in IOR and DA strategy for IOR incomplete. First, our understanding of why and how DA impact IOR performance is inadequate and fragmented. Second, the focus of the preponderance of published empirical papers in understanding the value of DA is at the operational level, and the strategic implications of DA capabilities in IOR are not addressed. Third, the literature fails to consider the inherent heterogeneity among the user base of DA systems, and consequently, the findings are not generalizable. Finally, the literature fails to address the impact of external factors, such as complexity and volatility on DA strategy.

In this dissertation, I attempt to contribute to the literature by focusing on these research gaps and investigating them in three studies. In the first study, a holistic value-view of a firm's supply chain enabled by DA for improved business performance, is

presented based on two complementary views of market-oriented coordination and strategic supplier partnership. The study discusses how DA capabilities impact the constituents of this complementary view of supply chain to amplify business performance. I propose a theoretical model of the effect of DA capabilities on a firm's co-creation of value, with its partners for business performance. Then, I test the model empirically based on a survey of 198 practitioners. My findings show that DA capabilities improve upstream and downstream integration and leverage the co-creation of value.

The second study provides a better understanding of the impact of DA on interorganizational collaborations by answering two fundamental research questions: "How does a firm use its DA capabilities to improve collaboration and enhance performance?" and "What is the impact of DA capabilities on a firm's collaboration and performance?" To answer these questions and to provide a deeper insight from multiple perspectives, I utilized a mixed method research by conducting a thorough content analysis of 34 published case studies, followed by a confirmatory research based on a survey of 210 practitioners to empirically test the insights generated from my content analysis. My findings identify several paths to improved performance using DA capabilities. My analysis suggests that DA capabilities, used appropriately in an interorganizational collaborative environment, lead to reduced costs and the need for required working capital and ultimately better performance through improved collaborative relationships such as planning and scheduling.

In the third study, I expand the results of the two prior studies by analyzing the DA strategic focus. I employ an agent-based simulation to test different DA strategies in various business environments that are identified by levels of complexity and dynamism. My findings indicate that optimum DA strategy has a quadratic relationship with the levels of complexity and dynamism, which explains the prior contradictory findings of the IS literature.

These three studies contribute to the business value of IT and IS strategy literatures by investigating the business value of DA in IOR settings, identifying impacts of DA on value co-creation in IORs and determining a suitable DA strategy based on various environmental factors.

STRATEGIC VALUE OF DATA ANALYTICS IN

INTERORGANIZATIONAL RELATIONSHIPS

by

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To my parents, brother and sister for all their love and support. I appreciate their sacrifices and I wouldn’t have been able to get to this stage without them.

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APPROVAL PAGE

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CHAPTER I

INTRODUCTION

More than 50% of partnerships fail due to the complexity and dynamism of interorganizational relationships (IOR) (Gulati, Wohlgezogen, & Zhelyazkov, 2012). However, despite this high risk of failure, firms are increasingly forming interorganizational collaborations and rely on IORs to gain a competitive advantage (Phelps, 2010). Researchers suggest that achieving competitive advantage requires employment of various business intelligence and analytics tools (Oliveira, McCormack, & Trkman, 2012; Trkman, McCormack, de Oliveira, & Ladeira, 2010). The fluidity and speed by which business intelligence and analytics evolves, make it difficult to agree on a unified definition for these terms. As a result, in this dissertation, the business intelligence and analytics terms are collectively referred to as Data Analytics (DA) (Hsinchun Chen, Chiang, & Storey, 2012).

Firms invest heavily in their DA capabilities to improve their decision making (Kappelman, McLean, Johnson, & Torres, 2016) and enhance their IORs' performance (Hsinchun Chen et al., 2012; Oliveira et al., 2012). However, and despite the potential healing impact of DA capabilities, firms face challenges in regard to effective use of their DA capabilities (Burton-Jones & Grange, 2012). The massive investment in DA, as well as the need for an effective use of DA in IORs, created the potential opportunities for two research streams: understanding business value of DA in IORs; and configuration of DA strategy for IORs (Fink, Yogev, & Even, 2017; Günther, Mehrizi, Huysman, & Feldberg, 2017; Trieu, 2017). This dissertation aims to contribute to these two research streams by investigating the impact of DA on the performance of IORs. More specifically, this dissertation aims to unveil the impact of DA capabilities on value creation in IORs. In addition, the study seeks to understand the mechanisms through which DA capabilities lead to enhancement of IORs and their value creation. Also, the study tries to investigate the impact of DA strategy on performance of IORs and identify appropriate configurations of DA strategy for IORs. For further development of the discussion, I introduce DA and IOR in the following paragraphs.

1.1 Data Analytics Capabilities and Strategy

1.1.1 Data Analytics Capabilities

The aim of DA is to transform decision support technologies to strategic weapons (Davenport, 2006). Chen et al. (2012) discuss DA as a general set of tools and technologies that encompass ordinary data and big data analytics (BDA). Contemporary DA are the result of advances in decision support systems (Holsapple, Lee-Post, & Pakath, 2014). There are different viewpoints on the use of DA and the rationale for adoption of DA in firms including “a transformation process,” “a capability set,” “a decisional paradigm,” and “a collection of practices and technologies” (Holsapple et al., 2014). Each perspective is discussed by different authors and there are various definitions for DA per each rationale. Since I am focusing on the impact of DA capabilities on the performance, I study it from the dynamic capability theory perspective. This perspective considers DA as a set of capabilities and defines DA as an "extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions" (Davenport & Harris, 2007, p. 7). The rationale for employment of DA in this perspective is to improve the competitiveness by making the best decisions.

Organizational capability is defined as "a high-level routine (or collection of routines) that, together with its implementing input flows, confers upon an organization's management a set of decisions options for producing significant outputs of a particular type" (Winter, 2003, p. 991). My definition for DA capability is a combination of definition of DA from capability set perspective and definition of organizational capability. I define DA capability as *the ability of an organization to effectively combine DA into its decision-making processes for on-time and enhanced decisions at different levels of the organization*.

With the widely available data from different resources, firms can generate insight through DA for their business improvements (Hsinchun Chen et al., 2012; Hopkins, LaValle, & Balboni, 2010) and the generated insight provides unlimited opportunities for business improvement (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011). Accordingly, the literature discusses business value of DA, and establishes a positive association between DA capabilities and performance (e.g., Fink et al., 2017; Vukšić, Bach, & Popovič, 2013). However, the literature on the business value of DA capabilities is mainly focused within the boundaries of a firm, and there are limited studies focused on IORs (e.g., Oliveira et al., 2012). Also, those that address IORs are mainly focused on improved performance of supply chain through enhanced supply chain processes (Chae, Yang, Olson, & Sheu, 2014; Oliveira et al., 2012; Trkman et al., 2010), and there is a dearth of knowledge about the mechanism through which DA impact IOR (Tiwari, Wee, & Daryanto, 2018). For instance, the majority of the nearly 40 papers that are published on the impact of Big Data on supply chain management are devoted to frameworks and mathematical models, and few empirical studies are available (Tiwari et al., 2018). A selected list and summary of published studies on the business value of DA is presented in Appendix A.

1.1.2 Data Analytics (DA) Strategies

Organizations need to be efficient and do well in their day-to-day business activities while they maintain their innovativeness in order to adapt to varying environments in the future (Tushman & O'Reilly, 1996). Ambidextrous organizations are able to handle both types of activities: short-term efficiency (exploitation) and long-term innovativeness (exploration) (March, 1991). The theory of organization conceptualizes organizations as systems that process information, solve problems, and generate knowledge to deal with uncertainties (Daft & Lengel, 1986; Nonaka, 1994; Tushman & Nadler, 1978). Therefore, an important antecedent for attaining ambidexterity is the ability of the top management team (TMT) to decide on the right decision alternatives based on available information (O'Reilly & Tushman, 1997). Accordingly, IT tools that support decision making, specifically DA tools, are important means of achieving ambidexterity (Fink et al., 2017).

The literature proposes that IS strategy should maintain its alignment with business strategy and IOR needs through explorative, exploitative, or ambidextrous focuses (D. Q. Chen, Mocker, Preston, & Teubner, 2010; Subramani, 2004). Since DA strategy is a subset of IS strategy, researchers used exploration-exploitation focus for the DA strategy recently (Fink et al., 2017; Maghrabi, Oakley, Thambusamy, & Iyer, 2011). Similarly, I develop my discussions for DA strategy based on explorative, exploitative, and ambidextrous focuses.

Aligning IS/DA strategy with business priorities is the main concern for chief information officers (CIO) of the US firms (Kappelman et al., 2016). Accordingly, configuring a suitable IS/DA strategy is vital for achieving a competitive advantage and is a critical component of the business value of IT (Robert D Galliers, 2006). The type of information that is required by TMT is contingent on the environmental and organizational antecedents (Jansen, Volberda, & Van Den Bosch, 2005). These antecedents identify the focus of DA strategy on exploration, exploitation, or ambidexterity. For instance, firms require exploitative IS strategy to improve their performance in stable business environments while ambidextrous IS strategy is desired in turbulent settings (Jansen et al., 2005). Therefore, identification of strategic direction of DA plays a role in the success of TMT decisions.

Despite the reviewed anecdotal evidences, which shows the performance implication of explorative, exploitative, and ambidextrous DA, there is no empirical study to support the role that DA strategic focus plays in a collaborative relationship. I further explain these strategic focuses in later chapters of this dissertation.

1.2 Interorganizational Relationships

The topic of IOR is discussed extensively from different perspectives under various theoretical lenses. The importance of the topic lies in its complicated nature and multifaceted factors that influence it (T. Y. Choi, Dooley, & Rungtusanatham, 2001). The nature of IOR is complex due to various factors, including differences in cultural backgrounds, inconsistencies between goals, and mismatches between technological infrastructures that add to the complication of the relationship (Lavie & Rosenkopf, 2006). The inherent complexity in the IOR reduces the chance of a successful collaboration to a great deal. In addition to the failure risk for collaboration at the beginning of the relationship due to the complexity, an increase in the duration of a partnership has a positive impact on chance of commitment breach and failure potential (Ring & Van de Ven, 1994). The time associated risk is related to the dynamism of the business environment, which impacts the initial assumptions of a designed collaboration. Published scholarly works find that the misaligned incentives of partners leads to consequences ranging from gradual demise of the collaboration to opportunistic behavior of partners and cause the collaboration to fail (Gulati et al., 2012). The change coupled with the inherent complexity increases the possibility of the failure in IORs, resulting in a failure in more than 50% of such relationships (T. Y. Choi et al., 2001; Gulati et al., 2012).

Companies are increasingly considering alliances as a source for new opportunities, innovation, and improved resources, despite the high potential of the IOR failure (Phelps, 2010). IORs play a critical role in the strategic success of businesses and its impact is extensively discussed in the literature. IORs are studied from two different perspectives: by focusing on gaining competitive advantage (e.g., Hitt, Dacin, Levitas, Arregle, & Borza, 2000), or by discussing costs and risks (e.g., Weele & Raaij, 2014). Each of these two perspectives provide a partial understanding of collaboration. Therefore, more recent studies suggest incorporation of various theoretical perspectives to investigate IORs (e.g., Dong, Xu, & Zhu, 2009). Accordingly, I will employ a combination of various theoretical lenses to study IORs in this dissertation.

1.3 Impact of Data Analytics on Interorganizational Relationships

Because of rapid organizational adoption of DA (Kappelman et al., 2016), researchers are rushing to better understand the business value of investments made in DA. Both academic and practitioner research have shown a positive impact of DA on organizational performance. Practitioner outlets are replete with success stories that address the implications of DA. Similarly, published case studies in academic journals, along with the empirically based research, provide evidence of DA positive business impact (e.g., Chae et al., 2014; Fink et al., 2017; R. Kohli, 2007; Trkman et al., 2010; Watson, 2010; Watson, Wixom, Hoffer, Anderson-Lehman, & Reynolds, 2006). However, despite these published studies, our understanding of business value of DA is still incomplete in several ways.

First, our understanding of why and how DA impact firms’ performance and the importance of its moderating effects in this process is still incomplete (Trkman et al. 2010). Second, although the literature may be rigorous, multi-faceted and voluminous, it is fragmented and does not comprehensively and fully measure the real business value of

DA (Richards et al. 2014; Lönnqvist et al. 2006; Solomon 1996). Third, the preponderance of published empirical papers discuss the impact of DA at the operational level (Chae et al., 2014; O'Dwyer & Renner, 2011; Trkman et al., 2010), and the strategic implications of DA capabilities are not addressed, especially in the context of IOR. Fourth, the business value of DA literature fails to consider the inherent heterogeneity among the users of DA systems and consequently, the results and findings are not fully generalizable to such a diverse user base (Mithas & Rust, 2016). Fifth, the strategic focus of DA and its impact on business value creation are rarely addressed (Fink et al., 2017; Maghrabi et al., 2011). Finally, the literature fails to address the impact of environmental factors such as complexity and volatility on DA strategy.

In this dissertation, I attempt to contribute to the literature by focusing and investigating the abovementioned research gaps. This dissertation comprises three studies to address the research gaps and answer the following research questions:

- Study 1:
    - What is the impact of DA capabilities of a firm on its customer value creation?
    - What is the impact of DA-enabled customer value creation on business performance?
- Study 2:
    - How does a firm use its DA capabilities to improve collaborations and enhance performance?
    - What is the impact of DA capabilities on a firm's collaboration and performance?

- Study 3:
    - What is the appropriate configuration of DA strategy for dealing with IORs' complexity and volatility?

In the first study, I present a holistic value-view of a supply chain enabled by DA for improved business performance. I incorporate two complementary views of market-oriented coordination and strategic supplier partnership to create a value view of a supply chain. Then, I examine how DA capabilities lead to creation of synergies in the constituents of this complementary view of supply chain to amplify business performance. Accordingly, I propose a theoretical model of the effect of DA capabilities on co-creation of value in supply chains and test it empirically.

In the second study, I am focused on an interorganizational collaboration and its main constituents: cooperation and coordination (Gulati et al., 2012), and I study the impact of DA capabilities on constituents of the collaboration. Also, I investigate the role of DA strategic focus, exploration and exploitation, on performance of an interorganizational collaboration. Accordingly, I develop a theoretical model based on an analysis of published case studies. This empirical examination contributes to understanding the effect of DA capabilities on collaboration and the moderating role of DA strategy on the relationship between collaboration and performance.

I expand the results of the second study by analyzing the DA strategic focus for various levels of environmental complexity and volatility in the third study. More specifically, I examine the heterogeneity of performance of firms with various DA strategies across collaborations in business environments with different levels of complexity and dynamism. This examination test various configurations of DA strategy in different environmental settings and proposes a suitable problem sensing and responding approach for each business environment. Each of these three studies are introduced in more detail in the following subsections.

1.3.1 Study One: Strategic Impact of Data Analytics

I focus on the strategic implications of DA from a supply chain management (SCM) perspective in this study. I assert that DA facilitate customer value creation through an improved understanding of customers' needs and alignment of business resources with these needs. I posit that DA capabilities enable a better strategic integration in supply chain partnership and enhance market awareness, resulting in an increase in value generation for customers. Accordingly, I develop a value-view of a supply chain and discuss the impact of DA on value creation. Further, I discuss the role of DA-enabled value creation in supply chains in business performance. My aim in this study is to show how DA contribute to business value through alignment of supply chain with customer needs.

Discussions on the importance of an integrative perspective of supply chain are rooted in the Porter's value chain (Porter, 1980, 1985). Since the value chain concept is introduced, researchers have examined the importance of upstream and downstream integration across supply chains from a value creation perspective that leads to strategic advantage and business growth (Bettencourt, Lusch, & Vargo, 2014; Frohlich & Westbrook, 2001; Slack, 2015; Vickery, Jayaram, Droge, & Calantone, 2003). The supply chain integration requires coordinated decision making across various partners that enables the supply chain to support the value creation and improve the business performance (Arshinder, Kanda, & Deshmukh, 2008; Roh, Hong, & Min, 2014). A value view of supply chains is composed of a coordinated integration with suppliers and customers (Frohlich & Westbrook, 2001). In the traditional view, customer value is considered as an entity that is created by discrete efforts of suppliers (Bettencourt et al., 2014). The efficiency of SCM increases if it is considered as a single coordinated and integrated entity rather than discrete business processes and functions. Therefore, integration in the supply chain is critical from a strategic stand point (Vickery et al., 2003) and provides customers with superior delivered value (Roh et al., 2014). Consequently, the value-view offers that value creation is a product of the partnership between supply chain players towards employment of the mutual resources and capabilities (Xie, Wu, Xiao, & Hu, 2016).

The dynamism and increased complexities of current business environment have complicated the nature of coordinated decision making and collective value creation (Arshinder et al., 2008; Chae & Olson, 2013) . Therefore, SCM requires enhanced decision making through application of DA tools to improve its alignment with customer needs and to enhance competitiveness (Holsapple et al., 2014). Despite the importance of DA for value creation throughout the supply chain (L.-B. Oh, Teo, & Sambamurthy, 2012; K. H. Tan, Zhan, Ji, Ye, & Chang, 2015; Waller & Fawcett, 2013), empirical positivist studies do not support this discussion. Therefore, our knowledge about the impacts of DA on supply chain value creation is limited to a number of case studies (e.g., Briggs, 2011; Watson, 2010).

I develop a value-view of supply chains based on levels of integration with suppliers and customers to account for the gap in the literature. I posit that the delivered value of a supply chain is enhanced through employment of DA tools. I develop a research model based on this argument and empirically test the impact of DA on supply chain upstream and downstream integration and the performance outcome of the analytics-enabled supply chain. Furthermore, since the literature suggests that improved value creation in supply chains requires an adjustment in the level of integration with customers and suppliers (Frohlich & Westbrook, 2001), I test the impact of a balanced integration between upstream and downstream on the performance. I anchor in the existing literature and established theories to develop and discuss the model and its associated hypotheses.

1.3.2 Study Two: DA Strategic Focus and Partnership Adaptability

A collaborative IOR is composed of cooperation and coordination, which together create synergy towards the success of the relationship (Gulati et al., 2012). Cooperation provides the resources that are required for gaining competitive advantages and succeeding in the market (S. Li, Ragu-Nathan, Ragu-Nathan, & Subba Rao, 2006). A coordination mechanism is required to enhance the utilization of shared resources of cooperation and keep the competitive advantage updated ahead of competitors. The coordination supports an IOR by reduced transaction costs (Brynjolfsson, Malone, Gurbaxani, & Kambil, 1994) and by enhanced preparedness to deal with the environmental volatility (Gulati et al., 2012).

The increasingly dynamic business environment imposes serious risks and challenges to IORs and cause a high failure rate (Gulati et al., 2012). Therefore, collaborators need to constantly predict changes in the environment and adapt to and align with the new condition to avoid the IOR failure. Sometimes, coping with the everchanging business environment requires a minor corrective action for realignment of IOR partners with the altered environment. In other occasions, the disruption in the environment forces firms to adapt to changes by reviewing their collaboration, terminating it, or finding new collaborators (H L Lee, 2004). Dealing with the constant need for minimal improvements or radical changes requires employing appropriate coordination mechanisms for an improved IOR management (Lavie & Rosenkopf, 2006). Since decision making is an important basis for coordination (Malhotra, Gosain, & Sawy, 2005), DA are deemed necessary for an improved coordination. Therefore, I discuss that a DA-enabled coordination mechanism improves the adaptability and alignment of a firm's IOR to its dynamic environment and improves the performance.

The strategic direction of collaboration is an important identifier of business success; therefore, DA need to be aligned with the specific needs and support the explorative or exploitative focus of collaboration (Lavie, 2006). Thus, the strategic focus of DA tools is an important factor in support of collaboration. More specifically, a suitable DA strategy enables coordination to employ an appropriate balance of exploration and exploitation for an improved collaboration. Despite the importance of DA for collaboration and the impact of DA strategy on coordination, the literature faces two shortcomings. First, IT-enabled collaboration models are either focused on coordination (e.g., Im & Rai, 2013) or cooperation (e.g., Hau L Lee, So, & Tang, 2000) and fail to consider the interaction of them (Gulati et al., 2012). Second, the strategic direction of DA is only investigated by a handful of researchers within the boundaries of a firm (Fink et al., 2017; Maghrabi et al., 2011) and is not addressed in the interorganizational settings. Therefore, the literature of IS business value needs an improved and more accurate conceptualization of the IT-enabled collaboration. Also, DA strategy and its role in the collaboration performance merits further attention.

I investigate the role of DA strategy in the context of IOR to address the abovementioned shortcomings. Accordingly, I conceptualize the DA strategy as an enabler for exploration and exploitation in collaborative relationships. I investigate the performance implications of DA capabilities and DA strategy in an IOR setting. for this investigation, I employ two different theoretical perspectives: namely, resource-based view (RBV) and transaction cost economics (TCE) to inform my research and theory development.

1.3.3 Study Three: DA Strategy in Complexity and Volatility

While I justify the importance of DA strategy in the first two studies. These studies are primarily focused on the business value of DA. Therefore, my third study is focused on DA strategy, and I aim to address the configuration of DA strategy. I argue that DA strategy is composed of two distinct, but interconnected components: problem-sensing focus and response approach. I propose appropriate configurations for these two components, contingent to various business environments. The suitable configuration improves the adaptability of a firm's IOR to its business environment in the face of complexity and volatility. This study is developed to provide an answer to “What is the appropriate configuration of DA strategy for dealing with IORs’ complexity and volatility?”

I aim to investigate DA strategy in IOR context, which is considered to have an explorative-exploitative characteristic (Lin, Yang, & Demirkan, 2007). IORs are affected by complexity and volatility of business environments. Specifications of today’s economy, including the globalization of sourcing, shorter product life cycles, and heterogeneity of customers are among important drivers of the complexity in IOR (Bozarth, Warsing, Flynn, & Flynn, 2009). Also, the fast pace of technological development and the variability of demands makes IOR an increasingly dynamic context (T. Y. Choi et al., 2001; Osborn & Hagedoorn, 1997). In this complex and dynamic environment, formation of an IOR faces challenges in its initiation due to environmental complexity (Reuer & Ariño, 2007). Also, the persistence of IORs is challenged by volatility of business environments. The change might cause the partners to desert their alliance or show opportunistic behavior, which in turn leads to an IOR failure (S. H. Park & Ungson, 2001). The two environmental factors, complexity and volatility, pose alignment and adaptability challenges to firms (Baker, Jones, Cao, & Song, 2011; Benbya & McKelvey, 2006).

The contribution of DA to adaptability and alignment is through identification of prominent opportunities for improving the business (problem sensing) and determination of appropriate methods to execute those identified opportunities (response approach).

Accordingly, I conceptualize the role of DA in the form of problem sensing and response approach.

The perpetual need for change and adaptation should be reflected in the DA strategy. Despite the important role of DA strategy in sustaining IORs, the literature fails to discuss DA strategy in the IOR considering its complex and volatile environmental characteristics (El Sawy, Malhotra, Park, & Pavlou, 2010). More specifically, the literature on IS strategy is descriptive and fails to address the complexity and volatility based on analytical models (Merali, Papadopoulos, & Nadkarni, 2012). Therefore, the existing findings on IS strategy, in the context of complexity and dynamism, are contradictory and inconsistent (D. Q. Chen et al., 2010). In addition, our knowledge about the equilibrium between exploration-exploitation is limited to discussions in strategic management (Raisch, Birkinshaw, Probst, & Tushman, 2009). The IS literature considers the balanced explorative-exploitative IS strategy as a generic construct of IS ambidexterity (e.g., Im & Rai, 2013), or discuss exploration and exploitation in a static manner and isolated from each other (Leidner, Lo, & Preston, 2011).

To address these gaps and contribute to the literature, I study the configuration of DA strategy in an IOR with various levels of complexity and volatility in its environment. In addition, I study the strategic alignment as a complex adaptive system (CAS) from the complexity theory perspective to address the critique on the theoretical gap. This theoretical support provides a new insightful perspective for the literature (Benbya & McKelvey, 2006).

1.4 Organization of the Dissertation

Each of chapters II, III, and IV present one of the mentioned studies. In each chapter, the problem is discussed based on the literature and related theories and a research model is developed. Then, the methodological approach to deal with the research model is explained. Then, data collection (for the first two studies) and simulation (for the third study) are discussed. Subsequently, the results are analyzed based on the proposed methodological tools and discussion of results is provided. In Chapter V, I discuss implications, contributions, and limitations of each of the three studies. Also, I review potential topics for future research in Chapter V.

CHAPTER II

STUDY 1: DATA ANALYTICS CAPABILITIES FOR VALUE CREATION

2.1 Introduction

In the era of big data and with widely available data from different resources, firms are in a rush to employ DA to gain a competitive edge and to cope with competitive pressures from the marketplace (Davenport & Harris, 2007). Employment of DA capabilities have been shown to help firms to generate useful and actionable insights that can lead to enhanced business performance (Hsinchun Chen et al., 2012; Günther et al., 2017; Hopkins et al., 2010; Trieu, 2017). Therefore, one can argue that utilizing the power of insights generated by DA can potentially provide significant opportunities for improvements at all organizational levels, including better understanding of markets as well as better integration with supply chain partners (LaValle et al., 2011). Viewing DA as an opportunity, firms are investing heavily in enhancing their capabilities in DA (Russom, 2011). As a result, acquiring DA related tools and technologies have been the top priority for IT investment in US based firms since 2009 (Kappelman et al., 2016). The increased attention to DA as a competitive resource, which has led to substantial increases in DA technology and infrastructure investment makes it imperative to study its business value and the mechanism through which it creates value (Trieu, 2017).

As a result of rapid organizational adoption of DA, researchers are rushing in to better understand the business value of investment in DA. Academic, as well as practitioners' publications have substantiated the positive impact of DA on organizational performance. Practitioner outlets are replete with success stories that address the implications of DA. Also, published case studies in academic journals provide evidence of how DA impact business (e.g., R. Kohli, 2007; Watson, 2010; Watson et al., 2006). Furthermore, empirical research supports the positive impact of DA on business performance (Chae et al., 2014; Trkman et al., 2010). However, despite these published studies, our understanding of business value of DA is still incomplete, and there are several gaps. First, our understanding of why and how DA impact firm performance and the important moderators' effects in this process is still incomplete (Trkman et al., 2010). Second, although the literature maybe rigorous, multi-faceted and voluminous, it is fragmented and does not comprehensively and fully measures the real business value of DA (Bontis, Keow, & Richardson, 2000; Günther et al., 2017; Lönnqvist & Pirttimäki, 2006; Trieu, 2017). Finally, the preponderance of published empirical papers discuss the impact of DA at the operational level (Chae et al., 2014; O'Dwyer & Renner, 2011; Trkman et al., 2010) and the strategic implications of DA are not addressed (Trieu, 2017), especially in the context of supply chain management (SCM).

To contribute to the existing literature in understanding the business value of DA, I focus on the strategic implications of DA from a SCM perspective. More specifically, I try to investigate my research questions: "what is the impact of DA capabilities of a firm on its customer value creation" and "what is the impact of DA-enabled customer value creation on business performance." I argue that DA capabilities provide a firm with an improved understanding of its customers' needs and an enhanced alignment of required business resources to serve these needs. Consequently, I posit that DA capabilities enhance market awareness of a firm and enable a vigilant craft of supplier partnerships towards efficient customer value creation, and eventually lead to improved business performance. Accordingly, I develop a value-view of a firm's supply chain and discuss the impact of DA on it. Further, I discuss the role of analytics enabled value creation on business performance. This study is an attempt to present a theoretically sound model to show how DA create business value through improved firm's supply chain strategies.

A value view of a firm's supply chain requires that the firm integrate with its suppliers and customers (Frohlich & Westbrook, 2001). In the traditional view, customer value is considered as an entity that is created by discrete efforts of suppliers (Bettencourt et al., 2014). The value-view suggests that value creation is a product of the partnership between supply chain players towards employment of the mutual resources and capabilities (Xie et al., 2016). Accordingly, a firm's ability to integrate its supply chain partners is critical from strategic stand point (Vickery et al., 2003) and provides customers with superior delivered value (Roh et al., 2014). The Porter's value chain initiated the discussions on an integrative perspective of value creation (Porter, 1980, 1985). Since then, researchers have examined firms' integration with their upstream and downstream partners from a value creation perspective (Bettencourt et al., 2014; Frohlich & Westbrook, 2001; Slack, 2015; Vickery et al., 2003). A firm requires advanced decision making capabilities to support the value creation and improve the business performance (Arshinder et al., 2008; Roh et al., 2014). However, the dynamism and increased complexities of current business environment have complicated the nature of decision making and collective value creation (Arshinder et al., 2008; Chae & Olson, 2013). Therefore, firms require enhanced decision making through application of DA tools to improve their alignment with customers' needs and to enhance their competitiveness (Holsapple et al., 2014). Despite the importance of DA for customer value creation (L.-B. Oh et al., 2012; K. H. Tan et al., 2015; Waller & Fawcett, 2013), empirical positivist studies do not support this discussion. Therefore, our knowledge about the impacts of DA on supply chain value creation is limited to a number of case studies (e.g., Watson, 2010).

I develop a value-view of a firm's supply chain based on levels of integration with its suppliers and customers, which leads to an improved value creation in supply chains (Frohlich & Westbrook, 2001). I posit that the enhancement of delivered value, in addition to adjusted upstream and downstream relationships, requires employment of DA tools. Accordingly, I construct my research model based on these arguments and empirically test the impact of DA on a firm's upstream and downstream integration. Also, I study the performance outcome of the DA-enabled value creation for customers.

My contribution to the literature is three-fold. First, my work is among the first studies that develop a model in which DA impact on the value creation of a firm's supply chain and improve its performance. The topic of DA-enabled SCM is rarely discussed in the literature, with the exception of a handful of notable studies (e.g., Trkman et al., 2010). Second, I contribute to the IT mediated co-creation of value, which is an important but rarely discussed topic in the business value of IT literature (R. Kohli & Grover, 2008). Finally, I conceptualize the co-creation of value in the form of a firm’s integration with its partners and customers, which is rarely addressed in the literature (Holweg & Helo, 2014; D. Kim, Cavusgil, & Cavusgil, 2013; Sarker, Sarker, Sahaym, & Bjørn-Andersen, 2012).

I anchor in literature and established theories to develop and discuss my research model and its associated hypotheses. My proposed model aims to better understand the role of analytics in supply chain performance from a strategic point of view. In the next section, literature related to DA and the importance of studying the value creation in supply chains are discussed. This literature review is followed by a discussion about the theory development and presentation of hypotheses. Next, the model is tested based on empirical data collected in a survey of business practitioners. The findings are analyzed in the discussion and implications section. Finally, I conclude the article by reviewing the findings, by discussing the limitations of the study, and by proposing the direction future research should take in the field.

2.2 DA and Co-Creation of Value in Supply Chains

Supply chain strategy is an extension of manufacturing strategy literature (Roh et al., 2014). In this stream of research, firms need to achieve the two criteria of “order winners” and “order qualifiers” by designing their supply chain strategy (Hilletofth, 2009; Mason-Jones, Naylor, & Towill, 2000). The firm’s capabilities to meet the quality, lead time, and service level requirements determine its ability to fulfil order qualifiers criteria. However, firms need more than order qualifiers to win customers. The order winners' criteria complement that of the order qualifiers and support the firm in its development of "differentiation" or "cost leadership" strategies. The manufacturing strategy literature suggests that different levels of integration, with upstream and downstream supply chain partners, support firms in their order qualifiers and order winning (Frohlich & Westbrook, 2001; Roh et al., 2014). Therefore, supply chain integration can fulfill the competitive strategies of differentiation, cost leadership, or focus (Porter, 1980; Roh et al., 2014).

The integration is further elaborated by the co-creation of value concept which is the means of improving supply chain strategy (Normann & Ramirez, 1993; Weele & Raaij, 2014). Co-creation of value is the connection of a firm and its partners with customers to develop tailored customers' needs (Prahalad & Ramaswamy, 2004). Marketing and supply chain literature discuss the co-creation of value from two different angles: cooperation with customers and partnership with suppliers. The marketing literature introduces the market orientation (MO) concept, which aligns business value creation with customers' needs, while monitoring competitors' moves (Gibbert, Leibold, & Probst, 2002; Narver & Slater, 1990). Also, the supply chain literature discusses supplier partnership orientation (SPO) as a means of joint value creation in supply chains (Agus & Hassan, 2008; Motwani, Larson, & Ahuja, 1998). While both concepts of MO and SPO can partially support the value creation concern, the enabling of a supply chain for co-creation of value requires an integrated approach that encompasses both MO and SPO.

MO is defined as “the organizationwide generation of market intelligence pertaining to current and future customer needs, dissemination of the intelligence across departments, and organizationwide responsiveness to it” (A. K. Kohli & Jaworski, 1990, p. 6). The MO strategy is focused on organization-wide understanding of customers’ needs and enhancement of customer service by tailoring products and services based on customers’ needs (Chang & Chen, 1998; Narver & Slater, 1990). With the advent and expansion of the SCM concept, the notion of MO, which was limited within the boundaries of a firm, is expanded to encompass the supply chain (Min, Mentzer, & Ladd, 2007). MO is intended to generate customer insight for the focal firm and its supply chain partners (Martin & Grbac, 2003; Min et al., 2007). The customer insight and focus that results from MO improves the value creation performance of a firm and its supply chain partners by enabling them to fulfil customers’ needs more effectively than competitors (Kirca, Jayachandran, & Bearden, 2005). The shared customer insight and coordination of business functions enable MO to support the differentiation strategy of a firm (Zhou, Brown, & Dev, 2009) through improving product quality, promoting the brand, differentiating products, and refocusing on new and more profitable segments of the market (Beverland & Lindgreen, 2007).

