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Factors Influencing Willingness To Adopt Advanced Analytics In Small Businesses

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FACTORS INFLUENCING WILLINGNESS TO ADOPT ADVANCED ANALYTICS

IN SMALL BUSINESSES

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ABSTRACT

Business analytics (BA) continues to be one of the top technology trends in recent years as well as one of the top priorities for CIO's in many large enterprises. Business analytic tools can significantly help small businesses in quickly responding to changing market conditions and improving their organizational performance. However, prior studies report that the adoption rate of business analytics in small businesses is extremely low such that only 32 percent small businesses have adopted Business Intelligence (BI) and analytics solutions till now (SMB Group, 2018). As small businesses constitute a major force in the US economy, a slow rate of adoption of significant technological innovations, such as BA, may be a critical concern that can affect the economy in the longer run. Despite this, the extant small business literature as well as the information systems literature fails to provide an understanding of why small businesses are not receptive to current BA trends. Therefore, drawing upon the theoretical underpinnings of organizing vision theory, strategic orientation literature, and theory of upper echelon, this study investigates the willingness of small businesses to adopt newer innovations in BA. More specifically, this study investigates the impact of the reception of organizing vision of BA by owner-managers, learning orientation of small businesses, analytics orientation of small businesses, and personal characteristics of owner-mangers on small businesses' willingness to adopt BA. By drawing its motivation from prior strategic orientation and

BA literature, this study is also among the first one to propose, formally develop, and validate the measurement construct of analytics orientation.

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CHAPTER I

INTRODUCTION

During last two decades, Business Intelligence and analytics (BI&A) have increasingly gained importance in both the academic as well as business communities (Chen et al., 2012). For past several years, business analytics (BA) and big data is considered as one of the major technology trends as well as top areas for investment and focus in organizations. About 97 percent of the companies with revenues exceeding $100 million use some form of business analytics in their day to day operations (BusinessWeek, 2011). The global revenues in BI&A market reached $18.3 billion in 2017 and is expected to reach $22.8 billion by the end of 2020 (Gartner, 2017). BA is often defined as group of approaches, and use of procedures and tools to collect data, analyze and interpret that data to gain actionable insights, create business value, and gain competitive advantage (Akter and Wamba, 2016). The key benefits of BA include overall improvement in the decision making process by improving the quality and relevancy of decisions, timely response to the needs of users due to faster decision making process (Ghasemaghaei et. al, 2017), better alignment of resources with the strategies of an organization, and realization of cost efficiencies (Computerworld, 2009). Despite all the promises surrounding BA, the adoption of BA tools and technologies is still low in small businesses. For instance, research by SMB Group (2018) reveals that 64 percent of midsize businesses have currently adopted BI and analytics solutions while 26 percent plan to use them in future. On the other hand, only 32 percent small businesses have currently adopted BI and analytics solutions and mere 24 percent plan to use them in future. These results indicate a vast difference in the adoption of analytic solutions between larger and smaller organizations. Moreover, the firms that have adopted BI and analytics solutions are mostly utilizing basic analytics and are not able to take advantage of advanced analytics and newer innovative solutions offered by BA.

The rise of unstructured data generated by search engines (e.g., Google), social media (e.g., facebook), services (e.g., Venmo, Uber and Spotify), digital photos and video sharing services (e.g., Instagram, Youtube), and Internet of Things (e.g., smart devices) (Aktera et. al, 2019) have created several opportunities to gain a better understanding of the market. However, it has also created unique challenges in handling and analyzing this form of data which is beyond the capabilities of traditional technologies. To make situation worse, a report by International Data Corporation (IDC) suggests that by 2025, 80 percent of worldwide data will be unstructured (King, 2019). Larger organizations are increasingly investing in acquiring newer set of technologies to handle this big data influx. Therefore, to survive in competitive markets, it is important for small businesses to understand the business value of implementing advanced BA technologies. While early efforts related to business analytics were targeted at larger enterprises, several leading BA vendors such as SAS, SAP, IBM, and Oracle are providing useful, simple to use and inexpensive analytical solutions to capture the interest (Tutunea and Rus 2012) and accommodate the requirements of small businesses. For example, cloud-based services provides a viable solution for business analytics since they are cost-effective, do not require any additional infrastructure and resources and have the ability to provide effective analytical insights and reports with easy to use interface (Alshamaila & Papagiannidis, 2013; Bowden, 2014). Similarly, several inexpensive tools, such as google analytics, are available to track and analyze the data generated from websites for marketing purposes. Thus, these newer set of technologies can provide small businesses with an opportunity to develop their markets, increase sales turnover, profitability, and gain competitive edge. Despite these advantages and the availability of several inexpensive business analytics solutions for small businesses (Tutunea and Rus, 2012), there is a lack of understanding on why small businesses are still hesitant to adopt these capabilities.

Small businesses constitute a major force in the US economy; therefore, a slow rate of adoption of significant technological innovations may be a critical concern that can affect the economy in the longer run. For instance, according to Small Business Administration (SBA), small businesses, defined as firms with fewer than 500 employees and with annual revenues less than $38M, contributed to 52% of all sales in US in 2017 (SBA 2017). Additionally, SBA reports that from 1993 to 2013, small businesses were responsible for creating 63% of the net new jobs in the U.S. Despite the fact that small businesses represent an important sector of the economy, the majority of the studies in Information System (IS) literature have mainly focused on the adoption of IT in large organizations. However, as suggested by several studies, the organizational theories that apply while studying larger firms may not be applicable to smaller firms and, thus, the findings from these studies may not be generalizable to small businesses (Thong, 1999;

Bharati and Chaudhury, 2006). Due to unique characteristics of small businesses (Thong 1999), there is a need to separately examine the adoption of advanced BA technologies in small businesses. Moreover, prior BI&A research also reveals some key differences between traditional IS and BI&A technologies (Popovič et al., 2012). Therefore, it is important to examine the adoption of advanced BA separately from traditional IS adoption perspectives.

To address these gaps in the literature, this study integrates several relevant theories to examine the factors that influence small businesses' willingness to adopt advanced innovations in BA. Prior studies suggest that several internal and external factors may affect an organization's willingness to innovation adoption (Zmud, 1984; Kendall et al.,2001; Delmas and Toffel, 2005). This study proposes that an organizations' willingness to adopt advanced BA is influenced by a diverse set of factors such as owner-manager's reception of BA's OV, organization's learning and analytics propensity, and owner-manager's personal characteristics. Therefore, drawing upon the theory of organizing vision (Ramiller and Swanson), strategic orientation literature (Miller, 1983; Kohli and Kaworski, 1990; Slater and Narver, 1995; Sinkula et al., 1997), BA literature (Davenport and Harris, 2007), and upper echelon theory, this study develops a theoretical model to explain several factors that can influence the organization's willingness to adopt BA.

By utilizing the socio-cognitive perspective of information technology (IT) innovation adoption, this study mainly draws on organizing vision theory (Swanson and Ramiller, 1997) to understand the adoption of advanced BA in small businesses. The organizing vision theory suggests that an innovation as a concept exists in a collective environment where members with similar interests such as adopters, vendors, consultants, journalists, analysts, and academics, form a heterogeneous community, and are interested in diffusing an IT innovation and its application in organizations. The sources internal and external to an organization work together to make sense of a technology they intend to adopt. The popularity of an innovation concept further aids the adoption of innovation. Taking this into consideration, it can be argued that the concept of organizing visions could be even more applicable to the context of small businesses. This is due to the fact that small businesses often have limited resources to experiment with every new technological innovation. Hence, they need to get involved in the sense-making process of a technology before its adoption, to ensure that only relevant innovations make their way into organizations. Further, studies suggest that depending on how the concept of BA is perceived by IT decision makers, their opinions toward BA can further influence the organizational adoption of BA (Marson et al., 2012a; Ramiller and Swanson, 2003). Therefore, in small businesses, as business owners and managers are the primary decision makers, this study examines the owner-manager's perceptions of BA's OV and their influence on the adoption of advanced BA.

Drawing upon the strategic orientation literature, this study also examines the impact of learning orientation on organization's willingness to adopt BA. While the organizing vision framework (Swanson and Ramiller, 1997) provides a sound conceptual foundation and rich analytical context for studying organizational receptivity, it alone does not provide a holistic view of an organization's willingness to adopt BA. Wang (2009) also contended that apart from adoption decisions being situated in broader interorganizational community, within an organizational plane, adoption decisions are also made independently and rationally. Therefore, it is argued that the adoption decisions of owner-managers may not only be limited to the reception of innovation in its broader community, but there are several other factors that decision makers take into account while making a technology adoption decision. Although innovation literature has identified several organizational factors that are determinant of adoption of innovation, more research is needed to identify critical factors applicable in small businesses and to the specific context of BA (Puklavec et al., 2018). The role of intangible assets such as organizational learning, specifically in small businesses (Reynoso, 2008), and their relationship with innovativeness and success of the firm has been recognized by several studies (Hurley and Hult, 1997; Yueng et al., 2007). An organization's learning orientation, which is considered as an organizational characteristic regarding a firm’s propensity to value generative and double-loop learning, has a significant impact on the learning outcomes and on organizational performance (Baker and Sinkula 1999). Research suggests that organizations with a strong learning orientation constantly expand their capacity and renew themselves (Vowles, 1993). Learning orientation has also been considered as an important antecedent of organization’s innovative performance (Kaya and Patton, 2011). According to Hurley and Hunt (1997), learning orientation influences an organization’s receptivity to new ideas and affects an organization’s capacity to innovate. This is because when organizations are committed to learning, owners and managers encourage their employees to constantly challenge the long-held routines, assumptions, and beliefs about their fundamental operating philosophies (Baker and Sinkula, 1999). In this respect, learning orientated firms promote innovation by encouraging their employees to engage in the generation and development of new ideas to transform into action (Baker and Sinkula, 1999, Huber, 1991). Thus, learning orientation is one of the key factors that has a direct impact on firm's innovation (Choi, 2014). When an organization's environment is not conducive to learning, it may reduce the acceptance of new ideas that may hinder the process of innovation within the firm (Lee and Tsai, 2005). As a result, owners and managers may even be skeptical to introduce new technologies in the firm. Therefore, it is essential to understand the impact of learning orientation on small business's willingness to adopt BA.

Prior studies suggest that due to fundamental differences between types of innovation (e.g. administrative vs. technical, incremental vs. radical, product vs process), it is difficult to develop a unifying model of innovation adoption (Fichman and Kemerer, 1993). Further, Fichman (1992) suggests that every innovation has a different level of knowledge burden and locus of adoption, and therefore, theories need to be tailored to the adoption context. In line with this suggestion, this study also examines the factors applicable to the specific context of BA. In BA literature, although factors that help organizations to achieve success and gain competitive advantage in analytics has been widely discussed (Davenport et al., 2001; Davenport and Harris, 2007), there is a limited understanding of the factors that drive the willingness of small businesses to adopt BA. After an extensive review of the BA literature, analytics orientation of organization has been identified as an important determinant of firm's willingness to adopt BA. Analytics orientation, from a strategic perspective, is identified as a firm-level capability that favors the idea of decision making based on comprehensive analysis of information rather than intuition. The concept of analytics orientation has been discerned in prior research by Davenport and Harris (2007), who asserted that analytics is a management strategy that requires people skills, applied methodologies, and technologies to gain firm wide adoption.

Drawing motivation from their work as well as building upon strategic orientation literature, this study formally develops and validates the measurement construct of analytics orientation. After the construct is validated, its contribution in explaining organization's willingness to adopt advanced BA was also assessed.

Finally, as the specific focus of this study is small businesses, the theoretic concepts of Upper Echelon theory (Hambrick and Mason, 1984) were also employed to study how the cognitive values or personal characteristics of owner-managers influence the organization's willingness to adopt BA. Prior studies on small business suggest that characteristics of owner-managers are extremely crucial in determining innovative attitude of small businesses (Thong, 1999). This is so because small businesses tend to have highly centralized structures where business owner-managers play a primary role in most of the critical decisions (Mintzberg, 1979) as compared to decentralized structures of large firms where decision to adopt an innovation involves diverse group of individuals. The central role of owner-managers suggests that their characteristics may influence their decision making abilities (Thong, 1999). Also, according to Upper Echelon theory, both the characteristics as well the perceptions of top management play a central role in guiding the strategic and other organizational decisions (Nielsen, 2010). Hence, this study also examines the characteristics of owner-managers and their impact on the reception of OV, and on organizational willingness to adopt BA.

To sum up, the purpose of this study is to develop an integrative model, which explores the relationships between key decision maker's characteristics, organizational factors, socio-cognitive factors, and organization's willingness to adopt BA. To explore these relationships, this study integrates concepts from the theory of Upper Echelon

(Hambrick and Mason, 1984), strategic orientation literature(Miller, 1983; Kohli and Kaworski, 1990; Slater and Narver, 1995; Sinkula et al., 1997), BA literature (Davenport and Harris, 2007), and theory of Organizing Vision (Ramiller and Swanson, 2003). This research study has following research objectives:

1. To examine the role of owner-manager's reception of public discourse of BA, learning orientation, and analytics orientation in driving the organization's willingness to adopt advanced BA.

2. To propose and develop the analytics orientation construct by reviewing the relevant literature relating to its dimensions and empirically validating the construct.

3. To examine the role of personal characteristics of owner-managers on organization's willingness to adopt advanced BA.

By investigating these objectives, this research study makes several contributions to research and practice. By developing and testing an integrative model of innovation adoption, this study contributes to the IS adoption and diffusion literature by isolating a set of theoretically grounded factors influencing organization's adoption decision. Organizing vision theory is an institutional alternative to the economic-rationality perspective of IT innovation diffusion. Fichman (2004) suggests that most of the research on IT innovation adoption has been mainly conducted within the confines of dominant paradigm mainly explained by economic-rationalistic models. Further, Fichman (2004) asserts that this dominant paradigm has sufficiently informed research and practice on how to promote effective innovations, and thus, may be reaching a point of diminishing returns. Therefore, future work needs to adopt a more innovative approach to study the adoption of IT innovation. Thus, by utilizing this view of innovation diffusion, this study also addresses the call for giving more attention to the socio-cognitive processes and structures in order to understand institutional mechanisms (Miranda et al., 2015). Further, by studying contextual factors specific to the context of BA and small businesses, this study also contributes to the emerging BA research as well as adds to the existing small business literature. One of the key contributions of this research is the development of the analytics orientation construct. The analytics orientation construct developed in this paper depicts an organization's overall readiness to initiate analytic efforts and provides an interesting area for future research. Overall, the results have significant implications for practice as it can guide practitioners (particularly technology vendors, consultants, business owners, and top managers) to understand how significant technologies, such as advanced BA technologies, can pave their way to small businesses.

The remaining sections of the dissertation are organized as follows. First a theoretical background grounded in organizing vision framework, strategic orientation literature, and theory of upper echelon is provided in section II. In section III, a research model based on these theoretical frameworks is developed and hypotheses are proposed. Research methodology, that includes construct operationalization, data collection method, data analysis procedures and results of analyses, are provided in section IV. The final section V discusses the theoretical and practical implications of this study along with limitations and directions for future research.

CHAPTER II

THEORETICAL BACKGROUND

2.1 Business Analytics Overview

Advanced Business Analytics (BA) is often referred to as a set of tools, skills, technologies, applications as well as practices used in combination with one another, that are required for continuous exploration and investigation of past business performance to gain insight and drive future business planning (Beller & Barnett, 2009). Data integration, data mining, and statistical analysis are some of the common components of analytics to recognize trends and patterns in data. Some other advanced techniques include fuzzy logic to handle incomplete and ambiguous data, and neural networks that assist in predicting likely outcomes (Bose, 2009). The origins of BA date far back to late 1960s when the first decision support applications, also referred to as decision support systems (DSS), emerged to help managers in planning and optimizing specific business goals and activities (Wixom and Watson, 2010). Over the years, a variety of other decision support applications were introduced including Executive Support Systems, Expert Systems, and Online Analytical Processing. In the early 1990s, the term business intelligence was used as an umbrella term to refer all the decision support applications. Business Intelligence relies on the collection, management, and reporting of decision-oriented data, and incorporates the analytical and computing techniques performed on the data (Davenport and Harris, 2007). The conventional view of business analytics is also associated with operating on data with a purpose of supporting decision-making. Thus, the technological aspect of business analytics has its roots in the decision support capabilities provided by business intelligence (Holsapple et al., 2014). In this study, we use the definition of BA as specified by Davenport and Harris (2007, pg. 7) as “the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions”. Depending on the business goal to be realized, BA is typically categorized into descriptive, diagnostic, predictive, or prescriptive analytics (Banerjee at al., 2013). Descriptive analytics help organizations to unravel ‘what is happening’ or ‘what happened’ in the past. By analyzing such trends, organizations can gain an understanding of what approaches to take in the future to improve business outcomes. Examples of descriptive analytics include management reports that provide information regarding sales, customers, operations, and finance that can be used to quantify the relationships between various variables or to categorize them into various groups. Diagnostic analytics evaluates ‘why’ something happened. It needs exploratory data analysis using tools such as visualization techniques in order to discover the root causes of a problem. Predictive analytics uses a variety of statistical, modeling, data mining, and machine learning techniques to predict potential future outcomes based on current and historical data. These predictions are expressed as likelihood that a particular event, opportunity, or behavior will take place. For example, predicting the sales of a product for the next month or the behavior of a target segment of the customers. Prescriptive analytics not only predicts 'what will happen' and 'when it will happen', but also 'why it will happen' and provide alternative decisions or recommendations based on the predictions to optimize business processes in order to achieve business objectives. Prescriptive analytics attempts to predict the impact of future decisions so that the decisions may be modified before they are actually made. For prescriptive analytics, tools such as optimization and simulation are used for decision analysis.

