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IMPACTS OF FIRM PERFORMANCE ON IT ADOPTION DECISIONS: INSTITUTIONALIZATION OF BUSINESS INTELLIGENCE AND ANALYTICS

Abstract

IT innovations are key to public firms' competitive advantage, even survival. We investigated the diffusion of a novel IT innovation – Business Intelligence and Analytics (BI&A) from a performance feedback perspective. We examined how decision-makers of underperforming firms engage with BI&A in response to performance shortfalls relative to aspirations. This important antecedent from the performance feedback perspective has been overlooked in IT innovation diffusion literature. Drawing upon Behavioral Theory of the Firm (BTOF), Strategic Reference Point Theory (SRPT), and social comparison theory (SCT), we argue that firms' performance relative to historical and social aspirations is a salient antecedent in firms' decisions to engage with IT innovations. Specifically, we hypothesize that radicalness of BI&A that firms engage with is driven more by social aspiration gap than by historical aspiration gaps; diversity of BI&A is driven more by historical aspiration gap than by social aspiration gaps. In addition, we examine the potential decoupling issue and argue that social aspiration gaps have stronger impacts on informational and material engagement than do material engagement; social aspiration gaps have stronger impacts on informational engagement than on material engagement. Using an institutionalization framework, we also argue that the relationships are stronger in the early BI&A diffusion stage than in the later diffusion stage. We use data from multiple archival sources (*CITDB, COMPUSTAT, EDGAR, ABI/INFORM, FACTIVA, CONGRESS.GOV, etc.*), to develop a longitudinal sample of 3,311 firm-year observations between 2010 and 2015. Our hypotheses are generally supported. In particular, we found that underperforming firms tend to engage with more radical BI&A; we did not observe

the diversity of BI&A is driven by either historical or social aspirations. Regarding decoupling, we found that social aspiration gaps do not exert significantly higher impacts on firms' engagement with BI&A than do historical aspirations. Instead, contrary to our prediction that informational engagement with BI&A reacts more to performance shortfalls relative to social aspiration gaps than would material engagement, we found that materially engaging with BI&A matter more to decision makers, extending the decoupling research – i.e., firms commit to the use of BI&A (doing things) rather than announcing it (saying). Regarding institutionalization of BI&A, we observed that these relationships between performance shortfalls and BI&A diffusion patterning are stronger in the early BI&A diffusion stage than in later BI&A diffusion stage.

Chapter 1: Introduction

IT innovation diffusion research has been nurtured by two dominant paradigms: economic rationality and institutional forces (Fichman 2004a). The economic-rationalistic paradigm emphasizes the significance of factors internal to organizations (e.g., firm size, IT governance structure, knowledge barriers). This paradigm assumes that decision makers make adoption decisions of IT innovation in a rational way; that is, decision makers assess costs and benefits of different strategic options and thus their choice made reflects utility-maximizing calculations (Coleman 1990). In contrast, the institutional forces paradigm emphasizes the salient role of factors external to firms (e.g., normative and competitive pressures) in influencing decision makers' IT innovation adoption decisions. This paradigm suggests that decision makers respond to social pressures external to focal firms, without or limitedly reflecting on their firm's own needs and interests.

In IT innovation diffusion research, the two paradigms are often assumed to be competing, and thus antecedents of IT innovation diffusion are examined within each paradigm separately. Rich understanding of the IT innovation adoption decision from either of the two paradigms alone is gained. However, when viewing the two paradigms from the conceptual lens of institutionalization of organizational practices (Tolbert and Zucker 1983; Zucker 1977; Zucker 1983), the two dominant paradigms should not be viewed mutually exclusive, but rather be viewed as compatible and complementary. Specifically, we argue that the economic rationality paradigm and institutional forces paradigm lie at two ends of a continuum of understanding how IT innovation adoption decisions are made – that is, the influence of institutionalization on decision makers' choices changes along the continuum over time, with economic rationality paradigm located on the left end exposed under weak institutionalization effects, and institutional forces paradigm located on the right end exposed under stronger institutionalization effects.

Further, two disparate approaches underlie the institutionalization: the environment-as-institution (e.g., DiMaggio and Powell 1983; Meyer and Rowan 1977) and the organization-as-institution approach (e.g., Selznick 1949; Zucker 1983). First, the organization-as-institution approach theorizes the source of institutionalization as *within organizations* and *from peer organizations*, whereas environment-as-institution approach theorizes the source of institutionalization as *external to organizations* (Zucker 1987). Second, the organization-as-institution approach theorizes that the motif of institutionalization is "meaning creation of new cultural elements at the organizational level", whereas environment-as-institution approach theorizes that the motif is the "reproduction of system-wide social facts on the organizational level" (Zucker 1987, p. 444). Due to the different sources and motifs, the consequences of the institutionalization from the two theoretical approaches are theorized differently, with the former emphasizing task-related efficiency depending on alternatives and the latter emphasizing decoupling from technical core (Zucker 1987).

While the environment-as-institution perspective has been examined in the IS research (e.g., Hsu et al. 2012), organization-as-institution view has not been addressed in IT innovation diffusion literature using the institutional paradigm. Moreover, although the positive impacts of IT innovations on firm performance have been well observed (Wang 2010; Zhu and Kraemer 2005), how performance feeds back to affect firms' decisions to engage with IT innovation remains unclear.

To address this gap, drawing upon the behavioral theory of the firm, social comparison theory, and strategic reference point theory, this dissertation first argues that relative firm performance (performance relative to other related firms and performance relative to the firm's own history) is an important aspect of a firm's institutional context that shapes its choices: this relative performance serves as a salient input in influencing how firms choose different engagement strategies of IT innovations (informational and material engagement with focal innovations). Different from the conventional two paradigms of IT innovation diffusion research, where either firm-specific internal factors or external institutional forces outside firms are examined alone (Fichman 2004a), the Behavioral Theory of the Firm (BTOF) attends simultaneously to both internal workings of firms and external environment (Argote and Greve 2007). A key theme of the BTOF is the mechanism of the "feedback-react" decision-making process – i.e., organizational response to external feedback in terms of feedback from peers and from the focal firm's past history (Mahoney 2004, p. 37). This environment-to-organization influence not only reflects aspects of the institutional forces paradigm, but also incorporates the mechanism of its consequences (problem-stimulated search for solutions). Furthermore, BTOF is a cognitive perspective. Unlike the rational choice models, BTOF addresses decision makers' cognitions about *other* aspects of the firm and its environment that shape its decision making about the focal IT innovations. This comprehensiveness allows for an integrated view of how firms' strategies of engaging with IT innovations are made in the presence of both forces. Second, this dissertation proposes that at an early diffusion stage, institutional pressures emanating within the organization prevail, whereas at later stages, pressures emanating from organizations' environments prevail. Third, this dissertation conceptually and empirically distinguishes between firms' choices to materially engage – i.e., invest in –versus informationally engage – i.e., talk about – the IT innovation, and consider the disparate effects of relative performance on these two types of engagement.

The objective of the dissertation is to examine how a firm's institutional context –

constituted by its relative performance – influences its technology adoption decision-making. Specifically, we attempt to answer the following research questions:

Research Question 1: To what extent does relative performance affect a firm's choice of IT innovation engagement strategies?

Research Question 2: To what extent does relative performance influence patterning of engagement with an IT innovation?

Research Question 3: How does relative performance affect firms' engagement with an IT innovation over time (i.e., at early and late diffusion stages)?

The context of this study is Business Intelligence and Analytics (BI&A) technologies, a set of functionally related technologies aimed at helping managers to make evidence-based decisions. The time frame investigated - 2010 to 2015 - is chosen based on Gartner's Hype Cycle, where 2010 was the inception point of big data, and 2015 the year by which big data was adopted by most Fortune 1000 firms. To better observe the BI&A diffusion, sample firms were drawn from the manufacturing and wholesale/retail sectors, two of the earliest sectors engaging with BI&A technologies (Davenport and Harris 2017). Using data from multiple archival sources (*CITDB, COMPUSTAT, EDGAR, ABI/INFORM, FACTIVA, CONGRESS.GOV, etc.*), we developed a longitudinal sample of 3,311 firm-year observations for 558 unique firms between 2010 and 2015.

Our hypotheses about the role of firm performance in adoption decision-making generally are supported. In particular, we found that underperforming firms tend to engage with more radical BI&A; we did not observe the diversity of BI&A is driven by either historical or social aspirations. Regarding decoupling, we found that social aspiration gaps do not exert significantly higher impacts on firms' engagement with BI&A. However, contrary to our prediction that informational engagement with BI&A reacts more to performance shortfalls relative to social aspiration gaps than would material engagement, we found that materially engaging with BI&A matter more to decision makers, extending the decoupling research – i.e., firms commit to the use of BI&A (doing things) rather than announcing it (saying). Regarding institutionalization of BI&A, we observed that these relationships between performance shortfalls and BI&A diffusion patterning are stronger in the early BI&A diffusion stage than in later BI&A diffusion stage.

Our research makes three theoretical contributions to IT innovation diffusion, performance feedback and institutionalization literatures. First, we contribute to the rich IT innovation diffusion literature by introducing a new antecedent (i.e., historical and social aspirations) of diffusion of IT innovations. Adding new antecedents is considered a salient contribution to a mature literature (Edmondson and McManus 2007).[1] Second, we contribute to the performance feedback literature by examining the relative impacts of the historical and social aspirations on BI&A engagement behaviors and offer nuanced and counter-intuitive insights. Moreover, we challenged BTOF by finding that decision-makers of underperforming firms tend to look broader than to focus on a narrow scope of peers in the BI&A diffusion context. Third, we found support for the institutionalization of BI&A – i.e., BI&A become more legitimate over time and thus bandwagon effects prevail. However, under the institutional pressure in the BI&A diffusion context, our results found evidence that decision makers make commitment (concrete actions) rather than do the window dressing. We observed an alternative manifestation of policy-practice decoupling – i.e., firms tend to materially engage with BI&A rather than informationally do it, different from conventional policy-practice decoupling in which informational engagement

[1] Methodology-wise, we developed a new text-based measure for construct radicalness, complementary to the currently dominant survey-based measure (Carlo et al. 2012).

predominates over material engagement (Westphal and Zajac 2001). Last, we also contributed to the growing knowledge about BI&A diffusion.

In the next chapter, we begin with a review of related literatures. In chapter 3, research model and hypotheses are developed. Chapter 4 describes methods. Chapter 5 reports the results of hypothesis testing. Chapter 6 discusses key findings, contributions and limitations.

Chapter 2: Literature Review

As the main objective of the dissertation is to examine how firms respond to performance shortfalls through engaging with a novel IT innovation, we began with a review of the IT innovation diffusion literature. Next, we briefly reviewed two forms of IT innovation engagement strategies that firms use, which serve as two dependent variables. Following this, we reviewed BI&A literature, with an aim to identify how BI&A differs from other IT innovations. Finally, we reviewed the theories we drew upon to understand why and how firms are motivated to respond to the performance shortfalls.

Two Paradigms in IT Innovation Diffusion Research

The dominant economic-rationalistic paradigm underlying IT innovation adoption examines adoption in relation to innovation-related capabilities (Fichman 2004a). In an early meta-analysis of this line of research, Damanpour (1991) reported a stable relationship between organizational factors (e.g., technical knowledge resources, slack resources, and centralization) and *organizational* innovations (rate of adoption of innovations and organizational innovativeness); that is, firms possessing greater technical knowledge resources, slack resources, and/or a decentralized governance structure will exhibit more extensive adoption of technologies. In this paradigm, firms that adopt IT innovations are rational agents, who fully assess the pros and cons of a focal technology before adopting it, evaluating their needs, then and assessing the alignment between the technology and the firms' capabilities. This paradigm neglects the role of external forces in IT adoption (e.g., Gosain, 2004; Pennings & Harianto, 1992). A more recent meta-analysis by Jeyaraj et al. (2006) examined a more comprehensive list of predictors and in the meantime focused exclusively on the adoption of *IT* innovations published between 1992 and 2003. They showed that among many factors affecting firms' adoption decisions of IT innovation, top management support, external pressures (e.g., from suppliers, industry standards), professionalism (IS unit), and external information sources turn out to be the most stable independent variables of predictive power for the adoption of IT innovations by organizations. This suggests that factors external to organizations, such as external pressures and external information sources, must be considered in influencing adoption decisions of IT innovations.

The second major paradigm in IT innovation adoption literature – the institutional paradigm — is gaining momentum. This paradigm assumes that, in addition to attributes of the focal technology and organization, firms' adoption and implementation decisions are influenced by factors in their institutional environment (Swanson 2012). For example, Hsu et al. (2012) found that institutional forces (both peer influence and supervisory authority influence) exert significant impacts on firms' adoption and assimilation of an administrative innovation in South Korea. Miranda and Kim (2006) found that institutional contexts mitigate organizations' application of a transaction cost logic when deciding to adopt IT outsourcing. Institutional pressures were also observed in a survey of Chinese firms that had implemented ERP, confirming that mimetic and coercive pressures (two types of institutional forces) contributed to post-implementation engagement with ERP systems (Liang et al. 2007). The assumptions, diffusion antecedents, and drawbacks of the two dominant paradigms in IT innovation diffusion are summarized in the Table A1 in Appendix A.

A related perspective on the role of institutional environments is organizing vision theory. Organizing vision is a community's understanding of an IT innovation (Swanson and Ramiller 1997). Organizing vision theory allows that prospective adopters do not make fully rational adoption decisions (Swanson and Ramiller 2004). Instead, as an institutional force, the organizing vision evolves, shapes, and is shaped by a community of members and focal technology. This organizing vision influences the adoption decision of focal IT innovation (Wang and Ramiller 2009). Under some circumstances, even if the focal technology does not match the needs or specificities for the prospective firm adopters, firms may still adopt and implement it. These sub-rational actions could be partly due to executives' intent to be perceived as an innovators (Swanson 2012) or to gain organizational legitimacy (Wang 2010). In other cases, firms simply jump on the innovation bandwagon by following what early adopting firms did mindlessly, especially when adopting firms perceive high levels of uncertainties (Swanson and Ramiller 2004). Organizing vision perspective echoes core tenets of institutional force paradigm by emphasizing the role of external sources outside adopting organizations. Yet, organizing vision perspective does not open the door to investigating diffusion from an institution-as-organization perspective in that little is explicated on the mechanism of adoption units' internal processes and their corresponding peers.

Forms of IT Engagement

The IT innovation diffusion literature has distinguished between informational and material engagement (Miranda et al. 2012; Wang 2010; Wang and Ramiller 2009). *Informational engagement* refers to organizational participation in discourse about the technologies before or without actually purchasing the focal technologies (Miranda et al. 2012; Wang and Ramiller 2009). For example, a firm's announcement of their plan to engage with Microsoft Azure in the next quarter is a form of informational engagement. Similarly, a firm's announcement of their participation in a BI&A workshop is also a form of informational engagement. *Material engagement* refers "to the adoption, implementation, and utilization of the IT" (Wang 2010, p. 66). A firm's actual purchase or use of BI&A represent their material engagement. Informational engagement permits firms to learn vicariously from the community, while material engagement requires learning-by-doing (Wang and Ramiller 2009).

The notion of symbolic versus substantive engagement parallels concepts of informational versus material engagement (Angst et al. 2017; Meyer and Rowan 1977; Westphal and Zajac 1994). Both informational and symbolic engagement reflect low-level commitment in terms of invested resources, while substantive and material engagement reflect a high-level of commitment. However, symbolic/ substantive engagement has a different connotation than informational/material engagement with respect to the underlying motives conceptualized. Symbolic/substantive engagement reflects a decoupling between means and ends, referring to the situations where actions are either unimplemented or actions are implemented but the intended outcomes are uncertain (Bromley and Powell 2012). In this sense, symbolic adoption is often considered a window dressing strategy aimed at enhancing legitimacy. In contrast, informational/material engagement designate potentially parallel or sequential forms of engagement with the technology without reference to institutional pressure. Given the association between the two related notions of organizational engagement with IT innovation and the difficulty of using archival data (e.g., press releases, shareholder letters) to directly measure decision makers' motives, we focus on informational/material engagement with technologies, rather than symbolic/substantive engagement.

Business Intelligence and Analytics (BI&A)

Business Intelligence and analytics (BI&A) is an umbrella term that describes a set of concepts and methods for improving evidence-based decision making (Trieu 2017). BI&A is defined as "the techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data to help an enterprise better understand its business and market and make timely business decisions" (Chen et al. 2012, p. 1166). According to Chen et al. (2012), BI&A evolves from BI&A 1.0, to BI&A 2.0, and to BI&A 3.0 in terms of agility and sophistication level, with BI&A 3.0 exhibiting the highest level of agility and statistical sophistication. Specifically, BI&A 1.0 is DBMS-based and can only handle structured data; BI&A 2.0 is web-based and can handle unstructured data; BI&A 3.0 is mobile and sensor-based and can handle both structured and unstructured data. BI&A is comprised of three layers: decision time, techniques, and analytics (Goes 2014). Embodied in the form of descriptive, predictive, prescriptive, and autonomous analytics (Davenport and Harris 2017), the analytics layer is the one most closely linked to decision making (Goes 2014). One overarching goal of BI&A is to enhance organizational decision making by knowledge workers such as executives, managers, data scientists and analysts (Chaudhuri et al. 2011).