SPO is the means of improving supply chain coordination, and it aims to reduce costs of value creation. SPO is defined as “a strategic coalition of two or more firms in a supply chain to facilitate joint effort and collaboration in one or more core value creating activities such as research, product development, manufacturing, marketing, sales, and distribution” (Agus & Hassan, 2008, p. 129). SPO supports cost based and differentiation strategies by providing access to various resources, which are required for customer value creation (Dess, Lumpkin, & McKee, 1999; Hilletofth, 2009).

The aim of the value-view of supply chain is to involve customers in the value creation process rather than seeing customer as “targets who passively receive value created by producers” (Bettencourt et al., 2014). Therefore, the co-creation of value requires an integrative view throughout the supply chain that links the market to suppliers. Thus, both concepts of MO and SPO should be combined to create a value-view of supply chains.

A firm must be able to align its supply chain partnerships with its customer’s needs for an efficient value creation (Wang & Wei, 2007). The supplier relationship requires improved understanding of customers. At the same time, satisfying customers’ needs is highly dependent upon the firm’s knowledge about its suppliers’ abilities. Both MO and SPO provide the firm with required resources for improved value creation process from supplier to customer. The interaction and transaction with partners and customers provide the firm with structured and unstructured data resources, which due to the rapidly increasing size and dimension, have the characteristics of big data. The provided data could be refined further for improved decision making using DA tools (Hsinchun Chen et al., 2012). I consider DA as firms’ required capabilities for extracting value from big data (Hsinchun Chen et al., 2012; Trieu, 2017). DA enable the firm to develop innovative services and products according to the specific needs of customers through bundling, upselling, cross-selling, and special offers. Also, DA help in supplier selection and identification of the resources required for improved customer value creation (Trkman et al., 2010). Therefore, DA are useful for improving a firm's ability to value co-creation through supporting MO and SPO.

Despite the import role of DA in supply chain decision making, the majority of prior studies focus on business value of IT (Dong et al., 2009) and few investigate the business value of DA (Chae et al., 2014; Trkman et al., 2010). Also, these published papers are focused on the performance implication of DA alone rather than recommended topic of co-creation of value through IT (R. Kohli & Grover, 2008). Therefore, there is a dearth of theory development based on empirical research on how analytics impacts co-creation of value and leads to business value in supply chains (Waller & Fawcett, 2013).

While empirical based theoretical discussions are rare, there are a few case studies on DA implementation. These case studies show that DA support business strategy through facilitation of "low cost leadership" (Exact, 2004; R. Kohli, 2007; Shanks & Bekmamedova, 2012b), improvement of product or service "differentiation" (Briggs, 2011; Shanks & Bekmamedova, 2012a), or a combination of "low cost leadership" and "differentiation" strategies (Watson, 2010; Watson & Wixom, 2007). These case studies show that DA have the potential to support the value creation for different customer segments. Despite these evidences, there is no direct discussion or empirical study on the impact of DA on the co-creation of value in supply chains.

2.3 Research Model

The literature discusses that firms incorporate their capabilities to efficiently exploit their resources and improve their performance (Xie et al., 2016). Accordingly, I extend the theoretical framework developed by Xie et al. (Xie et al., 2016) by discussing it in the context of a supply chain. In my research model, which is presented in Figure 1, the partnership between a firm and its supply chain partners provides the required resources for co-creation of value. For instance, big data resources provided by buyers and the big data platform provided by suppliers are shared resources that form the resource base. The DA technologies form the capability base in the research model. According to the RBV perspective, the resource base provides the firm with competitive advantages through an access to resources that are specific to supply chain partners. The DA capability base facilitates the efficient formation of the resource base. Also, the capability base improves value creation activities of a firm with its partners. As a result, the capabilities reduce transaction costs. Further, DA capabilities have other implications like innovative development of new products and services. Therefore, the provided capabilities and resources enable improved co-creation of value and lead to business value.

My proposed research model, which is developed based on the discussed literature and theories, leads to 6 hypotheses. The model integrates relationships between different constructs that have been established in the literature. In the model, MO and SPO form the resource base and DA capabilities form the capability base. The firm's DA-enabled management of MO and SPO results in co-creation of value, which eventually leads to business performance. The constructs and their relationships are discussed in the following sections.

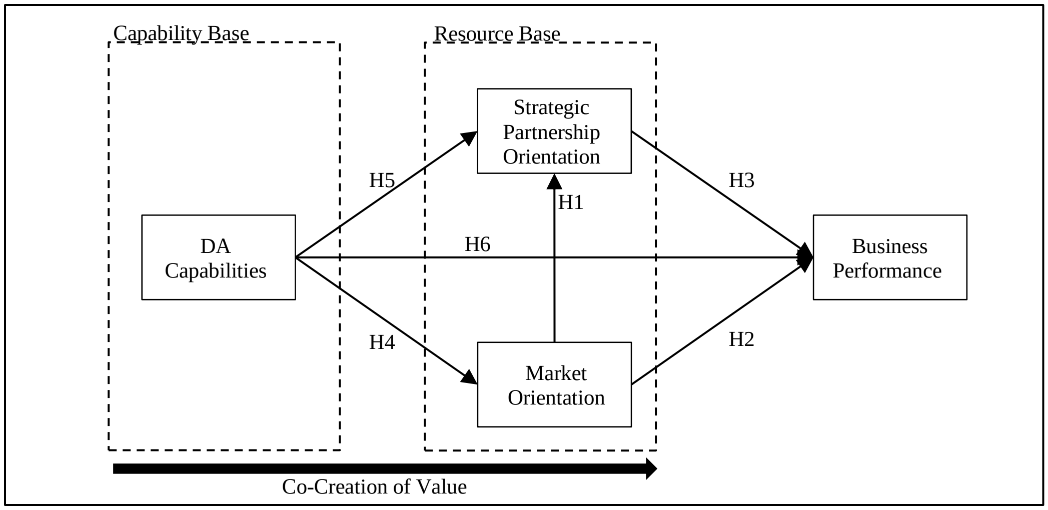

Figure 1. Strategic Value Creation and Performance Model

The co-creation of value in my model refers to utilization of DA capabilities inside a firm for alignment of its buyers' and its suppliers' resources towards customers' needs. In the research model, I discuss the co-creation of value, which requires the right mix of SPO and MO (Frohlich & Westbrook, 2001) and leads to strategic advantage and improve performance. In this section, I discuss the underlying theories that inform my research model first. Then, I develop my discussions and developed hypotheses according to these theories.

2.3.1 Theoretical Base

In studying the MO and SPO, it is important to understand the mechanisms through which interaction between firms creates value (Sarker et al., 2012). The partnership for co-creation of value has benefits and drawbacks. The partnership preserves resources, shares the risks among partners, improves the legitimacy of the firm, and increases market power (Eisenhardt & Schoonhoven, 1996). Despite the benefits, partnership has drawbacks, including lower flexibility, higher need for coordination, and increased transaction costs (Gereffi, Humphrey, & Sturgeon, 2005). Due to the possibility of various outcomes in the partnership, it is helpful to employ diverse theoretical lenses to study the co-creation of value from different perspectives.

The co-creation of value through partnership has overlap between its operational and strategic aspects. Therefore, both RBV of the firms and TCE theories prove useful in explaining co-creation of value "in complementary ways" (Williamson, 1999, p. 1098). Researchers use TCE as the main theoretical perspective to analyze and understand the partnership behavior (Weele & Raaij, 2014; Williamson, 1991). TCE facilitates the understanding of behavior in a buyer-supplier setting and explains supplier partnership and customer relationship (Eisenhardt & Schoonhoven, 1996). TCE states that formation of efficient transaction costs is the principal incentive for firms to form partnerships with their suppliers and customers (Eisenhardt & Schoonhoven, 1996). However, this explanation of buyer supplier relationship is limited to the operational level and fails to consider strategic aspects of the partnership (Eisenhardt & Schoonhoven, 1996). Therefore, there is a need for a complementary theoretical perspective that can consider the strategic importance of the partnership. RBV provides this complementary perspective by explaining strategic aspects of the partnership (Holcomb & Hitt, 2007). RBV yields an appropriate lens to focus on the reduction of transaction cost in the co-creation of value through its focus on resources that become available in partnership (Foss & Foss, 2005). Scholars who consider TCE and RBV simultaneously in their research adopt the ability of RBV and TCE to supplement each other in analysis of the co-creation of value (Holcomb & Hitt, 2007). I follow this stream and investigate the mechanisms of value creation in interfirm partnership from both lenses.

Many IS researchers who studied the effect of IT capabilities on business performance anchored their theoretical arguments in RBV (Mithas & Rust, 2016). Based on RBV, a firm relies on its strategic resources that are valuable, rare, imperfectly mobile, not imitable, and not substitutable (VRINN) to perform and gain sustainable competitive advantage in the market (Barney, 1991; Rungtusanatham, Salvador, Forza, & Choi, 2003). The early discussions on RBV were mainly focused on internal resources of a firm, but more recent RBV literature considers the importance of external resources, which make this theory suitable for studying supply chain (Haozhe Chen, Daugherty, & Landry, 2009). RBV discusses two mechanisms through which partnership impacts performance (Rungtusanatham et al., 2003). First, firms gain competitive advantage when they control resources that are VRINN (S. Li et al., 2006). When a firm forms its value chain from supplier to customer, it prevents competitors from establishing identical relationships with its major suppliers and customers. Therefore, these resources become rare and hard to imitate and provide the firm with a unique ability to create value for its customers and hence gain competitive advantage.

Second, interfirm connection enables the firm to acquire knowledge (also data and information as a form of explicit knowledge), which is a VRINN resource (S. Li et al., 2006; Rungtusanatham et al., 2003). In the partnership, customers provide data resources (for instance, through their activity on social media) and supply chain partners utilize their DA capabilities along with their resources to co-create value. The insight that is acquired (generated or shared) from interfirm related shared data enables improved flow and quality of material (Rungtusanatham et al., 2003). The shared relationship-based data in partnership has the unique characteristics that is specific to the partnership and is not available to other firms. Therefore, both SPO and MO provide VRINN data resources. DA are technologies that support in this matter and improve the utilization of this shared resource towards further development of tailored value for customers and enhanced competitive advantage.

In sum, MO and SPO provide the unique and hard to imitate resources that are required for customer value creation and DA improve the efficiency of the deployment of these resources. Through this partnership, MO provides the firm with the necessary customer data (Srivastava, Fahey, & Christensen, 2001) and DA convert these data resources to the knowledge that is required for efficient value creation. Also, within the partnership, SPO furnishes the firm with resources that are required for satisfying customers' needs (Agus & Hassan, 2008) and DA enhance the utilization of these resources. Therefore, based on RBV, DA enable a firm to focus on different levels of MO and SPO for customer value creation and development of competitive advantage.

The co-creation of value that is discussed from RBV lens, requires close partnership. This close partnership entails coordination and increases transaction costs in interfirm relationships (Gereffi et al., 2005), which is against customer value creation. The co-creation of value and related coordination could be understood from the lens of TCE (Dong et al., 2009). The need for greater coordination does not necessarily mean higher transaction costs, instead, firms can employ IT tools – specifically DA tools - to reduce their transaction costs (Brynjolfsson et al., 1994; Gereffi et al., 2005; Sahay & Ranjan, 2008). I elaborate on the impact of DA capabilities on improved MO and SPO to develop my research model.

2.3.2 Research Hypotheses

Firms can benefit from their external networks and improve their performance by aligning their acquired resources towards better customer orientation (C. Lee, Lee, & Pennings, 2001). The external partnership improves the responsiveness of a firm in satisfying customers' needs by reducing the lead time, providing access to merchandise in shortage periods, and through providing information on upcoming best-selling products and best prices (Ganesan, 1994). Although partnership is vital, its potential value depends on the extent of the firm's ability to benefit from MO (Day, 1994) by aligning its resources towards customers' needs. DA tools enable MO to provide the customer insight that is required for selection and coordination of supply chain partners. Therefore, MO and SPO are inter-related constructs that form the basis for delivering the value that is needed by customers.

Market-oriented organizations focus on "continuously collecting information about target customer's needs and competitors' capabilities … and using this information to create continuously superior customer value" (Slater & Narver, 1995, p. 63). Cross-functional sharing of this information is the link that ties MO with SPO (Martin & Grbac, 2003). This link aligns suppliers toward more focused and enhanced value creation for customers through reduction of bullwhip effect and double managerial effect (Fiala, 2005; I.-L. Wu, Chuang, & Hsu, 2014; Zhang & Chen, 2013). The improved supplier partnerships enhance the value being delivered to customers (Sila, Ebrahimpour, & Birkholz, 2006). Also, the customer knowledge improves the focus of the firm in selection and conversion of its required resources based on the customers' needs. Therefore, the customer knowledge enhances coordination of suppliers and improves the efficiency of resource utilization. Consequently, MO reduces transaction costs. Thus, MO boosts efficiency of transaction costs and creates incentive for forming partnerships (Eisenhardt & Schoonhoven, 1996). With this backdrop, I discuss that MO is the base for strategic partnership and provides SPO with the required intelligence resources for co-creation of value. Therefore, my first hypothesis is:

Hypothesis 1: Market orientation is positively and directly related to supplier partnership orientation.

It is also possible to argue that the SPO impacts MO, opposite to the causality that is hypothesized. However, since my focus is value creation, I posit that MO should lead firms' decisions regarding SPO and development of its resource base. Therefore, I do not study the opposite relationship. This focus is aligned with the pool production strategy.

A market-oriented firm is focused on customer orientation, competitor orientation, and inter-functional coordination (Slater & Narver, 2000). MO provides the firm with the unique knowledge about customers and their wants and needs. Through MO, customers can share their resources (for instance their data), which provide the firm with the means for partner selection and alignment. These data resources enable the firm to develop personalized products and services for customers. Thus, market-oriented firm can provide their customers with highly customized value that is specific to the organization, its customer insight, its competitor awareness, and its resources and capabilities. These products and services are highly related to the firm specifications and hard to imitate by competitors (Slater & Narver, 2000). Putting the discussion in the context of RBV, MO is the source of competitive advantage and impacts performance positively (Liao, Chang, Wu, & Katrichis, 2011). Also, MO improves goal orientation of the firm through providing the firm with the ability to cull out its market segments which are not lucrative. Then, the firm can change the focus of its resources on enhanced customer service for money making segments. So, MO results in overall reduction of transaction costs. In sum, MO improves performance and the second hypothesis is developed based on this background:

Hypothesis 2: Market orientation is positively and directly related to business performance.

There are mixed evidences on the impact of SPO on business performance (Leuschner, Rogers, & Charvet, 2013), and this relationship demands further investigation (Agus & Hassan, 2008). Many scholars found positive relationship between SPO or its related constructs (e.g., supplier integration and partnership quality) and performance indicators such as supply chain performance and cost performance (Agus & Hassan, 2008; Spekman, Jr, & Myhr, 1998; Srinivasan, Mukherjee, & Gaur, 2011; Yeung, Lee, Yeung, & Cheng, 2013). However, supplier partnership requires intensive investment and careful design and maintenance and imposes strategic and financial risks (Maheshwari, Kumar, & Kumar, 2006). This risk may lead to failure of partnership in achieving its initial goals in many cases (Boddy, Cahill, Charles, Fraser-Kraus, &

Macbeth, 1998), which is in contrast with the literature. To deal with mixed findings and contradicting explanations, I investigate the topic using the two complementary theoretical lenses, RBV and TCE.

From TCE perspective, the SPO and the close relationship among partners increase the cost of coordination and the chance of opportunistic behavior (Grover, Teng, & Fiedler, 2002). In addition to the transaction cost, one can argue that SPO, due to its impact on the tendency of partners to continue acting in the defined boundaries, has an adverse effect on flexibility. This inertia prevents from quick response (Lavie & Rosenkopf, 2006). The lower flexibility results in inability of firms in capturing potential opportunities and adapting to business environment trends. While SPO may have negative impact on transaction costs, it is critical for elimination of inefficiencies in supply chains and for customer value creation. Failing to create partnership in supply chain will result in poor quality of the shared data and poor linkage to the environment and causes inefficiencies like high inventory levels, bullwhip effect, and inability to timely response (Hau L Lee, Padmanabhan, & Whang, 1997).

RBV theory supports the argument that SPO contributes to competitive advantage and business performance. Firms develop unique capability through partnership with their supply chain partners (Leuschner et al., 2013). Capabilities are the complex alignment of resources that are entwined with organizational functions and processes, firm resources, and staff’s skills (Amit & Schoemaker, 1993; Day, 1994; Leuschner et al., 2013). Those capabilities that are developed through partnership are unique to that specific partnership and are hard to imitate. Resources, including knowledge, that are acquired through partnership improve competitive advantage (Rungtusanatham et al., 2003). Also, the commitment and cooperation associated with SPO prevent the competitors to access the supplier and their resources in the same way. This gives the VRINN characteristics to the resources that are available in SPO through partnership.

Despite the contradicting theoretical discussions, SPO is discussed in the literature as the means of productive pooling and exploitation of resources, which prevents from inefficiencies (Hsu, Kannan, Tan, & Leong, 2008; Hau L Lee et al., 1997). Also, SPO improves availability of shared resources and yields competitive advantage. Therefore, my third hypothesis is:

Hypothesis 3: Supplier partnership orientation is positively and directly related to business performance.

The improved flexibility, speed and information availability, which are pursued in SCM - and co-creation of value - cause management complexity and higher transaction costs (Gereffi et al., 2005; Su & Yang, 2010). Therefore, firms require enhanced decision making for their SCM to boost their performance (Arshinder et al., 2008), leverage their competitive gains through improved customer service at a lower cost (Christopher, 1999), and facilitate co-creation of value and/or reduces transaction costs (Gereffi et al., 2005). While decision making is important for co-creation of value, due to the complexity that is involved in the supply chain decision making, DA-enabled SCM leads to higher levels of efficiencies (Trkman et al., 2010).

DA are the result of advances in decision support systems (Holsapple et al., 2014) and is a comprehensive term that includes business intelligence, business analytics, and

BDA (Hsinchun Chen et al., 2012). Due to the comprehensiveness of the topic, researchers developed different perspectives on the use and rational for adoption of DA such as “a transformation process,” “a capability set,” “a decisional paradigm,” and “a collection of practices and technologies” (Holsapple et al., 2014). Since the focus of this research is on DA capability, I adopt Davenport’s definition of DA: “extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions” (Davenport & Harris, 2007, p. 7). The rational for adoption of DA, in the capability perspective, is to improve the competitiveness by making the best decisions (Holsapple et al., 2014). Accordingly, DA capabilities construct that is used in my research model refers to the availability and adoption of infrastructure and technology to process data that is collected through MO and SPO towards improved decision making of a firm. DA capabilities benefit the supply chain via multiple paths. For example, SPO is affected through improved demand forecast and MO is improved by identification of the right product mix for different marketing channels.

The operation of supply chains creates large volumes of data, which reflects different aspects of internal operations and external stimuli (Géczy, 2014). Therefore, analyzing this big data integrated with the transaction and legacy data and extracting useful information from it enhances the linkage between the SPO and the environmental realities. The increasing speed of data generation and diversified nature of data makes the conventional data management and engineering tools less useful and increases the importance of implementing the right tools for generating information and insight (R. J.

Kauffman, Srivastava, & Vayghan, 2012). Thus, improved SPO and MO require adoption of DA to enhance the implementation and interpretation of information across the supply chain (Gunasekaran & Ngai, 2004; Sahay & Ranjan, 2008). Both SPO and MO are means of improved information creation and sharing, which in turn are enabled by implementation of analytical tools. This improvement in SPO and MO lead to higher customer value creation and lower transaction costs (Gereffi et al., 2005).

The core of MO concept is employment of market intelligence and coordination of customer value creation based on the intelligence (Liao et al., 2011). Firms can create marketing interventions that profitably address customers' unique preferences through implementation of DA tools (Loveman, 2003). DA also use customer shared data and enables co-creation of value and improves the alignment of created value with customers' needs. Furthermore, DA enhance interpretation and implementation of information across the supply chain towards improved customer and competitor orientation (Germann, Lilien, & Rangaswamy, 2013; Trkman et al., 2010). Therefore, DA capabilities improve MO in supply chain.

DA empower the firm to analyze data resources shared by customers to co-create value. As discussed in prior sections, firms that actively adopt the MO concept have access to the market data sources. Further analysis and refinement of the VRINN market data resource, which is gained through a unique partnership, increase its value and make it nearly impossible for competitors to imitate. Also, DA enable firms to add another layer of sophisticated uniqueness to their data sources by customizing their value creation and providing products and services which are highly representative of customers' needs

(Germann et al., 2013). The specific customer knowledge and detailed response to customers' needs and wants differentiate the firm (Hauser, 2007) and further improves its MO. Accordingly, the fourth hypothesis is:

Hypothesis 4: Business intelligence and analytics capabilities are positively and directly related to enhance in market orientation.

The supplier partnership literature studies the cooperation in the context of value creation. SPO provides partners with the access to shared heterogeneous resources, which improves performance (Rungtusanatham et al., 2003). Efficient utilization of shared resources requires enhanced decision making, that results in alignment of interdependent activities (Okhuysen & Bechky, 2009) and enhances allocation of limited resources to defined interfirm activities (Crowston, 1997). Decision making is the core of SPO and improved decision support tools is required for effective SPO (Romano, 2003). Prior research shows that the application of DA tools improve SPO (Bronzo et al., 2013; Hazen, Boone, Ezell, & Jones-Farmer, 2014; Oliveira et al., 2012; Waller & Fawcett, 2013) through enhancement of the design or management of the supply chain practices in different business domains (Chae et al., 2014). Also, from TCE perspective, SPO entails governance and coordination efforts and increases transaction costs. However, implementation of IT tools, such as DA, for enhanced decision making reduces transaction costs (Brynjolfsson et al., 1994) and improves SPO. Thus, analytical abilities enhance relationships with partners. Therefore, the fifth hypothesis is as follows:

Hypothesis 5: Business intelligence and analytics capabilities are positively and directly related to achieving strategic partnership orientation.

Being equipped with an appropriate level of IT infrastructures as well as the knowledge creation tools enable organizations to improve their performance (Kretzer, Maedche, & Gass, 2014). DA improve both market and operational performance. The impact of s on market performance is through enhanced customer knowledge and improved targeting of different customer segments. DA enable identification of non-profitable customers and redirect the focus of firm's resources on the market segments with higher levels of profitability (Hauser, 2007). There are case studies that describe the role of DA in improvement of market performance. For instance, National Academies Press (NAP) employed a DA approach to improve the pricing of its products (Kannan, Pope, & Jain, 2009). The new employed analytical approach enabled NAP to reach its audiences and enhanced its product placement. In this case, DA improve resource utilization, enhances customer targeting, and allows for customization of product and service development, and results in higher levels of business performance (Kannan et al., 2009).

Analytical abilities support human decision making in different supply chain processes, which leads to improved operational performance (Trkman et al., 2010). The analytical abilities of a firm are important sources of knowledge and create awareness about new opportunities (Hazen et al., 2014). DA provide the firm with the insight that is required to improve revenue generation and cost reduction (Bose, 2009). Prior research established a strong relationship between the implementation of DA and operational improvements to the supply chain (Bronzo et al., 2013; Chae et al., 2014; R. J. Kauffman et al., 2012; Loukis, Pazalos, & Salagara, 2012; Oliveira et al., 2012; Trkman et al., 2010). IT reduces transaction costs and facilitates coordination activities (Brynjolfsson et al., 1994) through an alignment between customers' needs and employed resources. The resource selection and deployment process, that is informed by customer knowledge, improves the efficiency and performance of the firm. In summary, concluding from prior studies and based on TCE and RBV, DA improve market and operational performance, which leads to the sixth hypothesis:

Hypothesis 6: Business intelligence and analytics capabilities are positively and directly related to firm performance.

2.4 Methodology

2.4.1 Measures

I employ a multi-item scale to measure the constructs of the proposed model. I adopt measures from the existing validated studies in the literature wherever possible. Table 1 shows the list of sources that introduced and validated appropriate measures for the proposed constructs. The questions that are developed based on these measures are presented in the Appendix B.

Table 1. List of Constructs and Measures

Construct	Description	Source
Business intelligence and analytics (DA) capabilities	DA are measured based on top management team advocacy, presence of analytics culture, availability of analytical skills, and technical infrastructure	(Bronzo et al., 2013; Chae et al., 2014; Germann et al., 2013)
Strategic partnership orientation	Strategic partnership is measured based on mutual goal setting, process integration, and organization integration	(Agus & Hajinoor, 2012; Flynn, Huo, & Zhao, 2010)
Market orientation	MO is identified through customer orientation, competitor orientation, and inter-functional coordination	(Flynn et al., 2010; Gray, Matear, Boshoff, & Matheson, 1998)
Business performance	The measurement is based on market performance and operational performance	(Flynn et al., 2010; Keats, 1988; Whitten, Jr, & Zelbst, 2012)

For measurement of MO and SPO, validated measures are considered and incorporated into a questionnaire. Since this study is among the first empirical research on the effect of DA on supply chain strategic performance, I found few previously validated measures for DA in this context. Therefore, I followed the proposed method by Churchill (Churchill, 1979) to develop and justify my selected measures for DA. To do so, I created a pool of items for the analytical capability construct based on the validated instruments in literature (e.g., Bronzo et al., 2013; Chae et al., 2014; Germann et al., 2013; Trkman et al., 2010). Then, a group of academicians were asked to review and improve the list of measures. The improved list went through another refinement in a pre-test, which was administered to seven practitioners. Each practitioner responded to questions in a face-to-face meeting. In this meeting, questions were discussed separately to ensure that the question is clear, and the aim of question is communicated to respondents. In the next step, the refined measures went through a pilot study with twenty-four participants. The pilot study ensured researchers that the developed instrument created no concern among the participants and was clear and understandable. This resulted in finalized DA measures that are used in the questionnaire.

Business performance can be conceptualized in a number of ways depending on the discipline of management studied (Neely, Gregory, & Platts, 2005). While performance is widely used in the literature, there is no generally accepted definition and measurement for business performance (Yıldız & Karakaş, 2012). Each definition comes from a specific perspective and is based on the context and features of a business performance system (Franco-Santos et al., 2007). Each perspective has different sets of measures for business performance. In the marketing management literature, all or some of the following criteria are used as common measures for business performance: profitability, sale growth, and market share (K. Kumar, Subramanian, & Yauger, 1998; Matsuno, Mentzer, & Özsomer, 2002; Najib & Kiminami, 2011; Nwokah, 2008). In SCM-related research all or some of the following criteria are used as measures for business success: profitability, market share, customer satisfaction, return on sale (ROS), and return on investment (ROI) (Agus & Hajinoor, 2012; S. W. Kim, 2009; Sánchez & Pérez, 2005; K. C. Tan, 2001; Whitten et al., 2012). Research in the information systems (IS) context also has specific business performance measures, including profitability performance and sales performance (Salleh, Jusoh, & Isa, 2010).

To measure performance, I rely on a validated construct presented by Keats (Keats, 1988). This construct is comprehensive and encompasses those developed in each discipline (SCM, marketing, and IS). Keats (Keats, 1988) proposes the business performance as a multi-dimensional construct that is composed of operational performance and market performance. These measures are used as the dependent variable in my proposed model. To comprehend the overall performance implication of DA, it is important to consider MO, SPO, and business performance at the same time. This measurement conforms with the definition of Chakravarthy (Chakravarthy, 1986) from strategic performance, which suggests a combination of the performance measures with MO and SPO for measurement of strategic performance.

2.4.2 Survey Development and Administration

This study focuses on firms based in the US for data collection. The validation of my proposed hypotheses requires data collection from informants who are familiar with their firm performance as well as its external relationships and interactions. Therefore, my sampling relied on the C-level executives and other supply chain and IT informants. This approach follows the key informant logic (N. Kumar, Stern, & Anderson, 1993), and is used by other researchers as well. For instance, Trkman (Trkman et al., 2010) focused on related informed employees to study the effect of DA implementation in supply chains.

An online survey was developed and distributed via an email invitation among participants. The names and email addresses were obtained from my personalized contacts and a commercial database. As an incentive to promote the participation, I promised a customized report of the findings to those who participated in the survey. The survey was created, pretested and distributed online. A total of 3,561 emails were sent to the participants followed by two reminders and random phone calls. In response to the email, 198 complete responses were returned. Because of the wide use of spam blocking tools, I expect that less than half of the emails were directly placed in the inbox. Considering that at least 50% of emails were not delivered due to spam filtering, I got a response rate of at least 10.8%. This response rate is caused by limitations that are imposed by online surveys (Fan & Yan, 2010). Spam filters can restrict the number of emails that are placed in the inbox. Furthermore, companies might have policies that do not permit their employees to click on links to external resources. Also, target respondents might not trust to click on the links. Another reason for the low response rate could be due to the lengthy questionnaire.

Although response rate is important, nonresponse rate is not the cause of nonresponse bias (Groves, 2006). In fact, survey variables and measurement errors play a more important role in nonresponse bias compared to nonresponse rate (Groves & Peytcheva, 2008). Therefore, I developed the measures and items based on a rigorous procedure to minimize the nonresponse bias (Churchill, 1979). To ensure that the delay in filling out the survey does not result in nonresponse bias, authors compared the statistics related to key variables for the received responses after each email. This comparison did not reveal any significant difference (Armstrong & Overton, 1977). Also, the demographic information of respondents shows high level of similarity in company size and industry type with my initial selected sample, which supports that the nonresponse rate has minimal impact on nonresponse bias.

The majority of my survey participants are in positions that are highly knowledgeable about their firms and have a good understanding of what is going on in their businesses and supply chains. Table 2 shows a brief demographic information of survey participants. To ensure that the position (job title) of respondents do not create a bias in my results, I test my research model by omitting respondents with job titles like analyst, associate, and director. The comparison between results of the path analysis with the omitted observations and the path analysis with all observations do not reveal any significant difference. An overview of questions and results is presented in Appendix B.

Table 2. Survey Respondents

Job Title	**Percent**
Analyst / associate	22%
Manager / senior manager	35%
Director	10%
Vice president / senior vice president	15%
C level executive (CEO, CIO, CTO, COO, etc.) / president / owner.	18%
Annual Sale	**Percent**
Less than $1 million	12%
$1 million - $10 million	12%
$10 million - $50 million	14%
$50 million - $500 million	24%
$500 million - $1 billion	15%
> $1 billion	23%
Job Function	**Percent**
Business management	15%
Information and communication technologies	20%
Operations	20%
Supply chains management	19%
Sales/marketing	8%
Others	18%
Industry	**Percent**
Wholesale / retail / distribution	21%
Manufacturing and process industries (non-computer)	18%
Education	12%
Business services / consultant	11%
Computer manufacturer (hardware, software, peripherals)	11%
Computer / network services / consultant	7%
Transportation / utilities	8%
Others	12%

2.4.3 Analysis

The analysis for both measures and the model is done based on structured equation modeling (SEM). SEM is widely used in social science to analyze structure and measurement models (Gefen, Rigdon, & Straub, 2011). The presented research model, Figure 1, is analyzed using LISREL (v. 9.3). Also, SPSS (v. 24) is used for exploratory factor analysis (EFA) and some other statistical purposes.

2.5 Results

This article follows the two phase analysis approach (J. C. Anderson & Gerbing, 1988) for testing the proposed theory. First, I test the measurement model based on the convergent and discriminant validity to ensure that the measures are representative for constructs. Second, I test the structural model to assess the validity of proposed hypotheses.

2.5.1 Measurement Model: Reliability and Discriminant Validity

2.5.1.1 Exploratory Factor Analysis

I conduct an EFA first to ensure the measurement model is unidimensional and to present a parsimonious model. I load all the items on available factors and trimmed away items with loadings smaller than cut of value of 0.4, items that load on more than one factors and items that loaded on factors that were not conceptually reasonable. For identification of factors, I use the maximum likelihood method and do not fix the number of factors. Table 3 presents the results of exploratory factor analysis.

Table 3. Exploratory Factor Analysis: Pattern Matrix

	Factor			
	DA Capabilities	Market Orientation	Business Performance	Strategic Partnership
Eigenvalue	8.919	2.695	1.370	1.217
% of Variance	42.473	12.834	6.522	5.798
DA1	0.882			
DA2	0.832			
DA3	0.817			
DA4	0.761			
DA5	0.750			
DA6	0.665			
BP1		0.896		
BP2		0.785		
BP3		0.725		
BP4		0.723		
BP5		0.709		
SPO1			0.918	
SPO2			0.906	
SPO3			0.848	
SPO4			0.817	
SPO5			0.690	
MO1				0.945
MO2				0.806
MO3				0.799
MO4				0.798
MO5				0.662
Extraction Method: Maximum Likelihood. Rotation Method: Promax with Kaiser Normalization. Rotation converged in 6 iterations.				

The analysis identifies four factors based on eigenvalues larger than 1. These four factors explain 67.6% of the variance in the data. All the communalities are higher than 0.5 and the Kaiser-Meyer-Olkin measure is 0.912, which shows the adequacy of sample size for this study.

2.5.1.2 Model Fit

To test the measurement model, I conduct a confirmatory factor analysis and checked for model fit based on different fit statistics including the ratio of χ^2 to degrees of freedom, root mean square error of approximation (RMSEA), incremental fit index (IFI), comparative fit index (CFI), and standardized root mean square residual (SRMR). The results for the statistics are $\chi^2/df = 1.942$ (χ^2= 355.483, df = 183), RMSEA = 0.069, IFI = 0.943, CFI = 0.942, and SRMR = 0.054. All these statistics are within the acceptance levels and prove adequate model fit (Kline, 2015).