In sum, BA spans the past, present, and future to provide significant insights into making transformative decisions, solving complex business problems, improving performance, and anticipating and planning for change while managing and balancing risks. Further, it benefits all aspects of organizational value chain, such as, inbound and outbound logistics, operations, service, and marketing and sales (Nastase & Stoica, 2010).

2.1.1 BA in Small Businesses

BA includes capabilities and solutions that benefit a variety of disciplines and, therefore, considered as a function of both IT and business (Shanks et al., 2010). Thus, the concept of business analytics has been studied from several different aspects (Holsapple et al., 2014) such as marketing analytics (Branda et al., 2018; Germann et al., 2013; Hauser, 2007), customer analytics (Davenport, 2007), human resource analytics (Levenson, 2005; Royal and O'Donnell, 2008), supply chain analytics (Chen et al., 2015; Gunasekaran et al., 2017; O'Dwyer and Renner, 2011; Trkman et al., 2010; Nemati and Udiavar, 2012), risk analytics (Ray et. al., 2008), and finance analytics (Smelyanskiy, 2008). In IS literature, most of the studies are focused on providing insights on current and emerging trends in analytics (Brown et al. 2011; Holsapple et al., 2014; Kohavi et al. 2002; Pearson, 2012;

Sharda et al., 2013; Vecchio et al. 2020), and identifying opportunities and challenges related to their implementation and management (Ahmed and Ji, 2013; Bose, 2009; Chen et al., 2012; Vecchio et al. 2020). Some studies have utilized resource based view and dynamic capabilities framework (Chae et al., 2014; Sharma et al., 2010) to investigate how firms derive competitive advantage, and to explore the relationship between analytical capabilities and business performance (Nastase and Stoica, 2010). Further, few studies have also utilized Technology Acceptance Model (TAM) (Jiang, 2009) and Technology-Organization-Environment (TOE) framework (Bhatiasevi and Naglis, 2020; Malladi, 2013) to study BI&A adoption in organizations. Although these studies offer significant insights on how the BA adoption process may be facilitated, due to inherent differences among smaller and larger firms, the results may not be applicable to smaller firms. Moreover, there is a limited theoretical research pertaining to BA in small businesses and the existent research is mainly focused on providing insights on the current trends in analytics, and suggesting tools, solutions, and frameworks for utilizing and implementing BI&A. For instance, in their study, Vecchio et al. (2018), discussed main trends, opportunities, and challenges faced by SMEs and large corporations when dealing with Big Data for open innovation strategies. Similarly, Horakova and Skalska (2013) summarized the current trends in business intelligence (BI), discussed various aspects of BI tools and solutions and showed how the multidimensional analytical data model and related applications can be designed, created and implemented for small companies. Guarda et al. (2013) proposed a framework for BI&A implementation in small businesses and suggested Software-as-a-Service (SaaS) a viable alternative for small firms. While contending that small businesses often require lightweight, inexpensive and flexible solutions for decision support, Grabova et al. (2010) discussed several web-based BI approaches, their features, and their advantages and possibilities for small businesses. Similarly, Tutunea and Rus (2012) provided several BI&A software solutions for small businesses ranging from open-source to viable alternatives such as SaaS and Cloud-based solutions. To summarize, while the literature on BA so far has attempted to improve our understanding on the business value provided by BA technologies, as well insights on the on-going trends in analytics, there are limited studies explaining the factors that influence organizations to adopt BA in the first place (Bhatiasevi and Naglis, 2020; Malladi, 2013; Puklavec et al., 2018).Therefore, a deeper insight into theory-based research is required to understand the underlying motivators and inhibitors of BA adoption (Côrte-Real et al., 2014).Thus, by integrating several theoretical frameworks, this study examines the critical factors that influence small businesses' willingness to adopt BA.

2.2 Owner-manager's Reception of Organizing Vision

The underlying premise behind the theory of organizing vision is that an innovation as a concept exists in a collective environment where members with similar interests form a heterogeneous community and are interested in diffusing an IT innovation and its application in organizations. The adoption and implementation of any innovation, therefore, depends on the diffusion of the innovation concept. According to this theory, the sources internal and external to an organization work together to make sense of a technology by creating an organizing vision for it. The learning undertaken by potential adopters is thus tied to the learning unfolding in larger community. In other words, the community which consists of vendors, consultants, mass media, academic researchers, early adopters and practitioners interact in a public discourse which in turn shapes the OV.

According to Swanson and Ramiller (1997), to exploit a new technology, an OV serves three broad functions: interpretation, legitimization, and mobilization. Interpretation clarifies the innovation's existence and purpose relative to its broader social, technical, and economic context and reduces uncertainties related to its nature. Legitimation develops and propagates the underlying rationale for the innovation. Mobilization serves the function of coordinating entrepreneurial and market forces to provide the resources needed to support the material realization of the innovation. The interplay among these functions determines whether an innovation will diffuse into the wider community or dissipate, becoming yet another fad. The effectiveness of these functions may vary over time which reflects that organizing visions have a career constructed over time (Ramiller and Swanson, 2003). The career of an OV may be ascendant or descendant depending upon the level of discourse surrounding the innovation. When the interest of community members in a particular OV increases over time, i.e., when the volume of discourse grows over time, an OV's career is said to be ascendant. Ascendancy may indicate an increase in the diffusion of innovation (Marsan et al., 2012b). Similarly, when the volume of discourse decreases over time, an OV's career is said to be descendant. Descendancy may suggest that either OV is widely accepted and adopted by organizations or it may have been discredited and abandoned by organizations (Green, 2004). In brief, the adoption and diffusion of an innovation is related to the ongoing discourse of its OV and play an important role in the overall receptivity of the innovation.

Swanson and Ramiller (1997) argued that organizing visions play a critical role in driving the adoption and diffusion of the innovation. While extending the original conceptualization of organizing vision, Ramiller and Swanson (2003) identified four key dimensions of how executives respond to organizing vision discourse. These four key dimensions focus on an organizing vision's interpretability, plausibility, importance, and discontinuity. Interpretability refers to the degree to which an individual finds the representations of organizing visions as intelligible and informative in its associated public discourse. As argued by Weick (1990), an organizing vision can be uncertain, complex and can be subjected to several possible interpretations and misunderstandings. Interpretability, thus, refers to the clarity, consistency, and richness of the public discourse. The concept of plausibility complements interpretability and explains the confusion and basic lack of knowledge related to an organizing vision in its discourse as well as captures its deceptive exploitation, such as hype or exaggeration, in the public discourse. Plausibility, thus, refers to the degree to which an individual finds the representations of organizing visions in its associated discourse as free of distortions, misunderstandings, exaggerations, and misplaced claims. Importance refers to the degree to which an individual finds the public discourse of organizing vision as influential or having an evident value. This dimension comprises of three sub-dimensions: business benefit, practical acceptance, and market interest. Business benefit refers to the degree to which an individual perceives that an innovation offers a tremendous opportunity to deliver better organizational performance. Practical acceptance refers to the degree to which an individual perceives that an innovation is feasible to be adopted by organizations. Market interest refers to the degree to which an individual perceives that an innovation is attractive in drawing market attention. Finally, discontinuity refers to the degree to which an individual finds the representations of organizing visions as posing conceptual and implementation challenges, and thus, consists of two concepts: Conceptual and Structural discontinuity. Conceptual discontinuity explains how great a departure from existing ideas and notions of existing technologies does the OV pose. Structural discontinuity explains how much difficulty is entailed in implementing a new technology. Overall, these four dimensions form the underlying structure of an OV and will be examined to measure owner's perceptions related to BA.

Within IS research, a number of insightful investigations have been carried out by employing organizing vision theory. While extending the original conceptualization of organizing visions, Wang and Ramiller (2009) explored the organizing vision of enterprise resource planning systems and explored how community learning arises from the contributions of different organizational actors. In another study, Wang and Swanson (2007) examined the innovation of professional services automation and demonstrated the role of institutional entrepreneurship in launching visions for IT innovations. In a recent study, Miranda et al. (2015) examined the organizing vision for social media by employing a grounded theory method to uncover the underlying structure of the OV and to understand its effects on diffusion. In another study, while examining the career of the organizing vision for Web 2.0, Gorgeon and Swanson (2011) investigated how Wikipedia played the role of a discourse vehicle in facilitating the diffusion of new IT. In addition to these studies, a number of other investigations employed the organizing vision framework as a research lens to understand the diffusion of IT innovations. These studies included examination of the organizing visions for CRM (Firth, 2001), institutionalization process of CRM (Wang and Swanson 2008), application service provisioning (Currie 2004), and electronic medical records Green IS development (Fradley et al., 2012), cross-cultural comparison of organizing vision discourse (Carton et al., 2007), and legitimization function of OVs surrounding computerized physician order entry (CPOE) systems (Kaganer, 2010).

Further, prominent studies contributing to the perception dimensions of organizing visions have so far examined the perceptions for electronic medical records (EMRs) (Reardon and Davidson, 2007; Reardon, 2009), and perceptions for open source software (OSS) (Marsan et al., 2012a). For instance, Reardon (2009) performed descriptive analysis on four dimensions of OV to explore their role in shaping the physicians' perceptions and their interest in adopting and using EMRs. Marsan et al. (2012a) investigated the relationship between IT specialists' profiles, IT specialists' reception of the public discourse on OSS, and their organizations' receptivity to OSS. Their findings provided a strong support for the organizing vision theory and the idea that the popularity of an IT innovation concept in its discourse favors the adoption of the material IT innovation in organizations. To my knowledge, organizing vision theory has not been applied in the context of BA specifically in small businesses. Therefore, it would be interesting to examine how small businesses perceive the four dimensions of public discourse of BA (importance, desirability, interpretability, plausibility) and how these dimensions affect the receptivity of small businesses toward BA adoption. As suggested by Ramiller and Swanson (2003), the perceptions of innovation work its way into organizations. Therefore, identifying the impact of these dimensions on the receptivity of innovation is important, since a positive overall reception may drive an organization's actual decision to adopt BA. Further, the exploration of critical factors that shapes the receptivity of innovation will provide a better understanding of how owner-managers can effectively interpret or make sense of the concept of BA.

2.3 Learning Orientation and Analytics Orientation

Rather than simply scaled-down models of larger firms, several studies suggest that small businesses are significantly different from larger firms (Raymond, 1985; Thong et al., 1996). Although, small businesses face similar challenges as their larger counterparts in making better and more informed decisions, they suffer from several constraints such as inadequate financial and human resources, lack of professional expertise, and susceptibility to external forces, as they operate in a highly competitive environment (Thong et. al, 1996). Further, they underestimate the amount of time and efforts required for innovation implementation and tend to have a short-range management perspective with regard to innovation implementation. Due to these unique characteristics of small businesses, the role played by several organizational factors in small businesses may be significantly different from that in large businesses (Thong et. al, 1996). Hence, while the reception of public discourse of BA is considered as important determinant of organization's willingness to adopt BA, in this study, organizational factors might prove to be even more important in the small business context.

Prior adoption and implementation literature have investigated several factors that are possible determinants of organizational adoption of an innovation (Tornatzky and Fleischer, 1990; Iacovou et al., 1995; Jeon et al., 2006; Chan and Nagai, 2007; Damanpour and Schneider, 2009). These factors are mainly divided into three categories: technology, organization, and environment. In a technological context, the cost and complexity of innovation have been found to be the key determinants of IT adoption. Organizational characteristics that have been studied include size, competition, centralization, specialization, functional differentiation, top management support and slack resources.

Competitive and regulatory pressures, demands from trading partners and customers, and environment uncertainty have been considered as important environmental determinants. Although existing studies have yielded several insights on the factors that facilitate or hinder adoption, these variables may not translate well into the context of current study. For example, Fichman (1992) suggested that different IS innovations may have different levels of knowledge burden and locus of adoption. Therefore, the classical innovation theories should be tailored to the adoption context and should include the distinctive characteristics of the context under study. As none of the studies have yet investigated these factors in the context of BA and small businesses, there is a need to separately examine these factors. For instance, factors such as government pressures, regulatory pressures, centralization, and formalization are either not applicable to the context of BA or to the context of small businesses. However, certain factors such as the cost and complexity of innovation have been considered as the most important determinants of innovation adoption. But in recent years, multiple vendors have made available several cost effective and less complex analytic solutions (e.g. SaaS or cloud-based solutions) with flexible deployment options that are easily available to small businesses (Canes, 2009). Similarly, several online query and browser-based tools are emerging that are very affordable, easy to implement, and require little or no training. Despite the availability of cost effective and simple to implement solutions, it is difficult to ascertain as to why small businesses are not yet receptive to these solutions. Taking all this into consideration, this study also seeks to examine the specific factors that can fully explicate small businesses' willingness to adopt advanced BA.

Due to rapid technological evolutions, globalization, and increasingly sophisticated competitors, small businesses operate in extremely challenging environments (Brettel and Rottenberger, 2013). Despite the limited resources they possess, they must have the ability to identify and pursue available opportunities by adapting to the external dynamic environment. As a result, learning orientation is important for small businesses as they must deeply understand their outside environment and gain information about customer needs, market changes, competitor actions, as well as development or adoption of new technologies or products that are superior to those of competitors (Mahmoud and Yusif, 2012). Baker and Sinkula (1999) explained learning orientation as a mechanism that directly influences an organization's ability to sustain and organize its structure in order to compete in the market. Further, Hurley and Hunt (1998) emphasized that various characteristics of a firm's culture, such as learning orientation, are important antecedents of organization's openness to the innovation and an important determinant of innovativeness. Several other studies have also recognized the role of learning orientation and its impact on firm innovativeness, specifically in small businesses (Reynoso, 2008; Yueng et al., 2007). However, despite considerable progress in the field of learning orientation, little research has been conducted to examine how learning orientation can drive an organization's willingness toward the adoption of IT innovations. Further, most recent research suggests that analytic specific factors such as organization's analytic culture, analytic skills of employees, and infrastructure that supports analytics, drive the deployment of analytics in an organization (Germann et al., 2013). Therefore, this study identifies learning orientation as well as factors related to BA such as analytics orientation of the firm as important factors to be studied in the BA and small business context, and examines the impact of these factors on the overall willingness of small businesses toward the adoption of BA.

2.3.1 Learning orientation of the firm

Organizational learning is a process by which organizations learn through interaction with their internal and external environments. Some research studies have taken strategic and operational perspective of organizational learning by focusing on the learning orientation of the firm (Senge, 1990; Dixon, 1992; Slater and Narver, 1995; Sinkula et al., 1997). Learning orientation is one of the organizational dimensions that affects an organization's propensity to value generative learning and is reflected by set of knowledge-questioning values (Baker and Sinkula, 1999; Sinkula et al., 1997). Learning orientation represents the degree to which proactive learning occurs in an organization (Sinkula et al., 1997) due to which the rate of internal and external changes in a company may increase. Although learning orientation is analogous to organizational learning, learning orientation is more focused on the cultural aspects of an organization (Nasution et al., 2011). Learning orientation of a firm is reflected in its three organizational values: commitment to learning, open-mindedness, and a shared vision. Commitment to learning represents how much value an organization places on learning and how it promotes a culture of learning. Open-mindedness is linked to knowledge-questioning values such as continuously questioning long-held routines, assumptions and beliefs. Shared vision provides an organization-wide focus on learning that fosters energy, commitment, and purpose among the members of an organization. While commitment and open-mindedness influence the intensity of learning, shared vision influences the direction of learning (Sinkula et al., 1997). According to Hurley and Hult (1998), learning orientation establishes a culture to innovate in the organization. In addition, prior studies suggest that learning is an antecedent of innovativeness (Hurley and Hult, 1998; Cohen and Levinthal, 1990), enable firms to not only accomplish within-paradigm improvements but also paradigm shifts such as breakthrough innovations (Baker and Sinkula, 1999), and is a critical constituent of the process innovation (Meeus et al., 2001). This view was further supported by Lee and Tsai (2005) who assert that learning orientation has a significant and positive impact on innovativeness. Among most recent studies, Chen et al. (2009) also provides a strong support for the relationship between learning orientation and innovation. Further, Dodgson (1993) argued that learning orientation enables firms to effectively respond to the external market changes, customer preferences, as well as new technological advances. The lack of this knowledge may reduce their ability to respond quickly and effectively to external changes (Bennett, 1998). As small businesses must deeply understand their outside environments to survive in a competitive market, learning orientation is extremely important for small businesses. Although, none of the studies have directly explored the impact of learning orientation on organization's overall willingness to adopt BA, Hurley and Hult (1998) viewed learning orientation as a "precursor" to build a culture that is receptive to innovation. This suggests that learning orientation is a critical antecedent to organizational willingness to adopt BA and hence warrants further investigation. Further, as suggested by prior research, learning oriented firms are able to learn about external environment have higher likelihood of sensing and responding to changes in the marketplace (Day, 1994). Therefore, extending prior research I contend that small businesses that are learning oriented will also possess the ability to identify, sense, and evaluate knowledge about new technologies, such as BA. Learning oriented small organizations, through their commitment toward learning, shared vision, and open-mindedness, are likely to regularly scan their environments for new information, may view BA as new source of growth (Daft and Weick, 1984), may respond proactively to BA (Srinivasan et al., 2002), and also may be willing to reformulate their business strategies to exploit the opportunities associated with BA (Chen and Lien, 2013). As learning related activities will allow firms to acquire knowledge about new technological advances, these firms are more likely to be receptive toward the adoption of BA.