No single technology can cover the full spectrum of BI&A technologies (Watson 2009). However, several different complementary types of BI&A technologies together serve companies to gain business insights. Data management and integration tools and BI platforms (e.g., NoSQL data store or Hadoop/Spark) help firms "get data in," and advanced data science tools (e.g., RapidMiner) help firms to "get data out" (Watson 2009; Watson 2011). An early version the concept of BI&A is *Business Intelligence*, which refers to "a broad category of applications, technologies, and processes for gathering, storing, accessing, and analyzing data to help business users make better decisions" (Watson 2009, p. 491). A closely related concept is *analytics,* which refers to "the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions" (Davenport and Harris 2017, p. 25). Business intelligence strives to leverage the explosion and complexity of data, and the analytics seek to "provide insights and understandings not previously obtainable" (Swanson 2017, p. 16). Business intelligence and analytics are tangled and inseparable (Watson 2014).

BI&A technologies are less decentralizable (Miranda et al. 2015a; Yeoh and Popovič 2016). Unlike more decentralizable technologies (e.g., social media) where adoption and use decision are generally in the hands of organizational sub units (Miranda et al. 2015a), decisions of adopting and using BI&A need to go through more centralized decision making processes. The adoption and implementation of BI&A require high-level financial resources, and the complementary resources such as data scientists, and supporting platforms on which BI&A technologies operate (Miranda et al. 2015a). Moreover, BI&A technologies are key to organizational strategies and business performance (Davenport and Harris 2017). The adoption and use of BI&A may involve a drastic change in firms' business model (Davenport 2017). All these imply that adoption and use of BI&A is effortful, needs significant managerial attention.

Research suggests that business performance is positively related to its level of engagement with BI&A technologies, and there exists a strong consensus about the importance of BI&A in improving business performance (Simchi-Levi et al. 2017; Trieu 2017). Analytic ability becomes firms' core ability to outperform its competitors and maintain competitive advantages (Davenport and Harris 2017). In fact, many organizations have reaped benefits of adopting and use BI&A. A recent survey targeting C-level executive from Fortune 1000 firms revealed that firms are gaining measurable business benefits from investing big data technologies (2017). For instance, nearly half of the surveyed decision makers from Fortune 1000 firms observed decrease in expenses, and new avenues for innovations. Given that data volumes, sources, types continue to grow rapidly (McAfee et al. 2012), big data is not a transient issue that firms have to face tentatively. It is certain that data is increasingly omnipresent. Plus, data is increasingly considered a key asset (Kiron 2017; Short and Todd 2017). Thus, business intelligence and analytics technologies are worth investigating. We focus on BI&A technologies from the year 2010 to 2015 in that big data first appeared in Gartner's Hype Cycle emerging technologies in 2011 (Fenn and LeHong 2011), and moved off from Hype Cycle emerging technologies in 2015 (Burton and Walker 2015).

BI&A Definition, characteristics, and role are summarized in Table A2 in Appendix A.

Cognitive Foundations of Firms' Performance Feedback

The Behavioral Theory of the Firm (BTOF) provides a useful theoretical foundation for conceptualizing IT innovation diffusion. First, BTOF attends to both internal workings of firms and external environment simultaneously (Argote & Greve, 2007), providing a more complete picture of IT innovation decisions. Second, organizational impacts of adopting IT innovations have been widely discussed (e.g., Chen et al. 2015; Zhu and Kraemer 2005). For example, Zhu and Kraemer (2005) found a significant positive relationship between organizational use of e-business and firm performance for both developed and developing countries (e.g., increased sales, improved internal operation, and procurement). Similarly, the use of big data analytics is found to significantly improve business growth and asset productivity (Chen et al. 2015). In general, adoption and use of an IT innovation appears to improve firm performance. However, whether or to what extent performance affects the adoption of focal innovation is unclear. A key theme of BTOF is the mechanism of the feedback-react decision making process – i.e., organizational response to external feedback in terms of feedback from peers and from the focal firm's past history. This environment-to-organization influence not only reflects aspects of the institutional forces paradigm, but also incorporates the mechanism of its consequences (problem stimulated search for solutions). That is, the reverse causality is worth investigating.

BTOF is a theory of why and how firms make strategic choices (Cyert and March 1963). Unlike other macro-level theories (e.g., resource-based view), BTOF incorporates psychological decision-making processes, thus opening the black box of strategic decision-making in pursuit of organizational goals. It permits of the bounded rationality of organizational actors and their reliance on incomplete information (Gavetti et al., 2012). The bounded rationality-based decision making process may lead managers to focus on a limited number of alternatives and consequences (e.g., heuristic cues or specific problems) (Simon 1978). As such, decision makers are partial information processors and tend to use heuristics.

When problems arise, decision makers must search for solutions. If firms experience performance shortfalls, problem-directed search is activated to achieve aspirational levels. This performance feedback plays a central role in BTOF as it depicts the antecedents that triggered organizational responses. Literature on performance feedback has documented supporting evidence on this proposition. For example, strategy researchers observed that performance feedback drives multi-level strategic changes within firms. At the firm level, strategic changes can be made in the forms of adopting new and dropping existing technologies (Ketchen and Palmer 1999), and acquisitions (Kuusela et al. 2017).

According to Cyert and March (1963), a firm's aspiration levels in a particular time period are determined by three factors: past goals, the firm's own past performance, and the past performance of other comparable firms. A firm's own past performance and the past performance of other comparable firms are also termed as historical and social aspiration, respectively (Argote and Greve 2007; Gavetti et al. 2012). Historical aspiration refers to the aspiration in which a firm compares its current target performance with that of previous years. This historical comparison occurs within a firm. According to organizational learning theory (Levitt & March, 1988), organizational learning is history-dependent – i.e., firms learn from past direct experience and transfer its history to routines that guide its future behaviors. In this sense, historical aspiration not only enables a firm's decision makers to evaluate how good or bad its current target performance (e.g., overall financial performance, innovation performance, reputation rating) is in comparison to previous years, but also allows decision makers of the firm to make causal attributions regarding its past strategic actions and develop its subsequent corresponding organizational responses. Social aspiration refers to other comparable firms' past performance concerning the goal dimensions (Argote and Greve 2007; Cyert and March 1963). This social comparison occurs between firms (Cyert & March, 1963). Similarly, organization learning theory also speaks to the social aspiration, which is termed as vicarious learning, a second-hand experience gained by observing similar firms' behaviors. Park (2007) applied BTOF in strategic positioning research and investigated whether firm move close to or away from target firms regarding strategic position. He found that social aspiration significantly affects a firm's strategic positioning.

Porter (1978) advanced the concept of strategic groups as firms' competitors. Drawing upon prospect theory, Fiegenbaum (1996) proposed similar firms' behaviors serve as benchmarks for a focal firm's strategic action. Firms tend to be risk averse when perceiving themselves better than these strategic reference points (SRP) and tend to take risks when perceiving themselves worse than SRP. Rooted in strategic groups literature, strategic reference point theory (SRPT) provides similar insights into organizational decision-making processes and social comparison mechanisms. Strategic groups refer to a set of firms following similar strategies within the same industry (Peteraf and Shanley 1997; Porter 1979). For example, Walmart is more likely to make strategic moves in comparison with other retailing giants like Target or Costco than with technology giants like Google or Microsoft. SRPT posits that strategic groups serve as a reference point for members to make strategic decisions and adjust their strategic behaviors (Fiegenbaum and Thomas 1995). A firm's strategic reference point (SRP) has three sub-dimensions: internal (strategic inputs and outputs), external (competitors, customers, and stakeholders), and temporal dimensions (past and future). The three sub-dimensions are not mutually exclusive. Instead, a firm's SRP is simultaneously determined by the three dimensions (Shoham and Fiegenbaum 2002). A firm assesses its performance based on multiple sub-dimensions. In other words, decision makers may use multiple reference points anytime. For instance, comparison of financial performance between the previous year and next year suggests both temporal and internal dimensions. The reference point serves as a perceptual parameter (Meyer and Johnson 1995) or a decision frame (Shoham and Fiegenbaum 1999), which affect firms' strategic choices. When decision makers perceive that the firm is operating below the SRP, decision makers tend to be risk loving; when decision makers perceive that the firm is operating above the SRP, decision makers tend to be risk averse.

SRPT parallels the BTOF in that a firm can have historical aspirations (temporal and internal dimensions) and social aspirations (internal and external dimensions). Specifically, a firm's historical aspirations concern the comparison between its goals formed in the past and the results formed now. However, slightly different from BTOF, SRPT includes decision makers' risk tendency when choosing the selection of strategic choice behaviors. A firm's perceived position relative to the SRP influences risk-taking behaviors. Fiegenbaum et al. (1996) argue that firms make strategic decisions in the reference to firms in their strategic groups. A firm's strategic behavior and performance are influenced by reference points, which are consciously or unconsciously adopted. Firms within the same strategic groups tend to allocate their attention to other firms' strategic actions and view them as benchmarks to gain competitive advantages (Fiegenbaum et al. 1996; Fiegenbaum and Thomas 1995). SRPT predicts that strategic choice behavior will be risk-averse when firms perceive themselves as above (better than) SRP and risk-taking when below (worse than) SRP. Firm performance will be influenced by (1) the content and configuration of SRPs, (2) their frequency of change, and (3) the level of consensus between top managers and organizational members pertaining to SRPs. In sum, Fiegenbaum et al. (1996)

delineate the SRP construct and the process through which decision makers' attitudes towards risk tendency are shaped, and the selection of risk-seeking versus risk-avoidance strategy.

Social comparison theory posits that actors compare themselves with others with *similar* demographic attributes, ability, or position (Festinger 1954). Similarity among social actors plays a key role in comparing key performance indicators. If an actor perceives an increasing difference between his abilities and opinions and those of similar others, he will be less likely to make comparisons. Thus, at an individual level, social comparison occurs between comparable actors with respect to the focal dimensions of performance. Organizational researchers appropriated social comparison theory to the firm level (e.g., Kim and Tsai 2012; Porac et al. 1999). Empirical evidence supports similar social comparison mechanisms that can exist at firm level. For example, interfirm competition in the auto industry can lead automakers to frequently make comparisons with reference to others, and this competitive comparison can help a firm build a better reputation and market success (Kim and Tsai 2012).

Chapter 3: Research Model and Hypotheses

This chapter develops hypotheses addressing the research questions posed in Chapter 1. The hypotheses are summarized in the research model presented in Figure 1. First, the general patterns of engaging with BI&A technologies are hypothesized. Then, differential impacts of historical and social aspirations on engagements with BI&A technologies are hypothesized. Finally, the relationship between performance shortfalls and firms' engagement with BI&A and the temporal patterns of these relationships are hypothesized.

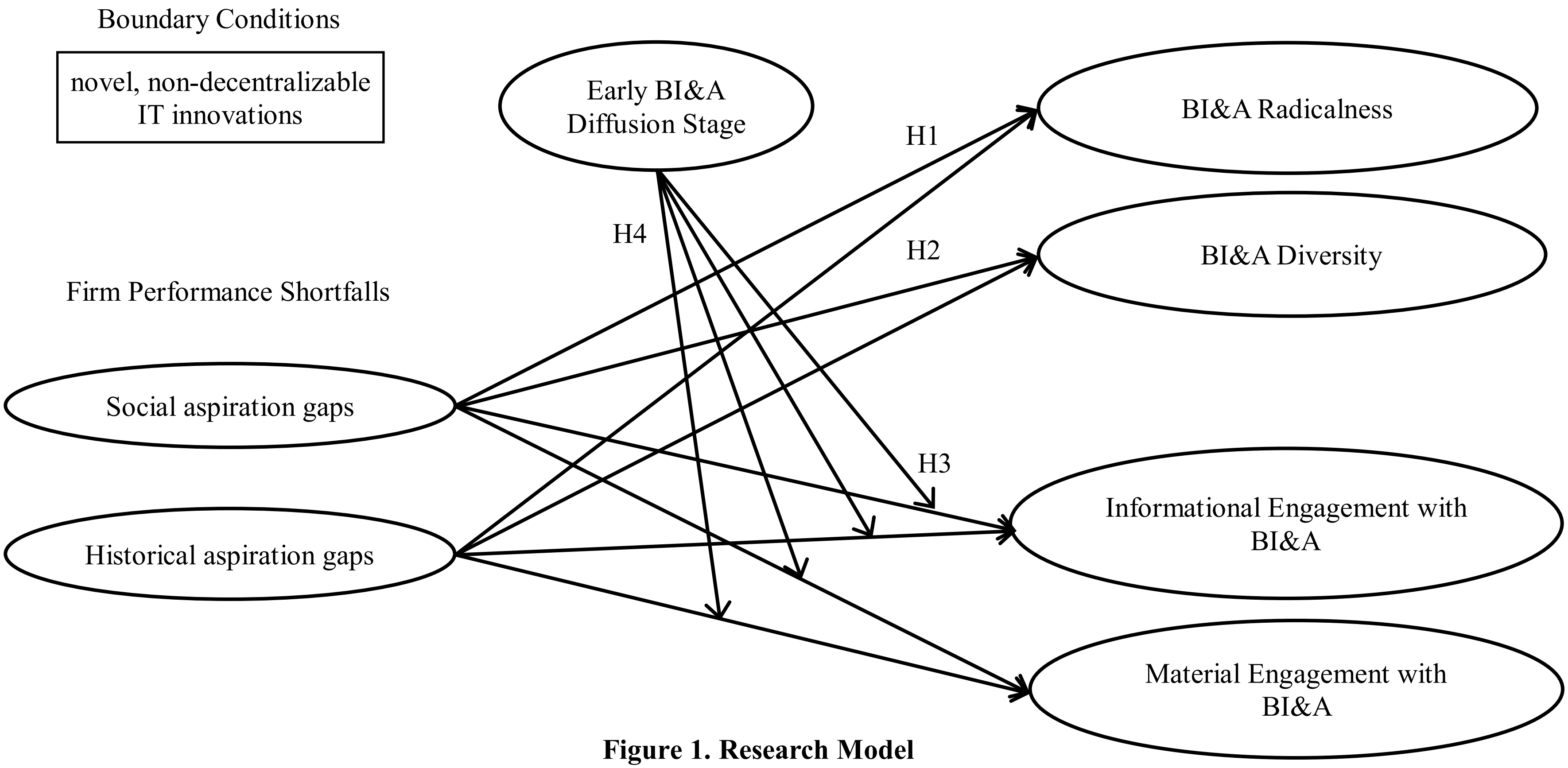

Figure 1. Research Model

Table 1. Constructs, Sources, and Conceptual Definitions		
Constructs	Sources	Conceptual Definition
Informational Engagement	(Miranda et al. 2012; Wang and Ramiller 2009)	Organizational participation in ongoing discourse about the technologies before or without actually purchasing the focal technologies
Material Engagement	(Wang 2010)	Material realization of engaging with the focal technologies
Radicalness of BI&A	(Dewar and Dutton 1986)	How radical the focal BI&A technologies are relative to the focal firm
Diversity of BI&A	(Harrison and Klein 2007)	How diverse set of BI&A technologies the focal firm is engaging with

How Firms Engage with BI&A Technologies

A central classification of IT innovations lies in the distinction between radical versus incremental innovations (Damanpour 1988; Fichman 2004b). Based on the uniqueness and novelty embodied in the innovations, IT innovations can be characterized on the continuum between incremental and radical (Carlo et al. 2012; Dewar and Dutton 1986). Radical innovations refer to “fundamental changes that represent revolutionary changes in technology” (Dewar and Dutton 1986, p. 1422). Radical innovations require a clear shift from firms’ current practices, preexisting skills, and knowledge (Attewell 1992). Unlike incremental innovations, where merely slight improvements are added to existing technologies, radical innovations represent a higher level of technological and process-related uniqueness and novelty (Carlo et al. 2012), and show a “clear departure” from extant practices (Damanpour 1988). In the context of BI&A technologies, autonomous analytics such as machine learning, artificial intelligence, and cognitive computing are considered more radical than conventional descriptive analytics technologies in that the autonomous analytics technologies require extremely low-level involvement of human analysts and hypotheses (Davenport and Harris 2017; Schlegel and Hare 2017), and thus shifts the manner in which firms operate and create values (Ransbotham et al. 2016).

Prior research on aspirations showed that decision makers are often exposed to decision-making biases under the condition of negative attainment discrepancies (Arrfelt et al. 2013; Salge et al. 2015). According to BTOF, decision makers under the pressures to improve performance tend to take risky actions (Cyert and March 1963). Labianca et al. (2009) surveyed business school deans about their response to their relative performance to competing schools, and the results showed that low-performing business schools plan more radical and extensive change regardless of uncertainty of future outcomes. Turning to the technology adoption context, Ketchen and Palmer (1999) examined organizational actions in responses to low performances using a sample of hospitals located in a metropolitan area. They found that decision makers within high-performing hospitals rely more on existing technologies that have been proven to work, whereas decision makers within low-performing hospitals tend to take aggressive strategic actions by deleting existing or adding new unproven high technologies because the chance of winning significant rewards. Similarly, sampling from 14 mobile phone manufacturer in U.K., Giachetti and Lampel (2010) found that when firms use the market leaders (i.e., extremely high-performing firms) as their reference point, the firms tend to adopt radical technologies, whereas when firms use the collective behaviors of industry peers as reference point, they tend to adopt incremental technologies. This suggests that how radical a technology is going to be adopted by a firm may depend on the focal firm's performance distance from its referent points. A large distance below social aspirations directs firms to adopt more radical technologies.

However, this relationship does not always hold as BTOF predicts. Mixed results were observed in empirical research. For example, in the context of robust design competitions, high-performing teams were found to be more likely to explore radically new designs in their robots than low-performing teams (Jha and Lampel 2014), because high-performing teams might want to achieve higher performance. But contrary to BTOF propose for problemistic search, low-performing teams were found to rely on the strategies used by successful teams (i.e., high-performing teams) instead of risking experimenting with radically new designs. This indicates that low-performing units are more inclined to rely on proven, unradical strategies.