2.5.1.3 Discriminant and Convergent Validity

Convergent validity requires that the measures of each construct are significantly correlated with each other. To check the convergent validity, I control the loadings of items on each factor. The outer loadings for the constructs are larger than 0.7 (Hair, Ringle, & Sarstedt, 2011) and these loadings are significant at the 0.05 level with all t-statistics larger than 10 (Appendix C). The pattern matrix (Table 3) shows that all the loadings are higher than 0.5 (which is higher than the threshold of 0.3). Also, the loadings average out above 0.7. Therefore, loadings are high enough to support the convergent validity. At the construct level, convergent validity requires the average variance extracted (AVE) to be larger than 0.5 (Bagozzi & Yi, 1988). The results show that all AVEs are larger than 0.5 (Table 4). I also analyze discriminant validity of the model (Table 4). All diagonal elements are larger than off-diagonal elements and the correlation between factors is less than 0.7, which supports that measures achieve discriminate validity (Fornell & Larcker, 1981). Also, the Pattern Matrix (Table 3) shows no item being cross loaded on multiple variables which supports discriminant validity.

Table 4. Correlation Table

	# of Items	1	2	3	4	Mean *	S.D.	AVE	CR	Cr α
DA Capabilities	10	1.000				4.970	1.210	0.620	0.865	0.913
Market Orientation	6	0.437**	1.000			5.305	1.904	0.651	0.864	0.906
Strategic Partnership	5	0.404**	0.524**	1.000		4.442	1.499	0.705	0.924	0.928
Business Performance	7	0.624**	0.511**	0.302**	1.000	5.263	0.998	0.594	0.810	0.883

* Measured by Likert scale of 1 to 7
** Significant at 0.01 level

I study the discriminant validity between constructs through comparing the original model with different constrained models (Table 5). I set the correlation between different constructs to be 1 for all possible dyadic relationships of constructs in the model (Flynn et al., 2010). Then, I compare the constrained model with the original unconstrained model based on difference in χ^2 and degrees of freedom. The results show that all the differences are significant at 0.01 level, and therefore, support the discriminant validity.

Table 5. Pairwise Comparison of χ^2 for Different Model Constraints

Model	χ^2	df	χ^2_{diff}	p-Value
Free model (original)	355.483	183		
DA-SPO	367.803	184	12.32	0.000
DA-MO	456.583	184	101.1	0.000
DA-BP	371.323	184	15.84	0.000
MO-SPO	487.653	184	132.17	0.000
SPO-BP	497.923	184	142.44	0.000
MO-BP	413.933	184	58.45	0.000

2.5.1.4 Reliability

I examine the measurement model for construct reliability using Cronbach's alpha (Cr α) and composite reliability (CR). As the results of my analysis show (Table 4), all composite reliabilities are larger than the recommended threshold of 0.7 and demonstrates a high level of internal consistency (Bagozzi & Yi, 1988). In addition, all Cronbach's alphas are larger than 0.8, which supports the reliability of the model.

2.5.1.5 Common Method Variance

After controlling the measurement model, I test the model for the potential impact of common method variance (CMV) on the results. Since the data is mainly collected from one respondents per firm, it is possible that the results are contaminated by CMV. Therefore, I employ procedural and statistical remedies to reduce the effect of CMV (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). For the procedural remedies, I follow Institutional Review Board (IRB) instructions to protect my respondents' anonymity and informed them about the considered precautions. I also improve the scale items by careful development of my survey instrument (Churchill, 1979).

These items converge to four constructs with eigenvalue of larger than 1. Total variance that is explained by these four constructs is 65.8% and the variance explained by the first construct is 43.1% and shows that majority of variance is not accounted by one general construct. I also analyze the Harman's single-factor model with CFA (Flynn et al., 2010). The fit measures for Harman's single-factor model are $\chi^2(189) = 1489.64$, and RSMEA=0.186, which prove to be a poor fit and supports the lack of CMV in my collected data.

2.5.2 Structural Model

I fit the data to the correlation matrix using LISREL 9.3 to test the model parameters. In this process, I implemented the Maximum Likelihood method and the analysis converge to an acceptable solution. The fit statistics are $\chi^2/df = 2.054$ (χ^2= 375.864, df = 183), RMSEA = 0.073, CFI = 0.935, IFI = 0.936, and SRMR = 0.057, which show acceptable level of fit for all statistics (Kline, 2015). Table 6 shows the results of the structural equation model. Also, the results are presented in Figure 2. The results suggest that the relationships between DA capabilities-strategic partnership orientation ($0.44, p < 0.01$), DA capabilities-market orientation ($0.43, p < 0.01$), DA capabilities-business performance ($0.55, p < 0.01$), strategic partnership orientation-market orientation ($0.38, p < 0.01$), and market orientation-business performance ($0.19, p < 0.05$) are supported and significant. This provides statistical support for hypotheses H1, H2, H4, H5, and H6. The statistical analysis rejects the relationship between strategic partnership orientation-business performance (H3).

Table 6. Structural Equation Model Results

Relationship	Hypothesis	Standardized Coefficient	t-Values
Market Orientation → Strategic Partnership Orientation	H1	0.38	5.56 **
Market Orientation → Business Performance	H2	0.19	2.07 *
Strategic Partnership Orientation → Business Performance	H3	0.06	1.19 *ns*
DA Capabilities → Market Orientation	H4	0.43	6.07 **
DA Capabilities → Strategic Partnership Orientation	H5	0.44	5.89 **
DA Capabilities → Business Performance	H6	0.55	6.21 **

ns Not significant
* Significant at .05 level
** Significant at .01 level

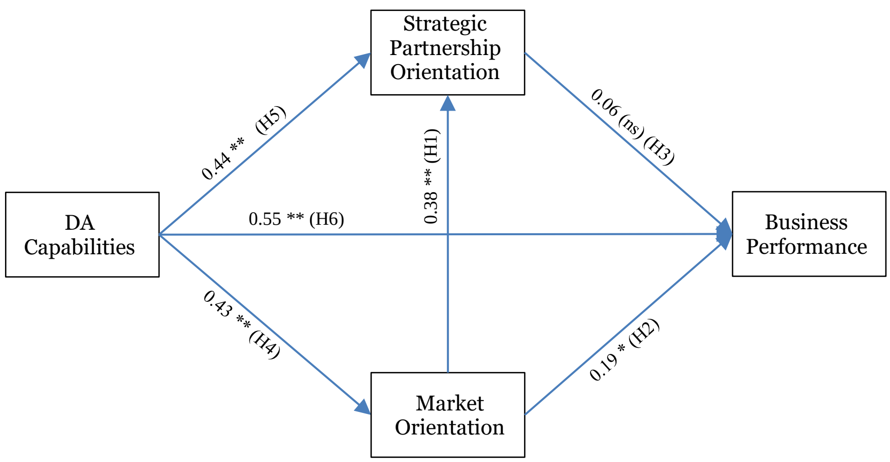

Figure 2. Structural Model with Path Coefficients

The findings, presented in Table 6 (Figure 2), do not completely clarify the distinctions between the supply chains with higher and lower levels of co-creation of value. It is possible that the unobserved heterogeneity in the collected sample data, from supply chains with various levels of value co-creation, causes type II error in rejection of the third hypothesis (Jedidi, Jagpal, & DeSarbo, 1997). To account for this potential issue, I further disaggregate the model constructs to glean deeper insights at a granule level. This analysis helps to investigate the third hypothesis which is rejected in contrary with the discussed theoretical background. I follow the unobserved heterogeneity discovery (UHD) process to reduce type I and type II errors in the results and further clarify my proposed theories for different underlying groups (Becker, Rai, Ringle, & Völckner, 2013).

The underlying framework for my research suggests that my sample data is composed of two major segments with lower and higher levels of value co-creation. Therefore, I conduct a multigroup comparison to discover the unobserved heterogeneity in my sample data, account for validity threats, and enrich my theoretical contribution. In the first step, I divide my data into two groups based on the median of MO and SPO. The observations which are high in both MO and SPO are grouped as high level of value co-creation (72 observations). The rest are observations with lower levels of value co-creation (126 observations). This technique disaggregates firms into those who emphasis on MO and SPO at the same time (dual emphasis) and those who emphasis on either MO or SPO, or have no specific emphasis.

For comparing the impact of the two groups, I conduct tests to examine the invariance of forms, invariance of measurement, and invariance of structural coefficient (Cao & Zhang, 2011; Kline, 2015). I use CFA to identify fit indices for each group and to test the form invariance (Table 7) (Dimitrov, 2006). The results show that the structural model fits the data for both groups and form invariance is in place.

Table 7. Fit Statistics for Configural Form Invariance

Group	N	χ^2/df	RMSEA	CFI	IFI	SRMR
High value co-creation	72	1.852 (338.912/183)	0.109	0.821	0.826	0.0872
Low value co-creation	126	1.633 (298.860/183)	0.071	0.919	0.920	0.0763
All fit statistics, except RMSEA which is sensitive to sample size, are within the acceptable threshold levels (Kline, 2015).						

Also, I test for measurement invariance (Dimitrov, 2006). I create four models with equal pattern with free parameters across the two groups (model 0), equal factor loadings (model 1), equal factor loadings and correlations (model 2), and equal factor loadings, correlations, and measurement errors (model 3). The results are presented in Table 9 and support the measurement invariance. The insignificant difference between the four models support that my model parameters are invariant across the two groups (Kline, 2015). Since form and measurement invariance are supported, I test invariance of structural coefficients to identify whether the impact of constructs on performance is different across these two groups or not. The results of tested relationships under model 3 show significant difference between the coefficient of SPO-BP and MO-BP in the two groups. The between group comparison do not show a significant difference between the impact of MO on BP across the two groups.

Table 8. The Moderation Effect of Co-Creation of Value

Model	χ^2	df	RMSEA	CFI	IFI	$\Delta\chi^2$	Δdf	p-value
Model 0: equal pattern	633.80	366	0.086	0.939	0.940			
Model 1: equal factor loadings	651.85	383	0.089	0.932	0.933	18.05	17	0.386
Model 2: equal factor loadings and correlations	668.08	393	0.101	0.911	0.912	16.23	10	0.093
Model 3: equal factor loadings, correlations, and measurement errors	700.50	414	0.104	0.880	0.880	32.42	21	0.053
SPO → BP	709.56	416	0.106	0.87	0.87	9.06	2	0.01
MO → BP	705.97	416	0.107	0.86	0.87	5.47	2	0.065
DA → BP	714.87	416	0.111	0.86	0.86	14.37	2	0.00

I proceed and test the structural model for both groups. The results are presented in Table 10 and plotted in Figure 3 to demonstrate the impact of model constructs on performance, based on different levels of co-creation of value.

Table 9. Structural Equation Model Results for Different Groups

	Standardized Coefficient		
Hypothesis	Low Levels of Value Co-Creation	All Segments	High Levels of Value Co-Creation
H1: MO → SPO	0.24**	0.38**	0.31**
H2: MO → BP	0.09*	0.19*	0.28**
H3: SPO → BP	-0.05 ns	0.06 *ns*	0.18**
H4: DA → MO	0.44**	0.43**	0.54**
H5: DA → SPO	0.30**	0.44**	0.30**
H6: DA → BP	0.54**	0.55**	0.59**

ns Not significant
* Significant at .05 level
** Significant at .01 level

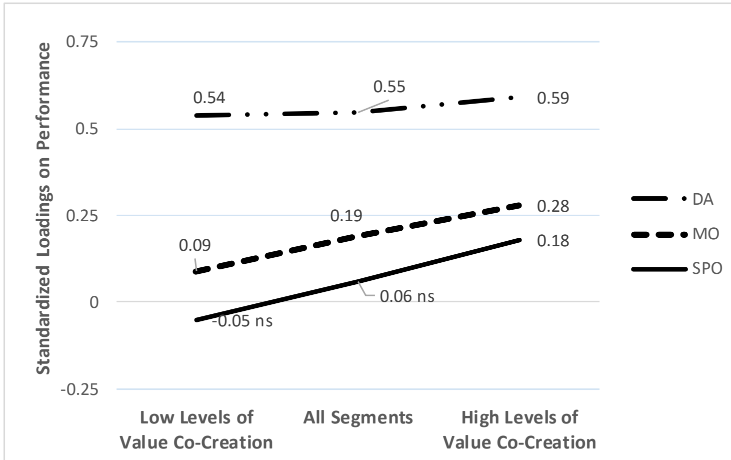

Figure 3. Comparison Between Different Levels of Value Co-Creation

2.6 Discussion

My results support the idea that the firms integrated value creation improves its performance. I conceptualize value creation in the form of partnership and discuss that the customer knowledge that is gained through MO provides partnerships with necessary insights for customers and enhances value creation. Also, I posit that DA improve the co-creation of value and alignment of supply chains with business strategies through further clarification of real customers' needs and associated resources that should be incorporated. The empirical data supports my general arguments. In the followings, different aspects of the model and proposed hypotheses are discussed.

My analysis reveals a positive association between MO and SPO (β= 0.38, $p<0.01$). This positive association is due to enhanced abilities of organization to focus on the resources that are required to serve customers' needs. MO enables the firm to become aware of competitor moves and customers' needs and select their partnership accordingly. Therefore, these partnerships are able to answer specific needs of the firm in regard to its market.

The empirical data shows the direct positive relationship between MO and business performance ($\beta= 0.19$, $p<0.05$). This hypothesis holds across different groups showing that MO is important in all levels of value co-creation .

The findings do not support the direct relationship between SPO and business performance ($\beta= 0.06$, $p>0.05$). As it is discussed in the literature, supplier integration has both negative and positive effects on the performance (e.g., Maheshwari et al., 2006). It poses some risks and at the same time it can result in improved operations. The positive side is the alignment between business processes and integration of operations, which reduces the complexity of the partnership and improves the management. This positive side is supported by a number of scholarly works that address the positive relationship between SPO and performance (Srinivasan et al., 2011). This positive association could be resulted from the established partnership and improved learning over a long period. The negative side of the SPO is that long term and stablished relationships between partners prevent them from finding new suppliers with better prices and qualities. Therefore, SPO can reduce the innovativeness of products and customer services, which lead to higher final costs, and lower quality. Based on my empirical results, firms differ in harnessing the benefits of SPO, which leads to different performance implications. I test two groups of firms with higher and lower focus levels on value co-creation with their partners. I find that in firms with higher levels of value co-creation, SPO has positive and significant association with performance ($\beta= 0.18$, $p<0.01$). My finding supports that partnerships should be directed towards customers' needs and, therefore, be supported by MO. The co-creation of value, due to its focus on customers' needs, improves resource selection and reduces adverse effects of partnership on business performance.

My structural model supports the association between DA and MO of a firm (β= 0.43, $p<0.01$). DA provide market orientation with different tools that are required for customer orientation, competitor orientation, and inter-functional coordination. There are success stories about the impact of DA in marketing, value creation for customers, and enhancement of market performance (Briggs, 2011; R. Kohli, 2007; Shanks & Bekmamedova, 2012b). There are tools like web analytics that provide a unique understanding of customer behavior. This customer knowledge leads to enhanced targeting communications and improved marketing campaigns, which leads to higher return on marketing investment and improves performance. DA tools also provide with benchmarking dashboards, which enables the analysis of competitors. Firms and their partners can improve their pricing strategies through linking competitor analysis results with pricing tools, which enables dynamic pricing in different segments of the market.

The results support the association between DA and SPO (β= 0.44, $p<0.01$). The impact of analytics on the operational aspect of supplier relationship is investigated and supported in literature (Trkman et al., 2010) and my results support the prior findings. DA facilitate SPO through supplier selection, supplier monitoring and measurement, and creation of market insight for upstream supply chain.

Also, I test the direct effect of DA capabilities on business performance. The analysis supports the association between these two constructs ($\beta= 0.55$, $p<0.01$). The relationship between DA and operational performance of a firm's supply chain is discussed in the literature (Chae et al., 2014; Trkman et al., 2010). Trkman et al. (Trkman et al., 2010) find that application of analytics in each of the main supply chain processes (plan, supply, make, and deliver) has a direct positive impact on operational performance of supply chains. Despite the findings by Trkman et al. (Trkman et al., 2010), the study by Chae et al. (Chae et al., 2014) does not reveal a direct and positive relationship between application of advanced analytics and performance. They argue that analytics improve operational performance through enhancing SCM initiatives and do not have direct performance implications. My results help in clarification of the inconsistency in the literature and confirm the association between the two constructs. The results hold across different levels of value co-creation.

My results show a very high association between DA and performance. In other words, although my study supports the indirect impact of DA on performance through value creation, the results suggests that other important mechanisms might be in place that moderate the relationship between DA and performance.

2.7 Conclusion

The effect of DA capabilities on co-creation of value is studied in this paper. The model is developed, discussed, and informed from literature and two theoretical perspectives, RBV and TCE. The collection of empirical data for testing the model is accomplished by administering a survey to executives in US-based firms.

This study reveals the strategic importance of DA-enabled SCM. I develop a value model of a firm's supply chains based on the incorporation of the MO concept along with SPO. This paper shows that MO can regulate the decisions regarding strategic partnerships and use of external resources and facilitate the co-creation of value. Both MO and SPO provide the firm with customer and supplier data sources. Therefore, it is important to employ right analytical tools in the refinement of data sources towards improved value creation. My empirical results support the positive impact of DA tools in improvement of MO and SPO. Also, the results show the positive impact of DA in business performance.

I used two theoretical perspectives to investigate the relationships. From the lens of RBV, I study the strategic importance of shared resources including data and discuss how the shared resources create competitive advantages for the firm. The RBV theory fails to support the dynamic aspect of resources and the need for maintaining the alignment of selected resources with customers' needs and business strategies. Therefore, I use TCE to investigate coordination and alignment. TCE supports my discussions on the importance of DA in improved coordination and reduced costs.

My empirical results support the majority of my discussions, five out of six hypotheses. DA capabilities have a direct positive effect on strategic partnership orientation and market orientation. Also, DA capabilities have a direct and indirect (through MO) impact on business performance. The empirical data do not reveal a direct association between strategic partnership orientation and business performance.

However, I found that the focus of supply chains on co-creation of value is a key for enhanced performance outcomes of SPO.

CHAPTER III

STUDY 2: DATA ANALYTICS CAPABILITIES FOR INTERORGANIZATIONAL COLLABORATIONS

3.1 Introduction

Firms form collaborative partnerships to expand access to new resources and new markets, as well as maintain competitiveness in today's business environment (Dyer & Singh, 1998; Ireland, Hitt, & Vaidyanath, 2002). Collaboration is about "pooling resources held by different firms in order to exploit new business opportunities and to increase the efficiency of existing business activities" (Mitchell, Dussauge, & Garrette, 2002, p. 204). Yet, the depreciation of resource value, which is the result of intense competition and rapid technological innovation, impose serious risks and challenges to alignment of partners in a collaboration and may lead to opportunistic behaviors detrimental to interorganizational partnership (Gulati et al., 2012; Lavie, 2006). As a result, more than half of collaborative initiatives end up in failure (Gulati et al., 2012). In response to this challenge, the literature emphasizes the importance of IT-enabled decision making for management of collaborations (Robey, Im, & Wareham, 2008; Schreiner, Kale, & Corsten, 2009). Specifically, IS scholars consider DA as a vital capability for improving collaborations (Hsinchun Chen et al., 2012; McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012). Despite the potentially significant impact of DA on improved collaborations, the two questions of "How does a firm use its DA capabilities to improve collaborations and enhance performance?” and “What is the impact of DA capabilities on a firm’s collaboration and performance?” are not adequately discussed in the literature.

The dynamic nature of business environments, which is the result of competition and rapid change in customer needs, impacts the management of collaborations (T. Y. Choi et al., 2001). Thus, firms should be aware of constant environmental changes and adapt and realign their collaborative relationships accordingly. This constant need for adaptation and realignment becomes even more challenging when considering the inherent complexity of collaborations. The success of collaboration in this complicated volatile environment requires accurate decisions (Chae & Olson, 2013). Therefore, DA hold promises for improvement of collaborations. However, and despite this potential impact of DA on collaborations, the literature fails to study the mechanisms through which DA impact collaboration and lead to performance improvements. More specifically, the literature exhibits three research gaps in this matter.

The first research gap stems from the lack of understanding of the mechanisms through which DA capabilities improve the performance of a collaborative relationship. The business value of DA is discussed, and positive association between DA and performance is established in the literature (Fink et al., 2017; Günther et al., 2017; Trieu, 2017; Vukšić et al., 2013). However, this stream of research is mainly focused within the boundaries of a firm and there are limited studies focused on IORs (e.g., Oliveira et al., 2012). Furthermore, prior studies in the interorganizational context are mainly focused on direct impact of DA capabilities on performance and few studies address the mechanism through which DA improve performance (Chae et al., 2014; Oliveira et al., 2012; Trkman et al., 2010). Despite the limited notable studies, the capabilities and practices that lead to performance require further investigation.

The second gap is related to the lack of understanding of the need for a strategic focus of DA in an interorganizational setting. Strategic IS alignment is an important concern for practitioners (Tallon & Pinsonneault, 2011) and many scholars have substantiated the strategic importance of IS in their empirical research (Mithas, Ramasubbu, & Sambamurthy, 2011). The findings suggest that the strategic direction of IS plays an important role in the realization of IS business value (Mithas & Rust, 2016) and DA strategic focus is important in this business value realization (e.g., Fink et al., 2017). Despite this importance, the DA strategy is only investigated by a handful of researchers and within the boundaries of a firm (Fink et al., 2017; Maghrabi et al., 2011). Since strategic management scholars consider an important role for strategic direction of collaboration (Lavie & Rosenkopf, 2006), it is insightful to address how DA strategic focus impacts collaborative relationships. However, and despite the anecdotal evidences that suggest the potential impact of DA strategic focus on the performance of collaborative relationships, there are no empirical studies to support this assertion. Therefore, DA strategic focus and its role in the collaborative performance merits further attention.

The third research gap in the literature is related to underlying theories that are used to inform the IT-enabled collaboration. The published scholarly works either discuss the impact of IT on the shared interorganizational resources (e.g., Hau L Lee et al., 2000) or on the governance of IORs (e.g., Dong et al., 2009; Im & Rai, 2013). While shared resources are considered as the source of competitive advantage (Mithas et al., 2011), governance and the need for coordination are activities that impose constraints on collaboration (Dong et al., 2009; Weele & Raaij, 2014). As a result, this single focus on either of these two interrelated aspects of collaboration leads to an incomplete or misleading understanding of the important issues to consider (Eisenhardt & Schoonhoven, 1996; Williamson, 1999). Since the nature of collaboration entails simultaneous pooling of resources and governing the use of shared resources (Gulati et al., 2012), it is vital to employ a more accurate conceptualization of the IT-enabled collaboration.

My research is focused on two questions, which study the impact of DA on collaboration at two levels. The first research question, which is exploratory in nature, is looking to better understand different scenarios on how DA may lead to success of a firm's interorganizational collaborations. Answering this question requires an inductive research approach meant to identify paths from DA to an enhanced performance of a firm through its collaborations. The aim of my second research question, which is confirmatory in nature, is to theorize the impact of DA on collaboration and performance. Therefore, a deductive research approach is needed to use empirical data and confirm my findings in the form of theories. Accordingly, the answer to my first research question needs to be grounded in an interpretive paradigm, while the response to my second research question demands a positivist approach. Therefore, I adopt a mixed-method research that is composed of two studies and links my interpretive understanding to the positivist understanding and theory testing (A. S. Lee, 1991). A mixed-methods research approach provides a richer insight to the problem through combining the strengths of qualitative and quantitative research methodologies (Venkatesh, Brown, & Sullivan, 2016). In this study, I follow the established guidelines for mixed-method research (Flint, Gammelgaard, Golicic, & Davis, 2012; Mingers, 2001; Venkatesh, Brown, & Bala, 2013; Venkatesh et al., 2016). Accordingly, I adopt a multiple paradigm stance and conduct the study in two phases of exploratory and confirmatory investigations. Due to the interrelationship of the questions, I conduct the study in two sequential phases. A detailed description of the employed methodology for each sub-study is embedded in the presentation and discussion of the two studies in the following sections.

My work is an interdisciplinary research, which contributes to the literature in IS, strategic management, and operations management (OM). The first contribution is through the explanation of how DA improve collaboration and leads to performance. The second contribution is providing a more focused view of the business value of IT by testing the impact of DA in collaborations. Unlike prior research, which has focused primarily on the impact of DA on business performance at the boundary of firms' activities, mine focuses on understanding of DA in an interorganizational collaborative setting. I measure the business value of DA through its impact on the performance of a firm that is the result of improving its external collaborations. Therefore, my research provides a confirmatory role in the analysis of DA impact on business performance. The third contribution of my research is that it addresses the DA strategy as an extension to IS strategy literature. Finally, my fourth contribution is the clarification of the contradictory findings of the literature on the impact of collaboration on performance. A collaboration relationship is composed of cooperative and coordinative components (Gulati et al., 2012). I study cooperation and coordination to address interorganizational collaboration and investigate the impact of the DA-enabled coordination and cooperation on a firm's performance.

Through the rest of this chapter, I develop my research model based on a case survey research to explain the impact of DA on a firm's collaborations and performance. Next, I present my research model and empirically test it and its hypotheses using survey data. Finally, I present my findings, discuss the results and their implications, deliberate on the limitations, and propose directions for future programs of research.

3.2 Development of Theoretical Model

The first step in the employed mixed-method approach aims to understand how DA lead to performance in collaborations. In this step, I am focused on a qualitative approach based on content analysis of multiple case studies (case survey) (Larsson, 1993). I choose this approach for several reasons. First, the topic is new in the context of collaboration and has rarely been discussed. Literature suggests an inductive research approach when "there is not enough former knowledge about the phenomenon or if this knowledge is fragmented" (Elo & Kyngäs, 2008, p. 109). Second, case study allows for the development of deeper insights required in studying complex phenomena, such as interactions of DA and business practices and understanding how this interaction leads to business performance. Third, analysis of multiple case studies provides a rich understanding of the phenomena from multiple perspectives that facilitates the generalizability of the topic (Larsson, 1993). Since I use the outcomes of this part of the study for developing theory, which is empirically tested in the second part of my this chapter, a multiple case studies approach serves my objective. To achieve this, I utilize already published case studies on the role of DA in interorganizational collaborations. The use of the multiple case survey method for the first part of my study (c.f., Rivard & Lapointe, 2012) is an inductive approach used by other IS researchers. For instance, Wang et al. (2017) used this approach to study the impact of big data on transformation of organizations (Y. Wang, Kung, Wang, & Cegielski, 2017).

3.2.1 Methodology

I follow a systemic procedure to select, prepare, organize, and conceptualize published case studies (Elo & Kyngäs, 2008; Larsson, 1993). My case studies are carefully selected from Informs' Business Analytics Case Study Database (INFORMS, 2017). I deliberately avoided using case studies provided by software vendors, since they may be potentially biased. The collected case studies are published by a scientific institution that is known for its top tier journals such as "Information Systems Research" and "Management Science." After a careful initial review of 100 case studies in the database, I identified 47 case studies that were related to my research question. More specifically, I found an impact of DA on supply chain management practices that leads to performance in those case studies. A more detailed analysis of my initial pool of selected cases, showed that only 34 case studies have the element of interorganizational collaboration. Some of these case studies discuss the collaboration of a firm with its suppliers and/or customers. The rest of them investigate the relationship between several partners, such as different production plants, multiple warehouses, or a combination of them with suppliers and customers. The selected case studies are related to companies from different business sectors including energy, electronic consumer goods, transportation, auto manufacturing, etc., and are focused on different business functions, such as new product development, procurement, manufacturing, and distribution. A list of the selected case studies is presented in Appendix C.

Each selected case study has one or more descriptive explanations as to how a specific DA initiative would impact business performance. I refer to this as a “path.” Each of these paths starts from explaining how DA capabilities impact business practices and ends by discussing the performance implications. I consider each path as a unit of analysis (Rivard & Lapointe, 2012; Y. Wang et al., 2017).

3.2.2 Coding Process

I followed the steps in inductive analysis presented by Hatch (2002) to analyze case studies (Hatch, 2002). I adopted an open coding approach based on an inductive approach to case survey (Elo & Kyngäs, 2008). This method is used by other IS scholars for case survey studies (Rivard & Lapointe, 2012; Y. Wang et al., 2017). I went through case studies several times to identify salient areas with a code. Then, I used identified codes for two purposes. First, I identified main themes, categories, and subcategories. Second, I reviewed the codes and their related themes to discover relationships among these elements in selected case studies. Several patterns emerged throughout this process, which identify how DA can improve interorganizational collaborations and lead to business performance.

I considered three measures to maintain the trustworthiness of my coding. First, two researchers coded the data separately through a systematic approach to ensure a reliable interpretation (Landis & Koch, 1977). After the initial coding, coders contrasted the results and discussed discrepancies. The initial differences were due to different definitions and conceptualization of terms. Therefore, the second step was development of consistent definition to use in the coding process. The definitions were extracted from literature and researchers agreed on them. Each researcher went through the coding process once again. The results were compared, and the remaining differences were discussed and resolved, which led to a final set of categories. The third measure that I employed to increase the trustworthiness of my coding process was having an experienced practitioner to code one third of cases (a sample of 11 case studies). The hired practitioner has a PhD in industrial engineering with more than ten years of experience (at the time of coding) in employment of analytical tools in supply chain management. I trained the practitioner and he coded 11 case studies. I contrasted the results of his work with my initial coding and found few differences. I discussed differences in a meeting and revised my codes accordingly. The employment of the practitioner ensures me that my coding is not biased due to personal mistakes, ignored information, or subjective perspectives and hypothetical assumptions of researchers (Larsson, 1993; Y. Wang et al., 2017).

3.2.3 Data Analysis

My aim, in the coding process, was to answer the first research question through identification of important categories and their relationship with each other. I found three main themes: namely, DA capabilities, collaboration, and performance. Each of these themes was identified based on categories and subcategories that were extracted from my data. A review of the identified categories, subcategories, and items is presented in following sections and a complete list is presented in Appendix D.

3.2.3.1 DA Capabilities

The first theme refers to DA capabilities, which is aligned with the definitions of organizational capability as the ability of a firm to consistently carry out a productive outcome by impacting its capacity for transforming inputs to products and services (Grant, 1996). Consequently, I identified three categories for DA capabilities. The first category is the *talent capability* that identifies how a firm uses analytical tools, stores and employs its existing knowledge, and trains its employees to use analytics towards improving its operations. The *technology capability*, which is the second category, provides tools for data management and systematically disseminates the results of DA in an appropriate presentation mode to be used in collaborative related operations. Finally, *management capability* is the constant monitoring and coordination of DA investment and capability development towards maintaining or improving the outcomes of DA.

3.2.3.2 Collaboration

I found two categories for collaboration: namely, *cooperation* and *coordination*, which are aligned with the literature. The literature suggests that collaboration is composed of two components: cooperation, defined as "joint pursuit of agreed-on goal(s) in a manner corresponding to a shared understanding about contributions and payoffs" (p.

533), and coordination, defined as “the deliberate and orderly alignment or adjustment of partners’ actions to achieve jointly determined goals” (Gulati et al., 2012, p. 537). The current literature is mainly focused on communication methods, such as information sharing and meetings that are used for coordination (Schreiner et al., 2009). Also, the literature is focused on designing roles and responsibilities of partners for coordination (Okhuysen & Bechky, 2009). However, and despite its importance, related practices for coordination are not discussed in the literature. Therefore, the constituents of the coordination category, which are identified in my case survey study, provide a different perspective from what is already discussed in the literature.

Our case survey shows that firms participate in cooperative practices by selecting their suppliers, developing partnership through investment in upstream and downstream supply chains, and sharing risk with their partners. However, the rapid development of new technologies and change in the market reduce the productivity of cooperation gradually. Also, cooperation is threatened by opportunistic behavior. Therefore, firms seek to improve the utilization of available resources that are provided in a cooperation through coordination. I found many instances of firms using contract design to control their partnerships. Also, relational practices for coordination, such as collaborative planning and scheduling, and collaborative product design and development, are discussed in the reviewed cases.

3.2.3.3 Firm Performance

While firm performance is widely used in the literature, there is no generally accepted definition or measurements of it (Yıldız & Karakaş, 2012). Each definition comes from a specific perspective and is based on the context and features of a business performance system (Franco-Santos et al., 2007). Therefore, firm performance can be conceptualized in a number of different ways depending on the discipline studied (Neely et al., 2005). Accordingly, the performance results in my case survey could be defined based on different categories from the existing literature. For instance, the literature places performance outcomes in categories such as business process, product quality, marketing, operational, financial, and strategic (Agus & Hajinoor, 2012; Elbashir, Collier, & Davern, 2008; Flynn et al., 2010; Whitten et al., 2012). However, since scholars in OM use operational and strategic performance categories to study performance outcomes of IORs (Flynn et al., 2010) and strategic performance are discussed extensively in the literature of IT business value (Dehning & Richardson, 2002; Nicolaou, 2004), I adopt the same categories.

3.2.4 Case Survey Results

I study the relationship between the three identified themes and their constituents to answer my first research question. My aim is to unravel the paths through which DA capabilities impact collaboration and firm performance improvements. Accordingly, I found 198 paths from DA capabilities to performance in my analysis. The number of paths for different case studies ranges from 1 to 24 (the number for each case study is shown in Appendix C). The reason for a higher number of paths in some case studies is the association of various performance outcomes to one DA capability. For instance, employing a specific decision tool for coordination that results in “Reduced Costs,” "Increased Revenue," and "Improved Customer Service" is recorded and coded as three instances. Figure 4 shows an aggregated view of performance paths.