2.4 Analytics orientation of the firm

In recent BA literature, several conceptual (Banerjee et al., 2013; Davenport et al., 2001; Watson, 2012) and empirical studies (Germann et al., 2013; Malladi, 2013) have discussed the role of several analytics related factors required for building strong analytical capabilities in order to gain competitive advantage, and to become a successful analytics-focused organization. For instance, according to Davenport et al. (2007), creating a culture that values data-based analysis and decision making is extremely crucial to maximize an organization's analytic capabilities. Further, to compete on analytics, a firm must also possess analytic skills and infrastructure capabilities (Davenport and Harris, 2007). Germann et al. (2013) also suggests that for a successful and widespread use of analytics in an organization, factors specific to analytics such as organizational culture supportive of analytics, analytical skills of employees, and data and IT resources are extremely critical. Similarly, Davenport et al. (2001) also identified several key contextual factors necessary for building a strong analytic capability such as skills and experience of employees, organization's strategy and culture, organizational structure, and data and technology resources. Although the current literature provides some useful insights on the factors necessary for achieving success with BA implementations and gain competitive advantage once it has been implemented in organizations, there is a limited understanding on what contextual factors influence organizations to adopt BA in the first place (Malladi, 2013). Therefore, drawing from strategic orientation literature and integrating the concepts from existing BA literature, this study proposes analytics orientation of a firm as an important contextual variable that can influence the adoption of BA in organizations. Further, I propose that analytics orientation as an important firm-level capability that can influence small businesses' willingness to adopt BA.

The strategic orientation of a firm, defined as a firm's philosophy of how to conduct business through a deeply rooted set of values and beliefs to achieve a superior firm performance, is considered as an important firm capability (Gatignon and Xuereb, 1997). Consistent with this research (Baker and Sinkula, 1999; Day, 1994; Kohli and Jaworski, 1990; Miller, 1983; Narver and Slater, 1990), I identify analytics orientation as a firm-level capability that favors the idea of decision making based on comprehensive analysis of information rather than intuition. Further, it is argued that in an analytic oriented firm, decision making based on information are the organizational norms guiding firm's activities and strategies. From a comprehensive review of literature (see Table 1), three critical and complementary dimensions emerge from prior BA studies reflecting firm's analytics orientation: analytic culture, analytic skills of the employees, and firm's IT and data infrastructure. As analytics orientation highlights the spirit of decision making through comprehensive analysis of information, I argue that this analytic strategy is accomplished by encouraging a culture that values the use of information in decision making, promoting analytical problem solving, and leveraging the technological capabilities of the firm.

Taking this into account, analytics orientation is defined as an organization's propensity to engage in decision making based on comprehensive analysis of information by promoting an information-based culture, analytic skills and knowledge of employees, and sophisticated data and IT infrastructure. Thus, analytics culture, analytic skills, and infrastructure are critical and inter-related dimensions of analytics orientation construct and are discussed next.

2.4.1 Analytics Culture

An important element of analytics orientation is firm's analytics culture. An organization's culture, through its specific set of behaviors, values, decision-making norms and outcomes, unites the business and technology around a common goal (Kiron et al., 2014). Thus, in organizations with strong analytics-focused culture, employees understand the value of information, and thus, collaborate toward common information-driven goals (Nerney, 2014). Further, in such a culture, the decision-making norms, values, and beliefs are aligned to assure that insights gained from the use of information generate a value and get incorporated into business decisions (Kiron et al., 2014; Germann et al., 2013). Thus, to develop an overall analytics orientation, organizations first need to foster an analytical culture where employees, regardless of the type of decision to be taken, make use of the available information in their decision making process (Popovic et al., 2012).

2.4.2 Analytic Skills

An organization can foster analytic culture; however, the transformation of information into knowledge is impossible without necessary analytical skills. Analytical skills are the ability to visualize, articulate, and solve both complex and uncomplicated problems or concepts and make decisions based on the available information (Saporito, 2014). These skills involve the ability to apply logical and analytic thinking to gathering and analyzing information and designing solutions to problems. Apart from an analytic mindset toward decision making (Saporito, 2014), analytic-oriented organizations must have access to people who have knowledge of necessary tools and techniques that are needed to extract, analyze, interpret, and present data (Davenport et al., 2001). Thus, in organizations with analytic orientation, analytical skills are not only limited to methodical approaches toward problem solving, but also involve the knowledge and use of various statistical tools and techniques for exploring, restructuring, and iterating upon the data to produce analytic outputs. Further, knowledge of business domain is equally important to ensure that analytic efforts are directed toward solving real business issues (Davenport et al., 2001). Without such knowledge, the generated solutions might not be applicable to real business problems and thus adequate value from analytic efforts might not be generated. Hence, organizations with an analytics orientation cultivate analytical skills that encompass methodical problem solving, knowledge of statistical tools and techniques as well as knowledge of the business domain.

2.4.3 Data and IT infrastructure

Data and IT resources are also a critical element of firm's analytic oriented strategy. Organizational decisions based on analytic enquiries often require information to be incorporated from organization's business processes, markets, competitors, and suppliers. Thus, organizations with an analytic orientation strive to identify and gather information from both external and internal sources and incorporate this information into decision making processes to make fully informed decisions. Such organizations also view information or data as a core asset to their firms. Further, analytic oriented organizations also have the capability to manage information effectively over the life cycle of information use which includes collecting, organizing, processing, and maintaining the information to ensure that information is always available for effective decision making (Marchand et al., 2000).Thus, organizations with an analytical orientation should also focus on deploying necessary software, hardware, and telecommunication networks to manage and distribute the information to facilitate decision making.

While analytic culture is an organizational value, analytical skills and IT resources are organizational assets. Both values and assets are required to build a comprehensive analytics orientation capability. Without an analytic culture, employees are less likely to value analytic problem solving and fact-based decision making. Similarly, even if an organization has an analytic culture, without appropriate analytic skills, and sophisticated IT and data infrastructure, employees will not be able to create reliable and valuable insights. Therefore, it is asserted that these three elements together form the analytics orientation of a firm. Table 1 presents the review of the conceptual and empirical studies that have discussed the dimensions pertaining to the proposed construct. In next section, I develop a research model that subsequently relates analytics orientation construct to small businesses' willingness to adopt BA.

Table 1: Key Factors Related to Analytics

References	Context	Factors Studied
Banerjee et al., 2013	Analytics adoption process	Data Inventory Processing Capabilities Business Acumen
Davenport et al., 2001	Analytics Success	Business Strategy Analytic Skills and Experience Organizational structure Organizational Culture Technology and Data

Davenport and Harris, 2007	Analytics Success	Analytics Strategy Enterprise-wide Analytics Approach Top Management Commitment to use Analytics
Germann et al., 2013	Analytics Deployment	Analytic Skills Analytical Culture IT and Data Infrastructure Analytics Prevalence
Malladi, 2013	Analytics adoption	Perceived Benefits of BIA Data-related IT infrastructure Data Standards
Nemati and Udiavar, 2012	Analytics implementation	Data and IT infrastructure Technical and Domain knowledge Organizational Culture and Strategy
Pearson, 2012	Analytics success	Analytical Talent Information Management Analytical Culture
Watson, 2012	Analytics Success	Fact-based Culture Data Infrastructure Analytical Tools Analytical Skills

2.5 Owner-Managers Characteristics

In small businesses, business owners are usually the managers and are primary decision makers involved in every organizational process including technology related decisions (Puklavec et al., 2018). As business owners and top managers are main decision makers, characteristics of decision makers are extremely crucial in determining the innovation attitude of the small businesses (Thong, 1996). Also, according to Upper Echelons theory, organizational outcomes are viewed as reflections of the values and cognitive bases of powerful actors in the organization (see Figure 1) (Hambrick and Mason, 1984). Further, studies suggest that the rate at which small businesses change depends not only on business size or other organizational factors, but it also largely depends on the abilities, attitude, and inclinations of decision makers (Thong, 1999). The IS literature has identified several individual characteristics that may impact the decision to adopt an innovation such as CEO attitude toward innovation and CEO IT knowledge (Thong, 1999), product class knowledge (Peltier et al., 2012), CEO innovativeness (Thong and Yap, 1995), CEO's personal risk orientation (Kitchell, 1997; Peltier et al., 2012), and managerial demographics such as age, tenure, functional background, and education (see Hambrick and Mason, 1984; Damanpour and Schneider, 2006; Hameed and Counsell, 2012). Among several individual characteristics, owner-manager's change-oriented behavior (Ekvall and Arvonen, 1991; Yukl, 1999; Damanpour and Schneider, 2006; Peltier et al. 2009; Li et al., 2008), risk-taking propensity (Sathe, 1989; Kitchell, 1997;Nasution et al., 2011), and CEO's IT knowledge (Thong and Yap, 1995; Jeon et al., 2006; Peltier et al., 2009) have gained significant attention, specifically in small businesses, and have been found to affect the adoption of innovation. Therefore, in this study, I examine business change orientation, personal risk orientation, and BA related knowledge of owner-managers and their impact on organizational willingness to adopt BA.

Further, according to Upper Echelon's framework (Figure 1), cognitive bases and values (personal characteristics) not only directly affect the strategic choices, but may also impact managerial perceptions, which in turn may influence strategic choices (Hambrick and Mason, 1984). For example, the perceptions of a decision maker may suggest a certain strategic choice, but that strategic choice may later be discarded due to the influence of cognitive bases and values (personal characteristics). Therefore, it is important to study not only the perceptions of owner-managers regarding BA, but also the influence of their cognitive bases and values on their perceptions of BA. Hence, this study also examines the impact of owner-manger's personal characteristics on OV's reception dimensions.

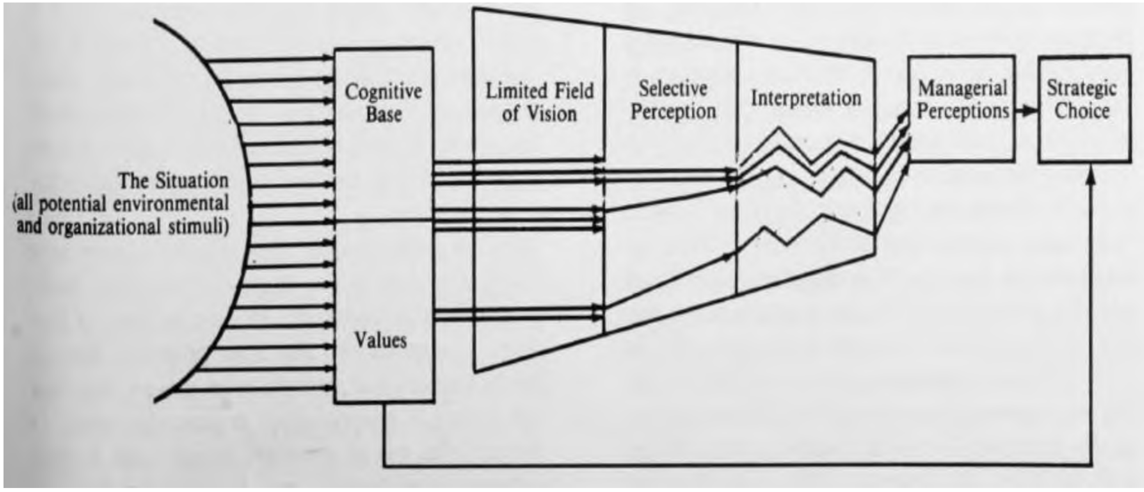

Figure 1: Upper Echelon Framework (Hambrick and Mason, 1984)

2.6 Controls

To ensure correct estimation of the research model, it is important to identify the confounding variables. The extant IT literature suggests that competitive intensity is important variable that can influence the adoption and diffusion of IS (Premkumar and Ramamurthy, 1995; Premkumar et al., 1997; Ranganathan et al., 2004; Zhu et al., 2004). Competitive intensity is defined as the degree to which a firm is affected by its peers or other competitors in the market (Zhu et al., 2004). Prior research suggests that to gain competitive advantage, firms that operate in intensely competitive environments are likely to adopt technologies at a much faster rate (Ranganathan et al., 2004). This is so, because competition leads to environmental uncertainty, which in turn increases both the need for as well as the rate of innovation adoption (Thong, 1999). Taking this into consideration, this study uses competitive intensity as a control variable.

CHAPTER III

RESEARCH MODEL AND HYPOTHESES

3.1 Organization's Willingness to Adopt BA

Organization's willingness is defined as a firm's sensitivity to and interpretation of BA technologies as well as firm's overall response toward its adoption (Delmas and Toffel, 2005). A firm may respond to a new technology in several ways, such as, it may ignore the technology, monitor the technology may perceive the technology negatively, or may show interest in its adoption (Srinivasan et al., 2002). In this study, *organization's willingness to adopt advanced BA* reflects an organization's interpretation of the BA technologies and response toward BA adoption. (Kendall et al., 2001; Marsan et al., 2012a). Thus, organizational willingness to adopt BA will help providing an understanding of low adoption rates of BA technologies among small businesses. Thus, drawing on several theoretical backgrounds, this study examines small businesses' willingness to adopt BA and the factors that influence small businesses' willingness to adopt BA.

3.2 Owner-Managers' Reception of Organizing Vision

Ramiller and Swanson (2003) suggest that the overall reception of an OV may depend on how an individual perceive an OV on each of the OV dimensions. Therefore, it is argued that the receptivity of the organizations toward the adoption of small business analytics will be influenced by how owner-managers perceive the overall concept of BA in terms of interpretability, importance, discontinuity and plausibility.

The importance dimension brings together a diverse set of judgments and encompasses three sub-dimensions: business benefits of innovation, practical acceptance, and market interest. Perceived benefits of innovation have been consistently identified as one of the most critical adoption factors (Damanpour, 1991; Premkumar and Ramamurthy, 1995) and as the most important factor for IT growth in small firms (Cragg and King, 1993; Iacovou et al., 1995). Business analytics has the potential to create competitive advantage and increase firm performance (Davenport and Harris, 2007). Organizations are increasingly recognizing the business benefits derived from business analytics, and as a result investing increasing amounts of money on business analytics (Shanks et al., 2010). According to Holsapple et al. (2014), the main driver for this growth is the perception or realization that BA investments yield a great business value. This suggests that higher understanding of the benefits related to BA increases the likelihood of the allocation of the managerial, financial, and technological resources necessary to implement the innovation (Iacovou et al., 1995). On the contrary, a report from Nucleus Research (2013) reveals that executives from many small and medium enterprises consider the experience and intuition of their employees more significant in decision making than data driven analytics. Further, the research report also reveals that the organizations that have failed to adopt analytics are the ones who believe that investments in BA will not yield significant business benefits as well as any improvements in their day-to-day operations. This implies that the lack of appreciation and understanding of the business benefits of BA may negatively impact the receptivity of small businesses toward BA adoption.

Another sub-dimension of importance, closely related to business benefits, is practical acceptance of organizing vision. Ramiller and Swanson assert that (2003) an innovation may be "hard to sell" if its practical acceptance is weak. This is so because some innovations are characterized by technology push (from parties who want to sell the technology) than by need pull. Therefore, an innovation may be considered important when it is effectively translated to real world problems. The importance of BA, in terms of its practical acceptance, is well established among large businesses. For instance, in a research conducted by ComputerWorld (2009), majority of the respondents agreed that BA has helped their organizations in improving and speeding up the decision making process, realizing the cost efficiencies, responding to the user's needs in a timely manner, and synchronizing the financial and operational strategies. Thus, the applicability of BA to the real-world problems has been recognized by large businesses. On the contrary, if the application of BA may still be in question, it may undermine the sense of its basic importance (Ramiller and Swanson, 2003). This implies that the importance of BA, in terms of practical application, is associated with the willingness of small businesses toward its adoption.

Along with business benefits and practical acceptance, market interest of organizing vision also contributes to the importance dimension. Ramiller and Swanson (2003) suggest that market interest is often regarded as a proxy for a direct rational calculation of organizational performance or business benefit. A lack of relative market interest may in turn reflect real and persistent problems of practical acceptance. In the context of BA, several industry reports have highlighted a significant amount of market interest in analytics (Bloomberg Businessweek, 2011; ComputerWorld, 2009). For instance, BA is considered as the fastest growing segment of Business Intelligence (BI) and top business priority for several organizations (Gartner, 2017). Further BA, apart from its techno-centric methodologies, also includes business-centric practices that can be applied to several applications such as e-commerce, market intelligence, e-government, healthcare, and security (Chen et al., 2012). Thus, several industries and business domains have a legitimate interest in the adoption of BA. Furthermore, in a survey conducted by Bloomberg Businessweek (2011), 97% percent of the large companies have adopted some form of BA. Therefore, increasing amount of market interest in BA can be related to organizations interest in BA adoption. Although the impact of market interest has yet to be explored in small businesses, I expect that increased amount of interest in a particular technology in small business market will drive the willingness of small businesses toward its adoption.