While the prior empirical research appears to be consistent with BTOF that a *very* high-performing firm is very likely to engage in slack search, where firms are motivated to explore new opportunities that can enhance the firm's current operations (Cyert and March 1963), under which conditions firms are likely to engage in problemistic search is less consistent. This conflicting finding in terms of problemistic search might be explained by whether firms consider the negative attainment discrepancy repairable or threats to survival (Audia and Greve 2006; Chen and Miller 2007; Ref and Shapira 2017). When a firm's performance is so low that its survival is threatened, decision makers within the extremely low-performing firms tend to focus their attention primarily on firm's survival (Chen and Miller 2007). They avoid exploring new opportunities such as adopting and using radical BI&A technologies. Instead, decision makers tend to focus on reducing resource spending, tighten controls. However, as the performance increases, decision makers may switch their attention to social aspirations rather than survival (Audia and Greve 2006). In this stage, BTOF's problemistic search propositions hold when gap between current performance and social aspirations. In the context of BI&A technology engagement, when decision makers' focus is not on survival, as negative attainment discrepancies increase, a firm's likelihood to adopt radical BI&A technologies increases because managers want to rapidly close the gap with the help of more advanced yet unproven BI&A technologies to catch up peers.

Taken together, both extremely high-performing and low-performing firms are expected to engage in more radical change than others. In other words, both a strong positive and strong negative performance discrepancies will prompt radical IT adoption. As such, it is expected that:

H1a: Engagement with radical BI&A is driven more by social aspiration gaps than by historical aspiration gaps.

H1b: There is a curvilinear relationship between performance shortfalls and the radicalness of BI&A with which firms engages, i.e., likelihood to of engagement with *radical BI&A increases to a certain point and then decreases.*

Adoption decisions are not only determined by institutional environment (i.e., environment-as-institution), but also by firms' direct experience (i.e., organization-as-institution), and the decisions to abandon the focal technologies appear to be particularly based on firms' direct experience (Burns & Wholey, 1993). Adapting it to the problemistic search, firms with successful direct experience with BI&A technologies have a stronger tendency to further engage with other BI&A technologies, whereas firms with disappointing direct experience with BI&A technologies have a weaker tendency to continue the further use of other BI&A technologies, even in the presence of other firms' success stories.

In a broad sense, technological diversity refers to the extent to which the technological engagement in a firm is concentrated on a broad range of technologies relative to a narrow set of technologies (Harrison and Klein 2007; Schildt et al. 2012). *Diversity of BI&A technologies* refer to the degree to which a firm pays attention to, uses and/or implements a diverse set of BI&A technologies. Materially engaging with a *diverse* portfolio of BI&A technologies **initially** is challenging because of high initial investments and lack of deep knowledge about each different BI&A technologies. With a limited budget, firms have to consider the trade-off between depth and breadth of technologies engaged (Schildt et al. 2012). Engaging with a single BI&A technology initially permits a firm to gain deeper understanding of the technology. In contrast, engaging with a diverse set of BI&A technologies initially will limit the firm to have deep understanding about each, and thus hinder the firm's efficient use of BI&A technologies in subsequent years. Admittedly, going up the learning curve with one BI&A technology should reduce the learning curve for and increase complementarities with other BI&A technologies in subsequent years.

It is less likely for a firm to initially engage with a diverse portfolio of BI&A technologies simultaneously. Often, firms begin with one BI&A project (e.g., data storage with Hadoop) to solve a specific business problem or aim at starting an initiative (Davenport and Harris 2017). After a desired project outcome or goal is achieved, and the initial engagement with the focal BI&A is proven to be successful, firms are familiarized with and gain confidence about the focal BI&A technology. Thus, they may believe in their ability to expand their BI&A technology portfolio and transfer their successful experience to the adoption and use of a new BI&A technology (e.g., data visualization). For instance, Lai et al. (2016) argued that the routinization of ERP systems within firms depends on the successful assimilation phase. In this sense, the engagement with diverse BI&A technologies is largely dependent on the past; that is, firms are more likely to expand their BI&A technology portfolio to a new domain until the current BI&A technologies prove to work, and fit in operations of current functional areas.

Further, when financial firm performance exceeds historical aspirations, managers will be more likely to interpret the previous adoption of BI&A technologies works in terms of either improving operational efficiency or lowering operational costs, and thereby be optimistic about their capability to manage new BI&A technologies in subsequent years. However, firm performance below its historical aspirations will prompt the managers to adjust the firm's ability of effectively managing multiple BI&A technologies downwardly, and thus may less likely to invest in a diverse BI&A technologies concurrently than sequentially. In other words, the higher a firm's financial performance is above historical aspirations, the more likely a firm will be engaged with a diverse portfolio of BI&A technologies; the higher a firm's financial performance is below historical aspirations, the less likely a firm will be engaged with a diverse portfolio of BI&A technologies.

Taken together, we hypothesize that:

H2a: Engagement with diverse BI&A is driven more by historical aspiration gaps than by social aspiration gaps.

H2b: The positive relationship between firm performance discrepancies and engagement with diverse BI&A is stronger when firm performance is above historical aspirations than when it is below historical aspirations.

Differential Impacts of Historical and Social Aspirations on Engagement with BI&A Technologies

Conceptualizing the two types of aspirations together assumes the vicarious learning/external influences (i.e., social aspirations) and experiential learning/internal benchmark (i.e., historical aspirations) leads to organizational change in the same direction and of same type. In the meantime, it assumes equal impacts of historical and social aspirations and their impacts on a firm's subsequent responses, and cannot differentiate the extent to which the impacts of historical aspirations significantly differ from those of social aspirations. For instance, Greve (2003a) conceptualized firms' performance relative to aspirations in general as a trigger to increase R&D intensity and innovation introduction. Although empirical evidence supported this conceptualization, it is unclear that what types of aspirations play a role in influencing R&D intensity and innovation introduction.

Most recently, however, a handful of scholars realized this issue and articulated the necessity to theorize and hypothesize historical and social aspirations separately (Arrfelt et al. 2013; Kim et al. 2015). Historical and social aspirations may result in different interpretations in that "the two are derived from distinct sources of performance feedback and are filtered through different cognitive and organizational processes, they may engender different interpretations, which, in turn, may induce different organizational responses" (Kim et al. 2015, p. 1364).

First, historical aspirations indicate how well firms **could** perform, whereas social aspirations indicate how well firms **should** perform (Kim et al. 2015). Historical aspirations are based on a firm's own past history or experiential learning. This tacit knowledge gives managers an evaluation of a firm's ability to perform. In contrast, social aspirations are based on a comparison between a firm's own performance and the average performance of other similar firms, with a performance above the average considered more favorable, and below the average considered less favorable (Fiegenbaum et al. 1996).

In terms of operationalization, prior studies normally combined historical and social aspirations into a single measure (e.g., Greve 2003a; Parker et al. 2017). While this single-measure approach takes into account differential weights from social and historical referent points, the resultant measure (i.e., aspirations in general) cannot reflect the degree to which impacts from each aspiration significantly differ from one another. While others argued and separated historical and social comparison measures (Baum et al. 2005; Mishina et al. 2010).

Salge et al. (2015) examined impacts of hospitals' performance shortfalls relative to aspirations on IS investment intensity by focusing only on social aspirations. Other studies realized the potential differential effect from social and historical aspiration, yet examined one type of aspirations (social aspirations) without considering the other type of aspirations (i.e., historical aspirations) throughout their studies (Wang et al. 2017), or the other way around (Ref and Shapira 2017). For instance, Wang et al. (2017) argued that social aspirations could be more relevant to technology races than historical aspirations due to salient pressures from competitors. However, in operationalizing independent variables (a firm's technological performance in relation to aspirations), they only investigated social aspirations. Another example is Ref and

Shapira (2017). Drawing upon BTOF, Ref and Shapira (2017) examined firms' decisions to enter new markets by focusing exclusively on performance relative to historical aspirations. This practice overlooks the potential differential impacts of attainment discrepancies on firms' subsequent responses, and may lose opportunities to offer more nuanced insights.

Firms' performance is exposed to external scrutiny by shareholders, mass media, and other stakeholders. Shareholders, especially, cannot bear poor performance in comparison to competitors (Kim et al. 2015). Moreover, although historic performance shortfalls may be attributed to changing economic environments, social shortfalls can only be attributed to management actions because competitors are operating in equally favorable/unfavorable circumstances. All else being equal, the same amount of performance shortfalls based on social aspirations send qualitatively different signals than those based on historical aspirations to the outsiders, since it signals managers' abilities to achieve what they should have. In other words, such deficiencies tend to be viewed more unforgivably in the eyes of stakeholders. Thus, firms are more responsive to the performance shortfalls based on social comparisons than to those based on historical comparisons. In the meantime, in the eyes of decision makers, performance shortfalls based on historical aspirations cannot provide sufficient information on which key resources are allocated (Arrfelt et al. 2013). Performance shortfalls in comparison to competing firms show the focal firm is losing its competitive advantages over others. In this sense, social aspiration-based comparison leads to more salience and impacts. As such, in the context of making decisions of IT innovations, firms' engagement with BI&A technologies are more strongly associated with social aspiration-based performance shortfalls than historical aspiration-based performance shortfalls. Further, because informational engagements are more immediately visible to shareholders and others evaluating management; in contrast, material engagements will be visible only in their subsequent impacts on firm performance, it could be expected that performance shortfalls based on social aspirations will have a stronger impact on informational than material engagement.

Taken together, we hypothesize that:

Hypothesis 3a: Performance shortfalls based on social aspirations have stronger impacts on informational and material engagement with BI&A technologies than do historical aspirations.

Hypothesis 3b: The social aspiration-based performance shortfalls have a stronger impact on informational than material engagement.

Performance Shortfalls and Their Temporal Patterns

Research on institutionalization integrated the rationalistic and institutional forces perspectives and found that at the early stage of diffusion of a focal innovation, internal factors (i.e., technical or performance gains) predict diffusion (Tolbert and Zucker 1983). However, the predictive power of internal factors decreases sharply over time and institutional forces' explanatory power becomes significant at the later stage of diffusion. Similarly, Westphal et al. (1997), in their study of diffusion of total quality management (TQM) among U.S. hospitals, showed that early adoption of TQM was driven primarily by the efficiency concerns, whereas later adoption was driven primarily by the legitimacy concerns (Westphal et al. 1997). This suggests that rationalistic and institutional forces operate at different diffusion stages.

From the perspective of discourse structure, at the early stage of diffusion, fewer success stories are observable (Strang 1997). Thus, firms tend to rely on their own needs and circumstances (Swanson and Ramiller 2004). In this case, at the early stage of diffusion, when a firm's performance falls behind performance of their peers, they should be more responsive to these shortfalls. In contrast, at the later stages of diffusion, success stories are easily observable. Moreover, media coverage of organizational innovation is often favorable regardless of whether there are positive outcomes of engaging with technologies (Strang 1997). As such, imitation of peers who have successfully adopted focal innovations, a form of institutional isomorphism, take place (DiMaggio and Powell 1983).

At the later stage of a diffusion cycle, the bandwagon phenomenon (known also as "herd behavior"), a macro-level consequence of institutional forces, has been observed (Rogers 2003). It refers to the diffusion processes wherein organizations adopted innovations due mainly to the sheer number of other adopting peers (Abrahamson and Rosenkopf 1993; Lanzolla and Suarez 2012; Swanson and Ramiller 2004). At the later stage of the diffusion, firms' assessment of own needs and circumstances are subject to prior adopters (Abrahamson and Rosenkopf 1993), and thus diffusion is further enhanced by contacting with prior adopters (Strang and Macy 2001).

Turning to the BI&A context, at the later stage of BI&A diffusion, BI&A is more commonly considered appropriate and necessary to efficient, rational firms. As such, BI&A becomes more institutionalized then than at the early stage. Under the wider pressure to engage with BI&A technologies, firms at this stage tend to rely more on institutional cues (i.e., environment-as-institution) rather than their performance concerns (i.e., performance aspirations/organization-as-institution). Adopting firms increase the isomorphism pressures for firms that have yet to engage with BI&A. Thus, as an innovation community enters later stages of BI&A diffusion, those prospective adopting firms are more likely to imitate the early adopter adopters, irrespective of firm performance relative to aspirations. In other words, performance shortfalls have a lot weaker explanatory power in predicting firms' engagement with BI&A at the later stage of BI&A diffusion. Conversely, at the early diffusion stage of BI&A, firms are more motivated by the gains in performance and efficiency, and the engaging with BI&A is viewed more as opportunities than risks in that it permits firms to gain first-mover advantages relative to competing peers (Kennedy and Fiss 2009). In other words, at the early BI&A diffusion stage, performance shortfalls have stronger explanatory power in predicting firms' engagement strategies than at the later stage. In sum, we hypothesize that:

Hypothesis 4: Effects of performance shortfalls on a firm's informational and material engagement are stronger in the early BI&A diffusion stage than in the later stage.

Chapter 4: Research Methods

The time frame investigated - 2010 to 2015 - is chosen based on Gartner's Hype Cycle, where 2010 was the inception point of big data, and 2015 the year by which big data was adopted by most Fortune 1000 firms. To better observe the BI&A diffusion, sample firms were drawn from the manufacturing and wholesale/retail sectors, two of the earliest sectors engaging with BI&A technologies (Davenport and Harris 2017). Using data from multiple archival sources (*CITDB, COMPUSTAT, EDGAR, ABI/INFORM, FACTIVA, CONGRESS.GOV, etc.*), we developed a longitudinal sample of 3,311 firm-year observations for 558 unique firms between 2010 and 2015. Note that not every firm appears every year because some firms started to participate in the annual CITDB survey after 2010 or stopped participating in the annual CITDB survey before 2015, which results in 549 unique firms in 2010, 553 unique firms in 2011, 552 unique firms in 2012, 553 unique firms in 2013, 553 unique firms in 2014, and 551 unique firms in 2015, respectively.

Data

The data used for this dissertation were compiled from several different archival sources including Computer Intelligence Technology database (CITDB), Compustat, Factiva, AnnualReports.com, Edgar, Mergent and Congress.com. We obtained data on material engagement with BI&A and diversity of BI&A from CITDB. CITDB provides information about the adoption and use of popular technologies, such as Enterprise Resource Planning (ERP), Customer Relationship Management (CRM), Business Intelligence and Analytics (BI&A), in over half million business locations located in North America. The adoption and use data were collected through interviews with IT professionals who are well-informed about the site's presence of these technologies. We obtained the performance data from Compustat. We obtained data on informational engagement and radicalness of BI&A from Factiva. We obtained data on top management support from Edgar and AnnualReports.com. We obtained data on normative forces from Mergent, data on coercive forces from Congress.com, and data on mimetic forces from CITDB.

Sample

Unlike some emerging technology innovations (e.g., Internet of Things) which lack wide consensus on definitions, BI&A technologies are relatively well defined with one overall goal of enhancing effectiveness of organizational decision making. Numerous failure and success stories of adopting and using BI&A technologies are readily available, which provide decision makers with visible opportunities to search for the pros and cons of the technologies. Second, adopting and using BI&A technologies is not an easy task (Yeoh and Popovič 2016). Instead, it requires the support of complementary resources (e.g., financial resources, supporting IT infrastructures, data scientists) (Miranda et al. 2015a).

BI&A technologies appear to be at a high level of abstractions and cover a variety of analytical aspects from data collection, cleansing, management, analysis, and reporting. BI&A may refer to proprietary or open-source software (Atriwal et al. 2016). In terms of sophistication level, BI&A can be classified as descriptive, predictive, prescriptive and autonomous analytics (Davenport and Harris 2017; Sharda et al. 2017).

We focus on two sectors: manufacturing and wholesale in that the manufacturing and wholesale sectors are among several of the earliest sectors engaging with BI&A technologies (Davenport and Harris 2017), permitting us to fully observe the diffusion of BI&A technologies[2].

The boundaries between adopters and vendors are blurring. Often, firms adopt BI&A not

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[2] In total, our final sample is comprised of 482 unique firms in manufacturing sector and 76 unique firms in retail and wholesale sector.

for their own end use, but to develop products and enhance services offered to the adopter's clients. For example, LinkedIn as a social networking firm serving professionals launched data-related products such as "Jobs You May Be Interested In", which include profile searching and matching analyses, a combination of descriptive and predictive analytic techniques. As another example, Microsoft has been a leading IT vendor for decades. Microsoft Studios, a subsidiary of Microsoft Corporation, produce video games. In an attempt to analyze video game live streaming performance, Microsoft Studios adopted and employed BI&A technologies (e.g., Microsoft Azure), including HDInsight, Data Lake Analytics and machine learning. In this sense, Microsoft Studios is video game vendor, yet it adopts and employs BI&A technologies to improve core product performances. This suggests that BI&A technologies are increasingly employed not as standalone software, rather as embedded within other software. In this sense, a firm will be coded as adopter if it adopts or implements any components of BI&A technologies, even though this firm is a conventional IT vendor.