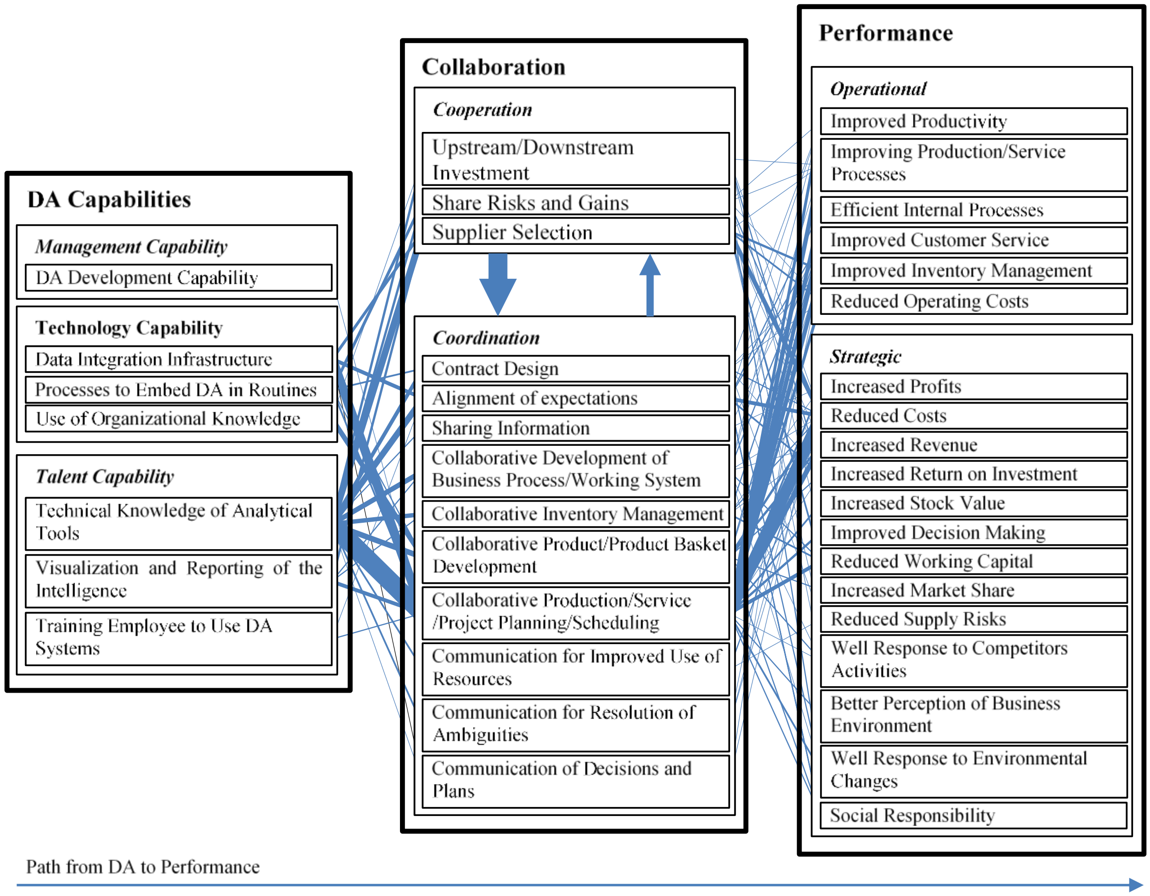

Figure 4. The Major Elements Identified in the Coding Process and Their Relationships (Number of Instances Between Items Identify the Width of Each Line)

Among the paths that are shown in Figure 4, the most repeated path is related to "Technical Knowledge of Analytical Tools," which through improved "Collaborative Production/Service/Project Planning/Scheduling" leads to strategic performance, such as "Reduced Costs" (12 instances) and operational performance such as "Improved Customer Service" (6 instances). The results show 131 unique paths, which start from

DA capabilities, then impact on collaboration practices, and lead to performance improvements. These paths are further discussed and explained in the following sections, where I develop and discuss my research model and its hypotheses.

3.2.5 Developing Research Model

I develop my research model based on the findings presented in Figure 4. I also inform my model development with the existing literature and suitable theories and provide additional support for the developed model. I discuss the relationships among constructs and develop hypotheses informed by the findings from the case survey, as well as existing theories and the literature, in the following sections.

3.2.5.1 Collaboration and Performance

I record several instances of interactions between cooperation and coordination. There are 21 instances that cooperation initiatives lead to improved coordination. For example, “Shared Risks and Gains” lead to development of control and reporting tools that impact the “Contract Design.” Also, I find 7 instances that coordination leads to higher levels of collaboration and results in performance improvements. For example, “Communication for Improved Use of Resources” leads to higher levels of “Upstream/Downstream Investment.” While the interaction between coordination and cooperation plays a role in performance, the literature fails to investigate it (Gulati et al., 2012).

The topic of collaboration can be discussed from different perspectives depending on the theoretical lens used. The importance of this topic lies in its complex nature and multifaceted factors that influence it (T. Y. Choi et al., 2001). The nature of collaboration is complex due to various factors, including differences in cultural backgrounds, inconsistencies among goals, and mismatches among technological infrastructures that add to the complexity of the relationship (Lavie & Rosenkopf, 2006). The inherent complexity in a collaboration reduces the chance of success at the beginning of a relationship. In addition to complexity, the duration of a partnership has a positive relationship with the chance of commitment breach and increases the failure potential (Ring & Van de Ven, 1994). This duration impacts the initial underlying assumptions of the collaboration design and cause misalignment between partners' goals. Dynamism coupled with the inherent complexity increase the possibility of failure in a collaboration (T. Y. Choi et al., 2001; Gulati et al., 2012). Much of scholarly works find that the misaligned incentives of partners lead to consequences ranging from gradual demise of the collaboration to opportunistic behavior of partners and cause the collaboration to fail. Such antecedents lead to failure in more than 50% of such relationships (Gulati et al., 2012).

On the one hand, firms need to focus on their competitive advantage for customer value creation and rely on external alliances for maintaining supplementary resources, which are needed for full realization of their customer needs. On the other hand, firms need to maintain their resources' fluidity and shift from one partner to another partner or change the nature of their relationships with current partners to maintain their harmony with the changes in the business environment (Doz & Kosonen, 2010). The need for collaboration and the constant need for adjustment and renewal of partnership makes maintenance of competitiveness of firms a challenging task (Spekman, 1988). Consequently, there are contradicting findings in the literature (Leuschner et al., 2013). While there are many examples of positive association between collaboration and performance (Agus & Hassan, 2008; Spekman et al., 1998; Srinivasan et al., 2011; Yeung et al., 2013), there are many instances collaboration failing (Boddy et al., 1998). Since collaboration requires heavy investment and creates strategic risk for firms, the consequence of its failure is drastic (Maheshwari et al., 2006). Therefore, researchers suggest that these contradictory findings are due to the partial analysis of the collaboration (Gulati et al., 2012). Accordingly, it is vital to consider the two aspects of collaboration, cooperation and coordination, for an enhanced understanding.

The results of my case survey analysis, in addition to revealing the interaction between cooperation and coordination, show consistency with two theories: namely, RBV and TCE. My analysis shows that firms form cooperation as a source for new opportunities, innovation, and improved resources to gain a competitive edge. This characteristic of collaboration is discussed in the literature based on RBV theory (e.g., Hitt et al., 2000). Also, my analysis reveals that the complexity of the relationship, the potential for failure, and the constant change in underlying factors of the IOR impose high costs to the collaboration. The literature discusses the associated collaboration costs through the lens of TCE theory (e.g., Weele & Raaij, 2014). The TCE theory suggests that a cooperation requires a coordination mechanism to control and reduce the transaction costs (E. T. G. Wang & Wei, 2007). Each of these two theoretical perspectives, TCE and RBV, provide a partial understanding of collaboration (Gulati et al., 2012). My study suggests that it is important to incorporate both lenses to investigate collaborative relationships. The combination of these two perspectives explains that the success in a collaboration depends on cooperation, which provides shared resources, and on coordination, which enhances exploitation of the shared resources (e.g., Dong et al., 2009).

My case survey findings suggest that the two facets are interconnected. Coordination is the means of evolution and improved performance in collaborations (Faems, Janssens, Madhok, & Van Looy, 2008), and according to the mutual adjustment perspective (Mintzberg, 1979), cooperation needs constant mutual adjustment through coordination to cope with environmental changes. Therefore, this interconnectedness makes the RBV and TCE theoretical lenses a good choice for examination of IOR (Dong et al., 2009). These theories could explain how the two facets of collaboration could improve performance through their interaction.

My case survey findings also suggest that the interaction between coordination moderates the relationships between cooperation and operational and strategic performance. The moderation impacts operational performance by increasing the productivity and effectiveness of mutual activities. Also, it impacts strategic performance through enhanced alignment of cooperation with environmental changes. This proposition is also supported by theories. The RBV theory indicates that the cooperation provides resources that lead to competitive advantage (Combs & Ketchen Jr, 1999). According to TCE theory, maintaining competitiveness in the long run requires coordination for effective use of resources and adaptability to environmental changes

(Gulati & Singh, 1998). Effective use of resources leads to improved productivity and enhances operational performance (Elbashir et al., 2008). Also, enhanced adaptability of cooperation to environmental changes through higher levels of coordination leads to performance at the strategic level (H L Lee, 2004; Phelps, 2010). Therefore, I posit that coordination moderates the impact of cooperation on operational and strategic performance. This leads to my first and second hypotheses:

Hypothesis 1: Coordination moderates the relationship between cooperation and strategic performance.

Hypothesis 2: Coordination moderates the relationship between cooperation and operational performance.

Also, my case survey results suggest that cooperation moderates the relationship between coordination and performance through providing resources such as *shared information*. For instance, the shared information, which is achieved through cooperation, could be used to identify and resolve operational issues in everyday business activities. Also, such information could be employed to revise contract terms for long-term success of the collaboration. Therefore, cooperation moderates the relationship between coordination and performance at operational and strategic levels. Based on the discussed background, my next hypotheses are:

Hypothesis 3: Cooperation moderates the relationship between coordination and strategic performance.

Hypothesis 4: Cooperation moderates the relationship between coordination and operational performance.

3.2.5.2 Data Analytics Capabilities and Collaboration

The literature does not explicitly address how DA impact collaboration and its constituents. Therefore, I discuss the impact of DA capabilities on collaboration based on theories. Then, I dig into this impact and discuss it based on the findings of my case survey and develop my research hypotheses.

Contemporary DA are the result of advances in decision support systems (Holsapple et al., 2014). Accordingly, I use DA as a comprehensive term that includes business intelligence, business analytics, BDA, and other similar topics (Hsinchun Chen et al., 2012). There are different viewpoints on the use of DA and the rationale for adoption of DA in firms including "*a transformation process*," "*a capability set*," "*a decisional paradigm*," and "*a collection of practices and technologies.*" I study DA from the capability set perspective due to the focus of my study. This perspective considers DA as a set of capabilities and defines DA as an "extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions" (Davenport & Harris, 2007, p. 7). The rationale of this perspective for employment of DA is to improve competitiveness by making the best decisions (Holsapple et al., 2014). Since organizational capability is defined as "a high-level routine (or collection of routines) that, together with its implementing input flows, confers upon an organization's management a set of decisions options for producing significant outputs of a particular type" (Winter, 2003, p. 991), DA capabilities should enable the organization to persistently get the required data, analyze it, and facilitate the implementation of its suggestions. My analysis in the case survey part of this study assumes a similar role for DA through identification of talent, technical, and management capabilities.

The RBV theory posits that assets and capabilities that are useful in the detection of environmental opportunities and threats, are the source of competitive heterogeneity in the business environment (Wade & Hulland, 2004). These assets and capabilities are employed by a firm to prepare products and services for its market (Wade & Hulland, 2004) with the aim of differentiation from its competitors (Hoopes, Madsen, & Walker, 2003). While RBV theory provides the basic foundation for analysis of competitive heterogeneity, it fails to explain the rise of this heterogeneity (Helfat & Peteraf, 2003) and to clarify how firms can achieve a competitive advantage in dynamic markets (Eisenhardt & Martin, 2000). Dynamic capability, which is defined as “the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments” (p. 516), is conceptualized to complement RBV theory (Teece, Pisano, & Shuen, 1997). Dynamic capabilities are organizational and strategic routines that support adaptation to a dynamic environment through managerial interventions (Eisenhardt & Martin, 2000). Therefore, I argue that DA capabilities are dynamic capabilities that enable a firm to continuously adapt to its changing business landscape by providing decision support for reconfiguration and adjustment of its external resources.

DA tools, due to their ability to process resources and to generate a distinctive value for a firm, are considered a set of dynamic capabilities (Chae & Olson, 2013). Decision makers use these dynamic capabilities to improve operations, adjust collaboration, identify new opportunities for revenue generation, and identify the future trends for the firm to adjust its path forward (Briggs, 2011; D. Q. Chen, Preston, & Swink, 2015; Watson et al., 2006). Therefore, DA supports managers in their decisions to improve performance of collaboration. Due to the variability of a firm's needs for resources over time (Doz & Kosonen, 2010), cooperation and coordination need dynamic adjustments. Cooperation helps the firm to access its required resources and coordination is the means of adjustment of the firm's access and use of acquired resources through partnerships (Chauhan & Proth, 2005). Therefore, both cooperation and coordination processes should be supported by sophisticated information about the business landscape provided by DA, so that collaboration could be adjusted with environmental changes. Adjustment of collaboration with business environments requires that a firm accesses data sources as a base for sensing their business environment. They also need analytical tools to convert data to more insightful information forms. Further, they need to disseminate the information across the organization and share it with their partners. These requirements are served by technical and talent capabilities. The dynamic capability theory suggests that DA capabilities are the source of required knowledge and empower decision makers to improve cooperation and coordination.

The technical capability contributes to organizations by creating access to the required data and existing knowledge and facilitating the implementation of results across the organization. The technical capability subcategories provide organizations with the ability to collect the required data, store and reuse organizational knowledge, and systematically disseminate the created insight and knowledge. This has an important impact on collaboration. Coordination requires on-time and informed decision making

(Sahin & Robinson, 2002) and technical capability, through real time sharing of data between IOR partners, improves the performance of coordination. In addition, access to the existing knowledge of firms further improves the decision-making process (Spekman, Spear, & Kamauff, 2002). Consequently, communication of decisions across organizations becomes easier through embedded DA in organizational routines, which facilitate inter-functional coordination (D. Q. Chen et al., 2015; Sahin & Robinson, 2002). This enhanced coordination impacts the quality of cooperation. Furthermore, the technical infrastructure streamlines the interfirm communication, which is essential for alignment of goals (e.g., Sahin & Robinson, 2005).

Talent capability contributes to organizations by providing them with capabilities to analyze data and facilitates the implementation of solutions. Talent capability, through its technical knowledge, enables a firm to use analytical methods to resolve complex problems. In addition, talent capability, through training and creation of high level user interfaces, empowers employees at different levels of organizations to use analytical tools more effectively. In addition, talent capability facilitates communication of results through implementation of reporting and visualization tools. Participating firms in a collaboration should be able to predict and identify shifts in market structure through extensive processing and use of data to maintain alignment in their cooperation (H L Lee, 2004). Dealing with the extremely complex problems associated with collaboration, especially in the context of new product development, creation of new product mix, management of inventory at the network level, and planning and scheduling the operation of several partners in a collaboration is impossible with conventional tools and requires sophisticated mathematical tools and computational power. Talent capability provides the required modeling knowledge, as well as computational power. While development of sophisticated mathematical models could be achieved by a relatively smaller group of employees, implementation requires appropriately communicating the results. This communication of results is achieved through training and developing reports that are easy to comprehend by their potential users. Talent capability enhances cooperation through improved use of shared resources. Furthermore, talent capability improves coordination through development of innovative solutions for current collaborative operations.

Finally, DA capabilities need to be available consistently. Management capability, through planning and developing DA talent and technology, provides the required consistency. This planning ensures that DA are improving and can continually support collaboration.

In summary, a firm needs to access data, analyze it, use it, and maintain its capability to achieve the management improvement goals to improve its collaborations. Therefore, DA capabilities positively impact both cooperation and coordination. This leads to my fifth and sixth hypotheses:

Hypothesis 5: DA capabilities are positively and directly related to cooperation.

Hypothesis 6: DA capabilities are positively and directly related to coordination.

3.2.5.3 Data Analytics Strategic Focus

The organizations that are efficient and do well in their day-to-day business, activities while maintaining their creativity in order to adapt to varying environments in the future, are ambidextrous (March, 1991; Tushman & O'Reilly, 1996). Ambidexterity is the ability of firms to manage continuous improvements along with radical changes simultaneously (Tushman & O'Reilly, 1996). An important antecedent for attaining ambidexterity is the ability of the management team to decide on the right decision alternatives based on available information (O'Reilly & Tushman, 1997). Therefore, the information processing ability of a firm plays a crucial role in the support of ambidexterity. Consequently, IT tools that support decision making, specifically DA tools, are important means of achieving ambidexterity (Fink et al., 2017).

The type of information that is required by decision makers is contingent on the environmental and organizational antecedents (Jansen et al., 2005). These antecedents identify the focus of DA on the type of decision support that is required for short-term efficiency and long-term innovativeness. Short-term efficiency and long-term innovativeness are discussed in the strategic management literature as *exploitation* and *exploration* respectively, and an ambidextrous organization is capable of handling both exploration and exploitation simultaneously. March (1991) explains that "exploration includes things captured by terms such as search, variation, risk taking, experimentation, play, flexibility, discovery, [and] innovation" (March, 1991, p. 71). Also, he adds that "exploitation includes such things as refinement, choice, production, efficiency, selection, implementation, [and] execution" (March, 1991, p. 71). Aligned with strategic management, IS scholars discuss different levels of exploration-exploitation as a strategic focus of IS in a collaboration (Subramani, 2004) and the exploration-exploitation focus of DA strategy in general (Fink et al., 2017; Maghrabi et al., 2011).

Designing the IS strategy is vital for achieving a competitive advantage and is a critical component of the business value of IT (Robert D Galliers, 2006). Therefore, business priorities and IT strategies are becoming increasingly important for chief information officers (CIO) of the US firms (Kappelman et al., 2016).The literature proposes that firms try to be exploitative or explorative by employing IS for an efficient use of their current resources or identification of new opportunities for developing the business (D. Q. Chen et al., 2010). Each of these strategies, i.e. exploration, exploitation, and their combination which is ambidexterity, have different performance implications for a firm (Mithas & Rust, 2016). While the exploration-exploitation hybrid was initially developed for organizational initiatives, this concept is also employed in interorganizational collaborations as an antecedents of performance (Gibson & Birkinshaw, 2004; Lavie & Rosenkopf, 2006). However, while DA strategy is rarely discussed in the literature, my case survey provides leads for better understanding the topic.

A code that appear repeatedly in my case survey is change strategy. The reviewed case studies discuss how firms improve their collaboration through incorporation of incremental improvements or innovative changes. Accordingly, I identify two potential DA strategies based on my case survey: namely, DA explorative focus and DA exploitative focus strategies (Fink et al., 2017). Since some of the case studies are not distinctly focused on either of the strategies and use a combination of them, I decide to indicate the level of exploration-exploitation of DA strategy in each case study based on personal judgement of the two coders, similar to the deductive process of case survey methodology (Elo & Kyngäs, 2008). I consider two groups of firms. The first group consists of firms that employ an exploitative strategy or employ an ambidextrous strategy with an exploitative focus for their DA. The second group includes firms with a pure explorative DA strategy or an ambidextrous DA strategy with a higher exploration focus. Consequently, I identify two classes of case studies based on the judgement of researchers: case studies that are related to explorative focus of DA strategy and case studies that discuss exploitative focus of DA strategy. After contrasting the results of coding, researchers agree on all cases. A visual representation of results is provided in Figure 5.

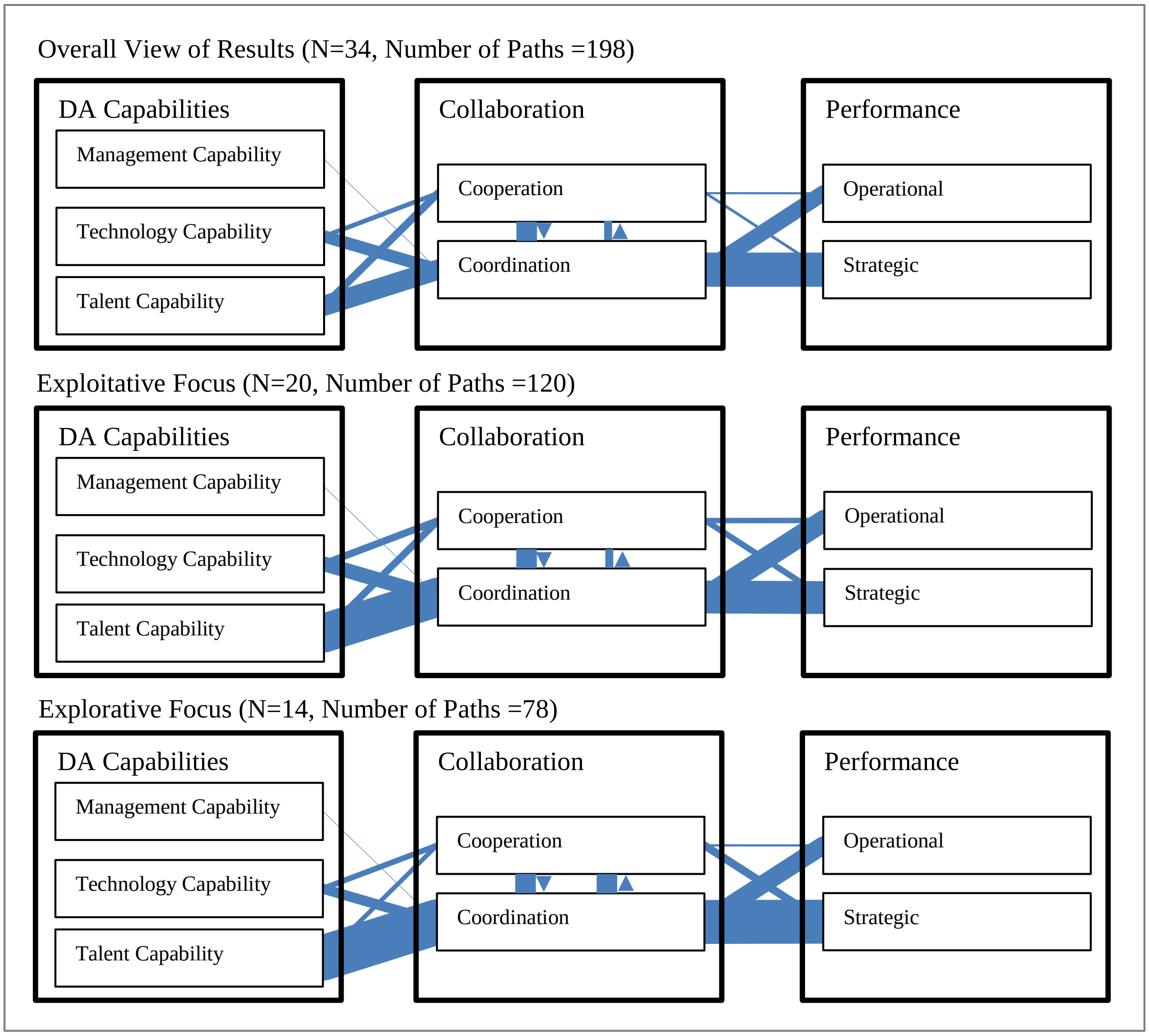

Figure 5. A Schematic Comparison between Paths in Different DA Strategic Focuses. The Width of Each Path is Proportional to Its Numbers of Occurrence.

A visual inspection of Figure 5 shows that explorative focus of DA strategy leads to relatively more instances with strategic performance outcomes and exploitative focus of DA strategy leads to relatively more instances with operational performance outcomes. Also, the results show differences across the relationships from DA capabilities to collaboration, where exploitative focus is more associated with coordination and explorative focus is associated with cooperation.

Exploitation is the ability of partners to increase productivity of capital and shared assets (Barringer & Harrison, 2000). Therefore, exploitation of DA encompasses initiatives that identify incremental improvements and cost reduction opportunities. For instance, improved prediction of demand through DA tools enhances inventory decisions and reduces inventory associated costs. The performance implication of exploitative focus of DA strategy is tacitly inferable from published case studies. For instance, it is explained that DA with exploitative focus lead to improved operations (Shanks & Bekmamedova, 2012b; Watson et al., 2006), workforce management (Exact, 2004), and resource productivity (R. Kohli, 2007).

Exploration, is related to the ability of partners to predict and track changes, discover new opportunities, innovate, and adjust themselves with trends (Barringer & Harrison, 2000). Consequently, explorative DA provide decision makers with support regarding available opportunities for developing their business, expanding their markets, improving a product or service, etc. DA support exploration by identifying complementary products to sell to current customers, proposing product bundling promotions, and identifying new potential customers for available products. The explorative strategic focus of DA leads to strategic performance through market development, revenue generation, (Shanks & Bekmamedova, 2012a; Watson et al., 2006) and enhanced profitability (Briggs, 2011; Watson et al., 2006).

To achieve the best performance in a collaboration, a balance of exploration and exploitation is needed (c.f., Brown & Eisenhardt, 1997), which is derived by a careful selection of exploration and exploitation levels based on environmental factors. Although the balance leads to performance, each of the different focuses lead to a different type of performance. Per definition, the exploitative focus of DA seeks local improvements for improving the productivity of current activities, which are at the center of collaboration. Therefore, it is more probable that the outcome of this focus impacts the operational performance. By contrast, the explorative focus of DA seeks opportunities for business development. For instance, an exploratively focused firm may be focused on developing new markets, new products and services, new partners, and new alliances. Accordingly, this focus leads to higher levels of strategic performance.

Per my discussion in prior paragraphs, the focus of DA strategy has an impact on the performance of a firm in its collaboration. Therefore, I test the impact of DA strategy on the performance by the following two hypotheses:

Hypothesis 7: The effect of collaboration on strategic performance is moderated by DA strategy and the effect is stronger when a DA strategy has an explorative focus.

Hypothesis 8: The effect of collaboration on operational performance is moderated by DA strategy and the effect is stronger when a DA strategy has an exploitative focus.

Like prior hypotheses, these two hypotheses are developed based on my finding and are aligned with theory and literature.

3.3 Confirmatory Study

I found several paths from DA capabilities to performance of a firm in its IORs in the case survey. These identified paths form the base for my research model (Figure 6), which I investigate in my confirmatory study. This research model represents the eight developed hypotheses in the case survey study and is supported by the reviewed literature. My second research question has a confirmatory nature; therefore, I employ a deductive positivist research approach to deal with my research model. This research approach is widely adopted by IS scholars for theory development. More specifically, many publications in the business value of IT and IS strategy research streams use survey methodology to test the relationship of constructs such as IT investment and IS capabilities with business performance (e.g., Bhatt, Grover, & GROVER, 2005; S. P.-J. Wu, Straub, & Liang, 2015).

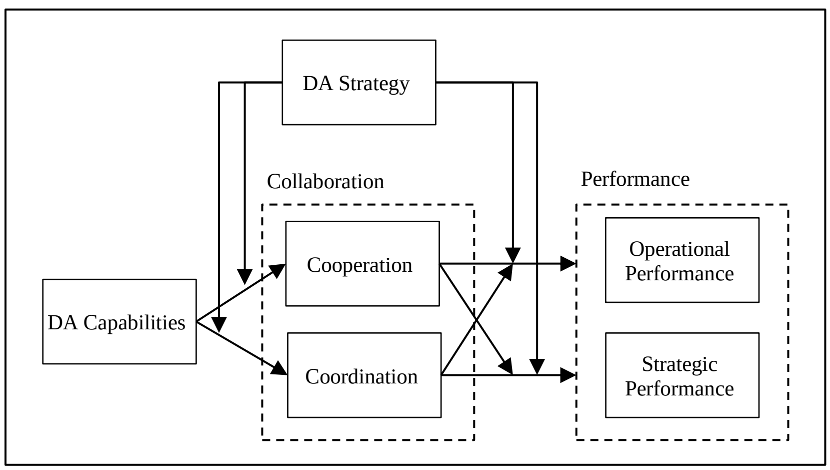

Figure 6. Research Model

3.3.1 Measures

A multi-item scale is employed to measure the constructs of the proposed model. The measures are adopted from the existing validated studies in the literature wherever possible. When there are different scales used in the literature, I select the one that is similar or close to my findings in the case survey study. However, since this study is among the first empirical research on the effect of DA capabilities on collaboration and performance, I adopted the method proposed by Churchill Jr (1979) to ensure that my instrument is well crafted (Churchill, 1979). For instance, to measure DA capabilities, I developed a comprehensive pool of measures based on my findings in the case survey part of this study and existing literature. Then, a group of academicians were asked to review and improve the list of measures. The improved list went through another refinement in a pre-test, which was administered to seven practitioners to ensure that the measures are clear and able to transmit the purpose of the measurement. Each practitioner responded to questions in a face-to-face meeting. In this meeting, each question was discussed separately to ensure that the question is clear, and the aim of question is communicated to respondents. In the next step, the refined measures went through a pilot study with twenty four participants. The pilot study ensured me that the developed instrument created no concern among the participants and was clear and understandable. This resulted in finalized measures that were used in the questionnaire. Table 10 shows the list of constructs, as well as the sources that introduced and validated measures for the proposed constructs. The questions that were developed based on these measures are presented in Appendix E.

Table 10. List of Constructs and Measures

Construct	Source
DA capabilities	The pool of the measures were created based on (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016) and complemented by other resources (Bronzo et al., 2013; Chae et al., 2014; Fink et al., 2017; Germann et al., 2013)
Strategic focus of DA	(Jansen, Van Den Bosch, & Volberda, 2006)
Cooperation	(Perry, Sengupta, & Krapfel, 2004; Schmoltzi & Wallenburg, 2012; Whitten et al., 2012)
Coordination	(Hoetker & Mellewigt, 2009; Paulraj, Lado, & Chen, 2008)
Operational performance	(Elbashir et al., 2008)
Strategic performance	(Elbashir et al., 2008)

3.3.2 Sampling

I aim to understand how firms develop strategies to use their DA capabilities in the context of their collaborations towards value creation. Therefore, my unit of analysis is a firm and I survey US-based firms to test my research model. I am focused on individual informants at C-level executives, including CEOs, CIOs, COOs, and other experts, specifically those who are knowledgeable in IS or OM. These individuals, who occupy strategic roles in their organizations, are more informed about the exchange relationships of their organization and its collaborative relationships. Surveying key informants is a common practice in interorganizational studies (N. Kumar et al., 1993), and my focus on key informants of a firm that is involved in a collaborative relationship is used in the supply chain management literature (Paulraj et al., 2008; Trkman et al., 2010).

3.3.3 Data Collection

The survey[1] was created online and distributed through an email invitation among participants. The names and email addresses were obtained from personal contacts and a commercial database. I offered a customized report of findings to participants as an incentive. Overall, 3,561 emails were sent to participants, followed by two reminders and random phone calls. In reply, I received 210 complete responses, which provided a response rate of 6%. Due to various reasons, including extensive use of spam blocking tools and corporate policy regarding responding to external emails (Fan & Yan, 2010), I expect that less than half of my emails were received by my proposed respondents. Therefore, assuming 50% email delivery, I consider my response rate to be 12%. While response rate is important, nonresponse rate is not the cause of nonresponse bias (Groves, 2006), and survey variables and measurement errors play a more important role in nonresponse bias as compared to nonresponse rate (Groves & Peytcheva, 2008). Therefore, I followed a rigorous procedural approach that is suggested in the literature (Churchill, 1979) to minimize the impact of nonresponse bias on my findings. I compared demographic information of respondents with my initial pool. This comparison did not reveal any significant difference between ratio of industry type and firm size (based on

[1] The survey results used in my second study are collected based on the survey instrument that is developed in my first study. The difference between the two studies is additional 12 responses that I received after completion of the first study. I incorporated the 12 additional responses in the analysis of my second study.

annual sale) in my collected responses and the initial sample. Also, the job functions and titles were not significantly different across responses and the main sample.

The responses were received in different stages. For instance, some were received instantly after the questionnaire was distributed and some were received after phone calls. Therefore, I compared the key variables for received responses to ensure that the delay did not lead to nonresponse bias (Armstrong & Overton, 1977). An overview of instrument items and results is presented in Appendix E.

The key informants who participated in my survey hold positions at strategic levels or are among business analysts, supply chain managers, or information systems experts. Also, my data is collected from a wide range of companies and industries. Table 11 provides demographic information of my participants.

Table 11. Survey Respondents

Job Title	Percent
Analyst / associate	21%
Manager / senior manager	34%
Director	11%
Vice president / senior vice president	15%
C level executive (CEO, CIO, etc.) / President / Owner	19%
Annual Sale	**Percent**
Less than $1 million	11%
$1 million - $10 million	11%
$10 million - $50 million	14%
$50 million - $500 million	24%
$500 million - $1 billion	17%
> $1 billion	23%
Job Function	**Percent**
Business management	15%
Information and communication technologies	20%
Operations	20%
Supply chains management	20%
Sales/marketing	9%
Others	16%
Industry	**Percent**
Wholesale / retail / distribution	22%
Manufacturing and process industries (non-computer)	17%
Education	11%
Business services / consultant	13%
Computer manufacturer (hardware, software, peripherals)	10%
Computer / network services / consultant	7%
Transportation / utilities	9%
Others	11%

3.3.4 Survey Results

I followed the two-phase analysis approach, which includes testing measurement model and testing structural model, to analyze my developed theory (J. C. Anderson & Gerbing, 1988). I did both analyses based on a structural equation modeling (SEM) approach, which is widely adopted by social science scholars (Gefen et al., 2011). I employed SPSS (v. 24) for an exploratory factor analysis (EFA), production of reliability indices, and development of covariance matrix. I used LISREL (v 9.3) for confirmatory factor analysis (CFA) and structural model analysis.