Overall, business benefits, practical acceptance, and market interest constitute significant sub-dimensions of importance. Further, Marson et al. (2012a) found that importance is the most significant dimension and is associated with organizational openness to innovation adoption. When the importance of new technologies, such as BA, is unproven in its public discourse, small businesses might not be receptive toward its adoption. On the contrary, if the public discourse of BA stresses upon the interest and acceptance of BA in small organizations as well as highlights the differential benefits to the business functions upon its adoption, small businesses are likely to be more receptive to BA adoption. Therefore, I posit, that when small business owner-managers find BA important in its public discourse, their organizations will be more receptive to the adoption of BA.

H1(a): Owner-Manager's perception of BA's importance is positively related to small businesses' willingness to adopt BA.

Interpretability reflects how intelligible and informative the owner-managers finds the representations of the organizing vision of BA in its associated public discourse and revolves around aspects such as clarity, consistency, and richness of the public discourse. While investigating the career stages of several organizing visions, Ramiller and Swanson (2003) found that the interpretability of organizing vision is relatively lower when the technology is on the verge of decline and abandonment. This may suggest that when an innovation's organizing vision is problematic and difficult to interpret, it may be discredited and organizations may not consider the IT for adoption (Marsan et al., 2012b). Further, Marsan et al. (2012a) found a significant relationship between interpretability dimension and organizational receptivity to innovation adoption. More specifically, they found that when IT specialists perceive the public discourse of the IT more interpretable, their organizations are open to innovation adoption and have an existing policy in favor of innovation adoption. The discourse of BA can be considered as interpretable when the questions and issues clouding the clarity of BA are resolved, when the community knowledge on BA is continuously expanding, and when small businesses find the representations of BA clear and consistent in its public discourse. As a result, when small businesses find the public discourse of BA easy to interpret, they are more likely to adopt BA in near future.

H1(b): Owner-Manger's perception of BA's interpretability is positively related to small businesses' willingness to adopt BA.

The plausibility dimension complements interpretability and addresses the qualities of community discourse that builds and sustains the organizing vision. While interpretability addresses the intelligibility and informativeness of the discourse, plausibility concerns the distortions in the discourse, focusing specifically on the misunderstandings, exaggerations, and inappropriate assertions of the OV. Marsan et al. (2012a) found that plausibility was significantly related to the organizational openness toward adoption of innovation. Further, they also found that the IT specialists who perceived the discourse more plausible already had an existing policy in favor of innovation adoption in their organizations. This suggests that plausibility of discourse is significantly related to organization's overall willingness to adopt BA. For instance, if the public discourse demonstrates that BA is just another hype that will probably vanish sooner or later, owner-managers may be skeptical regarding the plausibility of BA. Therefore, it is argued that owner-managers who find the public discourse of BA more plausible i.e. free of distortions and exaggerations, are more likely to adopt BA.

H1(c): Owner-Manager's perception of BA's plausibility is positively related to small businesses' willingness to adopt BA.

The concept of discontinuity is reflected by two related notions: conceptual discontinuity and structural discontinuity. It represents the extent to which the OV entails concepts and implementation challenges as compared to other competing or complementary IT. According to Ramiller and Swanson (2003), the detractors of the OV perceive the vision to be highly discontinuous as compared to the supporters of OV. These results are in line with Marsan et al. (2012a) who found that the detractors of OV perceived the public discourse associated with OV as more conceptually challenging than the supporters of OV. Reardon (2009) also found conceptual and implementation challenges as some of barriers to the adoption and assimilation of an OV. A recent research report (Nucleus Research, 2013) suggest that small and medium businesses often fail to adopt analytics due to misperceptions and doubts about the ease with which analytical tools can be deployed within the organization. Further, small businesses fear that analytics environment is too complex where multiple data sources, applications and spreadsheets are often difficult to bring together into a centrally managed environment. If small businesses perceive that BA is incompatible with their existing work practices, poses a significant conceptual departure from existing mental schemas of the organization, and poses several implementation challenges, they might not be receptive to the adoption of BA. Hence, it is argued that when small business owner-managers find the public discourse of BA more discontinuous (both conceptual and structural discontinuity), their organization is less likely to adopt BA. Hence,

H1(d): Owner-Manager's perception of BA's discontinuity is negatively related to small businesses' willingness to adopt BA.

3.3 Learning Orientation and Organizational Willingness to Adopt

Learning orientation has been considered as an important antecedent of innovativeness by several research studies (Baker and Sinkula, 1999; Hurley and Hult, 1998). This is because firms that are able to learn about external environment have higher likelihood of sensing and responding to changes in the marketplace (Day, 1994). Therefore, I expect that learning orientated small businesses are more likely to be aware of new technological advancements in the external environment. Because of their commitment toward learning, shared vision, and open-mindedness, they are more likely to be open toward the adoption of BA.

Commitment toward learning helps employees to challenge their status quo, develop new ideas, innovate, and continuously evaluate their activities to improve organizational performance (Mahmoud and Yusif, 2012). Further, higher levels of commitment to learning encourage small businesses to innovate (Tajeddini and Mueller, 2009). As commitment toward learning enhances knowledge acquisition in the surroundings (Sinkula et al., 1997; Slater Narver, 1994), it will allow small businesses to learn about BA tools and technologies from external environment. When organizations are committed toward learning, they are more likely to challenge old assumptions and beliefs (Baker & Sinkula, 1999a), and therefore, may be more likely to develop appreciation for and desire to adopt BA technologies (Hurley and Hult, 1998). This suggests that small businesses that are committed to learning may be more receptive toward BA.

H2 (a): Commitment to learning is positively related to small businesses' willingness to adopt BA.

Shared vision represents an organization's collective purpose and direction. Sinkula et al. (1997) explain that shared vision gives a common direction to employees that in turn help organizations to implement creative ideas and overcome problems that may arise in organizations (Calantone et al., 2002; Hurley and Hult, 1998). Shared vision also legitimizes the acquisition and assessment of new knowledge. When there is a lack of shared vision, employees of small business may be less likely to share dominant logics, such as organization's mission, or desired outcomes, such as profitability, market share, sales, and customer satisfaction (Sinkula et al., 1997). For example, when senior management in one firm wanted their employees to rely on data-based analysis for improving their businesses processes, employees resisted using the data and relied on other practices instead (Davenport et al., 2001). A lack of common direction or divergent views in small businesses may also lower the interpretation of market information which may restrict the ability of small businesses to quickly respond to emerging trends or problems. Thus, it is argued that a lack of shared vision may affect organizational members' collective interpretation of BA technologies due to which there will be a lack of agreement on the adoption of BA technologies among organizational members. On the contrary, convergent views may help small businesses in developing a focused response to current market trends and thus, may positively affect the willingness of small businesses toward adoption of new technologies such as BA.

H2 (b): Shared vision is positively related to small businesses' willingness to adopt BA.

Prior studies argue that open-mindedness is critical for examining the deeply held beliefs or conceptions of individuals that may confine them to familiar patterns of thinking and acting (Senge, 1990; Sinkula et al., 1997). At an organizational level, open-mindedness is necessary to evaluate an organization's operational routine and to accept new and innovative ideas (Sinkula et al., 1997). Open-mindedness also stimulates engagement in innovative behaviors (Hernandez-Mogollon et al., 2010). Thus, small businesses that support open-mindedness are likely to encourage new work methods and innovative processes. Further, Calantone et al. (2002) suggests that open-mindedness improves an organization's ability to adapt to the rapid technology changes and turbulent markets. Thus, it is argued that open-mindedness may inject new ideas into small businesses and increase the ability of small businesses to identify new opportunities in the market, such as BA technologies. Hence, when small businesses are open-minded, they are likely to support BA initiatives, and are likely to be receptive toward BA adoption.

H2 (c): Open-mindedness is positively related to small businesses' willingness to adopt BA.

3.4 Analytics Orientation and Organizational Willingness to Adopt

As the focus of analytics orientation is primarily on information-based decision making, it may have direct implications on the willingness to adopt BA. Because BA technologies involve analytical tools and technologies that provide useful insights into data, firms with analytics orientation are more drawn to adopt such technologies.

3.4.1 Analytical culture

As "culture carries the logic of how and why things happen" (Germann et al., 2013, p. 117), an organizational culture supportive of information-based decision making is critical in order to be receptive toward BA adoption. An analytics-focused culture provides an organization with shared understanding and beliefs of how the use of information in decision making can prove transformative for a firm. As analytical culture values information-driven decision making, it is expected that such a culture will value BA tools and technologies that have the capability to collect, analyze, and interpret large volumes of information to provide insights for decision making. However, when the decision-making norms don't encourage the use of information in decision making, employees may resist using the data or information (Davenport et al., 2001), which in turn may make them less appreciative toward BA tools and technologies. Therefore, it can be argued that small businesses that value information-based culture will be more receptive toward the adoption of BA technologies.

H3 (a): Analytical culture is positively related to small businesses' willingness to adopt BA.

3.4.2 Analytical skills

According to Attewell (1992), new technologies impose a substantial burden on organizations in terms of necessary skills and knowledge required to use them effectively. Due to this knowledge barrier, organizations tend to defer the adoption of a new technology until these barriers are lowered. In the context of BA, analytical skills of employees have been found to significantly impact the deployment of analytics in organizations (Germann et al., 2013). This is because when employees possess the necessary analytical skills, they are more likely to use the tools and techniques with which they are comfortable (Lounsbury, 2001). In line with this, I emphasize that to be receptive toward analytical tools and technologies, a firm must have access to people who possess analytical problem solving skills, have knowledge of the analytical tools, as well as knowledge of the business domain. As these skills are also prerequisites for BA initiatives, the availability of necessary knowledge and skills to execute BA may in turn influence the organization's overall willingness to adopt BA.

H3 (b): Analytical skills of employees are positively related to small businesses' willingness to adopt BA.

3.4.3 Data and IT Infrastructure

An organization's physical IT infrastructure and data are critical assets required for the adoption of analytics (Germann et al., 2013). Although each organization's data and infrastructure requirements vary, certain standard data and infrastructure requirements are necessary to carry out BA initiatives (Nemati and Udiavar, 2012). Prior research suggests that organizations that view data as a core asset are the ones who are most successful with analytics (Kiron et al., 2014). Further, research also suggests that a persuasive use of analytics and BI tools is largely driven by the availability of data captured from different sources (Banerjee et al., 2013). Data may originate from many places and provide the basis for deriving important information and insight for analytics. The variety of sources that firms report capturing data from besides firm's transactional systems include text from social networking sources, emails, chats, Web logs, GIS data, audio and video. To collect this structured and unstructured data from multiple sources, as well as to effectively integrate, store, manipulate, analyze, and distribute data across the organization (Davenport and Harris, 2007; Germann et al., 2013), a strong organization-wide infrastructure is required. Physical IT resources, such as computer and communication technologies, and shared technical platforms and databases, constitute the overall IT infrastructure of a firm (Germann et al., 2013). Inadequate IT infrastructure and lack of data can hamstring such BA initiative. Although several cloud-based solutions have emerged for small businesses that require limited IT infrastructure, these solutions have not yet been effectively communicated to the small businesses (Canes, 2009). Further, cloud-based solutions are still not considered as viable by many small and medium businesses due to several factors such as higher rent structure (Marks, 2012), security and privacy of data (Alshamaila and Papagiannidis, 2013; Kelly, 2011), reliability issues (Durkee, 2010; Mahesh et al., 2011), and downtime associated with clouds (Gupta et al., 2013). Research also suggests that businesses that have a higher need for sharing and collaboration with their stakeholders do not prefer cloud-based solutions (Gupta et al., 2013). Overall, small businesses prefer their old conventional methods for backup, storage, and other business needs and rely more on their physical devices within their proximity (Gupta et al., 2013). As cloud-based solutions have yet to gain popularity among small businesses, to carry out their BA initiatives, small businesses would require strong data and IT infrastructure. Prior research suggests that firms that possess sufficient data and IT infrastructure, are more oriented toward data collection, and are more likely to adopt BA (Malladi, 2013). Therefore, both data and IT resources are important and closely related prerequisites for effective deployment of analytics (Germann et al., 2013). Thus, we argue that small businesses with analytics orientation should possess sufficient data and IT resources required to carry out such initiatives. As analytics oriented firms focus on gathering and analyzing information for decision making, they must have systematic processes in place for collecting, gathering, organizing, and managing information that aligns with the objectives of BA. Thus, existence of such data and IT infrastructure will make these firms adopt BA. Hence,

H3 (c): Higher sophistication of Data and IT infrastructure is positively related to small businesses' willingness to adopt BA.

3.5 Owner-Manager's Characteristics

3.5.1 Business change orientation

Business change orientation reflects the general openness toward change, acceptance for new ideas, and/or a preference for innovation (Peltier et al., 2009; Shih and Venkatesh, 2004; Wieseke et al., 2008). Several studies in a variety of areas of research suggest that individuals who are open toward change tend to be more creative, have a more favorable attitude toward innovation (Stewart et al., 2003), are more venturesome (Rogers, 2003), are more confident decision makers (Kickul and Gundry, 2002) and thus more likely to adopt innovation (Wu et al., 2003). Further, Damanpour (1991) suggests that CEO's favorable attitude toward a new technology affects the adoption of IT in a positive way. According to Rogers (1983), the creation of attitude toward an innovation happens before a decision to adopt has been made. Mehrtens et al. (2001) found a direct link between CEO's positive attitude toward innovation and success of the adoption process. Hence, it is posited that owner's business change orientation will lead to an internal climate conducive to innovation and will affect the willingness of the firm toward adoption of BA.

H4 (a): Owner-Manager's business change orientation is positively related to small businesses' willingness to adopt BA.

3.5.2 Personal Risk orientation

Risk orientation is defined as the willingness of owner-managers to commit significant resources to pursue opportunities in the face of uncertainty (Nasution, 2011). The adoption of a new innovation often involves risk-taking because of the uncertainty of the outcomes (Kitchell, 1997). However, owner-managers with a risk-taking mindset challenge these risks and continue to maintain their enthusiasm by committing increasing amounts of resources toward innovation acquisition (Kollman and Stockmann, 2014). Further, risk taking boosts the speed of decision, and enables firms to seize opportunities characterized by a short window of opportunity. Even if the innovation is risky, risk-oriented individuals would engage in such innovations because of their potentially high paybacks (Lumpkin and Dess, 2001). Further, studies suggest that owner-managers who are more apt to take risks adopt more open-minded and adopt more innovative techniques (Troy et al., 2001; Peltier et al., 2012). Therefore, it is postulated that owner's risk orientation may favor new BA tools and technologies, and therefore, influence the organizational willingness to adopt BA.

H4 (b): Owner-Manager's personal risk orientation is positively related to small businesses' willingness to adopt BA.

3.5.3 BA related knowledge

Gable and Raman (1992) found that CEOs in small organizations lack the basic knowledge of IT and have insufficient awareness of the potential benefits of IT adoption. Further, due to the lack of innovation related knowledge, CEOs may not adequately understand the problems or identify new ideas or innovations that could be potential solutions (Marinova, 2004). Several studies have also found that CEOs who have more knowledge of a technological innovation are more likely to have a stronger technology adoption policy (Thong, 1999, Ettlie, 1990). Lack of IT knowledge creates uncertainty and it is only the awareness through knowledge that informs confidence in new innovation which facilitate adoption (Rogers, 1995). In case of BA, although decision makers may not need to be proficient in analytic tools, however, to make decisions based on the findings, they should have an understanding of the underlying analysis and familiarity with organizational data (Davenport et al., 2001). Thus, it is hypothesized that owners/managers who possess BA related knowledge are more likely to favor BA, and thus, will create an internal climate conducive to innovation resulting into organizational willingness to adopt BA.

H4 (c): Owner-Manager's BA related knowledge is positively related to small businesses' willingness to adopt BA.

3.6 Owner-Manager's Characteristics and the Perception of Public Discourse

The Upper Echelons' theory suggests that apart from organizational outcomes, the overall perceptions of the managers are also influenced by their own cognitive bases and values (Hambrick and Mason, 1984). This is so because managers cannot scan every aspect of organization and its environment, and therefore, perceptions about organization and environment are interpreted through the filter of their cognitive bases and values. These unobservable psychological constructs are often measured by observable constructs such as demographics and personality traits of managers (see Hambrick and Mason, 1984; Damanpour and Schneider, 2006; Hameed and Counsell, 2012; Thong and Yap, 1999; Kitchell, 1997). In brief, the individual characteristics of decision makers not only impact the organizational outcomes but also impact their own individual perceptions. Marson et al. (2012a) investigated several individual characteristics of IT specialists and found a significant relationship of these individual characteristics to the dimensions of the reception of public discourse of innovation. Thus, drawing from Upper Echelon theory and prior literature on organizational adoption, it is argued that the characteristics of small business owner-managers such as business change orientation, personal risk orientation, and their related BA knowledge may impact their overall reception of the public discourse of BA (importance, interpretability, plausibility, and discontinuity).

3.6.1 Business Change Orientation

The key decision makers are often victims of selective perception and attention, which may restrict them to the need for change (Miller, 1993; Hambrick and Mason, 1984). The conservative behavior of owner-managers may prevent organizations from even considering any new technology (Pare et al., 2009) and could prevent them from identifying and engaging in the existing public discourse associated with BA. While owner-managers with rigid and conservative mindsets can restrain creativity, their orientation toward change can foster an innovative culture (Miller, 1993). Prior studies show that decision maker's attitude toward change influences the rate and overall acceptance of new technology (Peltier et al., 2012). Further, owner-managers change orientation has also been linked to seeking and accepting new ideas as well as having a better understanding of the technology. As a result, this may impact how owner-managers perceive the overall concept of BA in its public discourse. More specifically, owner-manager's change orientation should translate into overall positive perceptions (i.e. when owner-managers consider an OV to be more important, interpretable, plausible, and less discontinuous) toward the public discourse of BA. Hence, I posit that:

H5 (a): Owner-manager's change orientation is positively related to the perceptions of the public discourse of BA.