Measures

Dependent Variables

Radicalness of BI&A is measured as the proportion of radicalness terms for the BI&A being used. The dominant measure for radicalness of an IT innovation is survey-based, we developed a new text-based measure. First, through CITDB, we identified each firm's BI&A vendors. Second, we turned third-party IT consulting firms or analysts' assessments on BI&A radicalness because the third-party analysts' reports on BI&A are more objective than press releases issued from focal vendors and partners, and more up to date and timely than academic journals. The primary assessment sources include Computerworld, InfoWorld Daily News, Gartner Research, InformationWeek, Frost & Sullivan, and Computer Weekly. Third, we collected the reports, news from those IT consulting firms for each BI&A vendor for each year (a total of 411 documents). Through iterations between the two co-authors, a custom dictionary for **radicalness,** comprised of 93 radicalness terms, was developed (see Table A3 in Appendix A for a list of radicalness terms). We used the Linguistic Inquiry and Word Count (LIWC) to context analyze documents for each BI&A vendor's in each year. LIWC computes radicalness category as a proportion of the total number of words in the text, thus controlling for the document length. Thus, a higher score indicates the more radical BI&A the focal firm is using.

Diversity of BI&A is measured using Shannon Index at BI&A vendor level. Shannon Index = $-\sum(P_{i,t} \times lnP_{i,t})$, where $P_{i,t}$ is the proportion of BI&A vendor *i* used by a focal firm among all BI&A vendors for the year *t* (Connelly et al. 2017; Harrison and Klein 2007). For example, a firm in a particular year engaging with BI&A technologies from only one IT vendor indicates a low diversity of BI&A, whereas a firm in a particular year engaging with BI&A from 5 different IT vendors indicates a higher diversity. As a robustness check, we also used Herfindahl–Hirschman Index (HHI) to measure diversity, which is comparable to Shannon Index (Straathof 2007). HHI= 1 - $\sum P_{j,t}^2$, where $P_{j,t}^2$ represents the squared proportion of BI&A technologies belonging to vendor j in all BI&A vendors being used (Miranda et al. 2015b).

Informational engagement. To measure informational engagement (i.e., what do firms say about the BI&A), first, for each year, we counted annual number of press releases issued from the sample firms containing any of the BI&A technologies. Second, to rule out the time-varying factors, the raw annual counts have to be normalized – i.e., first dividing them by the total number of press releases issued by the sample firms in that year, and then dividing the results by firm size (average normalized sales and assets) (Miranda et al. 2015b; Wang 2010). Third, we divided the firm size to avoid multicollinearity issues in the panel regression with firm size.

Material engagement is measured as revenue-weighted sum of site-level BI&A use (Ray et al. 2013). CITDB indicates whether any form of BI&A is being used at each site of a firm (Yes, No), we first re-coded this site-level variable as 1 (Yes) and 0 (No). Note that a missing value could indicate either "No" (i.e., BI&A technologies are not being used) or missing values. To distinguish between "No" and the missing values, we used an inferred approach. Since CITDB records each site's use of different technologies (e.g., Windows Systems, ERP, CRM, BI&A) each year, if the focus site has missing values for the use of all technologies, it suggests the focal site has not been reached, thereby indicating the true missing values. As such, we computed the number of non-missing values for these technologies for each site, and recoded blanc cells as "Site Not Reached" when it equals zero. Then we recoded the blank cells as zero and "Yes" as 1 for both variables. We aggregated the firm-level BI&A material engagement from the site-level to the firm-level using site revenue as weights.

Independent Variables

Performance. We used two financial indicators to capture firm performance: 1) ROI as the main indicator for firm profitability (Sørensen 2002; Tosi JR. and Gomez-Mejia 1994; Weill and Ross 2004) or value of IT investment (Kohli et al. 2012); and 2) market share as a key indicator for competitive advantage relative to others (Fang et al. 2018; Hansen and Wernerfelt 1989; Zheng et al. 2012).

Performance discrepancies. Social performance discrepancies are measured as difference between performance of focal firm and average performance of different social aspirations. Historical performance discrepancies will be measured as focal firm's historical aspirations – focal firm's performance in current year ($HAP_{i,t} = HA_{i,t} - P_{i,t}$) (Baum and Dahlin 2007).

Historical aspirations. In performance feedback literature, spline functions are often used to identify whether a firm's performance is below or above aspirations. Spline functions permit slopes of regressions to change based on different aspirations (e.g., Kuusela et al. 2017; Park 2007). we followed this established approach. Because we theorized and hypothesized the differential impacts of historical and social aspirations on the firms' choices of engaging with BI&A, unlike most prior studies in performance feedback literature where historical and social aspirations are modeled together, wed use a model separating historical and social aspirations. Following Baum and Dahlin (2007) and Greve (2003b), a firm's historical aspirations at time *t* is measured as: $\mathrm{HA}_{i,t} = \alpha\ \mathrm{P}_{i,t} + (1-\alpha)\mathrm{P}_{i,t-1}$, where $\mathrm{HA}_{i,t}$ represents historical aspirations for firm *i* at time t, $\mathrm{P}_{i,t}$ and $\mathrm{P}_{i,t-1}$ represents the focal firm i's performance at time t and t-1, respectively, and adjust parameter α. A high α value indicates more weight on recent performance, whereas a low α indicates more weight on past performance. The optimal α was obtained by estimating the models with all possible values of α and by choosing the one with the best fit. This procedure yielded results that ROI has an α of 0.47 and market share had an α of 1.

Social aspirations. Prior performance feedback research often set social aspirations to the average performance (i.e., mean or median) of all firms within the industry (e.g., Chen and Miller 2007). However, strategic reference point theory suggests that firms pay more attention to their strategic group members (i.e., similar peers) rather than all firms in that industry (Fiegenbaum et al. 1996). Thus, social aspirations were measured on several levels: industry leader, dyad level, strategic level, and industry average. To determine a firm's corresponding strategic group members, a matching approach are used. First, within the same industry, we cluster analyzed the sample firms in each year based on *revenue* and *total assets*, because the two performance metrics are widely used by decision makers to categorize firms (Kuusela et al.

2017). Second, to determine the number of the k closest matches, we set k =2 (dyad competitors), k = 3 to 5. Third, for each strategic group, the performance shortfalls based on social aspirations are the difference in value between mean performance and that of focal firm.

Early diffusion stage. To determine the early versus late diffusion stages, we followed Westphal et al. (1997) and Ritchie and Melnyk (2012)'s approach – i.e., the midpoint of the observed period – that is, from BI&A inception 2010 to 2012 as early diffusion stage, and from 2013 to end of 2015 as later stage of BI&A diffusion. This staged operationalization assumes that time is involved in a non-linear fashion in innovation diffusion (Westphal et al. 1997).

Control Variables

We statistically controlled for the following variables as they were found to be significant predictors of IT innovation diffusion in prior research.

Top management support is measured as the proportion of BI&A related terms in each corporate firm's annual report or proxy statement. IT innovation diffusion literature documented the role of top management support or commitment in the implementation and assimilation of technologies (e.g., Liang et al. 2007; Shao et al. 2016; Staehr 2010). In general, findings suggest that the higher the support or commitment from top management, the more successful implementation and assimilation of focal technologies. Given the longitudinal nature of the study, and C-level executives' difficulty of recalling prior attitudes towards BI&A technologies, relying on archival data appears to be a realistic and reasonable choice. Annual reports and shareholder letters are ideal source for examining executives' strategic plans or responses in communicating to shareholders. Unlike a single C-level executive (e.g., CEO, CIO, COO, CDO, etc.), annual reports and shareholder letters represent a collectively held views of top management teams on the commitment of BI&A technologies. In other words, it should contain less individual executive biases towards BI&A. Thus, we used annual reports and shareholders as primary sources to collect data on top management support of or commitment to BI&A. To measure top management support, similar to the measure of BI&A radicalness, we created a new text-based measure. First, we created a custom dictionary for top management support by developing an extensive list of BI&A related terms based on multiple archival sources, e.g., Gartner's *Magic Quadrant for Business Intelligence Platforms* between 2010 and 2012, and *Magic Quadrant for Analytics and Business Intelligence Platforms* between 2013 and 2015 and *Gartner Peer insight Review* for Analytics and Business Intelligence. The custom dictionary also includes high-level umbrella search terms such as "business intelligence" and "analytics"[3]. This category includes 119 BI&A unique terms (see Appendix A). Second, we performed text-analysis using Linguistic Inquiry and Word Count (LIWC) (Pennebaker et al. 2015; Pennebaker et al. 2014) with the custom BI&A dictionary on sample firms' annual reports to capture top management teams' collective support for BI&A. To do so, we collected annual reports from AnnualReports.com. For those samples firms whose annual reports in a particular year is not available on AnnualReports.com or each company's corporate website, we used proxy statements instead.

Institutional forces. Prior IS research on institutional theory found that institutional forces (normative, mimetic, coercive forces) are effective in driving IT innovation adoptions. To examine the effects of performance shortfalls relative to aspirations on BI&A engagement, therefore, we statistically controlled for institutional forces.

[3] For each year between 2010 and 2012, we read through Gartner Magic for BI Platforms report; for each year between 2013 and 2015, Gartner Magic For BI and Analytics Platform report. The name having "analytics" reflect the growing analysis capability that conventional BI platforms had. Those archival reports BI&A product names that obtained certain market attention are listed. For those BI-focused firms, we listed firm names rather than product names.

Normative forces. We measured normative forces in two ways. The first operationalization, measured as a binary variable, captures whether the sample firm has created an executive-level technology-focused function or a senior management position (e.g., CIO, CTO, CDO, vice president of information technology, etc)[4]. Specifically, within each sample firm's annual report and proxy statement, we manually read through the Executive Management Team Section or Executive Officers of Registrant Section and captured this information[5]. If this senior management position was created, it was coded 1, and 0 otherwise. Besides, the creation of these IT related positions is approved by board of directors (stakeholder), thereby reflecting the pressure from outside firms towards BI&A. The second operationalization captures the extent to which CEO is influenced by technologies education, which is consistent with Di Maggio & Powell's conceptualization of normative forces. We adapted the measure from Boritz et al. (2017), and focused on three indicators: 1) CEO's education (STEM), 2) whether CEO worked in a IT-related positions, 3) whether CEO worked in a tech firms. If any of the three indicators are true, this variable is coded as 1, 0 otherwise [6].

Coercive forces is measured as cumulative proportion of legislation (became law) promoting the adoption or use of BI&A (benchmark year is 2009).

Mimetic forces is measured as proportion of sample firms within the same sector that have used BI&A in the preceding period (Lanzolla and Suarez 2012).

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[4] Since no sample firms have created the position such as Chief Analytics Officer, Chief Data Officer, or Chief Business Intelligence Officer between 2010 and 2015, we turned to a proxy variable. Creation of CIO and CTO positions is often the first step for a company to commit to digital transformation (Davenport & Harris, 2007). That is, the indicators of pro-analytics norms and forerunner of committing to BI&A within firms. As such, we used this as normative forces for BI&A.

[5] Since board of directors' primary role is supervision – i.e., to ensure that chief executive officer's activities align with firm's objectives and shareholders' expectations. Executive officers are primary decision makers of a firm's daily operations. Thus, we focused on executive management teams instead of board of directors.

[6] we manually read through proxy statements of each sample firm, collected and identified bios of the top management teams. We pull out the detailed executive information from Mergent. If a particular executive's bio information is still missing, we turned to LinkedIn, Bloomberg or Google searches.

Knowledge barriers was included as a control variable because it was found to affect the adoption of innovations in prior research (Attewell 1992; Fichman 2004b). Knowledge barriers is operationalized as the total number of IT staff.

Slack, referring to "the stock of excess resources available to an organization during a given planning cycle" (Voss et al. 2008, p. 148) is measured as ratio of current assets to current liabilities. Prior slack research documented significant relationship between organizational slacks and the adoption of innovations (e.g., Damanpour 1991; Rosner 1968). Slack resources allow firms to *safely* experiment with novel technologies, making it easy to adopt and use focal technologies.

Firm age is included as a control because old firms tend to be constrained by legacy systems, whereas young firms tend not to be constrained by legacy systems, and be more willing to experiment with new technologies (Angst et al. 2010). Additionally, Angst et al. (2017) found that older hospitals tend to be symbolic adopters whereas young hospitals tend to be substantive adopters. *Firm size* is also a variable identified to have significant impact on organizational adoption and use of IT (Angst et al. 2010; Meng and Lee 2007). Large firms tend to possess more resources that allow them to engage with technologies substantively. On the contrary, small firms are more agile, and thus adopt and implement new technologies rapidly.

Year of performance shortfalls (dummy) is controlled to parse macro-level time-related confounding factors such as changes in economy, society, industrial environment.

Table 2. Operationalization of Variables

Variables	Data Source	Operationalization
Informational Engagement	ABI/Inform	$\frac{PRs_{i,t}\ on\ BI\&A}{PRs_{i,t} \times Firm\ Size_{i,t}}$ (Wang 2010) Where $PRs_{i,t}$ on BI&A is the annual count of press releases on BI&A issued by firm *i*; is the total annual count of press releases issued by firm *i* in year t.
Material Engagement	CITDB	Aggregate site revenue-weighted sum of BI&A use (Ray et al. 2013; Xue et al. 2017)

Radicalness of BI&A	Factiva	Proportion of BI&A radical terms for BI&A technologies used by the focal firm in year t. (a text-based new measure)
Diversity of BI&A	CITDB	Shannon's index = $-\sum(P_{i,t} \times lnP_{i,t})$, where $P_{i,t}$ is the proportion of BI&A vendor i used among all BI&A vendors for the year t. (Connelly et al. 2017; Harrison and Klein 2007)
		HHI = 1 - $\sum P_{j,t}^2$, where $P_{j,t}^2$ represents the squared proportion of BI&A technologies belonging to vendor j in all BI&A vendors being used (Miranda et al. 2015b)
Performance (ROI)	Compustat	Annual return on investment = net income / total invested capital
Performance (Market share)	Compustat	Annual market share = sales / industry total sales (2-digit sic)
Historical aspirations	Compustat	$\mathrm{HA}_{i,t} = \alpha\ \mathrm{P}_{i,t} + (1-\alpha)\ \mathrm{P}_{i,t-1}$, where $\mathrm{HA}_{i,t}$ represents historical aspirations for firm i at year t, $\mathrm{P}_{i,t}$ and $\mathrm{P}_{i,t-1}$ represents the focal firm i's performance at year t and t-1, respectively, and adjust parameter α.
Social aspirations	Compustat	$\mathrm{SA}_{i,t}$ is measured as the average performance of industry leader, target competitor (dyad), strategic group members, sector, and industry. To determine a firm's corresponding strategic group members, a matching approach are used. First, within the same industry, we cluster analyzed the sample firms in each year based on *revenue* and *total assets*, because the two performance metrics are widely used by decision makers to categorize firms (Kuusela et al. 2017). Second, to determine the number of the k closest matches, we set *k* =2 (dyad competitors), *k* = 3 to 5.
Top management support	Edgar, AnnualReports.com	Proportion of BI&A related terms in shareholder letters from the sample firms
Knowledge barriers	CITDB	Total number of IT staff (categorical variable) (Attewell 1992)
Slack	Compustat	Quick ratio (Damanpour 1991)
Firm age	CITDB	Nature logarithm of number of years since foundation (Angst et al. 2010)
Firm size	CITDB	Nature logarithm of total number of employees (Steelman et al. 2019; Wang 2010)
Normative forces	Edgar, Mergent, Bloomberg	The 1st operationalization, measured as a binary variable, 1: existence of technology executives; 0: nonexistence. The 2nd operationalization: 1) CEO's education (STEM), 2) whether CEO worked in a IT-related positions, 3) whether CEO worked in a tech firms. If any of the three indicators are true, this variable is coded as 1, 0 otherwise (adapted from Boritz et al. 2017).
Coercive forces	Congress.gov	Proportion of legislation (became law) promoting the adoption or use of BI&A

Mimetic forces	CITDB	Proportion of sample firms within the same sector that have used BI&A in the preceding period (Lanzolla and Suarez 2012)

Analytic Strategy

Overall, we examine how firms respond to performance shortfalls using BI&A over time. Our unit of analysis is firm-year observations. The panel data structure yields both changes within each firm over time and cross-sectional differences among firms. Since dependent variables are continuous variables (BI&A radicalness, diversity, informational and material engagement), a pooled OLS estimation does not really account for the panel data structure. As such, we used random or fixed effects models (Stata xtreg) to analyze the effects of aspirations on BI&A engagement patterning. We justified our choice based on Hausman test.

Chapter 5: Results

Table 3 reports descriptive statistics and correlations among variables. The data is an unbalanced panel comprising 3,311 year-firm observations for 558 unique firms between the years 2010 and 2015. The largest variance inflation factor (VIF) for all hypotheses is 1.85, well below the typically-recommended threshold of 10.00 (Hair et al. 2010), or even the more stringent criteria of 3.33 (Cenfetelli and Bassellier 2009). Thus, multicollinearity is not a concern in this study.