3.3.4.1 Exploratory Factor Analysis

I conducted an EFA to ensure the measurement model is unidimensional and to produce a parsimonious model. In the initial results of EFA, I trimmed away items with loadings smaller than a cut of value of 0.4, items that loaded on more than one factors, and items that loaded on factors that are not conceptually reasonable. I used the maximum likelihood method, used the Promax method for rotation, and did not fix number of factors in the EFA analysis. The results are presented in Table 12.

Table 12. Results of Exploratory Factor Analysis (Pattern Matrix)

	DA Capabilities	Operational Performance	Strategic Performance	Cooperation	Coordination
DA3	0.894				
DA1	0.794				
DA4	0.725				
DA2	0.709				
DA5	0.692				
OPP3		0.970			
OPP2		0.886			
OPP1		0.778			
OPP4		0.691			
STP1			0.808		
STP2			0.743		
STP3			0.702		
COP2				0.800	
COP1				0.782	
COP3				0.605	
COP4				0.532	
COD4					0.802
COD1					0.712
COD2					0.685
COD3					0.616
Eigenvalue	7.550	2.540	1.693	1.577	1.018
% of Variance	34.708	11.905	6.643	6.125	3.234
All the cross loadings are smaller than 0.2					

Five factors were identified based on eigenvalues larger than 1, which match the presented factors in the research model. These five factors explain 62.6% of the variance in the data. To check adequacy, I relied on the total variance explained, the communalities, and the Kaiser-Meyer-Olkin measure. All the communalities are higher than 0.47 and the Kaiser-Meyer-Olkin measure is 0.893, which supports adequacy of my sample size for this study.

3.3.4.2 Model Fit

I tested the measurement model by CFA and check for model fit based on different fit statistics (Kline, 2015). These fit indices are 1.652 for the ratio of χ^2 (264.279) to degrees of freedom (160) (< 3), 0.056 for root mean square error of approximation (RMSEA) (< 0.8), 0.955 for comparative fit index (CFI) (> 0.9), 0.883 for goodness of fit index (GFI) (> 0.9), 0.847 for adjusted GFI (> 0.8), and 0.052 for standardized root mean square residual (SRMR) (< 0.08). Based on the literature and discussed acceptance thresholds in various scholarly works, the fit indices suggest a good fit (Hu & Bentler, 1999; Kline, 2015).

3.3.4.3 Convergent and Discriminant Validity

Convergent validity requires that the measures of each construct are significantly correlated with each other. I checked the loadings of items on factor for the convergent validity. The outer loadings for the constructs are larger than 0.69, except one that is 0.64, (Hair et al., 2011) and these loadings are significant at the 0.01 level with all t-statistics larger than 8.45. The Pattern Matrix (Table 12) shows that all the loadings are higher than

0.616 (which is far more than the threshold f 0.3). Also, the loadings average out above 0.7. Therefore, loadings are high enough to approve the convergent validity.

At the construct level, convergent validity requires the average variance extracted (AVE) to be larger than 0.5 (Bagozzi & Yi, 1988). The results show that all AVEs are larger than 0.5. I also analyzed discriminant and convergent validity of the model. Assessment of discriminant validity is presented in Table 13. All diagonal elements are larger than off-diagonal elements. Therefore, all measures achieve discriminate validity (Fornell & Larcker, 1981). The Pattern Matrix (Table 12) shows no item being cross loaded on multiple variables, which supports discriminant validity. Also, the factor correlation matrix (Table 13) shows that the correlation between factors is less than 0.7 and supports discriminant validity.

Table 13. Correlation Table

	#	1	2	3	4	5	Mean*	S.D.	AVE	CR	Cr α
DA Capabilities	5	1.000					5.314	1.380	0.591	0.878	0.876
Operational Performance	4	0.399	1.000				5.115	1.229	0.635	0.839	0.908
Strategic Performance	3	0.421	0.262	1.000			5.402	0.962	0.721	0.911	0.838
Cooperation	4	0.508	0.249	0.404	1.000		5.558	1.053	0.501	0.801	0.800
Coordination	3	0.618	0.591	0.407	0.345	1.000	5.444	1.172	0.579	0.846	0.844
* Measured by Likert scale of 1 to 5											

Also, I studied discriminant validity between constructs through comparing the original model with different constrained models (Table 14). I set the correlation between different constructs to be 1 for all possible dyadic relationships of constructs in the model. Then, I compared the constrained model with the original unconstrained model based on a chi square difference test. The results show that all the differences are significant at 0.05 level and therefore support the discriminant validity.

Table 14. Pairwise Comparison of χ^2 for Different Model Constraints

Model	χ^2	df	χ^2_{diff}	p-Value
Free model (original)	264.279	160		
Constrained model for DA Capabilities and Cooperation	433.094	164	168.815	0.000
Constrained model for DA Capabilities and Coordination	443.913	164	179.634	0.000
Constrained model for Cooperation and Operational Performance	538.388	164	274.109	0.000
Constrained model for Cooperation and Strategic Performance	398.596	164	134.317	0.000
Constrained model for Coordination and Operational Performance	500.007	164	235.728	0.000
Constrained model for Coordination and Strategic Performance	453.059	164	188.78	0.000

3.3.4.4 Reliability

I also examined the measurement model for construct reliability and validity. I used Cronbach's alpha (Cr α) and composite reliability (CR) for measuring reliability. As results of analysis show (Table 13), all composite reliabilities are larger than the recommended threshold of 0.7 and show high levels of internal consistency reliability (Bagozzi & Yi, 1988). Also, all Cronbach's alphas are larger than 0.7. This supports the reliability of the model.

3.3.4.5 Common Method Variance

After controlling the measurement model, I tested the model for the potential impact of common method variance (CMV) on results. Since the data was mainly collected from one respondents per firm, it is possible that CMV affects the results. To reduce the effect of CMV, I followed procedural and statistical remedies (Podsakoff et al., 2003). For the procedural remedies, I followed Institutional Review Board (IRB) instructions to protect my respondents' anonymity. I also improved the scale items by following paradigm introduced by Churchill (1979) for careful development of survey instrument items (Churchill, 1979).

To test the collected data for the effect of CMV, I used Harman's single-factor test (Flynn et al., 2010). The fit measures for Harman's single-factor model are $\chi^2(170) = 1188$ and RSMEA=0.169, which prove to be a poor fit. Also, all items for different constructs converge to five constructs with eigenvalue of larger than 1 in my EFA. Total variance that is explained by these factors is 62.7% and the variance explained by the first factor is 34.708% (Table 12) and shows that the majority of variance is not accounted for by one general factor.

3.3.4.6 Structural Model

I fitted the data to the correlation matrix using LISREL 9.30 to test the model parameters. In this process, I implemented the Maximum Likelihood method and the analysis converged to an acceptable solution. The fit statistics are $\chi^2/df = 1.636$ (χ^2= 268.291, df = 164), RMSEA = 0.055, CFI = 0.955, IFI = 0.956, NNFI = 0.948, and SRMR = 0.054, which show acceptable level of fit for all statistics and suggest adequacy of the research model for path analysis (Kline, 2015). Table 15 shows the results of the structural equation model. Also, the results are represented at the top of Figure 7. The results suggest that the relationships between business DA capabilities-cooperation ($0.497, p < 0.001$), DA capabilities-coordination ($0.634, p < 0.001$), cooperation-strategic performance ($0.336, p < 0.001$), coordination-operational performance ($0.754, p < 0.001$), and coordination-strategic performance ($0.294, p < 0.001$) are supported and significant. This provides statistical support for hypotheses H5 and H7. I also test the relationship of cooperation and coordination with strategic and operational performance in the later parts of this section.

Table 15. Structural Equation Model Results

Relationship	Hypothesis	Standardized Coefficient	t-Values
DA Capabilities → Cooperation	H5	0.497	6.342
DA Capabilities → Coordination	H6	0.634	8.880
Cooperation → Operational Performance		0.016	0.179
Cooperation → Strategic Performance		0.336	4.577
Coordination → Operational Performance		0.754	7.611
Coordination → Strategic Performance		0.298	4.453

To complete my analysis and test the remaining hypotheses, I identified the moderating impact of DA strategic focus on my model first. Then, I studied the interaction between cooperation and coordination. To study the moderating and interaction effect, I used multigroup analysis (Venkatraman, 1989). This method enables me to test the moderating impact of each construct on the relationship between the other construct and operational and strategic performance. To analyze the moderating impact of DA strategic focus on my research model, I used a categorical variable from my survey instrument to split my observations into two groups of firms, those with exploitative focus of their DA strategy (N=94) and those with explorative focus of their DA strategy (N=116). Also, I split my data based on levels of cooperation and coordination. To identify the levels of coordination and cooperation, I used the median for each construct and divide my sample dataset in two groups accordingly. For coordination, I identified two groups of high coordination (N=93) and low coordination (N=117). Also, I identified two groups with higher levels of cooperation (N=83) and lower levels of cooperation (N=127).

Prior to the direct comparison of path coefficient, I conducted necessary tests to ensure that form invariance, invariance of measurement, and invariance of structural coefficients for the multi-group analysis are in place (Cao & Zhang, 2011; Kline, 2015). To test the measurement invariance and ensure that items assess the same constructs in different groups, I conducted a group comparison with different constraints, based on four different nested models (Table 16) (Kline, 2015). I construct four models with free parameters across the two groups (model 1), with equal factor loadings (model 2), with equal factor loadings and correlations (model 3), and with equal factor loadings, correlations, and measurement errors (Cao & Zhang, 2011). Since the number of observations in each of these groups is not large, I used a chi-square difference test to compare the nested models (Kline, 2015). I repeated this process across all three factors and test path difference hypotheses across DA strategy, coordination levels, and cooperation levels. The test results are presented in Table 16.

Table 16. Testing for Path Difference Across Groups

Model	χ^2	df	RMSEA	CFI	NNFI	Nested Models	$\Delta\chi^2$	Δdf	p-value
Grouping based on DA Strategy									
1: Equal pattern	487.302	320	0.071	0.968	0.962				
2: Equal loadings	496.406	335	0.068	0.969	0.965	2-1	9.104	15	0.872
3: Equal loadings and correlations	504.699	350	0.067	0.969	0.966	3-2	8.293	15	0.911
4: Equal loadings, correlations, and measurement errors	529.145	370	0.064	0.970	0.969	4-3	24.446	20	0.223
4a DA → CP	504.497	369	0.061	0.973	0.973	4a-4	24.648	1	0.000
4b DA → CR	504.672	369	0.061	0.973	0.972	4b-4	24.473	1	0.000
4c CP → OP	504.960	369	0.061	0.973	0.972	4c-4	24.185	1	0.000
4d CP → SP	504.466	369	0.061	0.973	0.972	4d-4	24.679	1	0.000
4e CR → OP	500.080	369	0.060	0.974	0.973	4e-4	29.065	1	0.000
4f CR → SP	498.320	369	0.059	0.974	0.974	4f-4	30.825	1	0.000
Grouping based on cooperation levels									
1: Equal pattern	446.668	320	0.062	0.972	0.967				
2: Equal loadings	458.660	335	0.064	0.967	0.963	2-1	11.992	15	0.68
3: Equal loadings and correlations	467.840	350	0.066	0.963	0.960	3-2	9.180	15	0.868
4: Equal loadings, correlations, and measurement errors	496.982	370	0.091	0.929	0.927	4-3	29.142	20	0.085
4a CR → OP	490.514	369	0.0632	0.965	0.964	4a-4	-6.468	1	0.000
4b CR → SP	497.776	369	0.0650	0.963	0.961	4b-4	0.794	1	0.373
Grouping based on Coordination level									
1: Equal pattern	413.231	320	0.0528	0.962	0.954				
2: Equal loadings	430.11	335	0.0554	0.955	0.949	2-1	16.879	15	0.326
3: Equal loadings and correlations	441.484	350	0.0556	0.951	0.947	3-2	11.374	15	0.726
4: Equal loadings, correlations, and measurement errors	493.776	370	0.0595	0.942	0.941	4-3	52.292	20	0.000
4a CP → OP	504.210	369	0.0734	0.955	0.951	4a-3	62.726	1	0.000
4b CP → SP	495.887	369	0.0714	0.957	0.954	4b-3	54.403	1	0.000
DA: Data analytics capabilities CR: Coordination CP: Cooperation SP: Strategic performance OP: operational performance									

3.3.4.7 Moderating Role of DA Strategic Focus

The results of a chi-square difference test show that the fit of Model 2 across both groups of observations is not significantly worse than Model 1 ($\Delta\chi^2 = 9.104, \Delta df = 15, p\text{-}value = 0.872$). Similarly, Model 3 is not significantly worse than Model 2 ($\Delta\chi^2 =$

$8.293, \Delta df = 15$, *p-value* $= 0.911$), and Model 4 is not significantly worse than model 3 ($\Delta\chi^2 = 24.446, \Delta df = 20$, *p-value* $= 0.223$). Therefore, I conclude that the factors are measured comparably across each group. Consequently, I test invariance of structural coefficients across groups through nesting new constrained models in Model 4. In these new constrained models, I set different path coefficients to vary freely across the two groups. The results show that all nested models fit the data better than Model 4. For instance, when I set the coefficient of DA and cooperation to be measured independent from each other across the two groups of observations, the new model (Model 4a) fits the data better compared to the initial model (Model 4) ($\Delta\chi^2 = 24.648, \Delta df = 1$, *p-value* $=$ 0.000), which means the coefficient between DA and cooperation is significantly different across the two groups. Therefore, and in all cases, the path coefficients of my research model are significantly different across firms with exploitative focus of DA strategy and firms with explorative focus of DA strategy. Now that the research model is invariant across the two groups of observations, but path coefficients are different, I test my structural model for each group. The results of structural model analysis and the related fit indices are presented in Figure 7 (the second and third structural models).

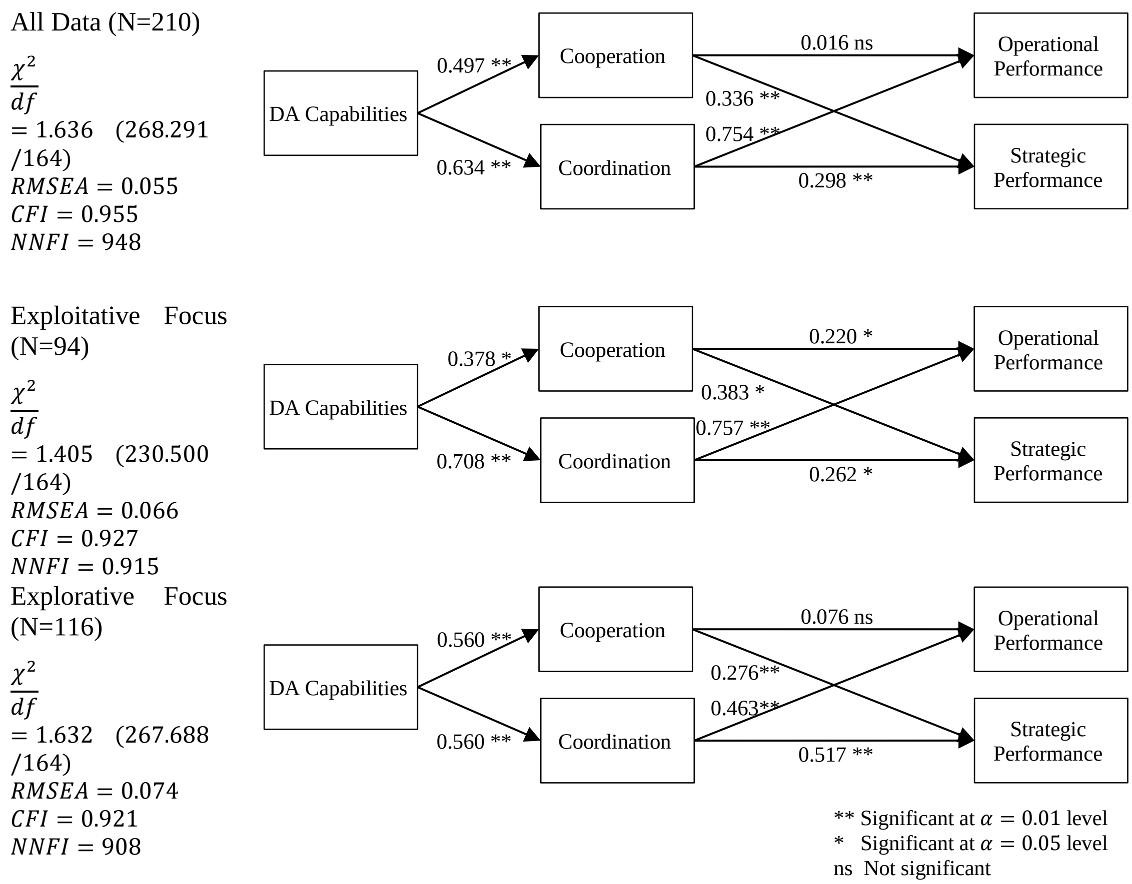

Figure 7. Moderating Effect of DA Strategy

The findings suggest that exploitative focus has higher impact on coordination compared to explorative focus ($\beta = 0.708$ vs $\beta = 0.560$). While exploitative focus of DA leads to higher levels of operational performance through cooperation and coordination, explorative focus has less impact on operational performance. Also, with the explorative focus of DA, the cooperation does not lead to operational performance. When the focus of DA strategy becomes explorative, the collaboration leads to higher levels of strategic performance ($\beta = 0.59$ vs $\beta = 0.47$ for coordination and $\beta = 0.39$ vs $\beta = 0.22$ for cooperation). These findings support hypotheses H7 and H8.

3.3.4.8 Interaction between Coordination and Cooperation

To test for the interaction between cooperation and coordination, I conduct my second multi-group analysis, with its results presented in Table 16. Regarding the two groups of observations that are created based on different levels of cooperation, the chi square test of nested models fails to reject difference between models. Therefore, the model is invariant across the two groups, and I proceed to compare structural paths between the two groups. My results suggest that the coefficient between coordination and operational performance is different across the two groups. However, my test fails to reject the similarity of the path coefficient of coordination and strategic performance (p-value = 0.373).

I also tested for invariance across the two groups of observations that are formed based on level of coordination. While the chi-square difference test across nested models suggest no significant difference between Model 1 and model 2, and model 2 and Model 3, the analysis rejects the similarity of Model 3 with Model 4 (p-value = 0.000). The literature suggests that this difference stems from variances in the data. Therefore, it is valid to test the invariance across groups based on the first three nested models. Accordingly, I accept the invariance across the two groups of coordination. Therefore, I test invariance of structural coefficients and compare the path from cooperation to operational performance and from cooperation to strategic performance as a nested model in Model 3. The results suggest that the path coefficients are different across both groups (p-value = 0.000).

Now that the invariance is in its place, I test my structural model based on each of the two groups of coordination levels and cooperation levels. The results and the impact of each construct on the relationship of the other construct and performance are shown in Table 17 and depicted in Figure 8.

Table 17. Interaction Effect between Coordination and Cooperation

	Operational	Strategic
effect of coordination on performance		
High cooperation (N=83)	0.90 (9.97)	0.40 (4.36)
Low cooperation (N=127)	0.44 (5.50)	0.24 (2.80)
Effect of cooperation on performance		
High coordination (N=93)	0.29 (2.78)	0.51 (2.40)
Low coordination (N=117)	-0.14 (-1.31)	0.38 (3.12)

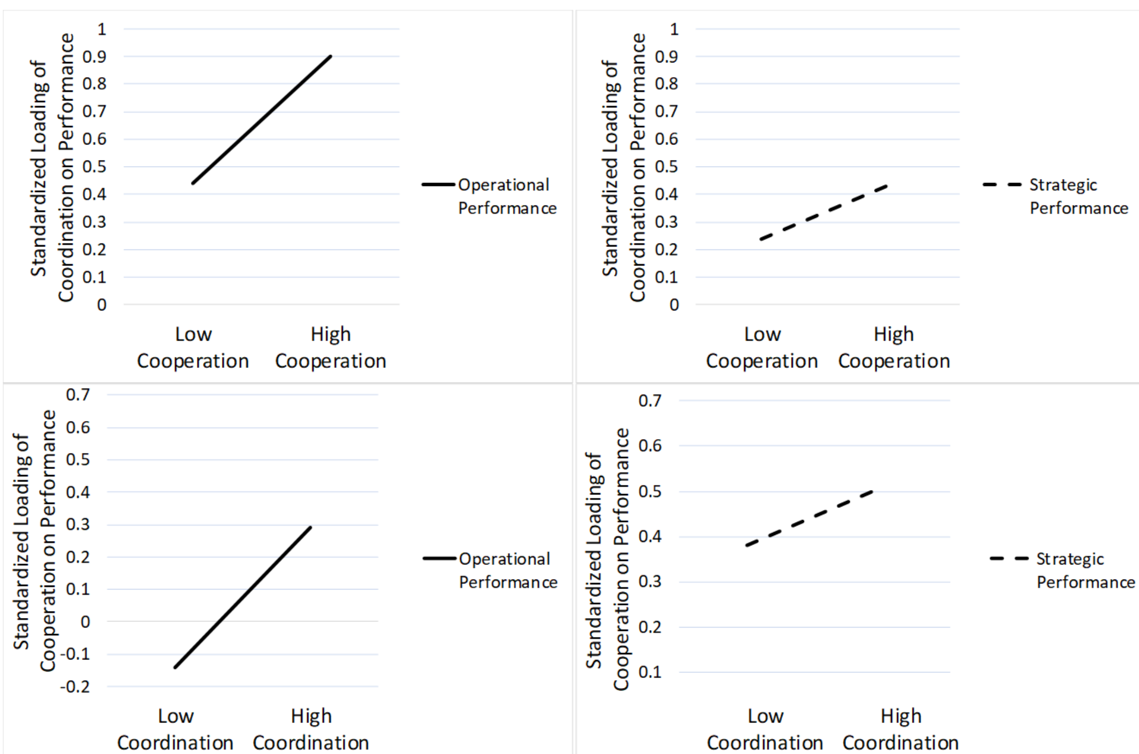

Figure 8. Interaction Effect between Coordination and Cooperation and Its Impact on Performance

The findings support the idea that the interaction effect between the two constructs lead to higher levels of performance. The results support that when cooperation is at its higher levels, coordination has more impact on strategic and operational performance indices. Also, with higher levels of coordination, cooperation leads to higher operational performance levels. This provides support for hypotheses H1, H2, and H4. My results do not support hypothesis H3.

3.4 Discussion

The business value of DA is discussed in the literature and its impact on performance is substantiated (Günther et al., 2017; Trieu, 2017). However, due to the newness of BDA in the business world, many firms are exploring it. While this exploration leads to heavy investment in infrastructure and analytical tools (Kappelman et al., 2016), firms may fail to realize the real business value of DA investment. Since firms are exploring the mechanisms through which DA can lead to improved performance, the causality of the relationship between DA capabilities and performance is not clear. It is possible to argue that DA lead to more informed and fact-based decisions and improve performance (Günther et al., 2017). It is also possible to claim that high-performing firms invest in DA with the hope that they can increase their competitiveness. Therefore, the direction of the causality is not clear. Also, the mechanisms that lead DA to improve performance are not understood clearly, especially in an interorganizational setting. Therefore, I employ two studies to address these issues, as well as discussed gaps in the current literature. These two studies, which inform each other, show how firms can improve their performance through incorporation of DA in their IOR. The findings in my case survey study provide evidence on the direction of casualty and identify the mechanism through which DA impact performance. Also, the results of my confirmatory study support the positive impact of DA on cooperation and coordination, which in turn leads to operational and strategic performance. In this research, I tried to investigate the impact of DA strategy on performance. Also, I tried to understand the interaction between cooperation and coordination.

Strategic focus of DA is addressed in the literature (Bhimani, 2015; Ghoshal, Larson, Subramanyam, & Shaw, 2014; Gillon, Aral, Lin, Mithas, & Zozulia, 2014; Woerner & Wixom, 2015). However, most of discussions are at qualitative levels. Furthermore, the impact of DA strategic focus is not discussed in the interorganizational setting. The literature suggests that a coordination mechanism searches for local improvement (exploitation) and global opportunities (exploration) to remain efficient and maintain long term competitiveness for the collaborative relationship. Both explorative and exploitative functionalities of coordination require DA as decision support tools (Maghrabi et al., 2011). Therefore, the strategic focus of DA tools becomes an important factor in support of coordination. In other words, a suitable DA strategy enables coordination to employ an appropriate balance of exploration and exploitation for improved collaboration. Despite the importance of the strategic focus of DA for coordination, the IT-enabled collaboration and the DA strategy are not discussed in the literature. My research addresses this gap. In my case survey study, my results suggest that DA strategy has a moderating impact on how DA capabilities affect practice and lead to performance. My confirmatory study supports this initial finding. My results suggest that exploitative focus of DA aims to improve coordination and leads to higher levels of operational performance. When the strategy of DA becomes more focused on exploration, the impact on cooperation increases and leads to higher levels of strategic performance.

I noticed the relationship between cooperation and coordination in my case survey study, where in many cases a coordinated use of shared resources leads to performance. Therefore, I followed the suggestion of Gulati et al. (2012) and studied the interaction of the two constructs in my research model in the confirmatory study. While the theory and prior literature are inconsistent about how cooperation impacts performance, my study sheds light onto the issue. My findings suggest that the interaction between cooperation and coordination has a significant impact on the performance. Cooperation leads to higher levels of performance in presence of coordination and vice versa. An interorganizational collaboration is composed of cooperation and coordination, which together create synergy towards the success of the relationship (Gulati et al., 2012). According to the RBV, cooperation provides the resources that are required for gaining competitive advantages and succeeding in the market (S. Li et al., 2006). However, a coordination mechanism is required to complement cooperation and enhance the utilization of shared resources and keep the competitive advantage updated. A coordination mechanism can follow business environment trends and constantly address the important modifications that are needed to be considered in collaborative relationships. Thus, coordination supports collaboration by reduced transaction costs (Brynjolfsson et al., 1994) and by enhanced preparedness to deal with the environmental volatility (Gulati et al., 2012). Since decision making is an important basis for coordination, DA are deemed necessary for collaboration. Therefore, I discuss that a coordination mechanism that is enabled by DA improves the performance of an IOR. While the literature studies both IT-enabled coordination and IT-enabled cooperation separately (e.g., Malhotra et al., 2005), the larger view, which includes the interaction of coordination and cooperation is rarely discussed. The importance of the large picture is that it can resolve the inconsistencies of prior discussions in the literature.

3.5 Conclusion

The effect of DA on collaboration and business performance is examined in this study. This study is composed of two interrelated sub-studies (the case survey and confirmatory studies) that employ different paradigms and methodological approaches. The case survey study investigates how firms use DA in their interorganizational collaborations. Results of this interpretive study, which are based on a case survey of 34 case studies, are used as a base for developing a research model. The model is tested in my confirmatory study based on survey data.

My findings suggest that DA lead to business performance improvement through enhancement of interorganizational collaborations. These findings are grouped into three sets of hypotheses. The first set of hypotheses are related to the impact of DA on collaboration and my results show that DA improve collaboration by enhancing coordination and supporting cooperation. The second set of hypotheses are related to the strategic focus of DA. My results suggest that explorative DA lead to higher levels of cooperation and that exploitative DA lead to enhanced coordination. In addition, the strategic focus moderates the relationship of cooperation and coordination with performance. My analysis shows that with an explorative focus, firms tend to achieve higher strategic performance outcomes in their collaborative relationships. Also, with an exploitative focus, firms achieve higher operational performance outcomes. The final set of hypotheses is related to the interaction of coordination and cooperation. My analysis shows that cooperation outcomes are highly dependent on coordination. When coordination is high, cooperation leads to higher performance achievements. Also, higher cooperation leads to better coordination outcomes. These findings contribute to the business value of IT literature, IS strategy literature, and interorganizational relationship literature.

CHAPTER IV

STUDY 3: DATA ANALYTICS STRATEGY IN A COMPLEX AND DYNAMIC INTERORGANIZATOINAL ENVIRONMENT

4.1 Introduction

DA capabilities are required for adaptability of a firm to its complex and dynamic business environment (Baars et al., 2014; Gosain, Malhotra, & El Sawy, 2004; Houghton, El Sawy, Gray, Donegan, & Joshi, 2004; Lau, Liao, Wong, & Chiu, 2012). The notion of adaptability refers to identification of problems with strategic importance and development of an appropriate response approach to these problems (Haeckel, 1999). Yet, despite the fact that "intentional problem solving depends on some awareness of the problem to be solved" (Kiesler & Sproull, 1982, p. 548), DA strategy is primarily discussed from the perspective of employing DA capabilities for explorative-exploitative responses (c.f., D. Q. Chen et al., 2010). In addition, DA strategy literature rarely discusses problem sensing. Therefore, I manifest DA strategy as a configuration of DA capabilities for "problem sensing" and "response approach." I aim to prescribe a suitable DA strategy for environments with various levels of complexity and dynamism.

One of the highly complex business environments is the context of IORs that imposes "unintended consequences" (MacKay & Chia, 2013, p. 221) on a firms decision making. Especially, the IOR context increases the challenges of adaptability

(Lord, Dinh, & Hoffman, 2015) and leads to failure in more than 50% of IORs (Gulati et al., 2012). As a remedy, the literature suggests that DA capabilities can improve the performance of IORs (c.f., Gunasekaran & Ngai, 2004; Subramani, 2004) and researchers investigate heterogeneity in the business value of DA (e.g., Melville, Kraemer, & Gurbaxani, 2004; Tallon & Pinsonneault, 2011). However, the following discussions highlight the current gaps in the literature that need further investigation.

The first gap is related to the partial consideration of environmental factors, as there has been a single focus on complexity or dynamism. The literature suggests that adaptation to a complex environment requires exploitation, whereas adaptation to a volatile environment is facilitated by exploration (D. Q. Chen et al., 2010; Leidner et al., 2011; Rivkin & Siggelkow, 2007). Therefore, it is not facile to identify the appropriate configuration of IS strategy in the presence of complexity and volatility. Failing to consider the two environmental factors together can lead to higher levels of type II errors in findings associated to empirical studies.

The second gap is under investigated impact of complexity on IS strategy (Chan & Reich, 2007). Also, findings on the impact of volatility on IS strategy are inconsistent and contradictory (D. Q. Chen et al., 2010). On the one hand, the mainstream IS literature suggests that exploration works better than exploitation in dealing with volatility (D. Q. Chen et al., 2010; Leidner et al., 2011; Wholey & Brittain, 1986). On the other hand, there are contradictory ideas between IS scholars, who suggest that dealing with volatility requires simple strategies. Therefore, an explorative strategic focus, which is hard to achieve, is not a good choice in dynamic environments (Eisenhardt & Sull, 2001;

Williamson, 1991). Also, strategic management literature suggests that exploration has a negative impact on adaptability in a dynamic environment (Posen & Levinthal, 2012; Stieglitz, Knudsen, & Becker, 2015). Therefore, configuring the IS strategy to deal with business complexity and dynamism merits further investigation.

Finally, the third gap is the separate focus of scholarly works on problem sensing (hereafter: sensing) and response aspects of DA capabilities, despite the complementary role of these capabilities and their interrelationships (Seddon, Constantinidis, Tamm, & Dod, 2017). The strategic management literature considers sensing as an important antecedent of response approach and deems it important for a firm's strategy (Hambrick, 1982; Kiesler & Sproull, 1982). In spite of this, the main body of IS strategy literature is focused on configuration of explorative-exploitative response capabilities of IS (D. Q. Chen et al., 2010) and does not discuss the sensing focus. There are few scholarly works that address the sensing capability of IS and deem it necessary for IS strategy (e.g., Houghton et al., 2004). Also, there are few notable studies that analyze the impact of sensing-response capabilities of DA/IS on organizational agility[2] (Y. Park, El Sawy, & Fiss, 2017; Roberts & Grover, 2012). While sensing and response are interrelated capabilities and play an integral role in DA strategy, the literature is fragmented on this aspect and address the two topics separately.

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[2] While the concept of adaptability is close to agility, is distinct based on the definition (H L Lee, 2004). Adaptability is focused on long term reconfiguration of organization to embrace the environmental changes and agility is the ability to respond to short-term changes in supply or demand.

To fill the abovementioned gaps, I aim to identify which DA strategy configurations improve adaptability of firms and their IORs in the face of complexity and volatility. However, study of adaptability in the context of complexity and volatility requires analytical approaches with a longitudinal focus (E. T. G. Wang, Tai, & Wei, 2006). In addition, employing empirical methods for this study is ineffective (Chan & Reich, 2007) and challenging, due to the hardship of collecting the required data for all comparisons. Consequently, I employ an agent-based simulation to study the longitudinal consequences of different configurations of DA strategies.

I employ an agent-based simulation to study the longitudinal consequences of different configurations of DA strategies in the face of various levels of business complexity and dynamism to address the mentioned gaps. In the simulation, I model DA strategy in forms of problem sensing focus and response approach. This conceptualization allows the dynamic alignment between DA strategy and organizational strategy through support and complementation (Reich & Benbasat, 1996). This method enables us to assess the impact of DA strategy on performance and account for heterogeneity by studying populations per complexity and volatility of business environments. I study alignment of DA strategy with business needs and employ the complex adaptive system (CAS) and complexity theory to develop my propositions, and consequently, I provide a new insightful perspective for the current literature (Benbya & McKelvey, 2006).

I organize this chapter as follows. First, the theoretical background of the problem is discussed; then the importance of studying the remedies from complex and volatile environments is established; and finally, the impact of IS strategy on the adaptability of a firm is reviewed. In the next section, a model of interaction between agents is developed that can simulate IOR's decisions in a complex and dynamic environment. In the subsequent section, the agent-based simulation is executed. The findings are discussed and analyzed in the discussion and implications sections. Finally, I conclude the article with a brief review on the findings, a discussion of the limitations and proposals related to future research directions in the field.