3.6.2 Personal Risk Orientation

When the owner-managers have low risk propensity, they lack the capacity to deviate from existing strategies and routines to assimilate new external knowledge (Atuahene-Gima and Ko, 2001). Such owner-managers may not be interested in engaging with the public discourse and may not have accurate perceptions of the discourse associated with BA. For instance, findings from the study conducted by Marsan et al. (2012a) suggest that risk-averse individuals perceived that innovation represents a structural discontinuity i.e. it poses unprecedented implementation challenges. Therefore, risk-averse owner-managers can prevent organizations from identifying opportunities to adopt BA that could be beneficial for their firm. On the contrary, risk-taking individuals are more open-minded and have a better grasp of the world outside of their immediate social system (Maxwell and Westerfield, 2002). This implies that owner-managers with risk taking propensity are more likely to be engaged in the public discourse of BA and may have favorable perceptions of the public discourse of BA. Hence,

H5 (b): Owner-Managers' personal risk orientation is positively related to the perceptions of the public discourse of BA.

3.6.3 BA Related Knowledge

CEO's skill base and knowledge have been consistently shown to be significant and positively related to adoption of innovation by prior studies (Kimberly and Evanisko, 1981; Thong, 1999; Damanpour and Schneider, 2006; Marson et al., 2012a). For instance, while studying the organization's receptivity to innovation adoption, Marson et al. (2012a) found that IT specialists who were less exposed to the innovation were the ones who were the detractors rather than supporters of the innovation. Further, their study found that the detractors perceived the public discourse of an OV as less important and plausible. This suggests that due to lack of BA related knowledge, owner-managers may associate lower levels of importance, plausibility, and interpretability, as well as higher levels of discontinuity to BA technology. This in turn may translate into greater levels of cognitive efforts required to comprehend and evaluate BA and may impact the reception of BA. Hence,

H5 (c): Owner-Managers' BA related knowledge is positively related to the perceptions of the public discourse of BA.

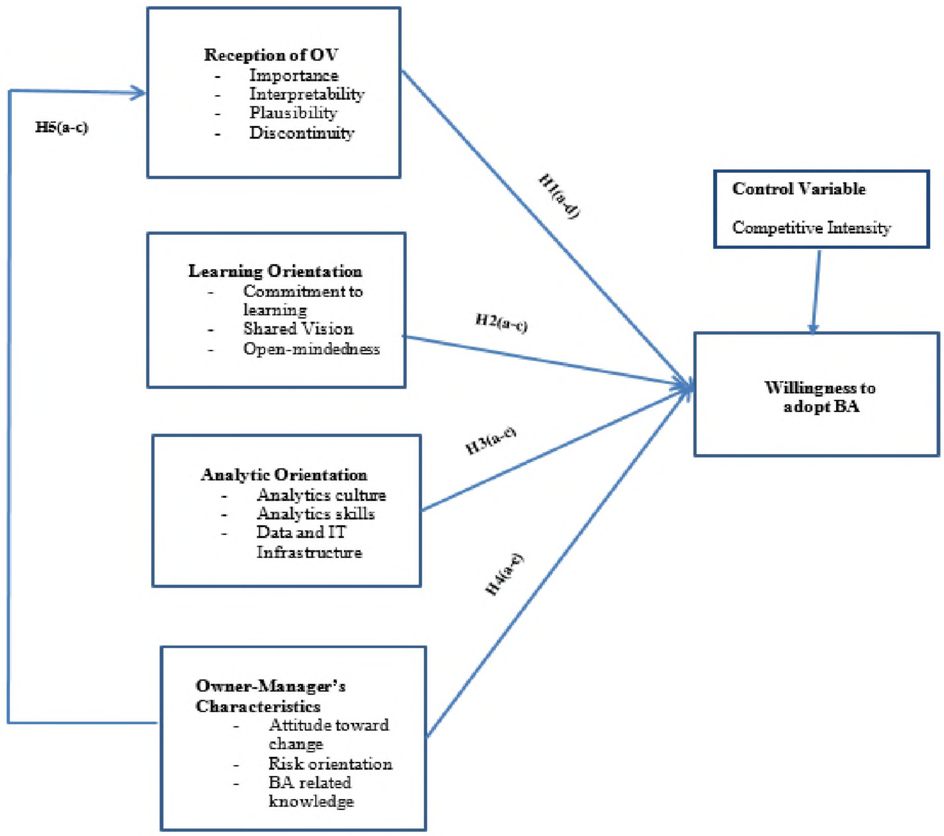

Figure 2: Research Framework

CHAPTER IV

RESEARCH METHODOLOGY

4.1 Construct Operationalization

To measure willingness to adopt advanced analytics, items were derived from Teo et al. (2003) and Liu et al., (2010) and modified to the context of BA. Drawing on Ramiller and Swanson (2003), the *reception of public discourse of BA* was operationalized on these four dimensions: importance, interpretability, discontinuity, and plausibility. Similarly, characteristics of owner include demographic variables and personality traits such as: *business change orientation, personal risk orientation,* and their *BA related knowledge*. These items were adopted from already existing literature (Kitchell, 1997; Peltier et al., 2012; Thong and Yap, 1995) and were modified where needed.

To operationalize learning orientation, existing strategic orientation literature was reviewed. The research seems to be inconsistent in terms of how this construct is defined and operationalized. In fact, several studies have viewed it as single dimension construct (Calantone et al., 2002). Table 2 provides an example of few studies that have measured strategic orientations in different ways.

Table 2: Strategic Orientations in Prior Studies

Strategic Orientations	Operationalization	Studies
Learning Orientation	One first-order factor	Kaya and Patton (2010), Mahmoud and Yusif (2012), Lam et al. (2011), Rahab (2012)
	Three first-order factors	Baker and Sinkula (1999), Choi (2014), Lonial and Carter (2015), Narver and Slater (1990)
	Three first-order One Second-order	Calantone et al. (2002), Sinkula et al. (1997)
Market Orientation	One first-order factor	Mahmoud and Yusif (2012), Rahab (2012)
	Three first-order factors	Choi (2014), Baker and Sinkula (1999), Narver and Slater (1990), Lonial and Carter (2015)
	Three first-order One Second-order	Zhou et al. (2005), Kaya and Patton (2010)

Thus, following the strategic orientation literature, learning orientation was operationalized as first-order construct consisting of three factors: *Commitment to learning, shared vision, and open-mindedness*. To operationalize the analytics orientation of the firm, the measures include- *analytics culture, analytics skills, Data and IT resources*. The items for these three dimensions that reflect analytics orientation were either derived from existing theoretical and empirical studies or were developed when necessary using an iterative procedure, as recommended in the literature (Churchill, 1979). Following this procedure, first a large pool of items was generated for each of the constructs from an extensive literature review. Second, to achieve item purification and refinement, multiple rounds of item sorting were established by obtaining responses from independent panel of informed judges. Finally, a formal pretest of the instrument (Appendix A) was conducted where survey was sent to a panel of seven academicians and two IT specialists/ practitioners with backgrounds in BA, to assess any weaknesses in the measurement items.

The panel completed the questionnaire and gave their opinion about phrasing of the questions, terminology, length of time to complete the survey, and the length of the questionnaire. After pre-test, minor editing changes were made to the questionnaire. A seven-point Likert scale was used to measure all indicators, which ranged from 1 (strongly disagree) to 7 (strongly agree). The final measurement instrument is presented in Appendix A.

4.1.1 Control Variables

Prior research studies on organizational innovation have highlighted the role of competition intensity in driving the adoption and diffusion of IT (Premkumar and Ramamurthy, 1995; Premkumar et al., 1997; Ranganathan et al., 2004; Zhu et al., 2004). As firms in intensely competitive environments are more likely to adopt innovation, competitive intensity is considered as a control in this study. Drawing upon a previous study examining the diffusion of IT (Ranganathan et al., 2004), three items were derived to capture the competitive intensity construct. These items assess the perceptions of the responding firm on the extent to which it monitors and keeps track of competitors in the industry.

4.2 Data Collection

A survey was conducted to test the research framework. According to U.S. Small Business Administration (SBA), small businesses are defined as firms with fewer than 500 employees and with annual revenues less than $30M. Therefore, data was collected through Qualtrics panel from Owners and Managers of small business firms that have not adopted any form of advanced BA. A total of 250 responses were collected. The responses were collected on a 7-point Likert scale, where 7= strongly agree, 1= strongly disagree, and 4= neutral response. Where respondents had entered "7" or "1" across the board on responses, regardless of survey item direction, these responses were removed. Following this removal, 232 usable responses were used in the final analysis. Further, to ensure all items are coded in the same direction, before performing any analysis, all negatively formulated items were reverse coded (Table 10). The demographic characteristics of respondents are presented in Table 3. As seen in Table 3, our respondents had 13 years of experience on average, and have worked in various industries such as manufacturing, services, finance and insurance, wholesale trade, construction and mining etc. Also, 40% of the respondents were also the owner of their firms while 60% were managers who participated in their firm's IT investment decisions. Furthermore, 72% of the respondents were actively involved in business analytics community by participating through industry, trade or professional bodies.

Table 3: Profile of respondents

Demographic Variables	**Category**	**Frequency (n=232)**	**Percent**
Age	<= 29	53	22.8%
	30 - 39	90	38.8%
	40 - 49	51	22.0%
	50 - 59	30	2.9%
	60+	8	3.4%
Gender	Male	132	56.9%
	Female	100	43.1%
Education Level	High School Diploma	18	7.8%
	College Diploma	45	19.4%
	University Studies (certificate)	16	6.9%
	Bachelor's Degree	100	43.1%
	Master's Degree	43	18.5%

Demographic Variables	Category	Frequency (n=232)	Percent
	Ph. D. Degree	10	4.3%
Industry	Services	65	28.0%
	Manufacturing	33	14.2%
	Wholesale Trade	13	5.6%
	Finance and Insurance	18	7.8%
	Construction and Mining	29	12.5%
	Communication	29	12.5%
	Other	45	19.4%
Annual Sales (US$ million)	Less than 1 million	105	45.3%
	1-10 million	69	29.7%
	10-20 million	12	5.2%
	20-30 million	4	1.7%
	Invalid/Missing	42	18.1%
Owner	Yes	93	40.1%
	No	139	59.9%
Number of Employees	<= 10	47	20.3%
	11 - 39	45	19.4%
	40 - 100	65	28.0%
	101 - 200	30	12.9%
	201 - 500	41	17.7%
	Missing	4	1.7%
Involvement with BA community	Yes	166	71.6%
	No	66	28.4%
Total Years with Current Organization	<= 10.0	166	71.6%
	10.1 - 20.0	48	20.7%
	20.1 - 30.0	15	6.5%
	30.1+	2	.9%
	Missing	1	.4%
		Average	Stand. Dev.
Years of Experience		13.39	8.54

4.3 Data Analysis

The data analysis was performed using SPSS Statistics 25 and AMOS 25 in following steps:

1. First, analytics orientation construct was developed by following the procedure suggested by Churchill (1979).

2. Factor analysis was performed on the dimensions of OV.

3. Using SEM, first, the evaluation of measurement model was performed using confirmatory factor analysis (CFA), and then, structural model was tested to validate the research model.

4.3.1 Development of Analytics Orientation Construct

By following Churchill's (1979) scale construction process of construct development, Analytics Orientation scale development is divided into following stages:

- Stage 1: Specify domain of the construct and identify items reflecting the construct.
- Stage 2: Generate sample of items and scale purification through exploratory factor analysis (EFA) and confirmatory factor analysis (CFA).
- Stage 3: Assessment of construct validity by discriminant and convergent validity through analysis of covariance structures.
- Stage 4: Nomological validity.

Stage 1: **Specify domain of the construct**

For Stage 1, analytics orientation was defined, and three sub-constructs were identified from literature: Analytical Skills, Analytical Culture, and Sophistication of Data and IT Infrastructure that reflects analytic orientation of the firm (see details in section 2.4).

Stage 2: **EFA and CFA on Analytics Orientation**

For Stage 2, I identified several items from already existing literature and refined the items in several iterations by discussing them with an academic expert. A total of 14 items were identified to represent three dimensions of Analytics Orientation. Cronbach's alpha values for the three proposed dimensions for all the items ranged from 0.71 to 0.89 (Table 4), clearly exceeding the 0.70 cut-off value recommended by Nunnally (1967) for scale purification. Further, an exploratory and confirmatory analysis was conducted to finalize the items.

Table 4: Reliability Statistics of Analytics Orientation Constructs

Scale	**Cronbach's Alpha**	**N of Items**
Analytical Skills	.898	5
Analytics Culture	.717	6
Data & IT Infrastructure	.890	3

EFA was performed using maximum likelihood extraction and promax rotation methods based on Eigen values greater than 1. The adequacy of the sample is measured by KMO in SPSS to ensure that distinct and reliable factors can be produced. The sampling is adequate if the value of Kaiser-Meyer-Olkin (KMO) is larger than 0.5 (Field, 2000). Bartlett's Test of Sphericity measures the strength of relationship. The significant value less than 0.05 indicates that these data do not produce an identity matrix and are thus approximately multivariate normal and acceptable for further analysis (Field, 2000; Pallant, 2013). As shown in table below, KMO value is 0.87, indicating sufficient items for each factor and Bartlett's Test of Sphericity is significant at $p<.001$.

The EFA of all 14 items of Analytics Orientation resulted in three factors, confirming the proposed factor structure for the Analytics Orientation construct. However, 3 items had to be removed from the instrument due to factor loading lower than 0.50, reducing the items from 14 to 11.

Table 5:KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.917
Bartlett's Test of Sphericity	Approx. Chi-Square	1979.579
	Df	91
	Sig.	.000

To evaluate the proposed Analytics orientation construct, these 11 items were further subjected to CFA with maximum likelihood extraction and promax rotation using SPSS's Amos 25. The analysis resulted in a clean structure, as shown in Table 6.

Table 6: Pattern Matrix

CFA on AO			
	Component		
	1	2	3
AO_AS_1	-.062	.069	.821
AO_AS_2	-.055	.160	.795
AO_AS_3	.152	-.033	.748
AO_AS_4	.217	-.079	.669
AO_AC_2	.524	-.071	.184
AO_AC_4	.708	.067	.041
AO_AC_5	.892	.122	-.147
AO_AC_6	.697	-.089	.135
AO_DIT_1	-.069	.864	.104
AO_DIT_2	.056	.867	.015
AO_DIT_3	.042	.777	-.040

Extraction Method: Maximum Likelihood.
Rotation Method: Promax with Kaiser Normalization.

To identify all plausible factor patterns, a series of CFA analyses were performed, and the alternative models were compared (Doll et al.,1994). Thus, based on prior strategic research studies, I tested a one-factor model, first order three factor model, and a second order model (J.-S Chen et al., 2009; Wang and Ahmed 2004). The goodness of fit indices for all these models are presented in Table 7.

As seen from the results, neither Model 1 nor Model 2 performed well on all the goodness-of-fit indexes. For example, GFI, CFI, TLI, IFI and NFI are all below the desired levels of .90 (Bagozzi). On the other hand, both Model 3 and Model 4 indicates a reasonable fit. All the important indices such as GFI, CFI and NFI are above the recommended thresholds and range from (0.94 to 0.98). Thus, according to results, both Model 3 and Model 4 provided a satisfactory fit with the data. This is also consistent with the strategic literature, where considerable amount of research studies has operationalized strategic orientations with both first-order factors as well as second-order factors of measurement. Overall, the results strongly support that analytics orientation should be conceptualized as a second-order construct.