Table 3. Descriptive Statistics and Correlation Matrix

	Mean	SD	1	2	3	4	5	6	7	8	9
1. BI&A Radicalness	1.48	0.52	1.00								
2. BI&A Diversity	0.95	0.59	0.06*	1.00							
3. Informational Engagement	0.11	0.41	0.01	0.09***	1.00						
4. Material Engagement	0.22	0.37	0.08**	0.22***	0.01	1.00					
5. Top management support	0.01	0.11	-0.04	0.10***	-0.00	-0.02	1.00				
6. Normative forces	0.37	0.48	0.01	0.17***	0.13***	0.05*	-0.04	1.00			
7. Coercive forces	-0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		
8. Mimetic forces	0.00	0.02	0.06*	0.04	-0.01	0.03	-0.00	-0.02	0.01	1.00	
9. Firm size	5.50	1.08	0.00	0.24***	0.09***	0.23***	0.09***	0.12***	0.12***	0.01	1.00
10. Firm age	2.15	1.76	-0.00	0.04	0.00	0.02	0.05	0.05	0.01	0.00	0.03
11. Knowledge barriers	2.16	1.44	0.04	0.41***	0.25***	0.11***	0.12***	0.32***	-0.03	-0.05	0.32***
12. Slack	1.32	0.84	-0.01	-0.19***	-0.07**	-0.07**	-0.02	-0.12***	0.04	-0.00	-0.09***
13. Performance (ROI) below Hist. Asp (ewma)	0.05	0.46	0.07*	0.05	-0.02	0.08***	-0.01	-0.03	-0.01	0.00	0.05
14. Performance (ROI) below Hist. Asp (ave2)	0.06	0.54	0.08*	0.03	-0.01	0.08**	-0.00	-0.03	0.00	0.00	0.05
15. Performance (ROI) below Soc. Asp. (sector)	0.16	0.50	0.06	0.04	-0.02	0.05*	-0.00	-0.05	-0.10***	0.00	-0.01
16. Performance (ROI) below Soc. Asp. (sic2)	0.16	0.65	0.03	0.02	-0.03	0.08***	-0.01	-0.04	-0.08**	0.00	-0.04
17. Performance (ROI) below Soc. Asp. (sic4)	0.11	1.18	0.03	0.01	-0.01	0.02	-0.00	0.03	-0.03	0.00	-0.03
18. Performance (ROI) below Soc. Asp. (sg1)	0.18	2.71	0.00	-0.03	-0.01	0.00	-0.00	-0.03	-0.01	0.00	0.02
19. Performance (MS) below Hist. Asp (ewma)	0.08	0.32	0.01	0.09**	0.00	0.02	0.12***	0.05	-0.14***	-0.01	-0.00
20. Performance (MS) below Hist. Asp (ave2)	0.09	0.40	-0.04	0.12***	0.01	0.02	0.16***	0.07*	-0.16***	-0.02	0.04
21. Performance (MS) below Soc. Asp. (sector)	1.44	1.14	0.03	-0.36***	-0.21***	-0.08**	-0.09***	-0.27***	-0.15***	0.00	-0.29***
22. Performance (MS) below Soc. Asp. (sic2)	1.36	1.78	0.02	-0.24***	-0.12***	-0.09***	-0.05*	-0.16***	-0.07**	-0.00	-0.23***
23. Performance (MS) below Soc. Asp. (sic4)	0.86	2.15	0.02	-0.12***	-0.05*	-0.02	-0.01	-0.10***	-0.01	-0.00	-0.04
24. Performance (MS) below Soc. Asp. (sg1)	0.98	2.62	-0.00	0.09***	0.07**	0.01	-0.02	0.08**	-0.00	0.00	0.16***

10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1.00														
0.04	1.00													
-0.03	-0.29***	1.00												
-0.01	0.01	-0.02	1.00											
0.01	-0.00	-0.02	1.00***	1.00										
-0.01	-0.02	-0.02	1.00***	1.00***	1.00									
-0.03	-0.06*	-0.02	1.00***	1.00***	1.00***	1.00								
-0.06*	-0.04	-0.02	1.00***	1.00***	1.00***	1.00***	1.00							
0.03	0.00	-0.02	0.99***	0.99***	0.99***	0.99***	0.99***	1.00						
0.03	0.17***	-0.04*	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	1.00					
0.03	0.21***	-0.05*	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.92***	1.00				
0.01	-0.59***	0.15***	0.01	0.01	0.01	0.01	0.01	0.01	-0.16***	-0.19***	1.00			
-0.00	-0.36***	0.11***	0.01	0.01	0.01	0.01	0.01	0.01	-0.11***	-0.12***	0.52***	1.00		
-0.04	-0.13***	0.07***	0.01	0.01	0.01	0.01	0.01	0.01	-0.06***	-0.08***	0.22***	0.44***	1.00	
0.00	0.26***	-0.07***	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	0.07***	0.07***	-0.16***	-0.13***	-0.09***	1.00

Notes. [a] 13-24: Different ways of operationalizing aspirations. [b] ROI: Return on Investment, MS: Market Share. [c] ewma: exponentially weighted moving average; ave2: average of prior two years. [d] sic2: 2-digit SIC; sic4: 4-digit SIC; sg1: strategic group. [e] Material Engagement: firm-level BI&A use is aggregated using revenue-weighted site-level BI&A use.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Prior to hypothesis testing, we ran a series of Hausman tests to choose between fixed and random effects models (Allison 2009; Clark and Linzer 2015). Thereafter, we performed the analyses required for hypothesis testing in accordance with the results of the Hausman tests.

We used two financial indicators to capture firm performance: 1) ROI as the main indicator for firm profitability (Sørensen 2002; Tosi JR. and Gomez-Mejia 1994; Weill and Ross 2004) or value of IT investment (Kohli et al. 2012); and 2) market share as a key indicator for competitive advantage relative to others (Fang et al. 2018; Hansen and Wernerfelt 1989; Zheng et al. 2012).

Table 4 (ROI-based performance shortfalls) and Table 5 (market share-based performance shortfalls) provide the results of tests for hypothesis 1. Hypothesis 1 predicts that BI&A radicalness is related more to social aspiration gaps than to historical aspiration gaps. Recall that we operationalized our dependent variable based on third-party IT consulting firms' or analysts' assessment on radicalness of BI&A; models 1 to 7 include independent variables in addition to the control variables. Note that model 1 through model 6 are not nested models. Rather, they are different ways of operationalizing social and historical aspirations from extant performance feedback literature (e.g., Bromiley and Harris 2014).

Table 4. Effects of ROI-based Performance Shortfalls on Radicalness of BI&A

	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Top management support	-0.24	-0.24	-0.31^{+}	-0.24	-0.31^{+}	-0.24	-0.31^{+}	-0.24
Normative forces	-0.01	-0.00	-0.03	-0.00	-0.03	-0.00	-0.03	-0.00
Coercive forces	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mimetic forces	1.86*	1.79*	-0.44	1.80*	-0.18	1.84*	0.04	1.83*
Firm size	-0.00	-0.01	0.05**	-0.01	0.05**	-0.00	0.05**	-0.00
Firm age	-0.00	-0.00	0.00	-0.00	0.00	-0.00	0.00	-0.00
Knowledge barriers	0.02	0.02	0.00	0.02	0.00	0.02	0.01	0.02
Slack	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Performance below Hist. Asp (ewma)		0.12		0.11*		0.09*		0.09*
Performance below Hist. Asp (ave2)			0.18**		0.12**		0.07^{+}	
Performance below Soc. Asp. (sector)		-0.02	-0.16*					
Performance below Soc. Asp. (sic2)				-0.02	-0.07^{+}			
Performance below Soc. Asp. (sic4)						0.01	0.00	
Performance below Soc. Asp. (sg1)								-0.00
Constant	1.35***	1.36***	1.23***	1.36***	1.21***	1.35***	1.20***	1.35***
Fixed or Random Effects Model	Random	Random	Random	Random	Random	Random	Random	Random
χ^2		0.8	9.32**	2.46	6.98**	2.65	2.38	5.25*
Soc. Asp > Hist. Asp.		No	No	No	No	No	No	No
N	1023	1021	760	1021	760	1021	760	1021
AIC	1622.08	1618.13	1155.73	1617.96	1158.66	1618.06	1162.25	1618.18
BIC	1671.39	1677.27	1211.33	1677.10	1214.26	1677.20	1217.85	1677.32
Degree of freedom	7.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00

Notes. [a] Model 1-7 are not nested models. Rather, they indicate different ways of operationalizing aspirations. [b] ewma: exponentially weighted moving average; ave2: average of prior two years. [c] sic2: 2-digit SIC; sic4: 4-digit SIC; sg1: strategic group. [d] Material Engagement: aggregate site revenue-weighted sum of BI&A use.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5. Effects of Market Share-based Performance Shortfalls on Radicalness of BI&A

	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Top management support	-0.24	-1.63	-0.27	-0.25	-0.27	-0.25	-2.02	-0.25
Normative forces	-0.01	0.11	-0.03	-0.01	-0.03	-0.00	-0.02	-0.01
Coercive forces	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mimetic forces	1.86*	0.84	0.09	1.87*	0.10	1.85*	0.42	1.86*
Firm size	-0.00	-0.06	0.05**	0.00	0.05**	-0.00	0.06	-0.00
Firm age	-0.00	0.00	0.00	-0.00	0.00	0.00	0.03	-0.00
Knowledge barriers	0.02	0.11*	0.01	0.02	0.01	0.02	0.14**	0.02
Slack	0.00	-0.06	0.01	0.00	0.01	0.00	-0.07	0.00
Performance below Hist. Asp (ewma)		0.02		0.01		0.01		0.01
Performance below Hist. Asp (ave2)			-0.06		-0.06		-0.01	
Performance below Soc. Asp. (sector)		0.16**	0.01					
Performance below Soc. Asp. (sic2)				0.01	0.01			
Performance below Soc. Asp. (sic4)						0.01	-0.11**	
Performance below Soc. Asp. (sg1)								-0.00
Constant	1.35***	1.28***	1.17***	1.31***	1.18***	1.34***	1.00***	1.35***
Fixed or Random Effects Model	Random	Fixed	Random	Random	Random	Random	Fixed	Random
χ^2		2.13	1.58	0.00	1.56	0.01	1.85	0.07
Soc. Asp > Hist. Asp.		No	No	No	No	No	No	No
N	1023	1021	760	1021	760	1021	760	1021
AIC	1622.08	1220.22	1164.67	1622.09	1164.64	1622.92	765.45	1623.44
BIC	1671.39	1269.50	1220.27	1681.23	1220.24	1682.06	811.79	1682.59
Degree of freedom	7.00	360.00	9.00	9.00	9.00	9.00	302.00	9.00

Notes. [a] Model 1-7 are not nested models. Rather, they indicate different ways of operationalizing aspirations. [b] ewma: exponentially weighted moving average; ave2: average of prior two years. [c] sic2: 2-digit SIC; sic4: 4-digit SIC; sg1: strategic group. [d] Material Engagement: aggregate site revenue-weighted sum of BI&A use.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The controls-only model (Model 0) in Table 4 reveals the only control variable to be significantly associated with firm investment in radical BI&A was mimetic forces. Neither the historical aspiration gap computed as the exponentially weighted moving average of firms' prior performance nor the sector-based social aspiration gap, introduced in Model 1, related significantly to BI&A radicalness. The difference between these two gaps also was insignificant (χ^2= 0.80). Historical aspiration gap computed as the prior two-year average and sector-based social aspiration gap, introduced in Model 2, were found to relate significantly to BI&A radicalness. However, contrary to expectations, the sector-based social aspiration gap was *negatively* related to BI&A radicalness. Thus, as firms' ROI distance from peers in their sector increased, their material engagement with radical BI&A technologies decreased. The difference between these observed effects of historical and social aspiration gaps was significant (χ^2= 9.32, $p < 0.01$). However, contrary to the prediction of hypothesis 1, historical aspiration gaps exerted *higher* impacts on BI&A radicalness. In Model 3, we see that the historical aspiration gap computed as the exponentially weighted moving average of firms' prior performance was significantly related to BI&A radicalness, but the 2-digit-SIC-based social aspiration gap was not. The difference between these two gaps also was insignificant (χ^2= 2.46). In Model 4, we see that the historical aspiration gap computed as the prior two-year average of firms' performance was significantly related to BI&A radicalness, and the 2-digit-SIC-based social aspiration gap was marginally significant. The difference between these two gaps was statistically significant in model 2 (χ^2= 6.98, $p < 0.01$). In Model 5, the historical aspiration gap computed as the exponentially weighted moving average of firms' prior performance was significantly related to BI&A radicalness, but the 4-digit-SIC-based social aspiration gap was not. The difference between these two gaps also was insignificant (χ^2= 2.65). In Model 6, the historical aspiration gap computed as the two-year average of firms' prior performance was unrelated to BI&A radicalness, and the 4-digit-SIC-based social aspiration gap was again negatively related to BI&A radicalness. The difference between these two gaps was insignificant (χ^2= 2.38). In model 7, the historical aspiration gap computed as the exponentially weighted moving average of firms' prior performance was significantly related to BI&A radicalness, but the strategic-group-based social aspiration gap was not. The difference between these two gaps also was significant (χ^2= 5.25, $p < 0.05$).

Table 5 shows results of hypothesis 1a where performance is operationalized as market share. Similar to the ROI-based performance shortfalls in Table 4, the controls-only model (Model 0) reveals that the only significant predictor was mimetic forces. In Model 1, social aspiration gap computed as sector significantly related to BI&A radicalness, but the historical aspiration gap computed as exponentially weighted moving average of the firms' prior performance did not. Neither the historical aspiration gap computed as the average of previous two year's performance nor social aspiration gap computed as sector related to BI&A radicalness in Model 2. In Model 3, we see that either historical aspiration gap computed as exponentially weighted moving average or social aspiration gap computed as 2-digit SIC industry were not significant. In Model 4, neither historical aspiration gap computed the average of previous two years' performance nor social aspiration gap computed as 2-digit SIC industry were insignificant. In Model 5, either historical aspiration gap computed as exponentially weighted moving average of firms' prior performance or 4-digit SIC industry unrelate to the BI&A radicalness. In Model 6, the 4-digit-SIC-based social aspiration was significantly related to BI&A radicalness but the historical aspiration gap computed as the two-year average of firms' prior performance was not. In Model 7, the historical aspiration gap computed as the exponentially weighted moving average of firms' prior performance was not significantly related to the BI&A radicalness and social aspiration gap computed as strategic group member members (closest match) was not either. The difference between the two gaps was insignificant in all models (Model 1 through 7). Social aspirations were significant predictors, indicating that sectors attract more attentions than industry or strategic group members.

For hypothesis 1B, we did not observe curvilinear relationship between BI&A radicalness and either social or historical aspiration gaps. For market share, we observed similar pattern – social aspiration gaps do not exert statistically higher impacts on BI&A radicalness than do historical aspirations. To check for the robustness of results, we also operationalized BI&A radicalness based on BI&A tools generation gaps – the increase in the proportion of BI&A applications in a focal year relative to previous year. The results are summarized in Table B1 and B2. The hypothesis 1B is supported in model 1 (ewma and sector: $\chi^2 = 4.72$, $p < 0.05$) for ROI and marginally supported in model 4 (average of prior two years and sector: $\chi^2 = 3.16$, $p < 0.1$) for market share. For strategic group members, we identified strategic group members based on Mahalanobis distance[7] from total assets and revenue (Kuusela et al. 2017), and focused on the closest match (k=1) to the average of the three closest matches (k=3). The results are consistent across all models. However, only the strategic group members with closest match (k=1) is displayed in all tables.

Hypothesis 2A predicts that diverse BI&A is related more to historical aspiration gaps than to social aspiration gaps. As shown in Table 6 and Table 7, we did not observe this relationship across all models for ROI- and market share-based performance shortfalls. For a

[7] Since total assets and revenue correlate with each other, we opted to use Mahalanobis distances instead of Euclidean distances because 1) Mahalanobis distance weighs both variables (total assets and revenue) equally; 2) Mahalanobis can adjust for the correlations between variables (Hair et al. 2010).

robustness check, we also operationalized diverse BI&A using Herfindahl-Hirschman Index (HHI), and consistent results were observed. Hypothesis 2B predicts that the positive relationship between performance shortfalls and diverse BI&A is stronger when above historical aspirations and weaker when below historical aspirations. Table 8 shows that model 1 through 4 support this hypothesis, indicating that sector ($\beta = 0.03$, $p < 0.05$ in model 1) and industry (SIC2: $\beta = 0.02$, $p < 0.05$ in model 3) remain decision makers' focus of the aspirations in terms of diverse use of BI&A.