4.2 Decision Analytics and Adaptability

IORs are characterized by complexity and volatility. The globalization of sourcing, the shorter product life cycles, and the heterogeneity of customers, which are specifications of today's economy, are among important drivers of complexity in IORs (Bozarth et al., 2009). Also, the fast pace of technological development and the variability of demands create an increasingly volatile business environment for IORs (T. Y. Choi et al., 2001; Osborn & Hagedoorn, 1997). This complex and volatile business environment causes challenges for initiation of IORs, and persistence of them can have a negative impact on adaptability of firms. The initial process of finding a good match for collaborative relationships is extremely challenging due to inherent complexity of the alliance, which is caused by differences in culture, procedures, management systems, etc. (Reuer & Ariño, 2007). Assuming a successful inauguration of a collaboration, the volatile business environment changes goals of IOR partners and impacts the initially designed governance mechanisms. Therefore, partners may show reactions ranging from desertion of the alliance to opportunistic behavior, which in turn can lead to an IOR failure (S. H. Park & Ungson, 2001). Thus, the two environmental factors, complexity and volatility, pose adaptability challenges to firms and hinder sustainable competitive advantage (Baker et al., 2011; Benbya & McKelvey, 2006; Claussen, Kretschmer, & Stieglitz, 2015; H L Lee, 2004).

Adaptability is defined as "the ability of the firm to sense long-term, fundamental changes in the supply chain and market environment … and to respond to such changes by flexibly adjusting the configuration of the supply chain" (Eckstein, Goellner, Blome, & Henke, 2015, p. 3030). Per definition, in order to adapt properly, a firm requires both sensing and response capabilities. Sensing capability refers to the ability of a firm to identify important problems, that are caused by behavior of stakeholders or change at the economic and technology levels (H L Lee, 2004; Overby, Bharadwaj, & Sambamurthy, 2006), whereas response capability refers to evolution of the firm when its existing business environment is untenable (Walker, Holling, Carpenter, & Kinzig, 2004). The existing IS literature assumes a fundamental role for DA-base as a support for sensing and response capabilities (Overby et al., 2006; Y. Park et al., 2017; Roberts & Grover, 2012; Setia, Venkatesh, & Joglekar, 2013). DA are defined as "the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions" (Davenport & Harris, 2007, p. 7). The definition assumes that DA enable sensing through analysis of environmental data. Also, DA enable response by developing, examining, and proposing various response options for decision making and action.

The perpetual need for change and adaptation should be reflected in the DA strategy, which is conceptualized as a dynamic alignment between DA and organization strategy (D. Q. Chen et al., 2010).[3] This alignment requires perception of changes and appropriate responses (El Sawy, 1985). Accordingly, DA strategy for an enhanced IOR adaptability is tantamount to configuration of sensing and response capabilities (Albright, 2004; Davenport & Harris, 2007; Krishnan & Prahalad, 2008). Nevertheless, DA and their impact on sensing and response capabilities are discussed in two separate streams of research. The first stream of research studies the role of DA in perception of change and improvement opportunities (e.g., Baars et al., 2014; Lau et al., 2012), and the second stream discusses DA-enabled response approach (e.g., Fink et al., 2017; Maghrabi et al., 2011). Despite the importance of simultaneous considerations of DA-enabled sensing-response capabilities for employment of DA tools (Y. Park et al., 2017; Seddon et al., 2017), the topic is not discussed adequately in the literature.

4.2.1 Problem Sensing Focus

Managerial problem sensing, which is discussed as an antecedent for organizational adaptability (Kiesler & Sproull, 1982), is the ability of a firm to perform environmental scanning and acquire information for identification of salient improvement opportunities (Hahn, Preuss, Pinkse, & Figge, 2015; Hambrick, 1982; Overby et al.,

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[3] Since IS strategy literature is a superset for DA strategy, when the literature is silent about DA strategy, I develop my arguments based on IS strategy literature. Also, I refer to IS strategy literature in some parts of my general discussions due to the higher level of maturity in this body of knowledge.

2006). The heterogeneity of firms' performance is due to their differences in problem sensing (Barr, 1998; Hambrick & Mason, 1984; Mintzberg, 1978). These differences impact how firms compete in the market; therefore, problem sensing is associated with firms' strategies (Hambrick, 1982; Johnson & Hoopes, 2003).

According to the problem discussed in the prior paragraph, firms' access to information is beyond their analytical capabilities (Mintzberg, 1978). Consequently, focusing on problems with higher promises to serve organizational outcomes is a challenge for organizations due to information overload. Even, a firm with high DA capabilities "needs to target its analytical efforts where they will do the most good" (Davenport, Harris, & Morison, 2010, p. 73). Limited DA resources coupled with information overload forces firms to select the focus of their problem sensing vigilantly (Choudhury & Sampler, 1997; Murer & Bonati, 2010; Seddon et al., 2017).[4]

The management cognition literature suggests that decision makers are rationality bounded and do not have an accurate perception of their business environments (e.g., Johnson & Hoopes, 2003; Martignoni, Menon, & Siggelkow, 2016; Nadkarni & Barr, 2008). Therefore, firms selectively decide to work on a number of emerging problems based on perception of decision makers from problems' potential impact on

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[4] My study is focused on active problem sensing, which aims to find areas with potential impact on organizational goals (Choudhury & Sampler, 1997), rather than passive problem sensing, which reactively responds to a specific arisen problem. Therefore, I am focused on filtered problem sensing based on strategic frame rather than broad mindset and explorative problem sensing. For a more comprehensive discussion on different types of sensing, I refer the reader to Nadkarni, Herrmann, and Perez (2011) and Maitlis and Christianson (2014).

organizational outcomes (Dutton & Jackson, 1987). Accordingly, decision makers are focused on a limited set of problems for interpretation and decision making (Hambrick & Mason, 1984).

The literature on managerial cognition and problem sensing discusses that contextual knowledge of managers identify their problem sensing focus (Maitlis & Christianson, 2014); however, the literature on organizational learning and strategic management indicates that firms develop a filter for problem sensing to manage problem sensing at a collective level (Dixon, 1992; Dutton & Jackson, 1987). Organizational filters are formed based on industry norms, culture, beliefs, internal and external capacities, and ideology (Dutton & Duncan, 1987; Huff, 1982; Marsick & Watkins, 2003; Whittington, 1988) and are imposed through structure, norms, and procedures to direct problem sensing focus (Dixon, 1992; Sinkula, 2002). Such focus is enforced by a strategy frame and mediates the problem sensing focus of decision makers in organizations (Narayanan, Zane, & Kemmerer, 2011).

Categorization theory indicates that natural phenomena are categorized based on their similar features (Rosch, 1975; Rosch & Mervis, 1975). While the theory is initially introduced for natural phenomena, it is adopted by organizational scientists to explain problem sensing in organizations (Dutton & Jackson, 1987; Hahn et al., 2015). Cognitive categories include members who share similar perceived attributes (Dutton & Jackson, 1987), and, categorization theory in the context of organization implies that decision makers who are focused on specific cognitive categories face lower levels of ambiguity in environmental signals and cognitive load (Hahn et al., 2015). These cognitive categories have correlated attributes; therefore, it is easier to store and retrieve their related information, to interpret them based on the available organizational knowledge, and to communicate them (Dutton & Jackson, 1987; Huber, 1991). Considering managerial cognition and their bounded rationality, sensing should become category-based when complexity increases (Hahn et al., 2015).

Organizations create categories for their problem sensing based on their strategy frames. Various categories are used for problem sensing in the literature. For instance, scholars identify two sensing focuses of service business, including primary versus complementary customers' needs (Fischer, Gebauer, Gregory, Ren, & Fleisch, 2010; Sawhney, Balasubramanian, & Krishnan, 2004). Other problem sensing categorization examples include problems related to innovation or acquisition (Hambrick & Mason, 1984), events with attribution to external or internal business environments (Ford, 1985; Ford & Baucus, 1987), and threats and opportunities (Dutton & Jackson, 1987). These sensing focuses create a base for the firm's response approach (Lüscher & Lewis, 2008).

Due to the focus of my research on IORs, I identify two sensing focuses: namely, focus on internally attributed problems (hereafter: internal focus) and externally attributed problems (hereafter: external focus). With internal focus, firms try to create opportunities for performance improvement through reconfiguration of decisions that do not have direct interaction with their partners. With external focus, firms examine their decisions with direct interaction with their partners to find improvement opportunities. The boundary between the two categories of internal focus and external focus is fuzzy, which is similar to other social objects (Dutton & Jackson, 1987). I will address this fuzziness in my model by framing problem sensing as a continuous variable rather than a discrete variable with two fixed levels.

I use three distinct attributes to identify internal focus and external focus categories (c.f., Fiske & Neuberg, 1990). These three attributes are locus of causality, controllability, and stability (e.g., Ford, 1985). These attributes justify the fit of the proposed categorization in the presence of IOR and environmental factors by addressing complexity, dynamism, and IOR. First, internal problems and external problems are different based on the locus of causality. Internal problems impact operations and administrations, whereas external problems impact products, markets, and customers. The other distinction between the two categories of problems is related to the level of control (Martignoni et al., 2016). A firm has complete control on internal problems, whereas it does not have full control over external problems. Finally, internal problems tend to be more isolated from environmental turbulences; therefore, internal problems are less prone to environmental changes. The difference between problems related to the locus of causality, control, and stability leads to distinct improvement opportunities across the two categories. The value of these improvement opportunities varies across environments, which make them suitable for my study. For instance, focusing on internal problems may lead to improvement opportunities that have longer lasting impacts in a volatile environment in which firms' knowledges erode rapidly.

The literature does not explicitly discuss the two categories of internal focus and external focus; however, the proposed sensing focus is tantamount to external and internal response strategies in the literature (Ford, 1985; Nottenburg & Fedor, 1983;

Siggelkow, 2001), in which, internal problems deal with operations and administrations, and external problems deal with products and markets.

4.2.2 Response Approach

The DA strategy literature discusses exploitative and explorative response approaches (e.g., Fink et al., 2017). In exploitation, the DA strategy is informed by business strategy and supports the improvement of the business (Qrunfleh & Tarafdar, 2014). The support of business strategy is achieved through collecting and analyzing organizational data, improved decision support, and enhanced performance measurement (Peters, Wieder, Sutton, & Wakefield, 2016). This exploitative DA strategy is defined as "technological innovation activities aimed at improving existing product-market positions" (He & Wong, 2004, p. 484). In an IOR, firms can exploit with their internal decisions or can focus on their interorganizational interactions and improve them. For instance, DA could be employed for an enhanced internal process flow as an internal focus exploitation (examples in: van der Aalst et al. 2007), or DA can be employed for an improved inbound logistics as an external focus exploitation (examples in: Waller and Fawcett 2013).

In exploration, DA strategy informs business strategy through identification of new business development opportunities (e.g., Briggs, 2011; Shanks & Bekmamedova, 2012a). In this perspective, DA provide innovative solutions for developing business. This explorative DA strategy is defined as "technological innovation activities aimed at entering new product-market domains" (He & Wong, 2004, p. 483). Like exploitation, exploration focus can be internal or external in an IOR. For instance, DA can provide a firm with internal-focused product development ideas (e.g., J. Li, Tao, Cheng, & Zhao, 2015) or external-focused new market development strategies (e.g., Briggs, 2011).

The strategic management literature discusses exploitation-exploration as firms' response approaches for enhancement of their adaptability (He & Wong, 2004; Lavie & Rosenkopf, 2006). An IOR environment has an explorative-exploitative characteristic through which firms are exploring to find new resources and exploiting their required complementary resources (Lin et al., 2007). Exploitation helps IOR partners to improve their alignment through adjustment of the parameters of their collaborative relationships, and exploration helps them to improve their adaptability (Leidner et al., 2011; March, 1991). In the literature, firms are recommended to have an appropriate balance of exploration and exploitation for their response (He & Wong, 2004). A balanced focus on exploration-exploitation is called ambidexterity, which is defined as the ability of firms to manage exploitation and continues improvements along with exploration and radical changes simultaneously (Tushman & O'Reilly, 1996). In addition, such ambidextrous response approach is expected to lead to higher levels of performance (Lavie & Rosenkopf, 2006). Achieving the right balance between exploration and exploitation in an IOR requires appropriate decision support through employment of DA (Fink et al., 2017). Therefore, a considerable body of research in IS strategy is devoted to the role of IS in ambidextrous response (D. Q. Chen et al., 2010; Merali et al., 2012), and researchers discuss the importance of explorative and/or exploitative focus of DA strategy (Fink et al., 2017; Maghrabi et al., 2011).

The response approach of DA is also discussed implicitly in a few case studies. For instance, United Parcel Service (UPS) uses its operational data to study its cost structure and to exploit improvement opportunities for enhanced value chain efficiencies (Kohli 2007). In contrast, the Cincinnati Zoo is an example for exploration that uses DA for analysis of its loyalty program data to boost its sale and profitability through identification of new marketing leads (Briggs 2011). Continental Airlines employs DA for an ambidextrous response (Watson et al., 2006). The company achieve explorative functionality of DA through supporting the marketing department for customer segmentation and targeting, which eventually leads to an increase in sale. Also, DA provide exploitation opportunities for Continental Airlines through flight management dashboards, which supports improvements of the airline's performance in on-time arrival.

A single focus on exploration or exploitation is likely to have some negative consequences for firms. A dominant explorative focus leads to superficial organizational learning and exploration traps due to a lack of implementation and internalization of the acquired knowledge (Sirén, Kohtamäki, & Kuckertz, 2012). A dominant exploitative focus of firms leads to limited innovative behavior and confines firms to a suboptimal state, which is not sustainable in the long term (March, 1991). Ambidexterity resolves the issues related to unbalanced exploration-exploitation. Ambidextrous organizations are efficient and do well in their day-to-day business activities while they maintain their creativity in order to adapt to varying environments in the future (March, 1991; Tushman & O'Reilly, 1996). While the business value of IT-enabled ambidexterity is substantiated in the existing literature (e.g., Im & Rai, 2013; Peters et al., 2016), the literature fails to address the level of balance. While both capabilities are needed, success in some environments needs a more explorative focus and other environments require a more exploitative focus. Accordingly, the alignment of DA strategy with IOR requires a suitable balance of explorative and exploitative responses.

4.2.3 DA Strategy and IOR Complexity and Dynamism

Context and focus of organizational strategy frame for problem sensing and response is contingent on the environmental and organizational antecedents (Jansen et al., 2005). Generally, environment plays a critical role in configuration of DA strategies (Finnegan, Galliers, & Powell, 1999). More specifically, two environmental characteristics make alignment of DA with organizational strategy highly challenging (Merali et al., 2012). On the one hand, firms and IORs are complex systems in which many components have interactions with each other (H. a Simon, 1997). On the other hand, business environments are dynamic and the outcome of a specific action changes across time (Stieglitz et al., 2015). Thus, firms and IORs are considered to be complex systems that are operating in a dynamic business environment (T. Y. Choi et al., 2001; T. Y. Choi & Krause, 2006). Adaptability to a complex and dynamic environment is a challenging task that is vital for the success of firms and IORs (T. Y. Choi et al., 2001; H L Lee, 2004). Researchers suggest that adaptability requires IT tools and DA capabilities (Baars et al., 2014; Gosain et al., 2004). Beside DA capabilities, the alignment of DA with organizational strategy is essential (Brynjolfsson et al., 1994).

In a complex environment, decisions are inter-related in a nonlinear way (P. Anderson, 1999). Therefore, understanding the outcome of each single decision without considering the interaction between different decisions is impossible. For instance, inventory policy, pricing policy, production scheduling, and customer service level have mutual impact on each other and none of them could be identified in isolation. Configuration of such policies in an IOR and across borders of several firms adds new factors such as lack of control on underlying decision factors and increases complexities.

In addition to complexity-related challenges, there are dynamism-related challenges, or those that are relevant to the timeliness of feedback related to decisions (Rahmandad, 2008). Predicting the outcome of inter-related decisions is difficult by itself. When I add the required time span to observe the consequences of a decision, the initial decision making becomes more demanding. The dynamism of business environments adds to these challenges by altering the interrelationships between systems' components and changing the outcomes of decisions over time. Therefore, dealing with the decision-making problem in complex and dynamic business environments requires employment of appropriate DA tools.

From the perspective of complexity and dynamism, the previously discussed sensing focus strategy has not been investigated. The complex environment of a firm imposes cognition challenges to decision makers of the firm and prevents them from higher levels of performance (D. A. Levinthal, 1997; Rivkin, 2000). The limitted cognition of decisoin makers prevents them from full comprehension of internal and external structural patterns, which are related to interrelationships and interactions between decisions. This limitation impacts the sensing focus of firms and bounds it to a limited number of variables at a time. This challenge, coupled with limited analytical resources (Davenport et al., 2010), increases the importance of well-chosen targets. Therefore, firms should focus on areas that may yield higher performance outcomes. However, and despite the important role of sensing focus in enhancement of decision making, this topic is not addressed in the IS literature. Furthermore, sensing focus is not studied in the context of dynamic environments where the cognitive fit of decision makers changes as the business landscape alters. Therefore, due to the contingency of sensing focus of DA on environmental turbulence, this topic merits further investigation.

Discussions and findings related to the balance of exploration-exploitation in the face of complexity and dynamism are also inconsistent. Researchers who study IS strategy in complex environments argue that the increased complexity and interaction between decisions requires a broader exploration (Rivkin & Siggelkow, 2007). Other resarchers argue that exploration consumes resources that are needed for exploitation of the existing opportunities in complex environments (March, 1991). In addition, in the IS strategy literature, some researchers claim that in a volatile environment, firms must focus on exploiting their existing partnerships and resources (Podolny, 1994), whereas others state that a volatile business environment requires exploration (Lin et al., 2007). Moreover, a detailed scrutiny of discussions reveals that there is a mix between volatility and complexity concepts in the literature of complex adaptive systems. More specifically, the conceptualization of complexity is mixed with traces of dynamism. This tacit transition from complexity to dynamism (e.g., discussed in Rivkin & Siggelkow, 2007) impacts findings in the existing literature.

These inconsistencies and gaps in the literature make it vital to investigate how DA support organizational strategy and facilitate adaptability in the face of complexity and dynamism. Accordingly, I posit that the configuration of DA strategy requires appropriate sensing focus and response approach for different business environments (Figure 9). The spectrum of sensing focus ranges from more isolated internal problems to problems with external interaction and the spectrum of response ranges from exploitative to explorative responses. Identification of a suitable configuration of sensing-response in various environments constitutes the central question of this research: “what is the appropriate configuration of DA strategy for dealing with IOR’s complexity and dynamism?”

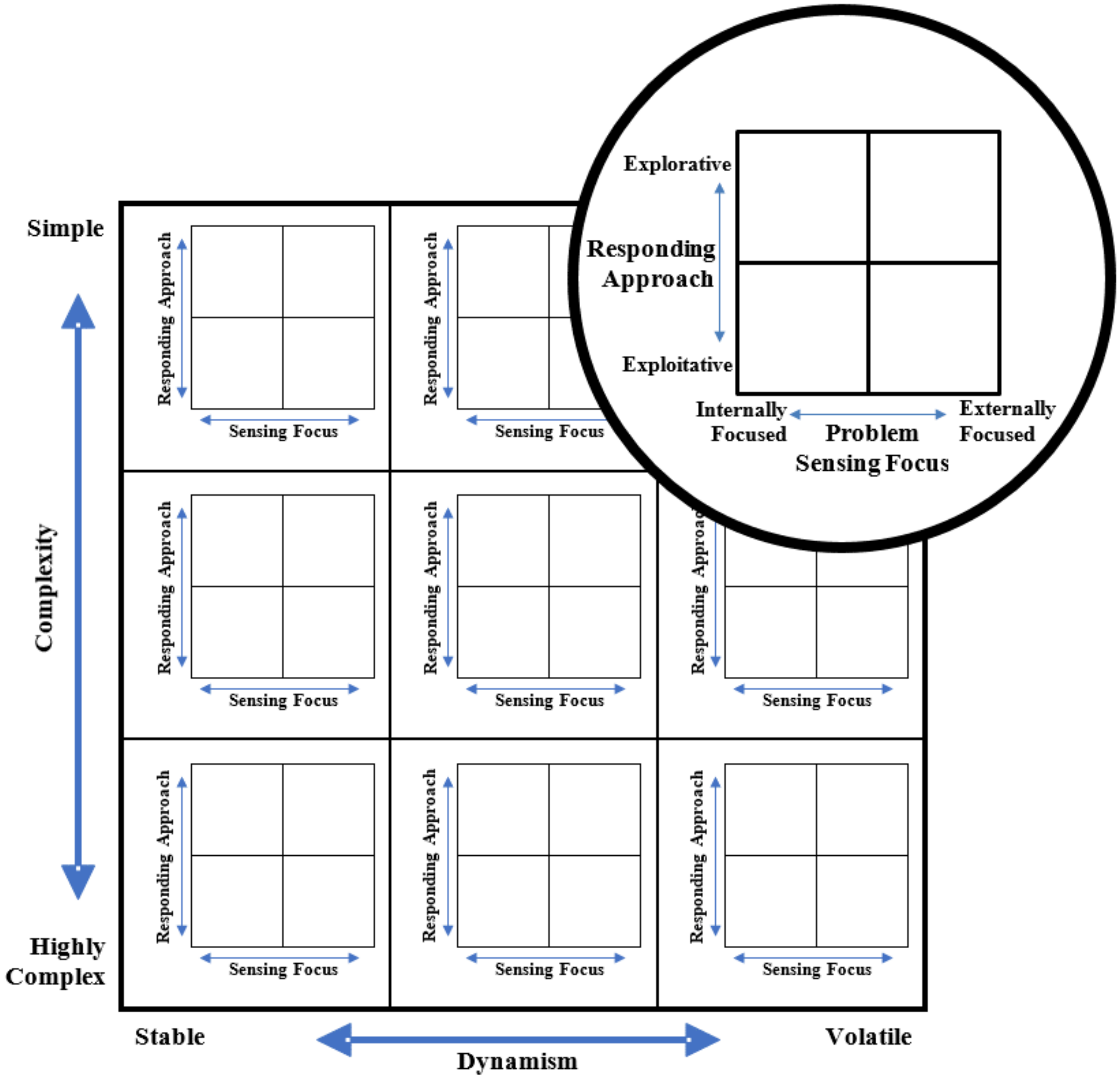

Figure 9. Framework for Demonstration of Strategy and Environment.
To Identify a Suitable Configuration of DA Strategy for Each Business Environment, Proposed Configurations Should Be Tested Across Business Environments with Various Levels of Dynamism and Complexity

4.3 Methodology and Research Model

Complexity of IORs leads to nonlinear relationships between their design configurations and their outcomes (P. Anderson, 1999). In particular, IORs can be studied by incorporating a complex adaptive systems (CAS) perspective since it brings new insights to study of IORs (T. Y. Choi et al., 2001) by providing a simplified understanding of associated complexity (P. Anderson, 1999; Gottinger, 2012). In addition, IORs are CAS because of their two essential characteristics (T. Y. Choi et al., 2001): their high number of stakeholders involved (e.g., collaborators, customers, and competitors) and their autonomous interaction between stakeholders.

Generally, CAS conceptualizes a system composed of agents that interact autonomously (Amaral & Uzzi, 2007). The agent-based simulation method is a prevailing approach that is used for analysis of CAS, and is widely adopted in the strategic management literature (e.g., Stieglitz et al., 2015) and IOR studies (e.g., Aggarwal, Siggelkow, & Singh, 2011; Posen & Levinthal, 2012). Also, the method has recently been adopted in the IS strategy literature (Nan, 2011; Nan & Tanriverdi, 2017). Overall, the agent-based simulation has several merits. First, the agent-based simulation method allows controlled examination of complex interactions. This method enables us to analyze how firms adapt in their business environments by isolating and focusing on the impact of a specific parameter (Ethiraj & Levinthal, 2004a). Second, agent-based simulation works well in studying a longitudinal phenomenon (Davis, Eisenhardt, & Bingham, 2007) and is suggested for assessing the IS strategy (Merali et al., 2012; W. Oh & Pinsonneault, 2007).

I develop an agent-based simulation based on an NK model, in which two firms that are involved in an IOR try to improve their organizational adaptation. The NK models are widely used for theoretical studying of organizational adaption in complex and volatile environments (e.g., Claussen et al., 2015; Siggelkow & Rivkin, 2005). The

NK models are able to represent the problem in the form of several agents with various characteristics that are interacting with each other (S. A. Kauffman & Weinberger, 1989). Consequently, I employ and adjust an NK model to investigate the configuration of DA strategy based on two aspects: sensing focus and response approach.

I study an IOR with a modular governance structure, which is also discussed as horizontal governance in the literature (Aggarwal et al., 2011). In a modular governance, it is assumed that the two partner firms that are involved in the IOR are focused on their own business and each of them tries to maximize its own performance by controlling its decisions. Also, the sequence of decisions in this governance mechanism is simultaneous and firms decide independently.

In the NK model, each firm is represented as a set of binary decisions (Rivkin, 2000). Each decision is related to a problem that decision makers try to address (as discussed in problem sensing), and hereafter, the terms decisions and problems are used interchangeably. As a hypothetical example, consider an IOR with two firms. Each firm has two decisions. Firm A decides on: (1) increase or decrease in in its safety stock; and (2) increase or decrease in its customer service level. Firm B decides on: (1) maintain or increase its current production lot size; and (2) use multimodal transportation or maintain its current shipping mode. A combination of these interrelated decisions configures the IOR and leads to a performance outcome (payoff). Since there are numerous ways to configure the IOR, there are many associated payoffs to these configurations. This creates a multi-dimensional surface, which assigns a payoff value to each configuration of the IOR. This multi-dimensional surface is called fitness landscape. Figure 10 presents a simplified multi-dimensional fitness landscape for the hypothetical IOR. Since each of these decisions has two states, the IOR can assume 16 different configurations. Firms need to search the fitness landscape by revising their decisions to move from their current state to a state with higher payoff.

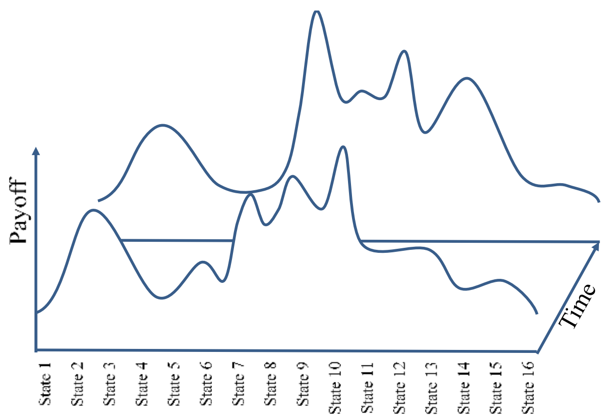

Figure 10. All Possible Configurations of a Hypothetical IOR and Their Payoff

When business is complex, the expected payoff of the even slightly reconfigured situations changes rapidly. The landscape of such business environments is called rugged and, it is hard for IORs to find a configuration that leads to the optimum performance state (D. A. Levinthal, 1997). Specifically, the limited cognition of IOR’s decision makers about the fitness landscape prevents that firm from reaching to the global optimum, and in many cases the firm ends up in a local optimum (Martignoni et al., 2016). One should note that the optimum payoff for IOR may not necessarily yield the highest performance for both firms. I will discuss the payoff of an IOR and its constituent firms in later sections. For instance, if the hypothetical IOR is in state 4, it can assume two directions by moving towards state 3 or state 5. While moving to state 3 might increase the payoff considerably more than state 5 in the short-term, it would lead to a local optimum. In such local optimum configurations, the firm cannot find any better alternative, unless it makes significant changes in its current configuration.

Since firms have limited resources, they cannot search all their landscape points (i.e., their decision states or configurations) in order to reach the optimum configuration with the highest payoff. The presence of search cost along with the dynamism of business environments, forces firms to manage their landscape search process (i.e., or their decision-making processes). The following example illustrates how firms need to cope with dynamism in their search process. Assume that the hypothetical IOR is in state 10 at period 1. While this state is the global optimum and provides the highest possible payoff for the IOR, a change in the market alters the landscape in period 2. Accordingly, the payoff of state 10 is not the maximum and the firm needs to search and find a better state to adapt to the new business environment.

In the next sections, I first design the task structure and performance outcomes. Then, I identify the business environment. Next, I discuss sensing focus and response approach. Finally, I discuss the dynamism of business environments.

4.3.1 Task Structure and Performance

To model the task structure and performance in this section, I first explain the configuration of an IOR and its participating firms, which is also known as decision set or state. Next, I clarify how configuration is mapped to performance. Table 18 presents a list of notations used in the model.

Table 18. List of Notations

N_A, N_B	Number of binary decision in Firm A and Firm B
N	Total number of binary decisions in both firms: $N = N_A + N_B$
N_1, N_2	Number of decisions with internal (N_1) and external interactions (N_2)
d_i^t	State of decision i at period t (d_i is used when talking about a specific decision, without considering time)
S_A^t, S_B^t	State of Firm A and Firm B in period t
S^t	State of the system in period t: $S^t = \{d_1^t, d_2^t, \dots, d_N^t\} = \{S_A^t, S_B^t\}$
$f(d_i^t)$	Payoff of decision i in period t
$f(S^t)$	Payoff of IOR at time t
$f(S_A^t), f(S_B^t)$	Payoff of Firm A/Firm B at time t
K_A^h, K_B^h	Number of internal interactions in Firm A/Firm B respectively
K^h	Total number of internal interactions between decisions: $K^h = K_A^h + K_B^h$
K^b	Number of external interactions between decisions of Firm A and Firm B
P_A, P_B	Sensing focus index for Firm A and Firm B (probability of selecting a decision with external interactions)
p_i	Probability of selecting d_i
$e(d_i^t)$	Expected contribution of decision i at period t to firm's payoff
τ	An index for identification of the response approach of firms (For τ close to 0, firm is exploitative and as τ increases, firms become explorative)
Δ	Probability of change in the business environment at each period
C	Magnitude of change in the landscape
γ	Direction of change in the landscape
$\emptyset$	Step size parameter, which is an identifier of learning rate

Aligned with the literature and rooted in the information processing theory of the firm (Cyert & March, 1963; Galbraith, 1977), Firm A and Firm B, which are partners in an IOR, are modeled based on N_A and N_B binary decisions respectively (D. A. Levinthal & Warglien, 1999). Each of these decisions are related to a specific problem that the firm is focused on. These N decisions ($N = N_A + N_B$) are denoted by $N = \{d_1^t, d_2^t, \dots, d_N^t\}$ with $d_i^t \in \{0,1\}$. The d_i^t identifies the state of decision i at period t. I denote the state of the IOR at period t with $S^t = \{d_1^t, d_2^t, \dots, d_N^t\}$ and S_A^t and S_B^t represent the state of Firm A and Firm B ($S^t = \{S_A^t, S_B^t\}$). At the beginning of the simulation, the state (S^0) is identified based on a random assignment of 0 and 1 to each decision. This assigned decision set is an identifier of the status of an IOR and its fit to its business landscape. For example, with $N_A = N_B = 8$, the IOR may start the simulation with $S^0 = \{1,0,1,1,0,1,1,1,0,1,0,1,0,0,0,1\}$, which is a random assignment and is composed of $S_A^0 = \{1,0,1,1,0,1,1,1\}$ and $S_B^0 = \{0,1,0,1,0,0,0,1\}$. Moving to the next period, Firm A can flip one of the d_1 to d_8 decisions and Firm B can flip one of the d_9 to d_{16} decisions. If Firm A and Firm B flip d_3 and d_9 decisions, respectively, the second period starts with $S^1 = \{1,0,0,1,0,1,1,1,1,1,0,1,0,0,0,1\}$. I refer to the selected decision for transitioning from one state to the next state as an action. During each period of simulation, each firm has two choices: selecting an action or staying put.

There are 2^N states for the IOR in my model and the NK model assigns a specific payoff to each of these states. This payoff, which is also called fitness, is calculated as a function of contributions associated with each individual decision. When there is no interaction, each decision has only two contributions, one for when its state is at "1" and another for its state being “0.” Accordingly, there are 2^N different payoffs for all the possible decision states. When the interactions are factored, each decision interacts with K other decisions and lead to 2^{K+1} different contributions. The K in the power is related to K dependent decisions with 0 or 1 state and the 1 in the power is related to the decision itself.

Contributions of each decision, $f(d_i^t)$, are generated by a uniform distribution ($U[0,1]$), and each of which is assigned to each potential state of that particular decision at the beginning of the simulation. The assignment of payoff based on the uniform distribution is employed in the literature (e.g., Aggarwal et al., 2011). I denote payoff functions for IOR, firm A, and Firm B by $f(S_A^t)$ and $f(S_B^t)$, respectively. These payoff functions are calculated as an average of the relevant contributions of all decisions as follow:

$$f\left(S^t\right) = \frac{\sum_{i=1}^{\mathrm{N}} f(d_i^t)}{\mathrm{N}}, f(S_A^t) = \frac{\sum_{i=1}^{N_A} f(d_i^t)}{N_A}, \ f(S_B^t) = \frac{\sum_{i=(N_A+1)}^{N} f(d_i^t)}{N_B} \tag{1}$$

4.3.2 The Business Landscape and Complexity

Figure 11 represents the business environment with the left side being a schematic representation of the business environment and the right side being the same business environment in the form of a binary influence matrix. The binary influence matrix is used in the literature to demonstrate complexity of environment (Woodard & Clemons, 2014). The presented environment is composed of two agents (Firm A and Firm B) that form an IOR and interact with each other. This interaction is through interdependent decisions (Aggarwal et al., 2011) that represent problems with internal and external interdependencies. Each of these decisions identifies a specific problem that firm's decision makers aim to address. For instance, assume Firm A is a major supplier of Firm B. Each firm has two departments, which are configured by several decisions. Firm A has two departments: production $\{d_1^t, d_2^t, d_3^t, d_4^t\}$ and distribution $\{d_5^t, d_6^t, d_7^t, d_8^t\}$. Also, Firm B has two departments: production $\{d_9^t, d_{10}^t, d_{11}^t, d_{12}^t\}$ and sales $\{d_{13}^t, d_{14}^t, d_{15}^t, d_{16}^t\}$. Decisions that configure each department interact with each other inside the department. For example, the distribution process of Firm A is configured by inventory level (d_5^t), service level (d_6^t), package size (d_7^t), and shipping mode (d_8^t), which are interrelated and interact with each other. Also, departments impact each other through their interrelated decisions. For the example in Figure 11, the distribution process in Firm A has direct interaction with the production process in Firm B, whereas the production process in Firm A and the sales process in Firm B do not interact directly.