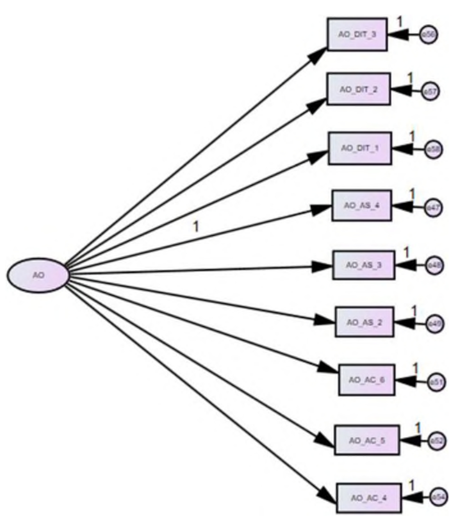

Figure 3: Model 1

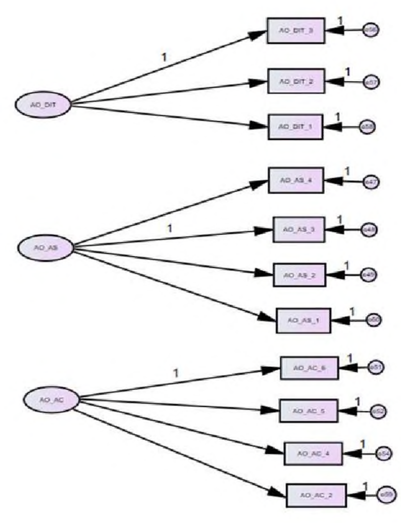

Figure 4: Model 2

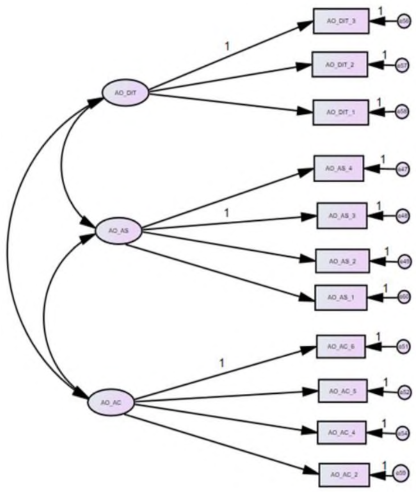

Figure 5: Model 3

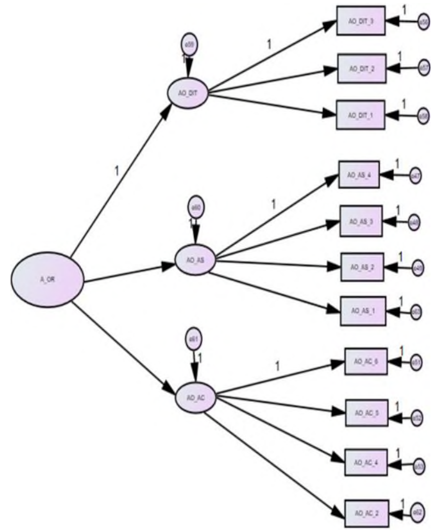

Figure 6: Model 4

Table 7: Comparison of Models

Model	Description	Chi-square (CMIN/DF)	CFI	NFI	IFI	TLI	GFI	RMSEA
1. One First-order factor	Analytics Orientation	9.55	0.76	0.74	0.76	0.70	0.71	0.19
2. Three First-order factors (uncorrelated)	Analytics Orientation	7.22	0.82	0.80	0.82	0.78	0.81	0.16
3. Three First-order factors (correlated)	Analytics Orientation	1.94	0.97	0.95	0.98	0.97	0.94	0.06
4. Three First-order factors One Second-order factor	Analytics Orientation	1.94	0.97	0.95	0.98	0.98	0.94	0.06

Stage 3 & Stage 4: Assessment of construct validity and Nomological validity

To further test the quality of Analytics Orientation construct, for Stage 3, I assessed the validity of construct by determining the discriminant and convergent validity. The nomological validity of the construct (Stage 4) was examined using SEM analysis. The results are presented and discussed in section 4.3.3.

4.3.2 EFA and CFA on Organizing Vision Dimensions

An EFA and CFA was also performed on all the four dimensions of OV using SPSS AMOS 25. Following a step by step approach, items were removed when loadings were inferior to 0.50 or when there were high cross loadings. The confirmatory analysis showed a clean structure as shown in Table 8.

Table 8: Confirmatory Factor Analysis

CFA on OV				
	Component			
	1	2	3	4
Importance_2_BB	.076	**.808**	-.061	.037
Importance_3_BB	-.081	**.870**	.017	-.033
Importance_4_BB	.020	**.833**	.041	.077
Interpretability_2R	-.109	.138	**.663**	-.293
Interpretability_3R	-.012	-.034	**.896**	.042
Interpretability_4R	.098	-.059	**.887**	.126
Plausibility_1R	**.892**	-.146	.049	.050
Plausibility_2R	**.936**	.076	-.192	-.087
Plausibility_3R	**.758**	.088	.140	-.051
Plausibility_4R	**.877**	.009	.079	.017
Discontinuity_2_CD	.108	.089	.010	**.933**
Discontinuity_3_SD	-.173	.040	-.032	**.724**
Discontinuity_4_SD	-.137	-.052	.023	**.751**

Extraction Method: Maximum Likelihood.
Rotation Method: Promax with Kaiser Normalization.

4.3.3 SEM Analysis

Data analyses was performed using SPSS's AMOS version 25. The maximum likelihood estimates (MLE) approach was used to perform Structure Equation Modeling (SEM). A two-step SEM analysis approach was used for data analyses (Anderson and Gerbing, 1988). In the first step, Confirmatory Factor Analysis (CFA) was carried out. CFA analyses provides an assessment of the fit between the collected data and the theoretical factor structure. CFA measurement model was also used to test the reliability, convergent validity and discriminant validity of the constructs. Following the confirmation of good psychometric properties, in the second step, the structural model was assessed, and hypotheses were tested.

4.3.3.1 Evaluating the Measurement Model using CFA

To assess the reliability and validity of the proposed constructs, confirmatory factor analysis (CFA) was conducted. All independent and dependent latent variables were included in one confirmatory factor analysis model. The initial model structure with several multiple-item constructs had a poor model fit. The model was refined, and items were removed one step at a time after following the modification indices. The loadings of items were compared against the value 0.70 on the construct being measured. Several items were deleted due to low loadings or high cross loadings. The final items used in model are presented in Table 9. The model also had a significant improvement over the previous versions. For a measurement model to have good model fit, the χ^2value normalized by degrees of freedom (χ^2/ df) should not exceed 3 (Bagozzi and Yi, 1988) and Non-Normed Fit Index (NNFI) and Comparative Fit Index (CFI) should exceed 0.9. The important robust indices such as Comparative Fit Index (CFI) (Bentler, 1990) and Tucker-Lewis Index (TLI)

(Tucker & Lewis, 1973) are well above their recommended thresholds. All model fit indices, presented in Table 12, provided satisfactory fit to the data. Following the recommendations of Sinkula et al. (1997), Learning Orientation was initially operationalized as a second-order construct with three dimensions: Commitment to Learning, Shared Vision, and Open-mindedness. Similarly, as suggested by the results of CFA analysis on Analytic Orientation (Table 7), Analytics Orientation was also operationalized as a second-order construct with three dimensions: Analytics Culture, Analytics Skills, and Sophistication of Data and IT Infrastructure. However, the results of full CFA model with Learning and Analytics Orientation as a second-order construct resulted in a poor model fit (CMIN= 1.7, CFI=.90, NFI= .81, TLI=.89, RMSEA=.06, SRMR =.06). Therefore, to achieve a better model fit and based on prior conceptualizations of strategic orientations in the literature (see Table 2), Learning Orientation and Analytics Orientation were both operationalized as first-order constructs consisting of three factors.

The measurement model was then tested for its reliability, convergent validity, and discriminant validity. The internal consistency of each dimension was assessed by computing the Cronbach's alpha and composite reliability (Hair et al. 1998). Table 10 presents the results along these dimensions. All Cronbach's alpha and composite reliabilities exceeded Nunnally's (1978) suggested threshold of .70 and thus supported the reliability of the measures.

Convergent validity ensures that all items measure a single underlying construct (Bagozzi and Fornell, 1982). The standardized loadings for the indicators and Average Variance Extracted (AVE) were used to test the convergent validity. As shown in Table 9, all indicator loadings were greater than the recommended value of 0.50. The AVE for a construct reflects the ratio of the construct's variance to the total amount of variance among the items. Table 10 shows that the AVE values for all the constructs, except for Attitude toward change construct, were above the limit of 0.50 as advised by Fornell and Larcker (1981). The Attitude toward change construct did not contribute the problem of internal consistency and only had three items, therefore, all items from this construct were retained.

Discriminant validity refers to the extent to which a given construct differs from other constructs. Discriminant validity is assessed by applying the square root of the AVE, which should be at least 0.7. Also, the square root of the AVE between the construct and all other constructs should be greater than the construct's maximum correlation with the other constructs. Our results indicate satisfactory discriminant validity for all the constructs. Furthermore, the correlations between all pairs of constructs are also below the threshold value of .90 (Bagozzi et al., 1991) suggesting that the constructs are distinct.

Table 9: Construct, Items and Loadings

Construct	Items	Loadings
Importance		
	Importance_2_BB	.701
	Importance_3_BB	.741
	Importance_4_BB	.821
Interpretability		
	Interpretability_2R (rc)*	.648
	Interpretability_3R (rc)*	.774
	Interpretability_4R (rc)*	.810
Plausibility		
	Plausibility_1R (rc)*	.823
	Plausibility_2R (rc)*	.834
	Plausibility_3R (rc)*	.839
	Plausibility_4R (rc)*	.893
Discontinuity		
	Discontinuity_2_CD	.759

	Discontinuity_3_SD	.838
	Discontinuity_4_SD	.714
Willingness		
	Willingness_1	.894
	Willingness_2	.920
	Willingness_3	.900
Attitude toward Change		
	PC_ATC_3	.733
	PC_ATC_5	.680
	PC_ATC_6	.641
Personal Risk Orientation		
	PC_RO_2	.742
	PC_RO_4	.830
	PC_RO_6	.806
BA related knowledge		
	PC_BAK_1	.907
	PC_BAK_2	.693
	PC_BAK_3	.771
Analytical Skills	AO_AS_2	.833
	AO_AS_3	.836
	AO_AS_4	.795
Analytics Culture		
	AO_AC_4	.780
	AO_AC_5	.815
	AO_AC_6	.765
Data & IT Infrastructure		
	AO_DIT_1	.891
	AO_DIT_2	.907
	AO_DIT_3	.776
Commitment to Learning		
	LO_CTL_1	.792
	LO_CTL_2	.758
	LO_CTL_3	.718
Open-Mindedness		
	LO_OM_3	.821
	LO_OM_4	.824

	LO_OM_6	.826
Shared Vision		
	LO_SV_2	.738
	LO_SV_3	.805
	LO_SV_4	.731
rc* = reverse coding		

Table 10: Assessment of Internal Consistency and Convergent Validity

Constructs	# of items	Mean (SD)	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Importance	3	5.41(1.17)	.796	0.800	0.572
Interpretability	3	3.65(1.54)	.784	0.790	0.558
Plausibility	4	3.97(1.59)	.911	0.911	0.719
Discontinuity	3	4.09(1.65)	.815	0.815	0.596
Willingness	3	5.38(1.33)	.929	0.931	0.819
Attitude toward change	3	5.93(1.03)	.728	0.726	0.470
Risk Orientation	3	4.98(1.38)	.830	0.836	0.630
BA Related Knowledge	3	5.79(1.18)	.839	0.836	0.633
Analytical Skills	3	5.41(1.23)	.858	0.862	0.675
Analytical Culture	3	5.66(1.09)	.827	0.829	0.618
Data and IT Infrastructure	3	5.26(4.24)	.890	0.895	0.740
Commitment to Learning	3	5.69(1.10)	.799	0.800	0.572
Shared Vision	3	5.36(1.23)	.822	0.829	0.619
Open Mindedness	3	5.63(1.23)	.863	0.864	0.678

Table 11: Intercorrelations Among Study Variables

	IMPR	INTPR	PLAUS	DISCON	LOR_CTL	LOR_SV	LOR_OM	AOR_AS	AOR_AC	AOR_DIT	PC_ATC	PC_RO	PC_BAK	WILL
IMPR	**1.00**													
INTPR	.077	**1.00**												
PLAUS	.027	.614	**1.00**											
DISCON	.260	-.537	-.721	**1.000**										
LOR_CTL	.526	.119	.050	.026	**1.00**									
LOR_SV	.465	.136	-.014	.160	.701	**1.00**								
LOR_OM	.283	.224	.224	-.156	.556	.681	**1.00**							
AOR_AS	.517	.235	.066	.046	.657	.799	.708	**1.00**						
AOR_AC	.544	.114	.017	.067	.598	.796	.726	.746	**1.00**					
AOR_DIT	.575	.153	-.015	.254	.545	.586	.436	.683	.566	**1.00**				
PC1_ATC	.610	.156	.056	.150	.574	.605	.528	.524	.674	.578	**1.00**			
PC2_RO	.427	-.030	-.234	.382	.334	.390	.213	.384	.427	.539	.695	**1.00**		
PC3_BAK	.649	.236	.011	.157	.600	.525	.377	.646	.545	.774	.635	.538	**1.00**	
WILLIN	.648	.156	-.007	.196	.506	.593	.407	.615	.577	.785	.589	.576	.787	**1.00**

Table 12: Goodness of fit indices for Measurement model

Goodness of fit indices	Model	Desired levels
CMIN	1168.73	
df	768	
Chi-Square	1.5	1.0 - 2.0
CFI	.94	>.90
TLI	.93	>.90
IFI	.94	>.90
NFI	.84	>.90
RMSEA	.05	0.05-0.08
SRMR	.05	<.08
PNFI	.71	>.50
GFI	.82	>.90

4.3.3.2 Common Method Bias

As the data is self-reported and collected through the same questionnaire, common method bias resulting from several sources could be a potential issue that can cause a systematic measurement error and also bias the estimates of the true relationship among theoretical constructs (Podsakoff & Organ, 1986; Podsakoff et al., 2003). Two tests were conducted to test the presence of common method bias. First, Harmon's one-factor test (Podsakoff and Organ, 1986) was conducted. For one-factor test, all variables in the theoretical model were entered into factor analysis using unrotated principal components factor analysis. If a single factor emerges or one general factor accounts for more than 50% of the covariance among the measures, then it is concluded that a substantial amount of common method variance is present (Podsakoff and Organ, 1986). The results from this test showed that mostly all important factors were present, and the most covariance explained by one factor was 31.39% (Table 13). This suggests that common method biases are not a likely contaminant of our results in this study.

Table 13: Harmon Single Factor Analysis

Total Variance Explained						
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	13.501	31.398	31.398	13.501	31.398	31.398
2	5.755	13.384	44.781			
3	2.851	6.629	51.410			
4	1.731	4.026	55.436			
5	1.504	3.498	58.934			
6	1.304	3.032	61.966			
7	1.194	2.778	64.743			
8	1.118	2.601	67.344			
9	1.003	2.333	69.677			
10	.897	2.086	71.763			

11	.838	1.950	73.713			
12	.812	1.888	75.601			
13	.760	1.768	77.369			
14	.642	1.493	78.862			
15	.617	1.434	80.295			
16	.595	1.383	81.679			
17	.543	1.263	82.941			
18	.500	1.163	84.104			
19	.477	1.109	85.213			
20	.452	1.051	86.264			
21	.432	1.004	87.269			
22	.405	.942	88.211			
23	.403	.938	89.148			
24	.380	.884	90.033			
25	.376	.875	90.907			
26	.343	.798	91.706			
27	.321	.747	92.453			
28	.299	.696	93.149			
29	.288	.670	93.818			
30	.280	.652	94.470			
31	.274	.638	95.108			
32	.256	.596	95.705			
33	.249	.580	96.284			
34	.228	.529	96.814			
35	.207	.482	97.295			
36	.192	.447	97.743			
37	.181	.421	98.164			
38	.162	.377	98.540			
39	.153	.355	98.895			
40	.145	.338	99.233			
41	.123	.285	99.518			
42	.106	.247	99.765			
43	.101	.235	100.000			
Extraction Method: Principal Component Analysis.						

Second, following the guidelines of Williams et al. (2010), the presence of CMV using CFA marker variable technique was tested. As shown in the Table 14, Method-C fits statistically better than the baseline model indicating the presence of CMV. However, as Method-U fits statistically better than Method-C (as indicated by CFI), it suggests that the presence of CMV is not the same for all indicators. Finally, Method-R is not statistically different (p=1.000) than Method-U indicating that the presence of CMV does not skew the relationships between the substantive variables. Therefore, as the presence of CMV did not skew any relationships in the model, no further measures are required.

Table 14:Model Fit Indices and Model Comparisons for CFA Models with Marker Variable

Model	X2 (df)	CFI	RMSEA (90% CI)	LR of ΔX2	Comparison
CFA with marker	1574.78 (1022)	0.92	0.048 (.044,.053)		
BaseLine	1665.38 (1042)	0.91	0.051 (.046,.055)		
Method- C	1632.41 (1041)	0.91	0.050 (.045,.054)	32.97, df=1, p=0.000	vs. Baseline
Method-U	1527.36 (999)	0.92	0.048 (.043,.053)	105.05, df=42, p=0.000	vs. Method-C
Method-R	1547.56 (1089)	0.93	0.043 (0.38,.047	20.2, df= 90, p=1.000	vs. Method-U

Note: CFA= Confirmatory Factor Analysis, CFI= Comparative Fit Index, RMSEA= Root Mean Square Error of Approximation, LR= Likelihood Ratio Test, U= Unconstrained, C= Constrained, R= Restricted

4.3.3.3 Structural Model and Hypothesis Testing

To analyze the structural model, SEM was performed using SPSS's Amos version 25. The maximum likelihood estimation was applied to estimate all the parameters. The test on goodness of fit indicated that the hypothesized model (Figure 7) is acceptable, CMIN = 1.4, CFI= .94, TLI= .93, RMSEA=.04, as shown in Table 15. The path coefficients and their significance level are presented in Table 16. The R^2 value of 0.76 shows that the model explains a substantial amount of variance for willingness to adopt. As shown in the results, Importance has a significant effect on willingness to adopt at C.R = 2.57 and p-value <0.05, thus hypothesis H1(a) is supported. On the other hand, Interpretability, Plausibility, and Discontinuity has insignificant effect on willingness to adopt, thus hypotheses H1(b), (c), and (d) are not supported. Similarly, H2(b) and H3(c) were supported. H5(a), (b), and (c) are partially supported. All other hypotheses were not supported. A summary of model hypotheses is shown in Table 17.