Table 6. Effects of ROI-based Performance Shortfalls on Diversity of BI&A

	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Top management support	0.35	0.34	0.53	0.35	0.53	0.35	0.53	0.35
Normative forces	0.01	0.02	0.00	0.01	0.00	0.01	-0.00	0.02
Coercive forces	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mimetic forces	0.18	0.15	0.78^{*}	0.19	0.82^{*}	0.19	0.80^{*}	0.18
Firm size	-0.00	-0.00	0.00	-0.00	0.00	-0.00	0.00	-0.00
Firm age	-0.00	-0.00	0.00	-0.00	0.00	-0.00	0.00	-0.00
Knowledge barriers	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01
Slack	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Performance below Hist. Asp (ewma)		0.01		-0.00		-0.00		-0.00
Performance below Hist. Asp (ave2)			-0.00		-0.01		-0.00	
Performance below Soc. Asp. (sector)		-0.01	-0.00					
Performance below Soc. Asp. (sic2)				0.01	0.01			
Performance below Soc. Asp. (sic4)						0.01	0.01	
Performance below Soc. Asp. (sg1)								0.00
Constant	0.91^{***}	0.91^{***}	0.89^{***}	0.90^{***}	0.88^{***}	0.90^{***}	0.88^{***}	0.90^{***}
Fixed or Random Effects Model	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed
χ^2		0.26	0.00	0.12	0.37	0.27	0.50	0.00
Hist. Asp. > Soc. Asp		No	No	No	No	No	No	No
N	1250	1248	928	1248	928	1248	928	1248
AIC	-1281.33	-1273.68	-1230.64	-1273.51	-1231.31	-1275.17	-1233.13	-1273.29
BIC	-1240.28	-1222.38	-1182.31	-1222.22	-1182.98	-1223.88	-1184.80	-1222.00
Degree of freedom	423.00	424.00	358.00	424.00	358.00	424.00	358.00	424.00

Notes. [a] Model 1-7 are not nested models. Rather, they indicate different ways of operationalizing aspirations. [b] ewma: exponentially weighted moving average; ave2: average of prior two years. [c] sic2: 2-digit SIC; sic4: 4-digit SIC; sg1: strategic group. [d] Material Engagement: aggregate site revenue-weighted sum of BI&A use.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7. Effects of Market Share-based Performance Shortfalls on Diversity of BI&A

	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Top management support	0.35	0.34	0.52	0.34	0.52	0.33	0.51	0.34
Normative forces	0.01	0.01	-0.00	0.02	0.00	0.01	0.00	0.01
Coercive forces	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mimetic forces	0.18	0.25	0.83^{*}	0.18	0.79^{*}	0.18	0.79^{*}	0.18
Firm size	-0.00	-0.00	0.00	-0.00	0.00	-0.00	0.00	-0.00
Firm age	-0.00	-0.01	-0.00	-0.00	0.00	-0.00	0.00	-0.00
Knowledge barriers	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01
Slack	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Performance below Hist. Asp (ewma)		0.00		0.00		0.00		0.00
Performance below Hist. Asp (ave2)			0.01		0.01		0.01	
Performance below Soc. Asp. (sector)		-0.03	-0.03					
Performance below Soc. Asp. (sic2)				0.00	-0.00			
Performance below Soc. Asp. (sic4)						-0.01	-0.01	
Performance below Soc. Asp. (sg1)								-0.00
Constant	0.91^{***}	0.96^{***}	0.94^{***}	0.90^{***}	0.89^{***}	0.91^{***}	0.89^{***}	0.90^{***}
Fixed or Random Effects Model	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed
Hist. Asp. > Soc. Asp		No	No	No	No	No	No	No
χ^2		1.79	2.36	0.00	0.37	0.36	0.49	0.07
N	1250	1248	928	1248	928	1248	928	1248
AIC	-1281.33	-1277.17	-1234.96	-1273.49	-1231.25	-1274.08	-1231.46	-1273.37
BIC	-1240.28	-1225.88	-1186.63	-1222.20	-1182.92	-1222.79	-1183.13	-1222.08
Degree of freedom	423.00	424.00	358.00	424.00	358.00	424.00	358.00	424.00

Notes. [a] Model 1-7 are not nested models. Rather, they indicate different ways of operationalizing aspirations. [b] ewma: exponentially weighted moving average; ave2: average of prior two years. [c] sic2: 2-digit SIC; sic4: 4-digit SIC; sg1: strategic group. [d] Material Engagement: aggregate site revenue-weighted sum of BI&A use.
$^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 8. Differential Effects of Market Share-based Performance Shortfalls on Diversity of BI&A When Above and Below Historical Aspirations

	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Top management support	0.35	0.26	0.44	0.21	0.37	0.33	0.49	0.31
Normative forces	0.01	0.02	-0.00	0.02	-0.00	0.01	0.00	0.01
Coercive forces	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mimetic forces	0.18	0.26	0.90^{**}	0.21	0.87^{**}	0.20	0.83^{*}	0.18
Firm size	-0.00	-0.00	0.00	-0.00	0.00	-0.00	0.00	-0.00
Firm age	-0.00	-0.00	0.00	-0.00	0.00	-0.00	0.00	-0.00
Knowledge barriers	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01
Slack	0.02	0.02	0.01	0.02	0.01	0.02	0.01	0.02
Performance below Hist. Asp (ewma)		0.03		0.02		0.01		0.00
Performance above Hist. Asp (ewma)		-0.02		-0.01		-0.01		-0.00
Performance below Hist. Asp (ave2)			0.03		0.02		0.00	
Performance above Hist. Asp (ave2)			-0.02^{+}		-0.02		-0.02	
Performance below Soc. Asp. (sector)		-0.02	-0.03^{+}					
Performance above Soc. Asp. (sector)		0.03^{*}	0.03^{*}					
Performance below Soc. Asp. (sic2)				0.00	-0.00			
Performance above Soc. Asp. (sic2)				0.02^{**}	0.03^{**}			
Performance below Soc. Asp. (sic4)						-0.01	-0.01	
Performance above Soc. Asp. (sic4)						0.01	0.01	
Performance below Soc. Asp. (sg1)								0.00
Performance above Soc. Asp. (sg1)								0.00
Constant	0.91^{***}	0.90^{***}	0.89^{***}	0.87^{***}	0.87^{***}	0.91^{***}	0.89^{***}	0.89^{***}
Fixed or Random Effects Model	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed
F value		3.15^{+}	5.25^{*}	2.01	4.87^{*}	0.53	1.36	0.24
Hist. Asp. (above) > Hist. Asp. (below)		No	No	No	No	No	No	No
F value		7.44^{**}	7.09^{**}	2.86^{+}	5.60^{*}	1.25	0.91	0.60
Soc. Asp. (above) > Soc. Asp. (below)		Yes	Yes	Yes	Yes	No	No	No
N	1250	1248	928	1248	928	1248	928	1248
AIC	-1281.33	-1282.33	-1241.16	-1281.25	-1242.39	-1271.98	-1230.30	-1270.75
BIC	-1240.28	-1220.78	-1183.17	-1219.70	-1184.39	-1210.43	-1172.30	-1209.20
Degree of freedom	423.00	426.00	360.00	426.00	360.00	426.00	360.00	426.00

Notes. [a] Model 1-7 are not nested models. Rather, they indicate different ways of operationalizing aspirations. [b] ewma: exponentially weighted moving average; ave2: average of prior two years. [c] sic2: 2-digit SIC; sic4: 4-digit SIC; sg1: strategic group. [d] Material Engagement: aggregate site revenue-weighted sum of BI&A use. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Hypothesis 3A predicts that performance shortfalls based on social aspirations have stronger impacts on informational and material engagement with BI&A technologies than do historical aspirations. Since information and material engagement are not measured in the same units, we standardized the two dependent variables before testing the hypothesis. As shown in Table 9, only model 3 and 4 (industry (SIC2)-based performance shortfalls) marginally supported this hypothesis ($\beta = -0.02$, $p < 0.1$ in model 3 and 4, respectively). Other models do not support this hypothesis. Hypothesis 3B predicts that social aspiration-based performance shortfalls have a stronger impact on informational than on material engagement. As shown in Table 10, contradictory to the hypothesis, we observed that social aspiration-based performance shortfalls show statistically significantly higher impacts on material engagement ($\beta = -0.10$, $p < 0.01$) than on informational engagement ($\beta = 0.00$) n model 1 (sector: $\beta = -0.03$, $p < 0.1$) and model 2 (industry SIC2: $\beta = -0.02$, $p < 0.05$).

Table 9. Different Effects of Market Share-based Performance Shortfalls on Informational and Material Engagement with BI&A

	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Top management support	-1.38	-0.68	-0.60	-0.68	-0.60	-0.67	-0.58	-1.36
Normative forces	-0.10*	-0.05	-0.09^{+}	-0.06	-0.09^{+}	-0.05	-0.08^{+}	-0.10*
Coercive forces	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mimetic forces	0.40	0.54	-0.18	0.54	-0.18	0.54	-0.13	0.42
Firm size	0.10***	0.12***	0.15***	0.12***	0.15***	0.12***	0.16***	0.10***
Firm age	0.03**	0.02**	0.04***	0.02**	0.04***	0.03**	0.04***	0.03**
Knowledge barriers	0.10***	0.06**	0.05*	0.06**	0.05**	0.06***	0.06**	0.10***
Slack	-0.05^{+}	-0.03^{+}	-0.02	-0.03^{+}	-0.02	-0.04^{+}	-0.02	-0.05^{+}
Informational Engagement		0.00	0.00	0.00	0.00	0.00	0.00	0.00
Material Engagement		-0.10**	-0.11**	-0.12***	-0.12***	-0.14***	-0.15***	-0.15***
Performance below Hist. Asp (ewma)		-0.00		-0.00		-0.01		-0.01
Performance below Hist. Asp (ave2)			-0.07^{+}		-0.07*		-0.08*	
Performance below Soc. Asp. (sector)		-0.01	-0.02					
Performance below Soc. Asp. (sic2)				-0.02	-0.01			
Performance below Soc. Asp. (sic4)						0.02^{+}	0.02^{+}	
Performance below Soc. Asp. (sg1)								0.00
Diff. Impacts of Hist. Asp. (ewma) between Info. and Mat. Engagement		0.01		0.02		0.03		0.03
Diff. Impacts of Hist. Asp. (ave2) between Info. and Mat. Engagement			0.01		0.01		0.02	
Diff. Impacts of Soc. Asp. (sector) between Info. and Mat. Engagement		-0.03	-0.03					
Diff. Impacts of Soc. Asp. (sic2) between Info. and Mat. Engagement				-0.02^{+}	-0.02^{+}			
Diff. Impacts of Soc. Asp. (sic4) between Info. and Mat. Engagement						-0.00	-0.00	
Diff. Impacts of Soc. Asp. (sg1) between Info. and Mat. Engagement								0.00
Constant	-0.61***	-0.58***	-0.79***	-0.56***	-0.80***	-0.65***	-0.87***	-0.53***
Fixed or Random Effects Model	Fixed	Random	Random	Random	Random	Random	Random	Fixed
N	3124	3110	2258	3110	2258	3110	2258	3110
AIC	4247.51	5955.95	4264.25	5950.72	4260.57	5956.76	4264.59	4170.02
BIC	4295.88	6046.58	4350.09	6041.36	4346.40	6047.40	4350.42	4248.57
Degree of freedom	557.00	12.00	12.00	12.00	12.00	12.00	12.00	557.00

Notes. [a] Model 1-7 are not nested models. Rather, they indicate different ways of operationalizing aspirations. [b] ewma: exponentially weighted moving average; ave2: average of prior two years. [c] sic2: 2-digit SIC; sic4: 4-digit SIC; sg1: strategic group. [d] Material Engagement: aggregate site revenue-weighted sum of BI&A use.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10. Models of Social Aspirations-based Performance Shortfalls (Market Share) on Informational and Material Engagement with BI&A

	Model 0	Model 1	Model 2	Model 3	Model 4
Top management support	-1.38	-0.68	-0.68	-0.67	-1.36
Normative forces	-0.10^{*}	-0.05	-0.05	-0.05	-0.10^{*}
Coercive forces	0.00	0.00	0.00	0.00	0.00
Mimetic forces	0.40	0.54	0.53	0.53	0.41
Firm size	0.10^{***}	0.12^{***}	0.12^{***}	0.12^{***}	0.10^{***}
Firm age	0.03^{**}	0.02^{**}	0.03^{**}	0.03^{**}	0.03^{**}
Knowledge barriers	0.10^{***}	0.06^{**}	0.06^{**}	0.06^{***}	0.10^{***}
Slack	-0.05^{+}	-0.03^{+}	-0.03^{+}	-0.03^{+}	-0.05^{+}
Informational Engagement		0.00	0.00	0.00	0.00
Material Engagement		-0.10^{**}	-0.11^{***}	-0.14^{***}	-0.15^{***}
Performance below Soc. Asp. (sector)		-0.01			
Performance below Soc. Asp. (sic2)			-0.02		
Performance below Soc. Asp. (sic4)				0.02^{+}	
Performance below Soc. Asp. (sg1)					0.00
Diff. of Soc. Asp. (sector) on Info. and Mat. Engagement		-0.03^{+}			
Diff. of Soc. Asp. (sic2) on Info. and Mat. Engagement			-0.02^{*}		
Diff. of Soc. Asp. (sic4) on Info. and Mat. Engagement				-0.00	
Diff. of Soc. Asp. (sg1) on Info. and Mat. Engagement					0.00
Constant	-0.61^{***}	-0.58^{***}	-0.57^{***}	-0.66^{***}	-0.53^{***}
Fixed or Random Effects Model	Fixed	Random	Random	Random	Fixed
N	3124	3124	3124	3124	3124
AIC	4247.51	5978.08	5972.83	5979.33	4181.31
BIC	4295.88	6056.69	6051.44	6057.94	4247.83
Degree of freedom	557.00	10.00	10.00	10.00	560.00

Notes. [a] Model 1-4 are not nested models. Rather, they indicate different ways of operationalizing aspirations. [b] ewma: exponentially weighted moving average; ave2: average of prior two years. [c] sic2: 2-digit SIC; sic4: 4-digit SIC; sg1: strategic group. [d] Material Engagement: aggregate site revenue-weighted sum of BI&A use.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Hypothesis 4 predicts that effects of performance shortfalls on a firm's informational and material engagement are stronger for the early BI&A diffusion stage than for the later stage. Table 11 and Table 12 summarizes the results pertaining to this hypothesis. For the temporal impacts on informational engagement, we observed that the effects are stronger for social aspirations (sector and SIC2) are stronger at early diffusion stage than later stage ($\beta = 0.08$, $p < 0.001$ in model 1 and $\beta = 0.08$, $p < 0.01$ in model 2). For the temporal impact on material engagement, we observed that only historical aspirations (ave2) show statistically stronger impacts at early diffusion stage ($\beta = -0.08$, $p < 0.01$ in model2; $\beta = -0.09$, $p < 0.05$ in model2). Figure 2 shows the temporal effects of market share-based performance shortfalls on informational engagement with BI&A. Figure 3 shows the temporal effects of market share-based performance shortfalls on material engagement with BI&A.

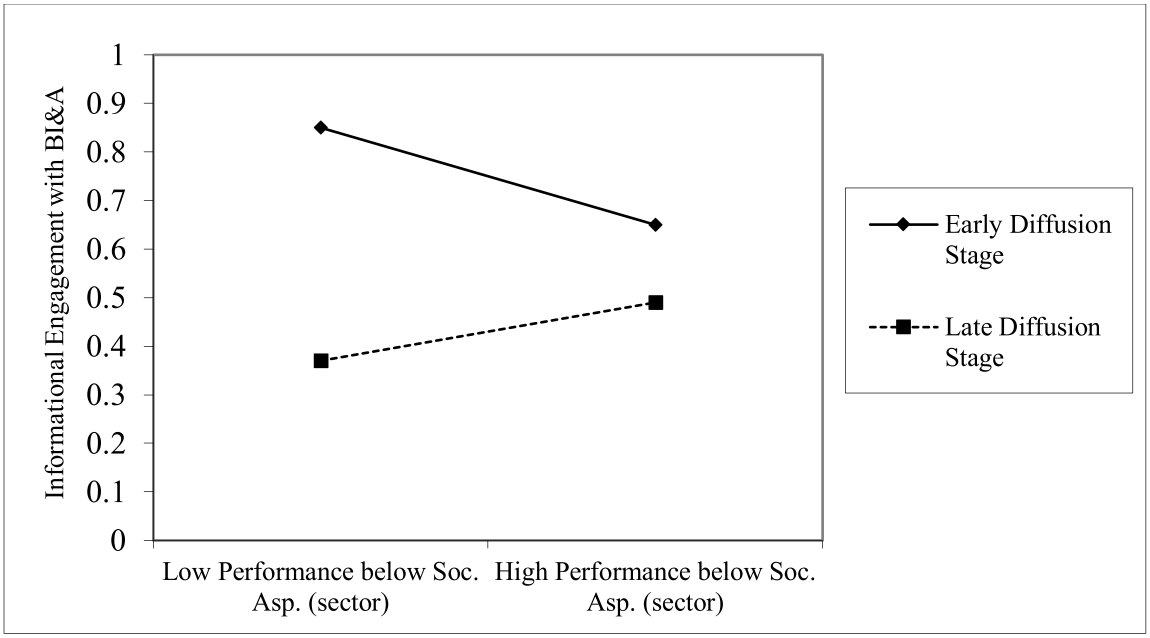

Figure 2. Temporal Effects of Market Share-based Performance Shortfalls on Informational Engagement with BI&A (Hypothesis 4)

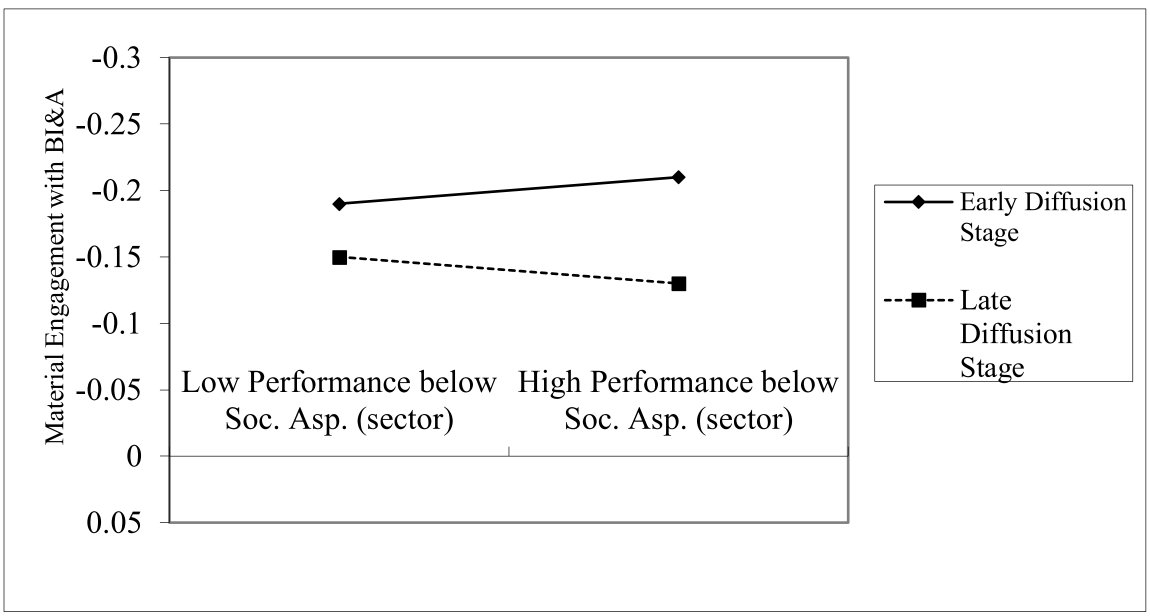

Figure 3. Temporal Effects of Market Share-based Performance Shortfalls on Material Engagement with BI&A (Hypothesis 4)