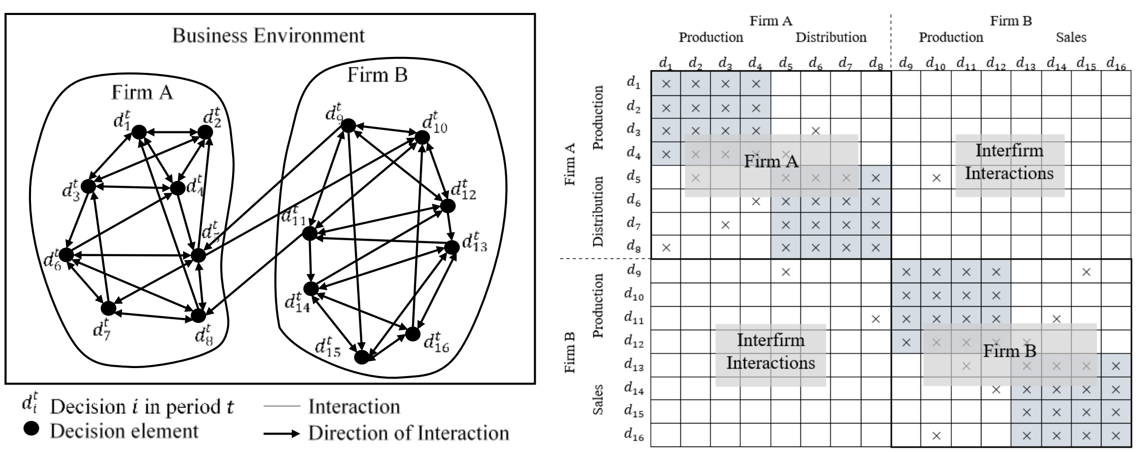

Figure 11. Business Landscape in Period t.
The Left Side Is a Schematic Representation of the Business Environment and the Right Side is a Binary Influence Matrix for the Left Side

Interactions between decisions are shown by edges in the schematic side of Figure 11 and by cross in the matrix. Interactions illustrate the impacts of decisions on the outcome of each other. For instance, a change in the state of d_{11}^{t} (Firm B) impacts the payoff of decisions d_{9}^{t}, d_{10}^{t}, d_{12}^{t}, and d_{14}^{t} in Firm B (internal relationships). Also, this change impacts the outcome of decision d_{8}^{t} in Firm A (external relationships). These interactions increase the complexity of the IOR and lead to the need for mutual adjustment of these decisions. Since a change in one decision may impact the optimum level of another decision, firms need to rethink and revise the impacted decision. This change, in turn, impacts other decisions. Therefore, one simple change in a highly interrelated (complex) environment can cause cascading impacts and makes it hard to predict outcomes. Therefore, identification of the best decision set for achieving highest payoff for an IOR is a complicated task due to these interactions and associated complexity. Since the complexity of each firm and the complexity of IORs increase as the number of interactions increase (H. A. Simon, 1962), I use the number of interactions (K) as a measure for complexity of IORs. I assume that all decisions in a department interact with each other (Aggarwal et al., 2011). Therefore, complexity (K) is composed of inter-departmental interactions ($K^{h} = K_{A}^{h} + K_{B}^{h}$) and external interactions (K^{b}), and is calculated with Equation 2 (e.g., Claussen et al., 2015). Accordingly, the complexity of business landscape of firms A and B are K_{A} and K_{B}, respectively.

$$K = K^{h} + K^{b},\ K_{A} = K_{A}^{h} + K^{b},\ K_{B} = K_{B}^{h} + K^{b} \qquad (2)$$

4.3.3 Organizational Sensing

In the binary influence matrix of Figure 11, I assume that each firm has N_1 decisions for problems with internal interactions and N_2 decisions for problems with external interactions. In this illustrative example, I consider $N_1 = N_2 = 4$. Also, I consider $K^b = 3$ and $K^h = 6$ for both firms. Interactions between departments and interactions between firms are assigned randomly, and I consider asymmetrical interactions in this example. I name decisions of Firm A that have internal interactions and external interactions $\{d_1, \dots, d_4\}$ and $\{d_5, \dots d_8\}$, respectively. Also, I name decisions of Firm B with external interactions and internal interactions $\{d_9, \dots, d_{12}\}$ and $\{d_{13}, \dots d_{16}\}$, respectively.

Firms search their landscape for higher pay-offs or fitness values. During this search process, firms evaluate their alternative solutions to decide for action. Sensing in each firm, which identifies well-chosen targets, focuses on problems with internal interactions or problems with external interactions. Accordingly, I identify a sensing focus parameter for each firm (P_A and P_B) that ranges from 0 to 1 and is the probability of selecting problems with external interactions. Thus, parameter $1 - P_A$ can be seen as the probability of selecting an internal problem at each time (selecting either internal or external problem is the only alternatives for each firm). When the index is 0, the focus is internal and as it approaches 1, the focus becomes external. For instance, if Firm A has pure internal focus ($P_A = 0$), it selects its problem alternatives from $\{d_1, \dots, d_4\}$.

4.3.4 Organizational Response

Firms follow two different response approaches in task selection, exploiting and exploring. In an exploitative response approach, firms use their current knowledge and select those tasks with the highest perceived payoff. The explorative response approach is based on testing new opportunities and selecting taks that can set the ground for higher payoffs in the future (Fang & Levinthal, 2009; Jain & Kogut, 2013). A commonly used approach to model exploitation is local search, which is adopted by researchers. In local search, also known as adaptive search, firms flip one of their decisions at a time and test the payoff of the new configuration. If the payoff of the new state is better than the current payoff of the firm, they choose the new configuration and improve their fit to the landscape. Otherwise, firms stay put and wait for later periods to test other alternatives for potential improvements. This method of alternative selection is also known as the greedy algorithm, because of the myopic behavior of the firm in selecting the immediate alternative with the highest payoff (Posen & Levinthal, 2012). The local search never tries alternatives that appear inferior and might lead to enhanced landscape fit in the long run (Posen & Levinthal, 2012).

Exploration is addressed in the literature through different algorithms. The majority of these algorithms discuss exploration based on neutrality. The neutral search approach looks for moving to states with potential for setting the base for higher performances in the future (Jain & Kogut, 2013). The Softmax method is capable of addressing the neutral search by considering the exploration-exploitation trade off (Koulouriotis & Xanthopoulos, 2008) and is extensively adopted by researchers in organization science and strategic management (Posen & Levinthal, 2012). The Softmax method, which represents the decision making process, incorporates a simple approach for balancing exploration and exploitation and can be fine-tuned to develop near optimal results (Koulouriotis & Xanthopoulos, 2008; Posen & Levinthal, 2012). Subsequently, I employ the Softmax method in this research. In the Softmax method, the probability of selecting d_i is identified by the following equation.

$$p_i = \frac{\exp(e(d_i)/\tau)}{\sum_{i=1}^{N/2} \exp(e(d_i)/\tau)} \tag{3}$$

In this equation, $e(d_i)$ identifies the expected contribution of decision i to the payoff. Therefore, decisions with higher expected payoff have a higher chance of being selected. Also, τ identifies the response approach of the firm. With τ close to 0, since a small difference between payoffs create a huge difference in the probability of being selected, the behavior shifts to exploitation and local search. With a larger τ, the difference between probabilities of selecting activities with different payoffs shrinks and firms show more explorative behavior.

Firms learn through trial and error in their exploration and exploitation (Puranam, Stieglitz, Osman, & Pillutla, 2015). More specifically, analysis and trial of different decision alternatives enhances the cognitive fit of decision makers and improves their perception about the structure of their business environment and contribution of decisions to payoff (Ethiraj & Levinthal, 2004a). In this learning process, firms analyze the feedback of their decisions. Accordingly, those decisions with higher historic payoff have higher chances of being incorporated again. The reinforced learning model (Equation 4), which resembles how firms adapt in their business environment, is employed in the literature to model the learning of firms for enhanced adaptability (Puranam et al., 2015).

$$e(d_i^t) = e(d_i^{t-1}) + \emptyset[f(d_i^t) - e(d_i^{t-1})] \tag{4}$$

In Equation 4, $e(d_i^t)$ is expected contribution of decision i at period t and $\emptyset \in [0,1]$ is step size parameter. The value of $\emptyset$ identifies learning rate. When learning rate is higher, a higher weight is considered for more recent feedbacks.

4.3.5 Volatility in the Landscape

The level of dynamism in business environment has impact on payoff of decisions and their interactions (Aggarwal & Wu, 2014). For instance, a change in the environment might impact the outcome of a decision. Consequently, interactions between the impacted decision and other internal and external decisions impact the payoff of each state. Accordingly, dynamism is modeled in the literature by a random change in the payoff of decision components (Siggelkow & Rivkin, 2005). The frequency of change, Δ, is the probability of a change in the landscape in each period of simulation (e.g., Ethiraj & Levinthal, 2004a). When the change parameter Δ is set close to 1, the environment is volatile and changes every period. With a Δ close to 0, the environment is stable and changes rarely. Accordingly, the probability that the payoff of each decision is impacted by the environment in each period is Δ. In those periods that environment changes, I change the contribution of half of decisions by assigning a random payoff to them

($U[0,1]$) (Posen & Levinthal, 2012). In the sensitivity analysis, I test other dimensions of change including: magnitude of change and direction of change (Stieglitz et al., 2015).

4.4 Results

I simulate the behavior of my research model through a custom developed code in R. The results that are presented in this section are based on the average behavior of IORs with different configurations of DA strategy in various business environments. For simplicity, without sacrificing the generalizability of the results, I consider that $N_A = N_B = 8$ ($N = N_A + N_B = 16$). Furthermore, I assume an equal number of decision with internal and external interaction for each firm ($N_1 = N_2 = 4$). Similar parameters are used by other researchers (e.g., Aggarwal et al., 2011; Claussen et al., 2015; Ethiraj & Levinthal, 2004b).

I create nine business environments based on three levels of complexity and three levels of dynamisms. IORs are categorized into simple ($K_A^h = K_B^h = 4$ and $K^b = 0$), moderately complex ($K_A^h = K_B^h = 4$ and $K^b = 1$), and highly complex ($K_A^h = K_B^h = 4$ and $K^b = 2$) (e.g., Claussen et al., 2015). Also, three levels of dynamism are stable ($\Delta = 0$), moderately volatile ($\Delta = 0.1$), and volatile ($\Delta = 0.3$)(e.g., Posen & Levinthal, 2012). I test firms with various sensing focuses and response approaches in each of these 9 business environments. For sensing focus, I gradually increase the focus index by increments of near 0.05 starting from 0. Accordingly, I create 20 categories for sensing focus, ranging from internally focused ($P_A = P_B = 0$) to externally focused ($P_A = P_B = 1$). For response approach, I gradually increase τ from 0.02 to 1 by increments near 0.05.

Accordingly, I create 20 categories for response that range from pure exploitative strategy ($\tau = 0.02$) to highly explorative strategy ($\tau = 1$)(Posen & Levinthal, 2012). Finally, I consider step size parameter to be $\emptyset = 1$ (e.g., Stieglitz et al., 2015). I discuss other values in the sensitivity analysis.

I identify IORs by a random assignment of decision sets and payoffs at the beginning of the simulation. This random assignment can work in favor of or against the payoff. Therefore, I create 100 IORs to eliminate the impact of initial state of IORs. I configure these 100 IORs with similar DA strategies and test their behavior in each business environment. Firm A and Firm B are similar in all parameters; therefore, I use $f\left(S^{t}\right)$ for identification of payoffs ($f\left(S^{t}\right) = f(S_{A}^{t}) = f(S_{B}^{t})$). There are 400 configurations of DA strategy (20 levels of sensing focuses and 20 response approaches), and there are 9 different business environments. I simulate the behavior of these 100 firms for 3,600 times (360,000 total simulations). I run each simulation for 200 periods. I notice that longer periods of simulation do not add to the findings, since results are stable after 200 periods of simulation.

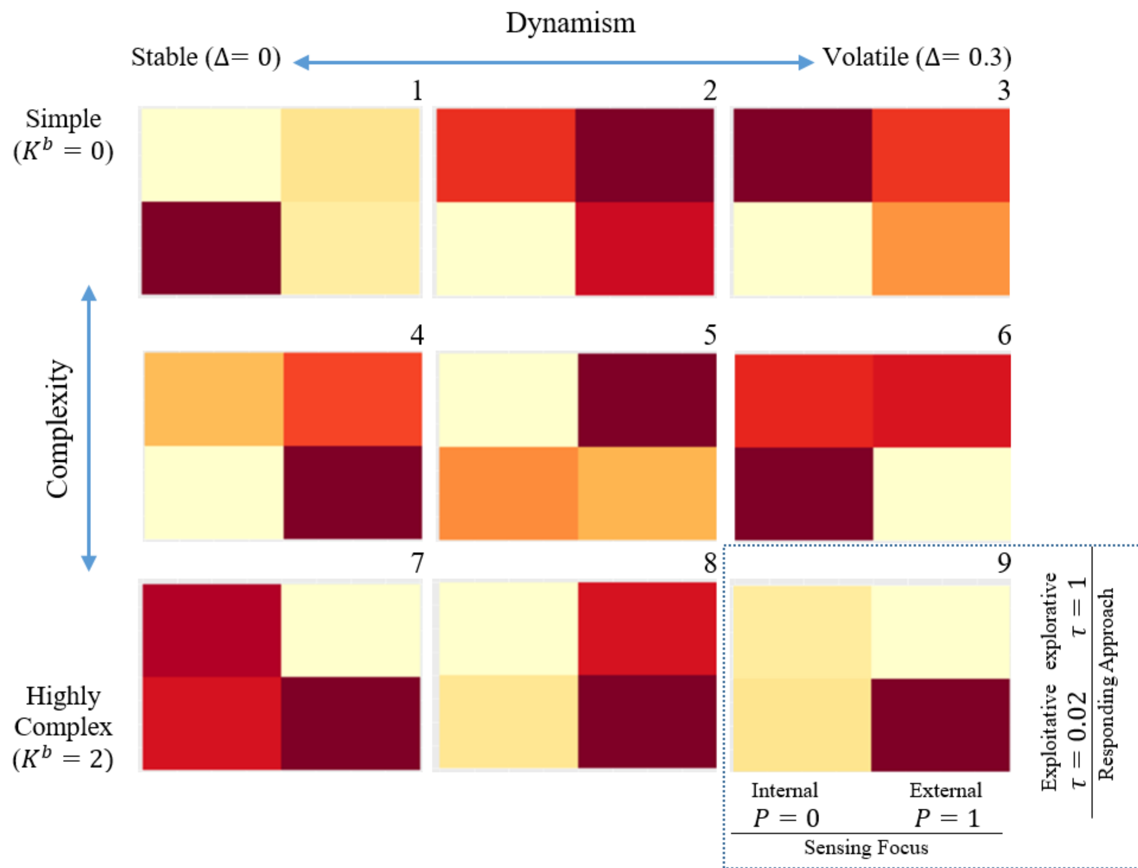

Figure 12. Overview of Simulation Results.
These results are for IORs with Modular Governance. Each Cell Represents a Specific Business Environment and there are 9 Simulated Business Environments Based on Complexity and Volatility. Each Heat Map Represents Performance of IOR Based on Sensing Focus and Response Approach. The Horizontal Axis of Heat Maps Represents Sensing Focus and Vertical Axis of Heat Maps Represent Response Approach. Sensitivity Analysis Shows that these Patterns Maintain their General Form with Higher Levels of Complexity, Dynamism, and Exploration.

Figure 12 is an aggregated summary of my simulation results. There are 9 heat maps presented in the chart, and each represents payoffs of IORs with different DA configurations in a specific business environment. Each business environment is identified with a number (from 1 to 9), and I use these numbers to address environment types. The four cells on each heat map represent four configurations of DA strategy. The horizontal axis is sensing focus. The lower values on the horizontal axis represent internal focus and larger values represent external focus. The vertical axis is related to response approach with its lower half representing exploitative focus and the upper half representing explorative focus. The darker colors on the chart show higher levels of payoff. For example, the first heat map (top left) identifies that focusing on internal problems with an exploitative response approach leads to the highest payoff in a simple and stable business environment.

Each cell of heat maps in the chart is an average on the results of 10,000 simulations. For instance, the first cell of each heatmap (internal focus, exploitative response) represents simulation of 100 different IORs with 100 different strategies that are configured based on 10 levels of sensing focuses (p_A and p_B ranging from 0 to 0.5) and 10 levels of response strategies (τ ranging from 0.02 to 0.5). This aggregated representation of results facilitates explanation and discussion of them.

My results show that a problem sensing focus has a quadratic relationship with the level of dynamism. Focusing on internal problems leads to the highest payoff in simple stable environments, as in region 1 (R1) of Figure 12. At moderate levels of volatility, firms need to focus externally to achieve the highest payoff (R2, R5, and R8). When an environment becomes volatile, internal focus is the optimum choice (R3, R6). In higher levels of complexity, external focus yields higher payoffs (R7, R8, and R9), and when an environment is volatile and extremely complex, the focus is external (R9).

Choosing an exploitative response approach leads to the highest payoff in a simple stable environment (R1). When volatility increases, the explorative response approach becomes the preferred method (R2, R3, and R5). But, in an extremely volatile environment, with moderate levels of complexity, exploiting is an optimum approach (R6 and R9). When the environment becomes extremely complex and volatile, exploration is the optimum response approach (R7, R8, and R9). A detailed explanation and discussion of findings is presented in following sections.

4.4.1 Robustness

To ensure that selected values for the incorporated parameters do not lead to biased results, I test my model with various levels of complexity (K^b), dynamism (Δ), response approach (τ), and learning ($\emptyset$). I add two levels of complexity to my model $K^b = 3$ and $K^b = 4$ (maximum possible number for external interactions) and notice that the optimum configuration of DA strategy does not change as I increase the level of external interactions beyond $K^b = 2$. Also, I test for higher levels of dynamism ($\Delta = 0.5$, $\Delta = 1.0$) and find that the increase does not have any impact on the pattern of change. Similarly, with an increase in the explorative behavior ($\tau = 1.5$, $\tau = 2$), the results remain the same. Finally, I test for learning parameter ($\emptyset$). An increase in this parameter, improves the payoff of an exploitative response approach, where exploitation is the preferred response approach. When exploration is preferred, a decrease in the learning parameter improves the payoff of exploration. However, in both cases, the general pattern and optimum behavior remains the same.

4.4.2 Sensing Focus

Firms' control on internal and external problems differ. Level of control impacts payoff improvement opportunities in different business environments. While problems with internal interactions provide higher levels of control for decision makers, decisions with external interaction are variable and beyond decision makers' control (Martignoni et al., 2016). Also, since internal problems have interdepartmental interactions and external problems have both interdepartmental and interfirm interactions, internal problems have lower levels of complexity compared to external problems. Therefore, internal focus means working on simpler decisions that are more controllable. In addition to being able to controlling internal decisions, collecting required information is easier within the boundaries of a firm (Santos & Eisenhardt, 2005). However, external decisions have higher complexity and create a more rugged landscape, which is associated with more opportunities for improving payoff (D. A. Levinthal, 1997). While payoff improvement is harder in a rugged landscape, it can provide hard-to-imitate outcomes and lead to competitive advantage. Therefore, both internal and external focuses have their promises for firms involved in IORs. In this section, I compare the payoff implications of internal and external focuses in various business environments.

Figure 13 compares the average payoff of IORs with various configurations of DA sensing focus across different business environments. The graph shows how IORs adapt to their landscape during 200 periods of simulation. In a simple stable environment, focusing on internal interactions leads to a steeper increase in payoff and yields higher overall payoff (Top left of Figure 13). Simple business environments are characterized by their relatively smooth business landscape with few spikes. These business environments impose minimal local optimum traps; therefore, firms can move towards the global optimum (D. A. Levinthal, 1997). This move becomes easier when firms have internal focus, which further reduces the complexity. This argument is also supported by the graph at the top left of Figure 13, where firms with internal focus can converge to higher levels of payoff faster. This finding is aligned with prior discussions and consistent with the literature (March, 1991; Posen & Levinthal, 2012). As complexity of environments increases, the optimum focus shifts from internal to external. The externally interrelated problems have higher levels of complexity due to more combined internal and external interactions. This complexity creates a highly rugged landscape, which in turn leads to more potential improvement opportunities. Therefore, external focus of firms provides more payoff improvement opportunities and leads to a steeper increase in the overall payoff (top right of Figure 13).

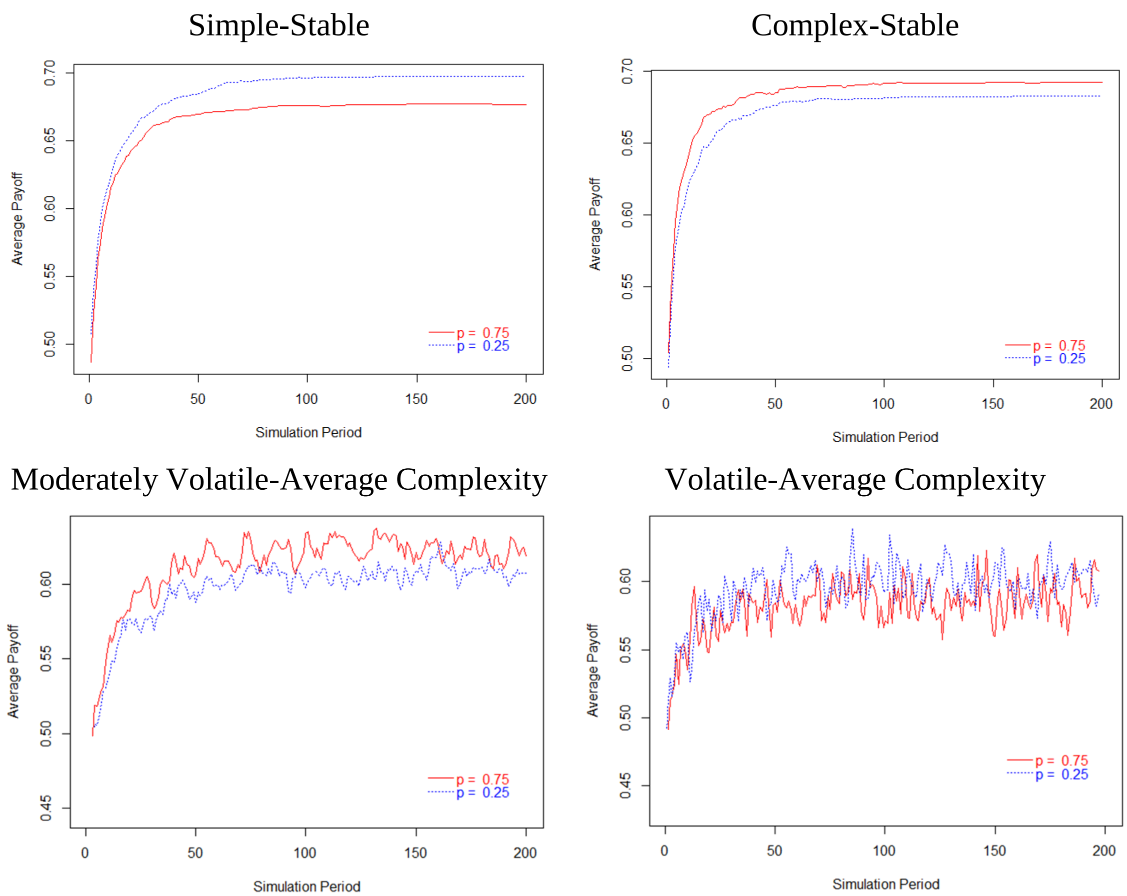

Figure 13. A Comparison between Different Sensing Focuses.
P **Stands for Sensing Focus Index ($P = P_A = P_B$) and Larger P values are Related to External Focus. Response Approach is Set to be Balanced($\tau = 0.5$)**

External focus leads to higher payoffs when an environment is moderately volatile. Any change in such environments has higher potential impacts on problems with external interactions, due to a higher number of interactions in these problems. Therefore, there are more out of tune externally interrelated decisions in volatile environments. Accordingly, external focus provides more payoff improvement opportunities. Comparison between internal focus and external focus is presented in the bottom left corner of figure 13. This comparison shows that the payoff of external focus converges to higher levels of payoff faster.

Internal focus is optimum in extremely volatile environments. While discussion in the prior paragraph explains that externally interrelated decisions have a higher number of improvement opportunities in volatile environments, the pace of change reduces the efficiency of external focus. External focus is more prone to change. Therefore, even though attempts for improving based on external focus may yield temporary results, these results will soon be undermined by the next change in the business environment. On the other hand, the outcome of improvement based on internally focused decisions holds for longer periods of time. The bottom right of Figure 13 compares the payoff of internal and external focus in extreme volatile environments.

In summary, with the lower levels of dynamism and complexity, firms can improve their performance in a controlled manner when they focus on problems with internal interactions. When complexity and dynamism increase, the IORs are not able to adequately improve their performance by merely focusing on internal problems and should examine external improvement opportunities. However, dealing with extreme complexity and volatility requires focus on internal decisions that are less prone to change.

4.4.3 Response Approach

Both firms in my model can choose to be purely explorative, purely exploitative, or ambidextrous. Accordingly, I simulate different levels of balance between exploration and exploitation in ambidexterity to identify the optimum response approach.

My analysis suggests that ambidexterity outperforms pure exploitation or exploration in all environments, which is consistent with the literature (Lavie & Rosenkopf, 2006). Having the opportunity of exploiting and exploring at the same time provides two benefits for firms. First, they can avoid exploration and exploitation traps. Second, in a rugged landscape, exploration supports an initial fast increase in landscape fit and payoff. Once the company approaches an optimum in the landscape, exploitation assists the firm in fine tuning and further improvement of this payoff. Although ambidextrous firms have higher payoffs, my results suggest that the optimum payoff in each level of complexity and dynamism is achieved at a specific balance of exploitative-explorative responses.

Decision makers can identify structural patterns of interactions in lower levels of complexity (Martignoni et al., 2016). Accordingly, it is easier for them to exploit. They can learn how reconfiguration of decisions through exploitation impacts their payoff. Therefore, they exploit and change their configuration in a vigilant way to improve their payoff. This exploitation eventually leads to optimum payoff in simple environments (D. A. Levinthal, 1997). A side by side comparison of response strategies in a simple environment, which are presented in the top left corner of Figure 14 shows that firms with exploitative response strategies converge to higher levels of payoff faster than firms with explorative response strategies. As complexity increases, the patterns of interaction become more complicated. Accordingly, any decision, while it might be a good decision standalone, will lead to a change in the payoff of many other decisions based on its interactions. Therefore, exploration is preferred to exploitation because of the unpredictable nature of decision making in this situation. Exploration provides the firm with the opportunity of avoiding local optimums and provides more improvement opportunities (D. Levinthal & March, 1981). Thus, the payoff converges to higher levels sooner. The top right corner of Figure 14 compares explorative and exploitative responses in a complex and stable environment.

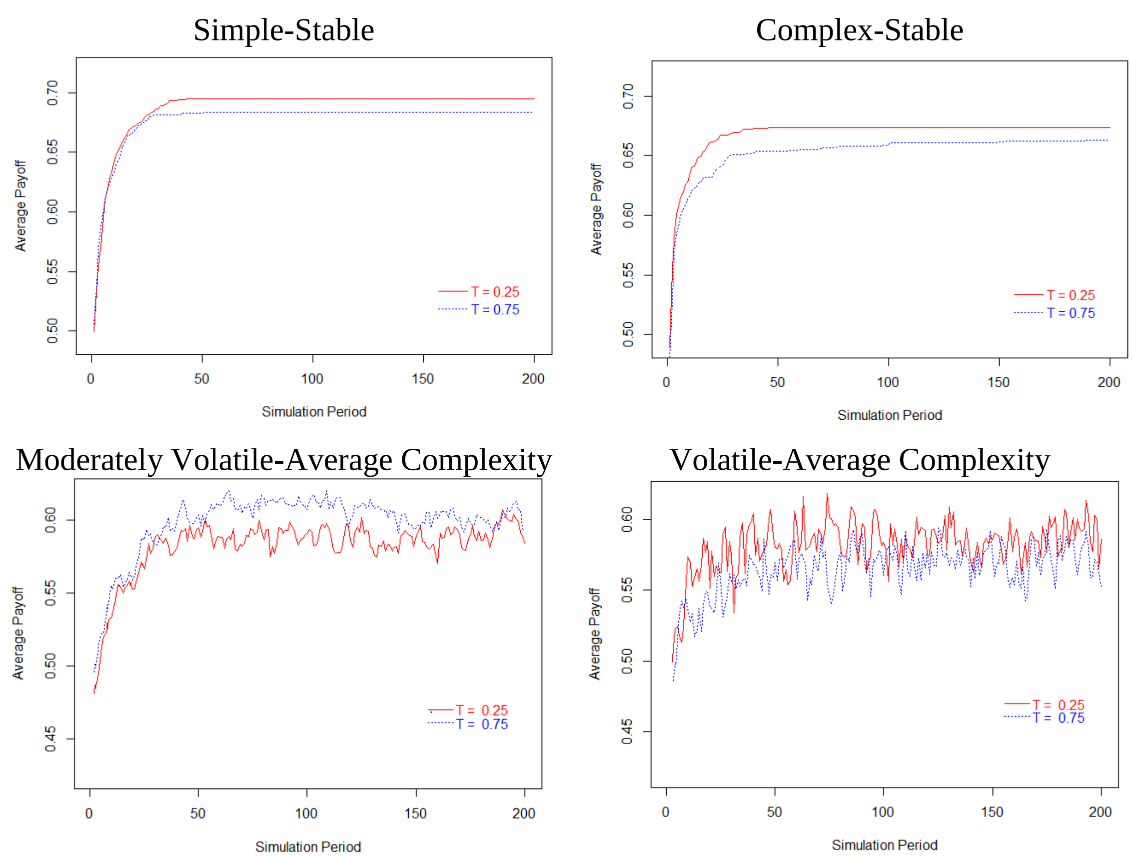

Figure 14. A Comparison between Different Response Strategies.
τ Stands for Response Approach and Larger τ Values are Associated with Exploration. Sensing Focus is Set to be Balanced ($P = 0.5$).

The literature suggests that a volatile environment requires an explorative search strategy (D. Q. Chen et al., 2010). The business landscape changes constantly and firms need to adapt to the new landscape in volatile environments. Adaptability is defined as the ability to “adjust supply chain design to accommodate market changes” (H L Lee, 2004, p. 1). Therefore, a firm should quickly converge its capability and resources after each change in its environment to maintain its competitive position in a volatile environment (Kerin, Varadarajan, & Peterson, 1992). After each change in the business environment, firms have a very limited time span until the next wave of change. Employing a suitable response approach enables firms to converge to higher levels of payoff before the next wave of change.

The increase in environmental change impacts the payoff of response strategies. In volatile environments, the prior knowledge of firms from business environments deviates from reality and mental models of decisions makers, have lower cognitive fit. Therefore, exploitation, which is based on prior learning of decision makers becomes less efficient in converging to higher payoffs compared to exploration. Exploration is the preferred strategy of response in a moderately volatile environment. The bottom left corner of Figure 14 compares different strategies in moderately volatile environments. However, when the speed of change in the environment increases, firms are not able to cope with the volatility. The rate of their performance improvement is slower than the speed of change in the environment. Therefore, exploration will not yield appropriate payoffs prior to the next change in the landscape. This finding is consistent with the literature (e.g., Claussen et al., 2015; Posen & Levinthal, 2012), which suggests that in an extremely volatile condition, firms need to exploit their available opportunities. The difference between the payoff of exploitation and exploration response strategies is depicted in the bottom right corner of Figure 14.

4.5 Discussion

IORs are situated in a rugged landscape and the performance of IORs is highly dependent on their ability to find a good fit in their landscape. Yet, the cognitive power of firms' decision makers is limited. Therefore, their perception of a problem might deviate from the real problem. Accordingly, analytical methods provide a solution for the perceived problem, not the real problem (Einhorn & Hogarth, 1981). Decision makers who are involved in IORs try to develop mental models of their environment. This mental model is an augmented reality that is the base of decision making for firms. Therefore, it is important for decision makers to improve their cognitive fit and reduce the gap between their mental model and the real world. Subsequently, the higher level of cognitive fit is an important precedent for achieving higher payoff levels in a rugged landscape. Yet, the complexity and dynamism of an environment, coupled with the cognition limits of decision makers, prevent firms from reaching the highest landscape fit. Therefore, firms need to focus their limited analytical resources on the areas with the highest potential payoffs. My study shows that impact of DA on payoff of IORs increases if it is configured vigilantly. Accordingly, my findings identify guidelines for configuring the DA strategy in an IOR environment. These guidelines are discussed in this section and seven propositions are provided accordingly.