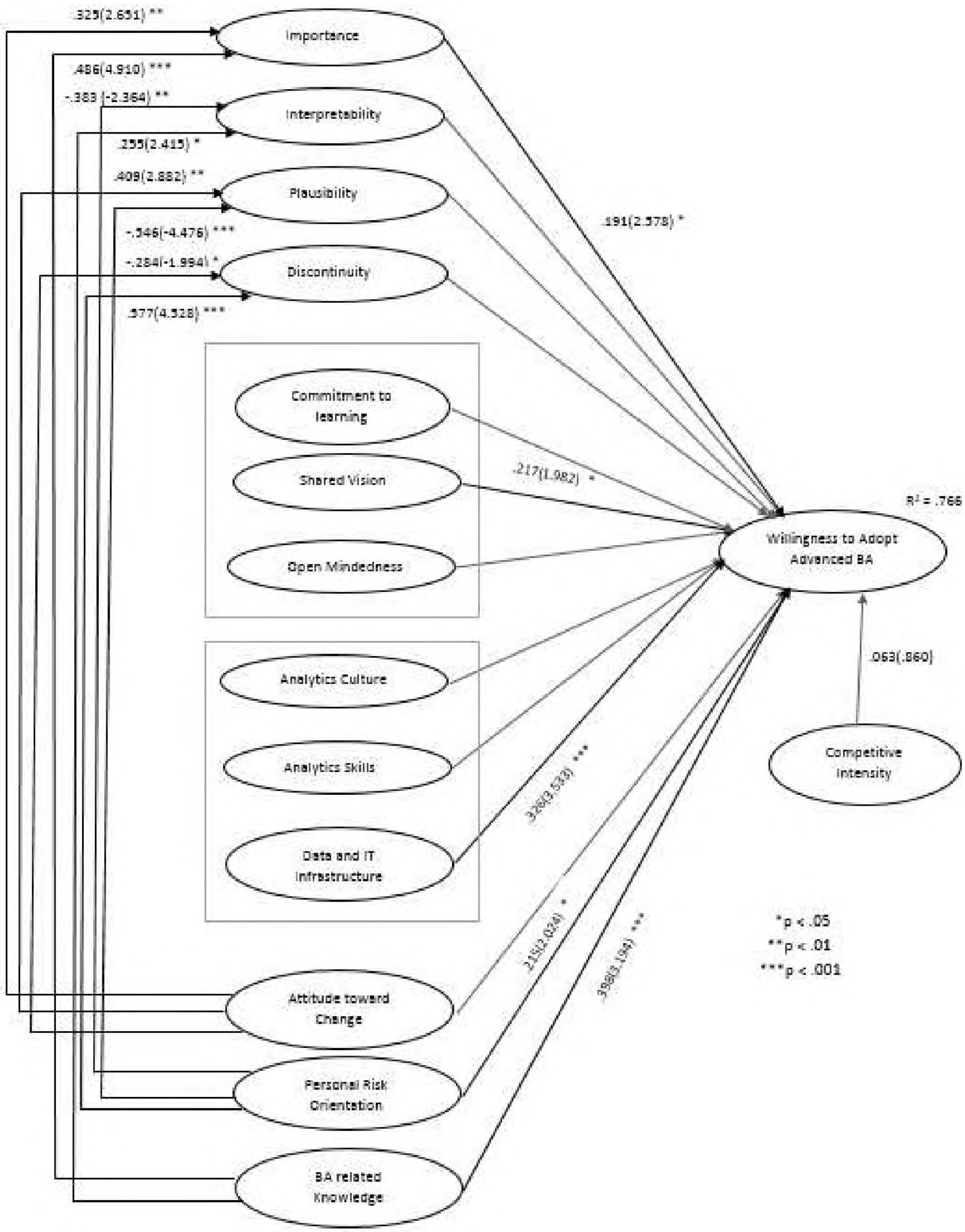

Figure 7: Research Model Path Analysis

Table 15: Goodness of fit indices for Structural model

Goodness of fit indices	Model	Desired levels
CMIN	1353.74	
Chi-Square	1.4	1.0 - 2.0
df	914	
CFI	.94	>.90
TLI	.93	>.90
IFI	.94	>.90
NFI	.83	>.90
RMSEA	.04	0.05-0.08
SRMR	.05	<.08
PNFI	.73	>.50
GFI	.80	>.90

Table 16:Results of Structural Model

Hypotheses	Path	Path Coefficient	SE	CR
H1 (a)	Importance → Willingness to adopt	.191*	.127	2.578
H1 (b)	Interpretability → Willingness to adopt	-.049	.067	-.714
H1 (c)	Plausibility → Organizational Receptivity	.019	.073	.229
H1 (d)	Discontinuity → Willingness to adopt	-.089	.085	-1.068
H2 (a)	Commitment to learning→ Willingness to adopt	-.095	.131	-1.136
H2 (b)	Shared Vision → Willingness to adopt	.217*	.149	1.982
H2 (c)	Open- Mindedness → Willingness to adopt	.088	.120	.894
H3 (a)	Analytical Culture → Willingness to adopt	.036	.162	.320
H3 (b)	Analytical Skills → Willingness to adopt	-.156	.147	-1.198
H3 (c)	Sophistication of Data & IT Infrastructure → Willingness to adopt	.326***	.087	3.533
H4 (a)	Attitude toward Change → Willingness to adopt	-.189	.291	-1.282
H4 (b)	Personal Risk Orientation → Willingness to adopt	.215*	.141	2.024
H4 (c)	BA related knowledge → Willingness to adopt	.398***	.168	3.194

H5 (a)	Attitude toward Change → Perception of BA (Importance)	.325**	.141	2.651
	Attitude toward Change → Perception of BA (Interpretability)	.194	.281	1.393
	Attitude toward Change → Perception of BA (Plausibility)	.409**	.312	2.882
	Attitude toward Change → Perception of BA (Discontinuity)	-.284*	.276	-1.994
H5 (b)	Personal Risk Orientation → Perception of BA (Importance)	-.036	.077	-.355
	Personal Risk Orientation → Perception of BA(Interpretability)	-.283**	.163	-2.364
	Personal Risk Orientation → Perception of BA (Plausibility)	-.546***	.180	-4.476
	Personal Risk Orientation → Perception of BA (Discontinuity)	.577***	.166	4.528
H5 (c)	BA related knowledge → Perception of BA (Importance)	.486***	.078	4.910
	BA related knowledge →Perception of BA(Interpretability)	.255*	.147	2.415
	BA related knowledge →Perception of BA (Plausibility)	.038	.155	.370
	BA related knowledge →Perception of BA (Discontinuity)	.058	.139	.550
Control variable				
	Competitive Intensity→Willingness	0.063	.066	.860

*p < 0.05; **p < 0.01; ***p < .001

4.3.4 Results

4.3.4.1 Results of Hypotheses H1(a)- H1(d):

The results show that out of four OV dimensions, only importance have a significant impact on willingness to adopt. This suggests that when owner/managers of small business perceive that BA provides several business benefits and can also help businesses to provide a competitive edge over their competitors, they are more willing to adopt newer innovations in BA. Thus, H1(a) was supported. On the other hand, the remaining dimensions of OV- interpretability, plausibility, and discontinuity does not seem to have any significant impact on willingness to adopt BA. Thus, hypotheses H1(b), (c), and (d) were not supported. This may suggest that representations of BA in its discourse in terms of its clarity, consistency, richness of available information, notions of conceptual and implementation challenges do not seem to impact their willingness to adopt BA. One possible explanation is that BA itself is not a complex technology as compared to other innovations such as Enterprise Resource Planning (ERP). Therefore, apart from its business benefits, other representations of the discourse might not be too valuable for owner-managers to have a considerable impact on adoption decision.

4.3.4.2 Results of Hypotheses H2(a)- H2(c):

For the effect of Learning Orientation on willingness to adopt, only shared vision was found be significant at $p<.05$. Commitment to learning and open-mindedness did not have any impact on willingness to adopt BA. In fact, commitment to learning, although insignificant, was found to be negatively related to willingness to adopt. Thus, H2(b) was supported and H2(a) and H2(c) was rejected.

4.3.4.3 Results of Hypotheses H3(a)- H3(c):

Sophistication of Data and IT infrastructure was found to be significantly and positively associated with willingness to adopt BA. However, Analytical skills and culture did not have any impact on willingness to adopt BA. Thus, only hypothesis H3(b) was supported. Analytical skills were insignificant but was found to be negatively associated with willingness to adopt BA.

4.3.4.4 Results of Hypotheses H4(a)- H4(c):

Personal Risk Orientation and BA related knowledge was found to be significantly and positively associated with willingness to adopt BA at $p<.05$ and $p<.001$ respectively. Attitude toward change did not have any impact on willingness to adopt BA. Thus, H4(a) was not supported, but H4(b) and H4(c) were supported.

4.3.4.5 Results of Hypotheses H5(a)- H5(c):

Hypotheses H5(a)- H5(c) were partially supported, indicating some role of personal characteristics of owner-managers in forming the perceptions about the discourse. Overall, attitude toward change and risk orientation found to have strong impact on the reception dimensions. Also, having prior knowledge about BA technologies strongly impacts how owner-managers perceive the importance of BA in its discourse.

The control variable, competitive intensity, was found to be not significantly related with willingness to adopt.

Table 17: Summary of Results

H1 (a)	Owner-Manager's perception of BA's importance is positively related to small businesses' willingness of BA adoption.	Supported
H1 (b)	Owner-Manger's perception of BA's interpretability is positively related to small businesses' willingness of BA adoption.	Not Supported
H1 (c)	Owner-Manager's perception of BA's plausibility is positively related to small businesses' willingness of BA adoption.	Not Supported
H1 (d)	Owner-Manager's perception of BA's discontinuity is negatively related to small businesses' willingness of BA adoption.	Not Supported
H2 (a)	Commitment to learning is positively related to small businesses' willingness of BA adoption.	Not Supported
H2 (b)	Shared vision is positively related to small businesses' willingness of BA adoption.	Supported

H2 (c)	Open-mindedness is positively related to small businesses' willingness of BA adoption.	Not Supported
H3 (a)	Analytical culture is positively related to small businesses' willingness of BA adoption.	Not Supported
H3 (b)	Analytical skills of employees are positively related to small businesses' willingness of BA adoption.	Not Supported
H3 (c)	Sophistication of Data and IT infrastructure is positively related to small businesses' willingness to adopt BA	Supported
H4 (a)	Owner-Manager's attitude toward change is positively related to small businesses' willingness of BA adoption.	Not Supported
H4 (b)	Owner-Manager's personal risk orientation is positively related to small businesses' willingness of BA adoption.	Supported
H4 (c)	Owner-Manager's BA related knowledge is positively related to small businesses' willingness of BA adoption.	Supported
H5 (a)	Owner-Managers' attitude toward change is positively related to the perception of the public discourse of BA.	Partially Supported
H5 (b)	Owner-Managers' personal risk orientation is positively related to the perception of the public discourse of BA.	Partially Supported
H5 (c)	Owner-Managers' BA related knowledge is positively related to the perception of the public discourse of BA.	Partially Supported

4.4 Discussion of Results

The research objective of this study was to determine the role of organizing visions, strategic orientations, and personal characteristics in BA adoption. This study also proposed, formally developed and validated the measurement construct of analytics orientation.

As small businesses are still behind in the adoption of new innovations in BA, a focal community's idea of BA in its discourse can help explain how small businesses identify and adopt such technologies. Therefore, this study investigated the effect of four dimensions of reception of OV - importance, interpretability, plausibility and discontinuity, on the willingness to adopt new innovations in BA. The results from SEM suggest that only one of the four reception dimensions, i.e. only importance dimension positively contributes to the willingness to adopt newer innovations in BA. The other three dimensions were not significant. Further, although insignificant, but interpretability dimension was found to be negatively related to willingness to adopt. The results indicate that as the perception of BA in terms of its business benefits increases in its discourse, the likeliness of owner-managers adopting the innovation also increases. This is also consistent with the innovation diffusion theory that have found relative advantage of an innovation to be the most important predictor of adoption (Roger 1983). Overall, the results may suggest that for small businesses, specifically in the context of BA, the business benefits of BA are the most important factor considered for adoption as compared to other factors such as complexity of implementation, cultural shift required in the organization due to adoption, adoption of BA by competitors etc. One possible explanation for why these dimensions were found to be insignificant may be that the items pertaining to these dimensions adopted from the literature were mainly studied in the context of large firms. Therefore, item refining such as rewording of the questions to simplify and modify them to the context of small businesses might be required. Also, most of the items comprising these four dimensions were negatively worded, which might have led to some unexpected results. Another possible reason could be the presence of large number of respondents that had neutral perceptions regarding the public discourse of BA (Table 18). According to Ramiller and Swanson (2003), an individual's perception for each dimension may be negative(detractor), majority, or positive (supporter). Supporters and detractors are the opposite poles that can help to charge or discharge community's discourse about the vision and that may further impact the adoption or rejection of the technology. As shown in table

18, respondents were classified as detractors, majority/neutrals, and supporters[1]. It is difficult to ascertain the underlying meaning of this large neutral group. In other words, it is unclear whether these respondents are simply neither supporters or detractors, or they are not knowledgeable enough to form an opinion about BA's OV. If the neutrality of owner-managers implies lack of knowledge or lack of interest in the OV, then the impact of their perceptions on willingness to adopt advanced BA is difficult to determine. Moreover, as indicated by results, due to lack of knowledge or interest in the phenomenon, the owner-managers might be less likely to adopt BA. Therefore, future research needs to unravel this important question. To address this, more success stories of successful implementations should be presented in public discourse and efforts should be made to engage owner-managers in the BA's OV. Despite these concerns, the results from this study can provide some valuable insights into how different stakeholders, such as vendors, consultants etc. can promote the importance of BA technologies in terms of what value these technologies can provide to the business and can encourage small businesses to adopt these technologies.

Table 18: Owner-managers' reception of BA's OV

Dimension	Mean	Standard Deviation	Detractors	Majority/ Neutrals	Supporters
Importance	5.41	1.17	27	170	35
Interpretability	3.65	1.54	27	178	27
Plausibility	3.97	1.59	37	164	31
Discontinuity	4.09	1.65	30	171	31

[1] A respondent whose score falls below the minimum for the interval is considered a detractor and whose score is above the maximum for the interval is considered a supporter (Marsan et al., 2012a). For example, Importance had a mean score of 5.41 and standard deviation 1.17. An individual who scored within the interval [1.0, 4.24] was considered a detractor, within interval [4.24, 6.58] as neutral, and within interval [6.58, 7.0] as supporter. On the other hand, as Discontinuity is an undesirable characteristic of an OV, an individual who scored within the interval [1.0, 2.44] was considered a supporter, within interval [2.44, 5.74] as neutral, and within interval [5.74, 7.0] as detractor.

As learning orientation enables firms to effectively respond to the external market changes, customer preferences, as well as new technological advances (Dodgson, 1993), it was hypothesized that learning orientation positively affects willingness to adopt BA. However, only shared vision was found to have a significant impact on willingness to adopt. This suggests that organizations that have organization-wide focus on learning, have a clear direction on what to learn, and have better internal communication, are the ones who form a common sense of the innovation (Calantone et al., 2002) and are more willing to adopt newer innovations in BA. Thus, organizations with greater shared vision are keener in adopting newer BA technologies. On the other hand, commitment to learning and open-mindedness were found to have insignificant impact on willingness to adopt. Commitment to learning is mainly related to investments in education and training. Open-mindedness is related to unlearning (Sinkula et al., 1997) by constantly questioning the organization's operational routines, and willingness to accept new ideas. Small businesses might have limited resources for investing in education and training of employees. Thus, there is a possibility that these dimensions are mainly relevant in the context of large businesses. Furthermore, in prior studies, learning orientation has been considered an important antecedent of firm innovativeness (Calantone et al., 2002; Damanpour, 1991; Narver and Slater, 1995; Sinkula, 1994). However, the direct impacts of learning orientation on other organizational outcomes such as firm's financial performance (Nybakk, 2012), firm's innovation capabilities (Aziz and Omar, 2013), specifically in small firms, were mainly found to be insignificant. These findings may also suggest that learning orientation might have an indirect impact on willingness to adopt advanced BA. Taking this into consideration, this research study proposed an alternative research model presented in Fig. 8, to test the indirect effects of learning orientation. The results from proposed alternative model suggests that learning orientation is an important antecedent of analytics orientation, which in turn impact willingness to adopt advanced BA. The alternate model is discussed in Sec 4.5.

This study also proposed an instrument for measuring analytics orientation of a firm comprising of three dimensions: Analytics culture, Analytics Skills, and Sophistication of data and IT infrastructure. The results of empirical analyses supported the proposed dimensions. The proposed analytics orientation construct can inform researchers and practitioners about an organization's overall readiness to initiate analytic efforts and provides an interesting area for future research. Further, the effect of analytics orientation on willingness to adopt newer innovations in BA was also tested. The results indicate that only sophistication of data and IT infrastructure had a significant impact on willingness to adopt. This suggest that only organizations that have adequate IT resources would consider adoption of new BA innovations. This finding is consistent with other studies in technological innovation literature that suggests that having adequate resources is necessary for an innovation adoption. Analytics skills and culture were found to be insignificant. It is possible that in small businesses, more emphasis is placed on the data and IT infrastructure for IT adoption rather than skills and overall culture. Conversely, the alternative model suggest that analytics orientation has a significant and positive impact on willingness to adopt, when learning orientation was considered as an antecedent. A deeper investigation of this relationship needs to be examined in future research.