Table 11. Temporal Effects of Market Share-based Performance Shortfalls on Informational Engagement with BI&A

	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5
Top management support	1.76^{+}	2.10^{*}	2.42^{*}	2.06^{*}	2.41^{*}	2.11^{*}
Normative forces	0.01	0.02	-0.03	0.01	-0.04	0.02
Coercive forces	0.00	0.00	0.00	0.00	0.00	0.00
Mimetic forces	-0.20	-0.22	1.17^{+}	-0.16	1.23^{+}	-0.14
Firm size	-0.07^{***}	-0.06^{**}	-0.12^{***}	-0.06^{**}	-0.12^{***}	-0.07^{***}
Firm age	-0.01	-0.01	0.01	-0.01	0.01	-0.01
Knowledge barriers	-0.06^{*}	-0.03	-0.02	-0.03	-0.03	-0.04
Slack	-0.03	-0.02	-0.01	-0.03	-0.02	-0.03
Early stage		-0.16^{***}	-0.17^{***}	-0.11^{***}	-0.06^{+}	-0.05^{*}
Performance below Hist. Asp (ewma)		-0.06^{*}		-0.05		-0.04
Performance below Hist. Asp (ave2)			-0.04		-0.02	
Performance below Soc. Asp. (sector)		-0.02	-0.01			
Performance below Soc. Asp. (sic2)				-0.01		
Performance below Soc. Asp. (sic4)					0.01	
Performance below Soc. Asp. (sg1)						0.01
Early stage x Performance below Hist. Asp (ewma)		-0.06		-0.08		-0.09
Early stage x Performance below Hist. Asp (ave2)			-0.11		-0.14^{+}	
Early stage x Performance below Soc. Asp (sector)		0.08^{***}	0.08^{**}			
Early stage x Performance below Soc. Asp (sic2)				0.04^{**}		
Early stage x Performance below Soc. Asp (sic4)					0.01	
Early stage x Performance below Soc. Asp (sg1)						-0.00
Constant	0.67^{***}	0.59^{***}	0.80^{***}	0.62^{***}	0.86^{***}	0.63^{***}
Fixed or Random Effects Model	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed
N	1562	1555	1129	1555	1129	1555
AIC	548.14	528.93	401.44	537.93	417.25	546.08
BIC	590.97	598.47	466.82	607.47	482.63	615.62
Degree of freedom	557.00	557.00	459.00	557.00	459.00	557.00

Notes. [a] Early stage: 2010-2012; Later stage: 2013-2015. [b] Model 1-5 are not nested models. Rather, they indicate different ways of operationalizing aspirations. [c] ewma: exponentially weighted moving average; ave2: average of prior two years. [d] sic2: 2-digit SIC; sic4: 4-digit SIC; sg1: strategic group. [e] Material Engagement: firm-level BI&A use is aggregated using revenue-weighted site-level BI&A use.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12. Temporal Effects of Market Share-based Performance Shortfalls on Material Engagement with BI&A

	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5
Top management support	-0.25	-0.20	-0.20	-0.20	-0.20	-0.34
Normative forces	-0.01	-0.01	-0.02	-0.01	-0.02	-0.04
Coercive forces	0.00	0.00	0.00	0.00	0.00	0.00
Mimetic forces	0.29	0.28	-0.03	0.29	-0.01	0.17
Firm size	0.06^{***}	0.06^{***}	0.07^{***}	0.06^{***}	0.07^{***}	0.04^{**}
Firm age	0.01^{*}	0.01^{+}	0.01^{*}	0.01^{+}	0.01^{*}	0.01
Knowledge barriers	0.02^{*}	0.02^{*}	0.02^{+}	0.02^{+}	0.02^{*}	0.04^{*}
Slack	-0.01	-0.02	-0.01	-0.02	-0.01	-0.02
Early stage		0.03	0.02	0.04^{*}	0.04^{*}	0.05^{**}
Performance below Hist. Asp (ewma)		0.02		0.02		0.01
Performance below Hist. Asp (ave2)			-0.01		-0.00	
Performance below Soc. Asp. (sector)		-0.00	-0.01			
Performance below Soc. Asp. (sic2)				-0.01		
Performance below Soc. Asp. (sic4)					0.01	
Performance below Soc. Asp. (sg1)						0.01^{+}
Early stage x Performance below Hist. Asp (ewma)		-0.10		-0.10		-0.11^{+}
Early stage x Performance below Hist. Asp (ave2)			-0.08^{+}		-0.09^{*}	
Early stage x Performance below Soc. Asp (sector)		0.01	0.01			
Early stage x Performance below Soc. Asp (sic2)				0.00		
Early stage x Performance below Soc. Asp (sic4)					-0.00	
Early stage x Performance below Soc. Asp (sg1)						-0.01^{+}
Constant	-0.17^{**}	-0.17^{*}	-0.25^{***}	-0.14^{*}	-0.27^{***}	-0.08
Fixed or Random Effects Model	Random	Random	Random	Random	Random	Fixed
N	1562	1555	1129	1555	1129	1555
AIC	782.72	779.89	566.43	778.73	565.64	-679.45
BIC	836.26	860.12	641.86	858.97	641.08	-609.91
Degree of freedom	7.00	12.00	12.00	12.00	12.00	557.00

Notes. [a] Early stage: 2010-2012; Later stage: 2013-2015. [b] Model 1-5 are not nested models. Rather, they indicate different ways of operationalizing aspirations. [c] ewma: exponentially weighted moving average; ave2: average of prior two years. [d] sic2: 2-digit SIC; sic4: 4-digit SIC; sg1: strategic group. [e] Material Engagement: firm-level BI&A use is aggregated using revenue-weighted site-level BI&A use.

$^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Chapter 6: Discussion

This dissertation aims to investigate how performance shortfalls influence decision makers' adoption decisions of an IT innovation – Business Intelligence and Analytics (BI&A). Understanding this decision-making process not only matters to firms' survival (Susarla and Barua 2011), but is also key to gaining competitive advantages (Giarratana 2004; Pan et al. 2019). The paucity of empirical investigation of the role of performance shortfalls relative to aspirations in IT innovation diffusion further enhances the value of the study.

Key Findings

Table 13 provides summary of Findings.

Table 13. Summary of Findings

Hypothesis	Support?
H1 (BI&A radicalness)	H1a is not supported (Counterintuitive: historical aspirations (ave2) > social aspirations (sector))
	H1b is not supported (no curvilinear relationship)
H2 (BI&A diversity)	H2a is not supported
	H2b is supported (only for sector and industry (SIC2))
H3 (decoupling)	H3a is marginally supported (market share: sic2 ave2)
	H3b is not supported (Counterintuitive: social aspirations: material engagement > informational engagement)
H4 (institutionalization)	H4 is supported (informational engagement: social aspirations (sector and sic2); material engagement: historical aspirations (ave2))

Performance feedback is an important and yet overlooked organizational process in the IT innovation diffusion literature (Jeyaraj et al. 2006; Kohli and Melville 2019; Rogers 2003). We examined this process by drawing upon BTOF framework and argued that the patterning of BI&A diffusion (e.g., BI&A radicalness, diversity, and their temporal effects) might be affected by aspiration-driven searches in a backward-looking manner. As such, this dissertation is an important step towards linking performance feedback literature and IT innovation diffusion literature. Specifically, we examined how decision makers react to performance shortfall relative to different aspirations (historical and social aspirations) to determine the extent to which they engage with BI&A to gain competitive advantages. In doing so, we addressed the following research questions: 1) to what extent does relative performance affect a firm's choice of IT innovation engagement strategies; 2) to what extent does relative performance influence patterning of engagement with an IT innovation; and 3) how does relative performance affect firms' engagement with an IT innovation over time (i.e., at early and late diffusion stages)?

Our results in general support the predictions that radicalness of BI&A and the extent to which firms engage with BI&A informationally and materially respond to historical and social aspirations (particularly performance shortfalls). Addressing RQ1, we found that underperforming firms tend to engage with more radical BI&A; we did not observe the diverse BI&A is driven by either historical or social aspirations. Answering the RQ2, we found that underperforming firms tend to engage BI&A informationally and materially. However, contrary to our prediction that informational engagement with BI&A reacts more to performance shortfalls than would material engagement, we found that materially engaging with BI&A matter more to decision makers, extending the decoupling research – i.e., firms commit to the use of BI&A (doing things) rather than announcing it (saying). Addressing RQ3, consistent with institutionalization literature (Tolbert and Zucker 1983), these relationships between performance shortfalls and BI&A diffusion patterning are stronger in the early BI&A diffusion stage than in later BI&A diffusion stage.

Historical versus Social Aspirations

Research on performance feedback generally conceptualizes and operationalizes historical and social aspirations together (e.g., Greve 2003a; Rhee et al. 2019; Rudy and Johnson 2016). In contrast, we did it separately, permitting insights into how decision makers differentially react to their historical and social aspiration levels. Of the two referents, historical aspirations show stronger impacts on BI&A radicalness, and information and material engagement with BI&A. It implies that when it comes to BI&A diffusion, decision makers respond to performance shortfalls more closely to their own historical performance than the performance shortfalls relative to peers', contradictory to the findings in recent performance feedback literature (e.g., Kim et al. 2015; Wang et al. 2017). This could be due to the fact that decision makers have more information about their own firms than about peer firms. Even with the same amount of available information about both own and peer firms, decision makers may put more emphasis on its own history BI&A than on peer firms, thus be more alert to performance shortfalls based on historical aspirations. Third, it could also because that decision makers are more familiar with their own businesses and feel more control over and thus more confident about the actions to be taken about engaging with BI&A.

Breadth and Depth of Aspirational References

Our results extend the views of Strategic Reference Point Theory (Fiegenbaum et al. 1996; Fiegenbaum and Thomas 1995) and performance feedback literature (e.g., Kim and Tsai 2012; Kuusela et al. 2017; Lucas et al. 2018). When it comes to BI&A engagement decisions, for social aspirations, underperforming firms tend to focus on a broader scope of peers (i.e., sector) rather than a narrower scope of peers (SIC-based industry) (Lucas et al. 2018) or close peers (i.e., strategic group members) (Ruckman et al. 2015) or a particular target firm (Kim and Tsai 2012). This tendency is consistent across almost all BI&A engagement behaviors (BI&A radicalness, information and material engagement). We also observed that decision makers tend not to look merely to immediately prior year's performance (e.g., Xu et al. Forthcoming). Rather, the average of previous two years' performance shows the strongest and consistent impact among all historical referents (e.g., prior years moving average, etc.). This tendency of recent two years' historical performance reflects the backward-looking depth of decision makers – neither too backward-looking such as all previous years moving average (Eggers and Kaul 2018) nor too recent like previous year, permitting a novel insight into the manner in which decision makers perceive their own performance.

Theoretical Contributions

Although historical and social aspirations are not novel constructs in the performance feedback literature, they are new to the IT innovation diffusion literature. More importantly, the way we conceptualize and operationalize the two aspiration levels permit us to reveal insights into the differential impacts on the diffusion patterning of BI&A.

Our research makes valuable theoretical contributions as follows. First, we contribute to the rich IT innovation diffusion literature by bringing in a new antecedent (i.e., historical and social aspirations) of diffusion of IT innovations. Methodology-wise, we developed a new text-based measure for construct radicalness, complementary to the currently dominant survey-based measure (Carlo et al. 2012). Second, we contribute to the performance feedback literature by examining the relative impacts of the historical and social aspirations on BI&A engagement behaviors and offer nuanced and counter-intuitive insights. Moreover, we challenged BTOF by finding that decision makers of underperforming firms tend to look broader than to focus on a narrow scope of peers in the BI&A diffusion context. Third, we found support for the institutionalization of BI&A – i.e., BI&A become more legitimate over time and thus bandwagon effects prevail. However, under the institutional pressure in the BI&A diffusion context, our results found evidence that decision makers make commitment (concrete actions) rather than do the window dressing. We observed an alternative form of decoupling – i.e., firms tend to materially engage with BI&A rather than informationally do it, different from policy-practice decoupling (Westphal and Zajac 2001) and means-ends decoupling (Bromley and Powell 2012). Last, we also contributed to the growing knowledge about BI&A diffusion.

Managerial Implications

Practically speaking, this study provides implications for managers and vendors. For the managers, our research findings provide insights about how adopting firms engage with BI&A. First, performance shortfall may drive firms to use more radical BI&A. Second, for those performance shortfalls-driven BI&A adopters, sector and industry provide a useful reference for evaluating performance. For BI&A vendors, our research suggests that marketing campaign efforts should be spent in the immediate post-launch period rather than the distant post-launch period because the BI&A institutionalization can facilitate bandwagon effect and thus the diffusion of BI&A will self-sustain in the distant post-launch period.

Limitations

Our sample is comprised of firms from only manufacturing and wholesale and retailing sectors and of years between 2010 and 2015. One concern, therefore, is that findings might be sample-specific. However, the two sectors are chosen for theoretical purposes because they are among several of the earliest sectors engaging with BI&A (Davenport and Harris 2017), permitting us to fully observe the diffusion of BI&A and more importantly setting up a boundary condition for the research findings – later adoption might reflect a mindless, bandwagon effect.

In examining the role of historical and social aspirations in BI&A adoption decisions, we chose performance indicators based on sector-specific characteristics. We reasoned that decisions regarding BI&A adoption driven by historical and social aspirations are based primarily on return on investment (ROI) and market share (MS). Clearly, decision makers may rely on other performance indicators to make BI&A adoption decisions. For instance, firms with different strategic goals may use different performance indicators, ranging from ROA to ROE to sales. Examining how BI&A adoption decision are made based on diverse performance indicators/criteria is a challenge. Our analyses control for an extensive list of variables that were found to be significant predictors in prior IT innovation diffusion research and its different streams (e.g., institutional theory or top management). Thus, the rigor of our findings is further enhanced. Additionally, we conducted several robustness checks and consistent results were observed.

Coercive forces are theorized as an institutional pressure for firms to engage with BI&A. We operationalized coercive forces based on data from U.S. Congress legislative documents. We noticed that the vast majority of became-law documents about BI&A do not necessarily pertain to the promotion, adoption, or use of BI&A. Instead, they are indirectly mentioned in legislation for other purposes (e.g., military training, small business innovation, etc.). Sector- or industry-specific regulatory actions germane to BI&A was unavailable. This limits the effects of coercive forces observed.

Suggestions for Future Research

First, since stock prices affect executives' decision making (Mannor et al. 2016), we will operationalize aspiration gaps in terms of stock prices. Second, in strategic management research, ROA and ROS have been used as performance indicators to operationalize performance discrepancies. However, in terms of BI&A diffusion, we observed that ROI and market share appear to matter more to the decision makers of underperforming firms than do ROA and ROS. As such, we will develop a multivariate performance index, which includes performance indicators of more relevance to the diffusion of IT innovations. Third, we will analyze sectors separately to further control for the variances induced by the heterogeneity across sectors.

Chapter 7: Conclusions

Drawing performance feedback perspective, this dissertation examines how firms' decision-makers engage with BI&A in response to performance shortfalls relative to aspirations. Our findings suggest that underperforming firms tend to engage with more radical BI&A. We also found that social aspiration gaps do not exert significantly higher impacts on firms' engagement with BI&A. However, we found that materially engaging with BI&A matters more to decision makers than does informationally engaging with BI&A, extending the decoupling research – i.e., firms commit to the use of BI&A (doing things) rather than announcing it (saying). Last, we observed that these relationships between performance shortfalls and BI&A diffusion patterning are stronger in the early BI&A diffusion stage than in later BI&A diffusion stage.