The literature suggests that IS capabilities are required for sustaining performance in a volatile landscape (Jarvenpaa & Leidner, 1998). However, the configuration of IS resources should vary across stable and volatile business environments (Wade & Hulland, 2004). The process of adaptation to volatile environments requires identification of potential opportunities and choosing from them. This can be achieved through DA, which facilitates finding business opportunities (e.g., Shanks & Bekmamedova, 2012a). The main challenge of external focus, even if partners seek alignment loyally, is differing views of partners on similar problems due to differences in their organizational knowledge. These differences lead to additional coordination requirements (Santos & Eisenhardt, 2005). Therefore, firms focus internally, where they have authority and control to impose their own views.

My findings suggests that in a stable environment, firms need DA support for exploiting their internal problems (Benner & Tushman, 2003). With an increase in volatility, DA should support exploration of problems with external interactions for improved adaptability. This is aligned with the findings of Nickerson and Silverman (2003), who observe that only firms who were focused on their IORs survived in the trucking industry after deregulation of transportation in the US. This means that those firms with external focuses succeeded as the competition increased in the industry and business landscape became more volatile. However, as the wavy environment becomes stormy (Pavlou & El Sawy, 2010), DA should become focused on exploitation of internal capabilities. The transaction cost economics literature in organizational science supports this argument (c.f., Santos & Eisenhardt, 2005; Sutcliffe & Zaheer, 1998). Organizational scientists argue that the complex organizations in extremely volatile environments seek to reduce their transaction costs by focusing internally through vertical governance, rather than focusing externally through market governance. Managers in such organizations focus on internal decisions to increase their efficiency (Santos & Eisenhardt, 2005). Therefore, I propose that:

Proposition 1: Sensing focus has a U-shaped relationship with environmental dynamism. At the extreme low and high levels of volatility, internal focus yields the highest payoff and moderate volatility requires external focus.

Proposition 2: Response approach has a U-shaped relationship with environmental dynamism. At the extreme low and high levels of volatility, exploitation yields the highest payoff and moderate volatility requires exploration.

DA support decision makers in dealing with complexities of IORs (T. Y. Choi et al., 2001; Trkman et al., 2010). Problem sensing focus imposes decision making costs and communication costs (e.g., Baldwin & Von Hippel, 2011). While internal focus imposes higher decision costs and limits contribution of the selected problem on the payoff, external focus imposes communication costs and may lead to misalignment. Therefore, sensing focus is contingent on specific environmental conditions. The internal focus of decision makers for exploitation yields highest payoffs in lower levels of complexity. As complexity increases, alternative development and decision making become challenging and time-consuming tasks. Therefore, firms are not able to develop and analyze many improvement alternatives. Being limited by the number of available alternatives, firms need to focus their alternative development and selection on areas that have the highest potential payoffs. Due to the rugged landscape in complex environments, working on those aspects of business that have higher interactions lead to more improvement opportunities. Therefore, it is important that DA are focused on exploiting decisions with external interactions for innovative improvements. Accordingly, I propose that:

Proposition 3: Internal focus leads to higher payoff at lower levels of complexity and external focus leads to higher payoff at higher levels of complexity.

These first three propositions, which consider either complexity or volatility, are generally consistent with my presented results in Figure 12. However, complexity and dynamism are interconnected, and business environments are identified with both at the same time. Therefore, it is vital to study the configuration of DA strategy and its impact on payoff by considering the two factors at the same time.

There are few interactions between decisions of IOR partners in a simple and stable business environment. These interactions have characteristics of an "[a]rm's length market relationship" (Dyer & Singh, 1998, p. 661), in which firms are not engaged in mutual investments and their technologies, processes, and functions are independent. Since both internal and external decision groups have a limited number of interactions, it might appear that the focus does not matter. However, focusing externally may lead to interaction between decisions of the two partners. Such interaction might cause inconsistency and negatively impact the payoff due to the delay of communication that is the nature of modular governance.

Due to simplicity of a business environment, any competitive advantage could be easily imitated by competitors. Therefore, maintaining competitive advantage requires flexibility in switching between suppliers. Since focusing externally requires investment in a relationship that may change in the short-term, such focus may lead to lower payoffs. Also, my results support that the response method should be exploitative. In this situation, due to the stability of the business environment, the configuration of DA strategy should be focused on exploiting incremental improvement alternatives for internal decisions. Accordingly, my fourth proposition is:

Proposition 4: DA strategy should be focused on exploitation of internally interrelated decisions for higher payoffs when environment is simple and stable.

My simulation results show that DA strategy needs to support exploitation of external interactions in a complex and stable environment. Externally interrelated problems have higher complexity; and therefore, focus on these operations provide more improvement opportunities. Since the environment is stable, exploiting these improvement opportunities provide the firm with learning opportunities. Decision makers of the firm can improve their cognitive fit of business environment based on the learning process that comes with exploitation. Therefore, decision makers can gradually test and analyze all improvement opportunities through exploitation and find the best configuration of the organization through analysis of its relationship with its partners. This argument is aligned with the strategic management literature, which discusses that focusing on IOR interfaces to complement resources and develop mutual products and services leads to a hard-to-imitate advantage and lower transaction costs (Dyer & Singh, 1998). Therefore, I propose that:

Proposition 5: DA strategy should be focused on exploitation of externally interrelated decisions for higher payoffs in complex and stable environments.

My simulation suggests focussing exploratively on internal problems in a simple but volatile environment. These internal problems are less prone to environmental impacts due to their lower levels of interaction. Therefore, exploring to solve these problems leads to higher levels of landscape fit prior to the next change. A change in the environment has lower impact on these activities compared to decisions with external interactions. However, due to volatility of environments, firms need quick adaptability to the landscape. Therefore, exploration may provide opportunities for faster payoff improvement. Accordingly, a firm can continue to improve its fit to landscape by focusing on these more isolated decisions. This is aligned with the literature. “In dynamic environments, the best-performing organizations are generally more inert than less successful organizations” (Stieglitz et al., 2015). This DA strategy enables the firm to improve the operations that are less prone to volatility and maintain the higher levels of landscape fit for longer periods. Therefore, I propose that:

Proposition 6: DA strategy should be focused on exploration of internally interrelated decisions in simple and volatile environments.

When an environment is highly complex and volatile, decision makers have lower cognitive fit and may not be aware of the structural patterns of interactions. Therefore, focusing on operations with external interactions, due to a rugged environment, provides a higher chance for improvements. Accordingly, a firm needs to focus on exploring their decisions with external interactions. This argument is partially supported by the literature. For instance, literature suggests that when technology is complex and changes rapidly, firms need to work on exploitation rather than exploration (Williamson, 1991). The complexity and change make exploration an extremely challenging task. If a firm choses to explore, the achieved rate of improvement in the payoff will be affected by the changes in the environment and the firm cannot improve its landscape fit significantly prior to the next landscape change. Therefore, it is important that the firm focuses on exploiting its external relationships. Consequently, my seventh proposition is as follows:

Proposition 7: DA strategy should be focused on exploitation of externally interrelated decisions in highly complex and volatile environments.

4.6 Conclusion

I investigate the alignment of DA strategy with IORs' needs by testing various sensing focuses and response approaches in IORs' business environments with various levels of complexity and dynamism. The current literature fails to address the contingency of DA strategy upon complexity and dynamism. Also, the literature does not discuss the sensing-response capabilities that are required for configuration of DA strategy. Therefore, I propose a suitable configuration for sensing and response capabilities for different IORs in various environmental situations to address these gaps in the literature.

My findings provide guidelines for configuration of DA strategy to support IORs. These guidelines, which are presented in the form of seven propositions, resolve discussed inconsistencies in the literature. For instance, my results suggest that while exploitative DA work in stable environments, exploitative DA have higher payoffs in more volatile environments. However, when both volatility and complexity are high, DA should adopt an exploitative response approach. Furthermore, my findings on the sensing focus of DA suggest that firms should focus on their internal operations in lower levels of volatility, and as the volatility increases, the focus should shift to external interactions. Also, my results suggest that at extreme volatile environments, firms should focus on their internally interrelated decisions.

CHAPTER V

IMPLICATIONS, CONTRIBUTIONS, LIMITATIONS AND FUTURE RESEARCH

The aim of this dissertation is to improve our understanding from the role of DA in IORs. Each of the three studies in this dissertation contributed to this understanding from a specific angle. The first study asserts that DA lead to business performance through an improved customer value creation across supply chains. More specifically, the results show that alignment between supplier partnership and market orientation is the key to customer value creation and leads to higher performance. The second study shows the mechanisms through which DA impact interorganizational collaborations and lead to performance. Also, this study shows that explorative strategic focus of DA leads to higher strategic performance outcomes and exploitative strategic focus of DA leads to higher operational performance outcomes. The third study is dedicated to DA strategy for IOR in various business environments. I test various strategies and identify the best configurations of DA strategy for dealing with complexity of IORs in dynamic environments. I will discuss implications, contributions, and limitations of each of the three studies in following sections.

5.1 Implications of Dissertation

The main objective of Study 1 is to investigate the role of DA capabilities on a firm's co-creation of value with its customers and suppliers. The findings support that DA capabilities improve a firm's performance and value co-creation. The findings have several implications for researchers and practitioners. These implications for researchers are related to marketing, OM, and IS. This study incorporates two concepts of market orientation and supplier partnership to develop a value view of a firm's supply chain. This work is aligned with the current literature on the strategic role of supply chain integration (Frohlich & Westbrook, 2001). The topic of supply chain integration through incorporation of SPO and MO is relatively new and is studied by few scholars in OM and marketing literature (Liu, Ke, Kee Wei, & Hua, 2013; Min et al., 2007). I elaborate the integration by incorporating SPO, which is discussed at different levels of integration. Also, I incorporate MO, which gives direction to SPO. The inclusion of MO and SPO and their impact on value co-creation creates a new window for practitioners to analyze and develop the strategy of supply chain.

The theoretical findings of Study 1 provide managers and practitioners with insight on mechanisms through which DA can improve a firm's co-creation of value with its customers and suppliers. Furthermore, it discusses DA capabilities as catalyst for enhanced performance of firms. This research creates a holistic understanding of the value co-creation process in the supply chain. Developing market knowledge and sharing with partners and providing firms with analytical tools to manage their partnerships is key to a successful partnership. My findings suggest that SPO is successful if it is aligned with market needs. In other words, MO provides the insight that is required for dynamic alignment of SPO with real market needs. This alignment sustains competitive advantage and leads to improved performance. Therefore, managers need to consider the two different sides of strategic partnerships, its positive strategic impact and its potential risks. It is important for firms to incorporate MO concepts and use DA tools to keep their partnerships current and minimize the potential risks.

Implications of Study 2 for practitioners are threefold. The first contribution is showing the important paths that lead DA capabilities to improve performance. The list of collaborative practices that could be improved through employment of DA tools is insightful for practitioners. More specifically, the role of DA in coordination of network activities through scheduling and planning of production, service, and projects and its impact on both operational and strategic performance, provides a good starting point for practitioners. The second implication of the study is identification of the importance of the interaction between cooperation and coordination. My results suggest that efficient use of shared resources requires careful coordination, and my first study suggests different practices that could be employed to improve coordination. Finally, the third implication of this research is discussing the strategic focus of DA. Practitioners can achieve their required performance outcomes by incorporating the right focus of DA in their collaborative relationships.

Study 3 has important and insightful implications for practitioners. I identify appropriate configurations for DA strategy in terms of sensing focuses and response approaches that are required in different environments. Employment of a suitable DA configuration improves the return on investment on DA and has a higher impact on the performance of the firm in dealing with complexity and volatility of IORs.

5.2 Contributions

The contributions of this dissertation, through three studies, shed light on the role of DA in improving performance of IORs. I use various theoretical lenses and methodological tools to enrich the literature at the intersection of DA and IOR. The following subsections present contributions of each study.

5.2.1 Contributions of Study 1

Study 1 contributes to the marketing, OM, and IS literatures in several ways. First, this study explores the relationship between "strategic partnership orientation" and "market orientation," as well as their effect on "business performance." Each part of these relationships has been discussed in the literature separately and some studies show inconsistencies and contradicting results. The contribution of this study is proposing an integrated view of these related constructs in the form of value co-creation, which has rarely been discussed before (Holweg & Helo, 2014; D. Kim et al., 2013; Sarker et al., 2012). My proposed model provides a value-view of a firm and its supply chain by focusing on customer value co-creation. The proposed model is tested empirically, and its association with business performance is established.

My second contribution is a discussion of analytics-enabled SCM. The existing literature, which is focused on IT value in supply chains, study the performance implication of IT systems in the context of supply chains. My research is among the first empirical research that investigates the value of DA in SCM. The result proposes that DA-enabled SCM emphasizes customer value creation while it is focused on effective exploitation of resources.

The third contribution is the strategic focus of this study. There are rare but notable publications on the operational impact of business analytics on supply chains (Chae et al., 2014; Trkman et al., 2010). The focus of this study is to explain strategic performance. I incorporate two theoretical views to discuss the impact of different aspects of DA on performance. I discuss the role of shared resources, especially data sources, in gaining competitive advantages based on RBV. Further, I discuss that DA refine data sources and create knowledge sources that are specific to strategies, processes, culture, and customers of the firm. The refined data through DA generates VRINN knowledge resources and leads to competitive advantages for the firm. The drawback of RBV is its inability to consider the occasional need for modification of partnerships due to dynamism of the business environment. To make up for the deficiency of RBV, I employ TCE to bring coordination and alignment as supplements to partnership and shared resources. The TCE supports my arguments through coordination and re-alignment of resources towards customers' needs. My results suggest that firms need a dual focus on SPO and MO to sustain their competitive advantage. The focus of firms on co-creation of value plays a key role in successful supplier partnerships. The co-creation of value enhances the focus of supply chain partners on customers' needs and improves the resource selection. This approach facilitates coordination, increases the alignment of activities towards value creation, and prevents the potential issues that are discussed in the TCE perspective. My study further contributes to OM literature by studying the inconsistencies of findings on the relationship of SPO and performance.

5.2.2 Contributions of Study 2

My second study has several contributions for the business value of IT, IS strategy, and interorganizational relationship literatures. This study contributes to the business value of IT in two ways. First, it shows how DA impact different aspects of business performance through various practices in collaborative relationships. The discussion on this topic is fragmented and anecdotal in the existing literature. My first study provides the necessary elements of this relationship and the impact mechanism. The second contribution is an empirical support of the business value of DA. While the topic is discussed in published scholarly works and the positive association between DA and performance is justified, I addressed the topic in the context of supply chain management. In addition, my study discusses the impact of DA on performance at both the strategic and operational levels.

My contribution to IS strategy literature is the identification of the role of DA strategic focus in business performance. More specifically, I identify instances that DA strategic focus (also change strategy) leads to strategic or operational performance through collaborative practices. My initial analysis shows that an exploitative focus of DA has higher impact on operational performance, as compared to an explorative focus. This impact and operational performance is achieved through enhanced coordination. Also, I find that an explorative focus increases strategic performance outcomes through improved cooperation. I empirically test the findings of my first study in the second study. My empirical results are aligned with my initial study and support the importance of DA strategic focus on different levels of performance.

Finally, my third contribution is to the OM and IT-enabled interorganizational relationship literatures, where my initial analysis provided support for the interaction between cooperation and coordination and impact of DA on the performance of this interaction. I examined my initial findings on the relationship between cooperation and coordination from RBV and TCE theoretical perspectives. Later, I tested the relationship with empirical data. My results suggest that management of interorganizational collaboration requires simultaneous consideration of the two concepts, where cooperation is related to pooling resources and coordination is related to alignment of companies to use shared resources. My results shed light on inconsistent findings in the literature on the impact of partnership on performance. My results also show that DA is an enabler of collaboration and improves firms' performance.

5.2.3 Contributions of Study 3

My third study contributes to the IS literature in four distinct ways. First, this study discusses heterogeneity of collaborative relationships and the importance of DA strategy for an enhanced adaptability. Second, this study addresses the role of DA strategy in dealing with complexity and volatility of IORs in their business environments (McKelvey, B., Tanriverdi, H., and Yoo, 2016). The combination of the two environmental factors is rarely discussed in the IS strategy literature. My findings address inconsistencies of the prior literature by separating complexity and volatility factors and discussing the right DA strategy for each condition. The third contribution of my study is the investigation of the equilibrium in exploration-exploitation balance of ambidexterity, which is not addressed in the IS strategy literature (Lavie, 2006). My findings suggest that ambidexterity leads to higher payoff compared to pure exploration and exploitation. Also, these findings suggest a focus for ambidexterity on exploration or exploitation in each business environment. Finally, the fourth contribution is methodological and is related to development of an agent-based simulation based on an NK model for coordinated and simultaneous search by two agents. This topic has gained attention recently and requires further discussion and research (e.g., Knudsen & Srikanth, 2014). Also, I employ an agent-based simulation in the context of IS. This method, despite the recent recommendations and the extensive need (Merali et al., 2012; W. Oh & Pinsonneault, 2007), is rarely used in the IS literature (Nan, 2011; Nan & Tanriverdi, 2017). All these contributions are vital for our improved understanding about the mechanisms through which DA impact IORs.

5.3 Limitations and Future Research

There are limitations and promises for future research. The first study faces limitations that need to be considered in expanding or using the results. My first limitation stems from my path analysis. The results show a high level of association between DA and business performance. This finding is a contribution by itself. However, it suggests that there are other moderators for the relationship between DA and business performance, which are not considered in my research model. Therefore, further qualitative investigation on the mechanisms through which DA create value would be insightful (Günther et al., 2017; Trieu, 2017).

The second limitation of Study 1 is its focus. The study is focused on the overall impact of DA on a firm's supply chain and its co-creation of value. Future research could help in understanding other important factors in this relationship. For example, the impact of different types of analytical tools, including interpretive, predictive, or prescriptive analytics, needs to be investigated. Also, the technology type and generation of analytical tools that is discussed in Liu et al. (Hsinchun Chen et al., 2012) needs further attention. For instance, the role of social media analytics or sensor-based data collection and analytics are variables that could bring more clarification into the use of DA as a general construct. My recommendation for future research studies is to focus on different types of DA and investigate their role in the performance of supply chains.

The third limitation of Study 1 is its low response rate. There are a number of reasons for this nonresponse rate, including the spam filtering software solutions that do not permit emails to be placed in my potential respondents' inboxes, the hesitation of target respondents to click on an unknown link in their email, and the lengthy questionnaire. Despite low response rate, I took all necessary measures to ensure that nonresponse bias did not impact my collected data.

My second study faces three limitations; and therefore, it offers potential paths for future research. The first limitation of Study 2 is its generic focus on the DA capabilities construct. Based on the findings in my first study, I suggest that researchers focus on each subcategory of DA capabilities, including managerial capability, technical capability, and talent capability and investigate the impact of each category separately.

This focus requires development and testing of appropriate survey instrument and collection of empirical data.

The second limitation of Study 2 is its negligence about factors such as environmental dynamism and complexity. The strategic management literature and the organization science literature consider a profound moderating role for complexity and dynamism in the relationship between collaboration and performance. However, the nature of empirical studies makes it very hard to study all such important moderating factors. Therefore, my suggestion for future studies is the incorporation of a simulation approach. Simulation enables the incorporation of various moderating factors in one study, which leads to identification of different paths for theory development and nourish empirical theory development studies.

Another potential issue of Study 2 that is inherent in survey research, is the inability of the research to accurately measure performance. More specifically, the timeframe for various types of payoffs for collaboration is different (Saxton, 1997), which is hard to capture in a survey research. For instance, an interorganizational collaboration on a research project may lead to a breakthrough and associated performance outcomes after years of mutual work. At the same time, a cooperation on sharing market network resources may lead to performance outcomes in a few months. I tried to incorporate my first study, with case studies that cover a long span of time, as a remedy for this potential problem. My findings in the second study are aligned with the results of my first study, which show that my empirical research can explain the observed situations. Also, I incorporated a wide range of performance indicators to capture the performance outcomes of a firm in its collaboration at different levels. However, a longitudinal study that is based on secondary data sources is very helpful in this situation. Also, a simulation model can deal with some parts of the challenge through adjustment of the length of study and other parameters, such as delay in observed payoff at different levels.

Study 3 faces limitations, which hold opportunities for future research. The first limitation is related to the design and assumptions of my simulation model. These assumptions are affected by the number of incorporated parameters. The limited scope and space for conducting all required tests prevents us from developing a more comprehensive discussion on the DA strategy in IORs. For instance, I considered all the firms to be the same in size and importance. They have the same number of equally important problems and have similar impacts on their supply chain. Furthermore, my focus was the modular governance and I did not investigate more vertical forms of IORs. Future research should consider different sizes, governance mechanisms, more complex organizational structures, and different levels of internal and environmental complexity and dynamism, among other parameters. The second limitation is related to the dependent variable of study. While the focus of this research is on adaptability, there are important variables such as agility and innovativeness that should be studied. Also, this research does not discuss the type of product. Future research should discuss the impact of product diversity on the results. The Third limitation is related to the nature of simulation. Davis et al. (2007) discuss that simulation studies are the link between qualitative studies and empirical research and offer propositions for further empirical tests. Accordingly, the developed insight in my research requires further refinement and justification through empirical studies.

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APPENDIX A

THE BUSINESS VALUE OF DATA ANALYTICS

The existing literature on business value of DA are qualitative or theoretical frameworks that show how DA lead to performance. Some of the published studies directly address the impact of DA on business performance. Other studies identify the potential risks and challenges that may have negative impact on business performance. Most of these publications are focused on single firms and few studies address the impact of DA on supply chains. A brief review of the literature is presented in the following table.

#	Paper	Summary
1	(Seddon et al., 2017)	This literature analysis paper identifies how DA lead to business performance. The paper uses a case survey approach to justify how the identified factors such as data quality, integrated platforms, leadership, and well-chosen targets, create business value.
2	(Ghasemaghaei, Hassanein, & Turel, 2017)	Authors develop and test a research model that identifies how DA lead to firm agility. The results suggest alignment between technological capabilities and talent capabilities is necessary for achieving agility.

#	Paper	Summary
3	(Ghasemaghaei, Ebrahimi, & Hassanein, 2017)	Authors study the impact of DA on the quality of decision making and suggest that data quality, analytical skills, and tools sophistication are among the factors that lead to higher decision quality and efficiency.
4	(Mani, Delgado, Hazen, & Patel, 2017)	Authors employ a case study to discuss the role of DA in reduction of supply chain risks. They justify the impact of DA on sustainability of environment, economy, and society by demonstrating their role in diminishing supply chain risks.
5	(Yu, Chavez, Jacobs, & Feng, 2017)	Authors show how DA-enabled supply chains achieve higher financial performance. They discuss that enhanced coordination and responsiveness are among capabilities that are empowered by DA and lead to higher levels of financial performance.
6	(Roßmann, Canzaniello, von der Gracht, & Hartmann, 2017)	Authors use Delphi method to identify how DA contribute to supply chain management in the future. Authors find that DA support decision makers with more accurate demand forecasting which leads to reduced inventory and enhanced supplier performance.
7	(R D Galliers, Newell, Shanks, & Topi, 2017)	Authors of this editorial take a critical approach to the potential risks and benefits of DA based algorithmic approaches to decision making and discuss it at different levels including organizations.

#	Paper	Summary
8	(Erevelles, Fukawa, & Swayne, 2016)	Authors develop a framework to show how analysis of consumer data leads to value creation. They discuss that value creation is through development of dynamic and adaptive capabilities, through which firms gain sustainable competitive advantage.
9	(T.-M. Choi, 2016)	This paper employs a mathematical model to identify the importance of social media analysis in improvement of response time of fashion supply chain. Accordingly, authors suggest that analysis of social media comments are beneficial for manufacturers.
10	(Popovič, Hackney, Tassabehji, & Castelli, 2016)	This research studies the mechanism that DA lead to business performance. Authors discuss that DA improve performance of manufacturing firms through affecting organizational readiness and design.
11	(Shollo & Galliers, 2016)	This paper synthesizes the literature to identify how DA support decision makers at different levels of organization and supports its findings with qualitative empirical data.
12	(Clarke, 2016)	Authors are focused on risks of DA, rather than opportunities that it may provide. This paper identifies important legal and moral responsibilities of firms that need to be considered to avoid potential risks of DA.

#	Paper	Summary
13	(Kowalczyk & Buxmann, 2015)	This study identifies challenges of decision making and discusses important and required strategies for DA to manage these challenges. Authors discuss ambidexterity as a resolution to the challenges of decision making, which leads to higher decision quality.
14	(D. Q. Chen et al., 2015)	This study is focused on understanding of how DA lead to value creation in supply chain by identification of antecedents of DA. Authors employ a survey method to justify the impact of DA on the value creation process. The paper studies the moderating impact of environmental turbulence on the relationship between DA and value creation and provide guidelines for an enhanced utilization of DA capabilities.
15	(Tambe, 2014)	Author uses DA technical knowledge of human resources and justifies the impact of this capability on the performance of the firm, using secondary data sources.

#	Paper	Summary
16	(Sharma, Mithas, & Kankanhalli, 2014)	Authors challenge the idea that investment in DA leads to higher performance in this editorial. They discuss understanding the impact of DA on organization requires improved understanding of how firms allocate their resources and create harmony between allocated resources. More specifically, authors discuss that DA impact on organizational performance is mediated by enhanced decision making.
17	(Işık, Jones, & Sidorova, 2013)	The paper uses a survey research to justify the importance of technological capabilities such as quality of the available data, ability of employees to use the required analytics, and integrated DA platforms are required for enhanced decision making in the firm.
18	(Lycett, 2013)	In this editorial, author broadly discusses how DA impact industry through review of data infrastructure, applications, tools, and best practices that are needed for effective data analysis for an informed decision making.

APPENDIX B

SURVEY INSTRUMENT FOR STUDY 1

Item	Measure (question)	Mean	Std. Dev.	Standardized Measures	t-Values
Please indicate the extent to which you agree or disagree with each statement as the statement relates to your company's business practices (1 – strongly disagree, 7 – strongly agree).					
Business Intelligence and Analytics Capabilities					
DA1	Our top management supports business analytics and its applications at all levels in our organization	4.99	1.224	0.74	-*
DA2	We actively invest in analytics technology, new talent and training	5.05	1.128	0.78	11.07
DA3	My organization identifies and employs appropriate analytics tools	4.90	1.162	0.74	10.36
DA4	If we reduced our analytics activities, then my organization's performance would suffer	4.70	1.333	0.87	12.34
DA5	Using business analytics improves our ability to meet our customers' needs	4.89	1.240	0.85	12.03
DA6	Our organization uses analytics based insights to support decisions at different organizational levels	5.25	1.168	0.81	11.50
Strategic Partnership Orientation:					
SPO1	We are committed to a long-term supplier relationship policy	4.60	1.527	0.87	-*
SPO2	We work jointly with our suppliers and partners in problem solving to improve performance	4.41	1.538	0.80	14.12
SPO3	Sales and marketing goal settings are done in collaboration with our suppliers and partners	4.57	1.437	0.93	18.69
SPO4	Our intra-organizational processes are integrated with suppliers and partners	4.25	1.530	0.86	16.18
SPO5	We share needed supply chain information with our suppliers and partners	4.38	1.461	0.80	14.28
Market orientation:					
MO1	My organization has a strong commitment to its customers	5.43	1.043	0.87	-*
MO2	My organization always looks for ways to increase customer value through development of new products and services	5.21	1.173	0.78	13.46
MO3	We regularly monitor our competitors' marketing efforts	5.43	1.121	0.86	15.75
MO4	We frequently collect marketing data on our competitors to help direct our development and marketing plans	5.28	1.046	0.80	14.19
MO5	In my organization people from various departments contribute to the development of new products and/or services	5.21	1.100	0.76	12.97
To the best of your knowledge, how would you rate your company's performance over the last three years in each of the following areas as compared to the industry average (1 – well below industry average, 7 – well above industry average).					
Business Performance:					
BP1	Return on investment	5.22	1.088	0.76	-*
BP2	Profit	5.25	0.978	0.73	11.01
BP3	Profit growth	5.31	0.981	0.73	11.08
BP4	Return on sales	5.22	0.975	0.82	11.68
BP5	Sales volume growth	5.30	0.967	0.80	10.95

APPENDIX C

LIST OF CASE STUDIES FOR STUDY 2

#	Name	# of Paths to Performance
1	Baosteel	7
2	Canadian Pacific Railway	3
3	Chevron	10
4	Coca-Cola Enterprises	4
5	Compañía Sud Americana de Vapores (CSAV)	12
6	CSX Railway	13
7	Dell	8
8	Federal Aviation Administration (FAA)	10
9	Fluor Corporation	6
10	GE Plastics	1
11	Hewlett-Packard*	5
12	Hewlett-Packard	18
13	IBM Microelectronics	4
14	IBM Personal Systems Group	24
15	Intel Corporation	8
16	Jeppesen Sanderson	4
17	John Deere	4
18	Mars	8
19	McKesson	8
20	Motorola Corporation	2
21	Omya Hustadmarmor	5
22	Philips Electronics	10
23	Procter & Gamble**	4
24	Procter & Gamble	7
25	Samsung	2
26	Schindler Elevator	4
27	Spicer Off-Highway Products Division	3
28	Swift & Company	7
29	Syngenta	4
30	TNT Express	3
31	United Parcel Service (UPS)	3
32	Visteon Chassis Systems	2
33	Warner Robins Air Logistics Complex	3
34	Xerox	16
	Total	**198**

* Two different case studies discuss Hewlett-Packard, one from supply risk management (#11 with 5 instances) perspective, and the other from product portfolio management perspective (#12 with 18 instances).

** Two different case studies discuss Procter & Gamble, one is focused on purchasing processes (#23 with 4 instances) and the other focused on inventory management (#24 with 7 instances).

APPENDIX D

CATEGORIES FOR STUDY 2

An Abstract Organization of Identified Themes, Categories, and Subcategories.

Themes	Category	Subcategory	# Instances
DA Capabilities	Management Capability	DA Development Capability (planning)	1
	Talent Capability	Technical knowledge of analytical tools	131
		Training employee to use DA systems	3
		Use of organizational knowledge	12
	Technology Capability	Data integration infrastructure	27
		Processes to embed DA in routines	11
		Visualization and reporting of the intelligence	13
Collaboration	Cooperation	Long Term Investment	5
		Share Risks and Gains	9
		Supplier selection	20
	Coordination	Alignment of expectations	18
		Collaborative business process/working system development	10
		Collaborative inventory management	9
		Collaborative product/Product basket development	19
		Collaborative production/service/project planning/scheduling	89
		Communication for improved use of resources	3
		Communication for resolution of ambiguities	3
		Communication of decisions and plans	2
		Contract design	9
		Sharing information	2
Performance	Operational	Improving Production/Service Processes	11
		Improved Customer Service	16
		Efficient Internal Processes	9
		Increased Labor Productivity	9
		Improved Inventory Management	14
		Reduced Operating Costs	10
	Strategic	increased ROI	10
		Reduced Costs	47
		Reduced working capital	14
		Improved Decision Making	5
		Increased Revenue	15
		Better perception of business environment	2
		Increased stock value	3
		Well Response to Environmental Changes	8
		Increased market share	2
		Well Response to Competitors Activities	5
		Increased Profits	7
		Reduced supply risks	3

	Social Responsibility	Community services	2
		Environmental Sustainability	6
		Total	198

APPENDIX E

SURVEY INSTRUMENT FOR STUDY 2

ID	Survey Item	Mean	SD	Standardized measures	t-Values
Please indicate the extent to which you agree or disagree with each statement as the statement relates to your company's business practices (1 – strongly disagree, 7 – strongly agree). Data Analytics (DA)					
DA1	Our top management supports business analytics and its applications at all levels in our organization.	5.57	1.09	0.84	-*
DA2	My organization identifies and employs appropriate analytics tools.	5.58	1.28	0.73	11.84
DA3	My organization uses both business analytics results and management experience when addressing key business issues.	5.09	1.63	0.85	14.63
DA4	We use advanced and precise methods in business decision making.	5.18	1.65	0.72	11.57
DA5	In my organization data is treated as a core asset.	5.16	1.12	0.69	11.04
Cooperation					
CP1	My organization actively promotes exchange of information with our supply chain partners.	5.79	1.21	0.70	-*
CP2	My organization seeks to develop long-term collaborative relationships with supply chain partners.	5.97	0.98	0.75	9.05
CP3	My organization equitably shares risks, costs, and gains from improvement initiatives with its supply chain partners.	5.31	0.98	0.69	8.45
CP4	We are committed to a long-term supplier relationship policy.	5.32	1.01	0.69	8.53
Coordination					
CR1	We work jointly with our suppliers and partners in problem solving to improve performance.	5.90	1.07	0.80	-*
CR2	Sales and marketing goal settings are done in collaboration with our suppliers and partners.	5.75	1.07	0.82	12.68
CR3	Our intra-organizational processes are integrated with suppliers and partners.	5.12	1.32	0.64	9.41
CR4	We share our chain analytics results with our suppliers and partners.	5.00	1.20	0.77	11.70
To the best of your knowledge, how would you rate your company's performance over the last three years in each of the following areas as compared to the industry average (1 – well below industry average, 7 – well above industry average). Operational Performance					
OP1	Our inventory levels are decreasing.	5.35	1.23	0.85	-*
OP2	Our operational costs are reducing.	5.64	1.36	0.91	17.49
OP3	Our customer service is improving.	5.22	1.25	0.91	17.46
OP4	Our internal processes are efficient in terms of time and cost.	5.23	1.05	0.71	11.87
Strategic Performance					
SP1	Profit growth	5.49	0.93	0.77	-*

SP2	Market share growth	5.34	0.92	0.83	11.22
SP3	Return on investment	5.37	1.03	0.79	10.90
* The parameter was fixed at 1.0					