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Appendix A

Table A1. Two Paradigms in IT Innovation Diffusion Research

Paradigm	Assumptions	Diffusion Antecedents	Drawback
Economic rationality	IT innovations are adopted because they can enhance firm performance; firms with greater innovation-related capacities will be more engaged in adoption in terms of frequency, earliness, and extensiveness of implementation (Fichman 2004a). Adopting firms are rational agents, able to fully assess pros and cons of focal technology, consciously evaluate their needs, and then make a decision that fully reflects their assessments of the alignment between the technology and the firms' specificities and that best represents the interests of adopting firms.	Technical knowledge resources, slack resources, decentralized governance structure, top management support, external pressures (e.g., from suppliers, industry standards) (Damanpour 1991; Jeyaraj et al. 2006)	Pays little attention to the role of non-technological and non-organizational aspects (e.g., environmental factors) in influencing the adoption of technologies; Overemphasis on technology itself and on organizational aspects neglects influential external forces that firms should not overlook (Gosain 2004)
Institutional forces	Other than the focal technology and organizational attributes, firms' adoption and implementation decisions are influenced by factors from their institutional environment (Swanson 2012). Adopting firms are rational bounded. That is, firms cannot fully assess their own specific needs and circumstances, and are subject to influence from institutional context.	Peer influence and supervisory authority influence (Hsu et al. 2012), institutional pressures (e.g., mimetic, coercive, normative forces) (Liang et al. 2007)	Overemphasize on institutional factors and pays little attention to internal factors (e.g., performance or efficiency concerns)

Table A2. Brief Review of Business Intelligence and Analytics (BI&A)		
Definition	Characteristics	Role of BI&A
Business intelligence and analytics (BI&A) is an umbrella term that describes a set of concepts and methods for improving evidence-based decision making (Trieu 2017). BI&A refers to "the techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data to help an enterprise better understand its business and market and make timely business decisions" (Chen et al. 2012, p. 1166).	Three layers: decision time, techniques, and analytics; the analytics layer is the one most closely linked to decision making (Goes 2014). No single technology can cover the full spectrum of BI&A technologies (Watson 2009). However, several different complementary types of BI&A technologies together serve companies to gain business insights. Data management and integration tools and BI platforms (e.g., NoSQL data store or Hadoop/Spark) help firms "get data in," and advanced data science tools (e.g., RapidMiner) help firms to "get data out" (Watson 2009).	BI&A technologies are less decentralizable (Miranda et al. 2015a; Yeoh and Popovič 2016). Unlike more decentralizable technologies (e.g., social media) where adoption decision are generally in the hands of organizational sub units (Miranda et al. 2015a), adoption of BI&A need to go through more centralized decision making processes. The adoption and implementation of BI&A require high-level financial resources, and complementary resources such as data scientists, and supporting platforms on which BI&A technologies operate (Miranda et al. 2015a). Moreover, BI&A technologies are key to organizational strategies and business performance (Davenport and Harris 2017). The adoption of BI&A may involve a drastic change in firms' business model (Davenport 2017). All these imply that adoption of BI&A is effortful, needs significant managerial attention. In other words, the adoption of BI&A is firm-level decision making.

Table A3. Custom Dictionaries	
Category	Terms
BI&A	Business intelligence, analytics, 1010data, ADVIZOR, AFS G2, Alteryx, Altosoft, Amazon QuickSight, Analytics for Capture, AnswerRocket, Antivia, Anzo Smart Data, Arcadia Enterprise, arcplan, Artus, Ayasdi, BDB Platform, BeyondCore, Bime, Birst, BIRT, Board International, CARTO Builder, Chartio, ClearStory Data, Cubeware, DataHero, Datameer, DataRPM, Datawatch, DecisionPoint Enterprise, DecisionPoint For Excel, Decisyon 360, Dimensional Insight, Domo, Dundas, Einstein Analytics, Eligotech, eQube BI, Exago BI, FICO, GoodData, Hadoop-Based Data Discovery, Halo Business Intelligence, IBM Analytical, IBM Watson, iDashboards, Incorta, InetSoft, InfoBusiness, Infor BI, Information Builders, Izenda, JackBe, Jaspersoft, Jedox, Jinfonet, Jreport, Karmasphere, Kofax Insight, KXEN, Lavastorm Analytics, Logi Analytics, Logi Info, LogiXML, Looker, Manthan, PowerPivot, MicroStrategy, myDials, Netezza, NovaView Analytics, NovaView BI, OpenText, Oracle BI, Oracle Big Data Discovery, Oracle Business Intelligence, Oracle Data Visualization, Oracle Endeca, Oracle Essbase, OTBI, Palantir, Panorama Necto, Pentaho, Periscope Data, Phocas, Platfora, Power BI, Prognoz, Pyramid Analytics, Qlik Sense, QlikView, ReportServer, Salesforce Wave Analytics, Salient ETL, Salient Interactive Miner, SAP BusinessObjects, Roambi, SAS Visual Analytics, SiSense, SpagoBI, Splunk Cloud, Spotfire, SPSS Modeler, Strategy Companion, SynerScope, Tableau, Targit, ThoughtSpot, Varicent, VizQL, WebFocus, Wordsmith, Xpert BI, Yellowfin, Yseop Compose, Zendesk Explore, Zoomdata, Zucchetti
Radicalness	above average, above-average, add*, additional, advanced analy*, aggressive*, ahead, ahead of the curve, ambitious strategy, amend, better-than-average, BI mobile, bold strateg*, boldest, breakthrough, chang*, changing the game, complete departure, completely rearchitected, completely rebuilt, completely redesigned, cutting edge, cutting-edge, different, differentiat*, disrupt*, dramatic, emerg*, enhanced, enhancement*, evolv*, extend*, fast-evolving, fresh, groundbreaking, higher-than-average, improvement*, in the top *, increment*, innovat*, leading, leading-edge, mobile BI, mobile business intelligence, mobile capabilities, mobile delivery, mobile platform*, modernized, modify, most advanced, most progress, near-top, new, new feature*, next-gen*, no longer, novel*, one of the top, original, phenomenal, pioneer*, promising, radical*, re-configure, redesign*, rethink, revis*, risk*, shift, smart * discovery, static, still, superhero, top score, top-notch, transform*, trending, unique*, unmatched, amaze*, amazing*, awe*, bizarre, creat*, discover*, excit*, genius*, inspir*, masterpiece*, pathbreak*, revolution*, unusual*, vision*

Appendix B

Robustness Tests

As an alternative to operationalizing BI&A radicalness as a proportion, we operationalized it as an indexed score based on the models used by sites, where DBMS-related applications were coded as 0, Business Intelligence and Analytics-related applications were coded as 1. This index score captures the extent to which a firm uses a more functionally radical BI&A. This measure differs from the text-based proportion measure we used in our main analyses. It is a bottom-up approach, whereas the text-based proportion measure is top-down approach. By bottom-up approach, we took into account each sample firm's actual site BI&A use and aggregated site-level BI&A radicalness scores to firm-level. In contrast, the text-based proportion measure neglects each site's actual BI&A use and assumes the homogeneity of actual BI&A use across sites of each sample firm. According to the BI&A vendor names each firm used for a particular year, we assessed the radicalness of the vendor's BI&A as a whole using third-party IT consulting firms' research reports from that year, which resulted in the final BI&A radicalness scores for each firm-year observation in our main analyses.

Having obtained the aggregated firm-level BI&A radicalness score, we computed a focal firm's move towards BI&A in current year relative to previous year – i.e., change in the proportion of BI&A applications in a focal year. BI&A radicalness (relative score) = $\%\ change\ of\ \frac{\sum_{i,j,k,t} DBMS\ APP_i + BI\ APP_j}{Total\ Counts\ of\ DBMS\text{−}BI_{\ k,t}}$ (sample firm k; t = 2010 ~ 2015). This percentage change score captures firms' BI&A radicalness gap in comparison to previous year. In contrast, the measure of BI&A radicalness in our main analyses does not capture the percentage change. Rather, it captures only the absolute radicalness of BI&A.

We reported the results below.

Table B1. Effects of ROI-based Performance Shortfalls on Relative Radicalness of BI&A

	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Top management support	-0.04	-0.04	-0.03	-0.04	-0.03	-0.04	-0.03	-0.04
Normative forces	-0.02	-0.02	-0.03	-0.02	-0.03	-0.02	-0.03	-0.02
Coercive forces	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mimetic forces	-0.71	-0.92^{+}	-0.41	-0.77	-0.35	-0.71	-0.28	-0.70
Firm size	0.01	0.01	-0.02	0.01	-0.02	0.01	-0.02	0.01
Firm age	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
Knowledge barriers	0.00	0.00	0.01	0.00	0.01	0.00	0.01	0.00
Slack	0.02	0.02	0.01	0.02	0.01	0.02	0.01	0.02
Performance below Hist. Asp (ewma)		0.08		-0.01		-0.04		-0.04^{+}
Performance below Hist. Asp (ave2)			-0.01		-0.02		-0.04^{+}	
Performance below Soc. Asp. (sector)		-0.13^{**}	-0.04					
Performance below Soc. Asp. (sic2)				-0.04^{+}	-0.02			
Performance below Soc. Asp. (sic4)						-0.01	-0.00	
Performance below Soc. Asp. (sg1)								-0.00
Constant	0.01	0.03	0.13^{*}	0.02	0.12^{*}	0.01	0.12^{+}	0.01
Fixed or Random Effects Model	Random	Random	Random	Random	Random	Random	Random	Random
χ^2		4.72^{*}	0.30	0.40	0.00	1.56	1.89	2.69
Soc. Asp > Hist. Asp.		Yes	No	No	No	No	No	No
N	1176	1174	877	1174	877	1174	877	1174
AIC	819.03	812.71	482.41	816.97	482.62	819.85	483.58	820.27
BIC	869.73	873.53	539.73	877.79	539.93	880.67	540.90	881.09
Degree of freedom	7.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00

Notes. [a] Model 1-7 are not nested models. Rather, they indicate different ways of operationalizing aspirations. [b] ewma: exponentially weighted moving average; ave2: average of prior two years. [c] sic2: 2-digit SIC; sic4: 4-digit SIC; sg1: strategic group. [d] Material Engagement: aggregate site revenue-weighted sum of BI&A use.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B2. Effects of Market Share-based Performance Shortfalls on Relative Radicalness of BI&A

	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Top management support	-0.04	-0.03	-0.02	-0.03	-0.02	-0.03	-0.02	-0.01
Normative forces	-0.02	-0.03	-0.03	-0.02	-0.03	-0.02	-0.03	-0.02
Coercive forces	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mimetic forces	-0.71	-0.67	-0.30	-0.73	-0.21	-0.72	-0.29	-0.72
Firm size	0.01	0.01	-0.02^{+}	0.01	-0.01	0.01	-0.02^{+}	0.01
Firm age	-0.00	-0.00	0.00	-0.00	-0.00	-0.00	0.00	-0.00
Knowledge barriers	0.00	-0.01	0.01	0.01	0.02^{+}	0.00	0.01	0.00
Slack	0.02	0.02^{+}	0.01	0.02	0.00	0.02	0.01	0.02
Performance below Hist. Asp (ewma)		-0.03		-0.02		-0.02		-0.03
Performance below Hist. Asp (ave2)			-0.02		-0.02		-0.02	
Performance below Soc. Asp. (sector)		-0.03^{*}	-0.00					
Performance below Soc. Asp. (sic2)				0.01^{+}	0.02^{**}			
Performance below Soc. Asp. (sic4)						-0.00	0.00	
Performance below Soc. Asp. (sg1)								0.01^{+}
Constant	0.01	0.10	0.13^{+}	-0.03	0.06	0.01	0.12^{+}	0.02
Fixed or Random Effects Model	Random	Random	Random	Random	Random	Random	Random	Random
χ^2		0.01	0.43	2.21	3.16^{+}	0.72	0.83	1.75
Soc. Asp > Hist. Asp.		No	No	No	Yes	No	No	No
N	1176	1174	877	1174	877	1174	877	1174
AIC	819.03	815.92	486.29	818.94	477.18	822.11	486.42	819.55
BIC	869.73	876.74	543.61	879.76	534.49	882.93	543.74	880.37
Degree of freedom	7.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00

Notes. [a] Model 1-7 are not nested models. Rather, they indicate different ways of operationalizing aspirations. [b] ewma: exponentially weighted moving average; ave2: average of prior two years. [c] sic2: 2-digit SIC; sic4: 4-digit SIC; sg1: strategic group. [d] Material Engagement: aggregate site revenue-weighted sum of BI&A use.
$^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table B3. Temporal Effects of Market Share-based Performance Shortfalls on Informational Engagement with BI&A

	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5
Top management support	1.76^{+}	1.71^{+}	1.97^{+}	1.71^{+}	2.00^{+}	1.79^{+}
Normative forces	0.01	0.03	-0.02	0.01	-0.04	0.02
Coercive forces	0.00	0.00	0.00	0.00	0.00	0.00
Mimetic forces	-0.20	-0.26	0.97	-0.20	1.10^{+}	-0.18
Firm size	-0.07***	-0.06**	-0.12***	-0.06**	-0.12***	-0.07***
Firm age	-0.01	-0.01	0.01	-0.01	0.01	-0.01
Knowledge barriers	-0.06*	-0.05^{+}	-0.04	-0.05^{+}	-0.05	-0.05*
Slack	-0.03	-0.02	-0.01	-0.03	-0.02	-0.03
Year		0.04***	0.06**	0.03**	0.02	0.02^{+}
Performance below Hist. Asp (ewma)		43.43		27.97		12.75
Performance below Hist. Asp (ave2)			5.29		-22.49	
Performance below Soc. Asp. (sector)		42.02**	56.83**			
Performance below Soc. Asp. (sic2)				17.39^{+}		
Performance below Soc. Asp. (sic4)					3.01	
Performance below Soc. Asp. (sg1)						0.09
Year x Performance below Hist. Asp (ewma)		-0.02		-0.01		-0.01
Year x Performance below Hist. Asp (ave2)			-0.00		0.01	
Year x Performance below Soc. Asp (sector)		-0.02**	-0.03**			
Year x Performance below Soc. Asp (sic2)				-0.01^{+}		
Year x Performance below Soc. Asp (sic4)					-0.00	
Year x Performance below Soc. Asp (sg1)						-0.00
Constant	0.67***	-85.02***	-120.78**	-51.88**	-34.38	-30.57^{+}
Fixed or Random Effects Model	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed
N	1562	1555	1129	1555	1129	1555
AIC	548.14	538.68	411.87	546.24	425.47	550.18
BIC	590.97	608.22	477.24	615.78	490.85	619.72
Degree of freedom	557.00	557.00	459.00	557.00	459.00	557.00

Notes. [a] Year as a linear continuous variable. [b] Model 1-5 are not nested models. Rather, they indicate different ways of operationalizing aspirations. [c] ewma: exponentially weighted moving average; ave2: average of prior two years. [d] sic2: 2-digit SIC; sic4: 4-digit SIC; sg1: strategic group. [e] Material Engagement: firm-level BI&A use is aggregated using revenue-weighted site-level BI&A use.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B4. Temporal Effects of Market Share-based Performance Shortfalls on Material Engagement with BI&A

	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5
Top management support	-0.25	-0.55	-0.23	-0.57	-0.23	-0.55
Normative forces	-0.01	-0.04	-0.02	-0.05	-0.02	-0.04
Coercive forces	0.00	0.00	0.00	0.00	0.00	0.00
Mimetic forces	0.29	0.16	-0.02	0.19	0.00	0.18
Firm size	0.06^{***}	0.04^{**}	0.07^{***}	0.04^{**}	0.07^{***}	0.04^{**}
Firm age	0.01^{*}	0.01	0.01^{*}	0.01	0.01^{*}	0.01
Knowledge barriers	0.02^{*}	0.04^{*}	0.02^{+}	0.04^{*}	0.02^{*}	0.04^{*}
Slack	-0.01	-0.02	-0.01	-0.02	-0.01	-0.02
Year		-0.01	-0.00	-0.01	-0.01	-0.01^{*}
Performance below Hist. Asp (ewma)		-15.10		-16.51		-16.94
Performance below Hist. Asp (ave2)			-17.82		-22.61	
Performance below Soc. Asp. (sector)		6.87	9.52			
Performance below Soc. Asp. (sic2)				0.98		
Performance below Soc. Asp. (sic4)					1.99	
Performance below Soc. Asp. (sg1)						-5.90
Year x Performance below Hist. Asp (ewma)		0.01		0.01		0.01
Year x Performance below Hist. Asp (ave2)			0.01		0.01	
Year x Performance below Soc. Asp (sector)		-0.00	-0.00			
Year x Performance below Soc. Asp (sic2)				-0.00		
Year x Performance below Soc. Asp (sic4)					-0.00	
Year x Performance below Soc. Asp (sg1)						0.00^{+}
Constant	-0.17^{**}	13.06	6.52	16.05	21.08	26.09^{*}
Fixed or Random Effects Model	Random	Fixed	Random	Fixed	Random	Fixed
N	1562	1555	1129	1555	1129	1555
AIC	782.72	-669.22	570.14	-670.78	569.17	-673.12
BIC	836.26	-599.68	645.58	-601.24	644.61	-603.58
Degree of freedom	7.00	557.00	12.00	557.00	12.00	557.00

Notes. [a] Year as a linear continuous variable. [b] Model 1-5 are not nested models. Rather, they indicate different ways of operationalizing aspirations. [c] ewma: exponentially weighted moving average; ave2: average of prior two years. [d] sic2: 2-digit SIC; sic4: 4-digit SIC; sg1: strategic group. [e] Material Engagement: firm-level BI&A use is aggregated using revenue-weighted site-level BI&A use.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix C

Potential for Endogeneity

It is possible that endogeneity is induced by omitted variables. To rule out this possibility, we employed the impact threshold for a confounding variable (ITCV) (Frank 2000). This ITCV is particularly well suited for a linear model and this method is often used to determine the degree to which an omitted confounding variable can invalidate a given inference (e.g., Gamache and McNamara 2019; Harrison et al. 2018).

To account for the potential for endogeneity, we conducted ITCV analysis for the statistically significant relationships. For hypothesis 1, for instance, our analyses suggest that, for an omitted variable to invalidate the results, it should have a correlation *r* with a value of at least 0.256 with both Performance below Soc. Asp. (sector) and BI&A radicalness or a value of at least 0.167 with both Performance below Hist. Asp (ave2) and BI&A radicalness. Of all the control variables included, the average correlation with BI&A radicalness is 0.009 and no control variable correlates with BI&A radicalness at a level higher than 0.256 and 0.167, indicating that it is very unlikely for an omitted variable to invalidate our findings. Thus, omitted variables are unlikely to be a concern for our findings.