The role of personal characteristics of decision makers in their willingness to adopt newer innovations in BA was also explored in this study. Owner-managers personal risk orientation and prior BA related knowledge was found to have a strong impact on their willingness to adopt BA. As the adoption of new innovations is a risky venture for small businesses, only decision makers with risk taking characteristics would be willing to take that risk. Also, the results show that owner-managers with prior BA knowledge are more likely to adopt newer innovations in BA. Since, having prior BA knowledge can lower the knowledge barriers related to BA, these organizations would be more confident in adopting new innovations in BA.

Finally, this study also explored whether personal characteristics impact how owner-managers perceive BA in its discourse. The results do suggest some role of personal characteristics on the perception dimensions. For example, owner-managers with positive attitude toward change and prior BA knowledge would probably engage more in its discourse and their perceptions will be impacted based on how different sources of information they explore to seek more knowledge about BA technologies. Thus, they may perceive BA as more important, plausible, interpretable and less discontinuous as compared to their counterparts. The fact that personal risk orientation was found to be negatively associated with perceptions of interpretability and plausibility, was rather unexpected. Moreover, personal risk orientation was found to be positively associated with discontinuity. One possible explanation is that risk-oriented owner- managers might also be engaged in the discourses of several other technologies, and as a result, either their understanding about BA could be still in earlier phases or they are still yet to fully engage in the BA discourse. As the perceptions could change over time based on the involvement of owner-managers in the discourse or adjustments in the discourse itself, probably longitudinal data can provide more accurate and deeper understanding of these relationships. Nevertheless, these findings are important as certain personality characteristics may increase the proactiveness of decision makers to engage in the sense making process of new innovations, ultimately shaping the opinions of community leading to its adoption.

4.5 Alternate Model

The relationships between learning orientation, innovativeness and firm performance has been extensively studied in prior literature (Baker and Sinkula, 1999; Calantone et al., 2002; Slater, 1995; Wang, 2008). The interplay between learning orientation and analytics orientation has not been examined before, therefore, to understand this relationship better, a simplified alternative model was proposed. In prior small business research, the direct impacts of learning orientation on organizational outcomes such as firm's financial performance (Nybakk, 2012), firm's innovation capabilities (Aziz and Omar, 2013), were mainly found to be insignificant. The findings of this research are therefore somewhat consistent with these aforementioned studies. This indicated a need to explore the indirect impacts of learning orientation on organizational outcomes. Baker and Sinkula (1999) asserted that learning orientation is a higher order learning that influences the organizational outcomes indirectly through qualitative improvement of other business processes. Learning orientation is the development of new knowledge in organizations and is an inside-out capability of a firm. Thus, it can be argued that for a firm to be analytics oriented, organizational learning needs to occur first. This assumption is also consistent with prior studies (Sinkula et al. 1997; Choi 2014), where learning orientation is considered as an antecedent to other types of strategic orientations.

To reduce the complexity of alternate model, the operationalization of learning orientation and analytics orientation was performed as recommended in prior studies. The strong correlation between three dimensions of learning orientation suggests that they converge to a common construct (see Table 11). Similar is the case with three dimensions of analytics orientation. Therefore, consistent with prior studies, these two constructs were operationalized as summates (Baker and Sinkula 1999; Jaworski and Kohli 1993; Narver and Slater, 1990). All the model fit indices of this alternate model were above their criterion levels (CMIN= 1.8, CFI=.94, TLI=.92, RMSEA=.06, SRMR =.06). The results of the alternate model (Figure 8) indicated an antecedent role of learning orientation influencing analytics orientation of the firm. The relationships between other constructs remained the same. The results of alternate model also confirm that analytics orientation significantly and positively influences willingness to adopt.

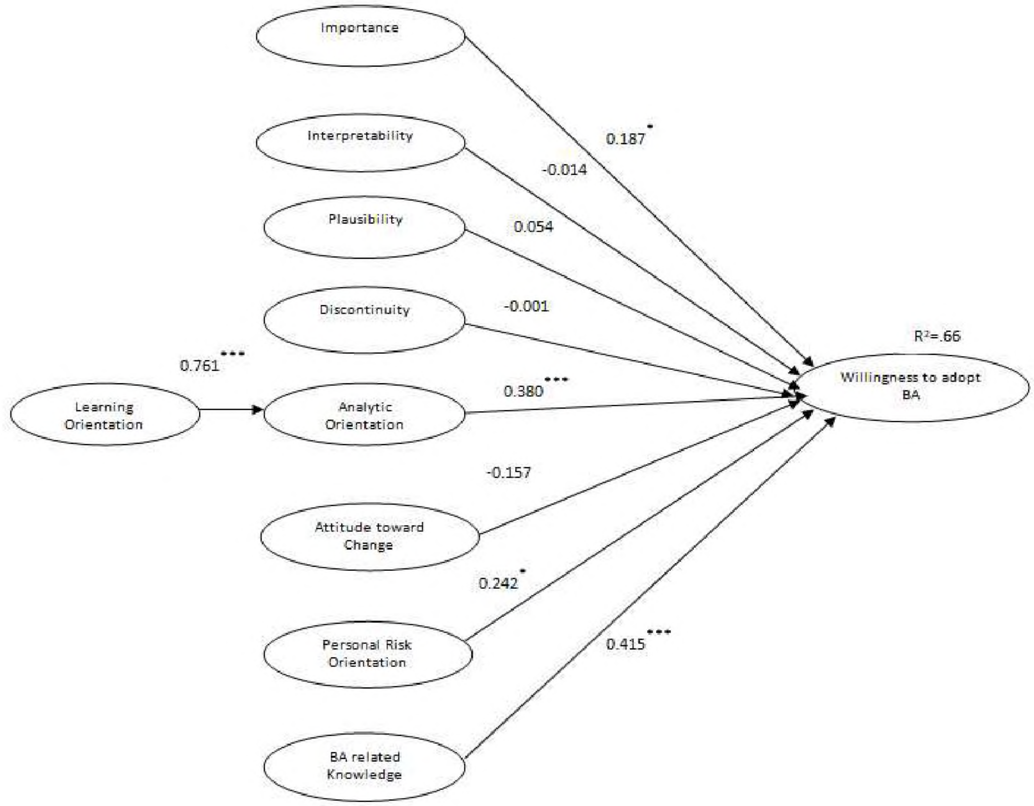

Figure 8: Alternate Model

CHAPTER V

IMPLICATIONS

5.1 Implications for Research and Practice

By drawing from IS innovation, strategic and organizational literatures, this study has developed and tested an integrated model of advanced BA adoption in small businesses. By doing so, this study makes several key theoretical and practical contributions and open interesting avenues for future research.

First, this study utilizes the socio-cognitive framework of innovation diffusion which suggests that IT innovation is not mere an organizational endeavor but a community wide undertaking that extends beyond organizational boundaries. By doing so, this study responds to the call by institutional theorists for stepping outside the dominant paradigm and examining the cognitive processes and structures in order to understand institutional mechanisms of innovation adoption. To the best of our knowledge, this is one of the first attempts to empirically investigate whether the interpretations made by small organizations about BA tools and technologies through its external environment play any role in the adoption of advanced BA analytics by the organizations. The interpretations or a collective image of innovation called organizing vision of BA created in the discourse was examined through four dimensions of importance, interpretability, plausibility, and discontinuity. The findings of this study provide insights on where the owner-managers of small businesses stand currently in terms of their understanding of business analytics. This information is important for the promotors of IT innovation such as policy makers, vendors, consultants, professional associations etc. to understand how small businesses perceive advanced analytics and how the discourse can be tailored further to encourage adoption of BA technologies. The results suggest that in case of small businesses, although, importance of BA technologies is communicated well, the discourse still needs some enrichment in terms of interpretability, plausibility and discontinuity of advanced BA technologies. This means that the concept of BA's OV is still in the process of shaping the opinions of IT decision makers and thus the promoters of BA needs to provide more clarification in the discourse regarding information such as implementation challenges involved in adoption, types of issues that can be resolved using these technologies, lessons learned, and success stories of organizations that have already implemented these technologies. The results have also shown a significant relationship between OV dimension of importance and willingness to adopt advanced BA technologies. Therefore, to increase adoption, the promoters of BA can use this information and communicate the business benefits of BA technologies by providing success stories or business use cases of improved product performances, new product successes, customer satisfaction and overall improved organizational performance. However, further research is required to understand the role of other reception dimensions on adoption decision.

Second, by developing the construct of analytics orientation, this study adds to the strategic orientation and growing BA literature. Although, factors pertaining to analytical orientation has been alluded to in the BA literature, this study developed the domain of the construct, specified its dimensions, and validated the construct. The proposed analytics orientation construct captures the critical elements of an organization's analytic propensity and assesses firm's overall readiness to initiate BA efforts. For small businesses that are considering the adoption of advanced BA, the results from the proposed model suggest that they must have a solid existing data and IT infrastructure in place to carry out such initiatives. However, in the suggested alternate model, analytics orientation proved an important antecedent of small businesses' willingness to adopt advanced BA adoption. The results suggest that owner-managers interested in exploiting the opportunities associated with BA may first need to focus on enhancing a culture that value fact-based decision making, analytic problem-solving skills, and overall IT and data infrastructure. A deeper understanding of analytics orientation capability could help in removing the barriers of BA adoption. Owner-managers of small businesses can assess this capability from time to time and take necessary steps to enhance it. For example, this can be achieved by providing training to new or current employees to enhance their analytical and problem solving skills, rewarding information-gathering and data-driven decision making, investing in improving quality of data to encourage its usage, and finally, investing in IT infrastructure that can support BA implementations.

Third, while the relationship of learning orientation has mainly been studied with outcomes such as organizational performance and new product development/success, in this study, I examine how learning orientation can drive an organization's IT adoption decision. By doing so, this study contributes to marketing as well as IT innovation research. The results indicate that small businesses that have a shared vision, i.e., organization-wide focus on learning, a clear direction for learning, and have better internal communication, are the ones who form a common sense of the innovation and are more willing to adopt newer innovations in BA. In the proposed research model, although the direct impacts of other learning orientation dimensions on adoption decision were not significant, consistent with prior studies, learning orientation was found to be significant in the alternate model when used as an antecedent to analytics orientation. Overall, the results indicate that learning orientation influence adoption decisions. Therefore, small organizations should incorporate learning orientation into their skillset by investing in education and learning activities for employees so that new knowledge about newer innovations can seep into the organizations.

Fourth, this study also investigates the role of owner-manager’s personal characteristics in small businesses’ adoption decision. The role of top management, specifically in large businesses, has always been considered important in prior IT adoption studies. However, as small businesses are often a reflection of their top management, their personal characteristics may play even more significant role in driving an organization’s overall adoption decision. This study specifically suggests a significant relationship between risk oriented and BA-knowledgeable owner-managers and their willingness to adopt advanced BA. When owner-managers are willing to take some risk pertaining to newer innovations such as advanced BA implementations, they may ensure that there are sufficient resources required to implement these technologies. Further, when top management have BA related knowledge, they are likely to foster analytics-driven decisions in organizations, which in turn will encourage analytic champions within organizations (Branda et. al, 2018). This may further assist in minimizing the conflict and resistance associated with BA implementations. These findings may guide the vendors and suppliers of BA products and services in the identification of the characteristics of the early adopters of technological innovations. This may help them concentrating their marketing efforts in those target markets that are more likely to adopt them. Further, BA related training opportunities can also be provided to owner-managers so that they can become acquainted with current tools and technological solutions available in the small business marketplace.

5.2 Limitations and Future Research

Since this study was conducted using Qualtrics panel of small business owners-managers, the findings may limit the generalizability to some extent in other small businesses and thus, some care must be taken when interpreting these results. Further, only one of the reception dimensions was found to have significant impact on the outcome variable. Perhaps further validation and refinement of scale items is required so that they can be applied in the context of small businesses. Also, several items in the instrument were negatively formulated which can cause potential issues in the reliability. Therefore, future research should aim at validating the reception instrument. Future research can also examine the role of these reception dimensions on other outcome variables such as assimilation of innovation. Further, consistent with prior studies (Marson et al., 2012; Ramiller and Swanson, 2003), our findings suggest a large neutral group for each of the dimensions. A deeper investigation is required to ascertain whether neutrals are neither detractors nor supporters of an OV or they are simply not knowledgeable enough to form an opinion about BA's discourse. As detractors and supporters can charge and discharge the community's discourse and can eventually lead to an innovations' adoption and rejection (Ramiller and Swanson, 2003), this is an important investigation to consider.

The development of analytics orientation construct in this study provides an initial framework to measure the analytic capacity of a firm. Future research can build upon, enhance this construct, and can also test its applicability by including large businesses. The new construct can also inform theory development on important strategic outcomes of the organizations. For example, future research can examine the impact of analytic oriented strategy on outcomes such as business processes, firm performance, decision-making quality, and overall BA success. Extending future research to explore the relationship of analytics orientation with other strategic orientations would also be useful. Future extension of this research also needs to examine the role of other personal characteristics of owner-managers such as age, gender, and educational qualifications, that can have a significant impact on strategic decision making, as shown in prior studies. Finally, this study has investigated a subset of variables that can impact an organization’s decision to adopt BA. Other factors such as institutional pressures might also play an important role in the adoption process and needs to be investigated in future research. Despite its limitations, this study has attempted to provide an integrated model of BA adoption and offered several insights into what factors can influence the adoption decision of small business owner-managers.

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APPENDIX

APPENDIX A

MEASUREMENT INSTRUMENT

Survey Items	Key References
Reception of the public discourse of BA (1= strongly disagree vs. 7= strongly agree)	
Importance (business benefit) 1. Business Analytics offers a tremendous opportunity to deliver business value 2. Business Analytics makes do-able some wonderful things that were previously only dreamed of 3. Companies that wait too long to adopt Business Analytics will fall dangerously behind 4. A company's success may depend on being able to adopt Business Analytics tools faster than its competitors **Importance (practical acceptance)** 1. Business Analytics is a solution still looking for the right problems to solve (reverse coded) 2. Business Analytics solutions do not transfer well to the real world (reverse coded) 3. The push for Business Analytics is coming mainly from parties with something to sell (reverse coded) **Importance (market interest)** 1. Business Analytics is currently a "hot button" in the information systems field 2. The market has lost interest in Business Analytics (reverse coded) 3. People are tired of talking about Business Analytics (reverse coded) **Interpretability** 1. We don't really have a common understanding of Business Analytics (reverse coded) 2. Key players are yet to be heard from concerning Business Analytics (reverse coded) 3. There are aspects of Business Analytics that one cannot easily grasp (reverse coded)	**Ramiller and Swanson, 2003** **Marsan et al., 2012**

4. Important questions about Business Analytics still remain unanswered (reverse coded) **Discontinuity (Conceptual discontinuity)** 1. Business Analytics involves a huge paradigm shift 2. Business Analytics calls for a fundamentally different way of thinking 3. Business Analytics seems to require some kind of wizardry to get it all to work out **Discontinuity (Structural discontinuity)** 1. Using Business Analytics basically turns an organization upside down 2. The skills and resources necessary for implementing Business Analytics are hard to come by 3. Complexity increases significantly when you implement Business Analytics **Plausibility** 1. Business Analytics is being touted for situations where it fits poorly (reverse coded) 2. A lot of what I have heard about Business Analytics seems like hype (reverse coded) 3. A lot of claims about Business Analytics are simply hard to believe (reverse coded) 4. Business Analytics tools have been oversold by its promoters (reverse coded)	
Learning Orientation: Learning Orientation is defined as a set of organizational knowledge-questioning values that influence a firm's propensity to value double-loop learning (Sinkula et al., 1997) **(1= strongly disagree vs. 7= strongly agree)**	
Commitment to learning 1. Managers basically agree that our organizations' ability to learn is the key to our competitive advantage 2. The basic values of this organization include learning as key to improvement 3. The sense around here is that employee learning is an investment, not an 4. expense	**Sinkula et al., 1997**

5. Learning in my organization is seen as a key commodity necessary to guarantee organizational survival 6. Our culture is one that does not make employee learning a top priority (reverse coded) 7. The collective wisdom in this organization is that once we quit learning, we endanger our future **Shared Vision** 1. There is a well-expressed concept of who we are and where we are going as an organization 2. There is a total agreement on our organizations' vision across all levels, functions, and divisions 3. All employees are committed to the goals of this organization 4. Employees view themselves as partners in charting the direction of the organization 5. Top leadership believes in sharing organizations' vision with the lower levels 6. We do not have a well-defined vision for the entire organization (reverse coded) **Open-mindedness** 1. We are not afraid to reflect critically on the shared assumptions we have about the way we do business 2. Managers in this organization do not want their "view of the world" to be questioned (reverse coded) 3. Our organization places a high value on open-mindedness 4. Managers encourage employees to "think outside the box" 5. An emphasis on constant innovation is not part of our corporate culture (reverse coded) 6. Original ideas are highly valued in this organization	
Analytic Orientation: Analytical orientation is an as an organization's propensity to engage in decision making based on comprehensive analysis of information by promoting an information-based culture, analytic skills and knowledge of employees, and data and IT infrastructure. **(1= strongly disagree vs. 7= strongly agree)**	
Analytic Skills 1. Employees in our organization are very good at identifying and employing the appropriate software tools that are	**Items 1-3: Germann et al., 2013**

needed to analyze and present data given the problem at hand 2. Employees in our organization are familiar with many statistical techniques for data analysis 3. Employees in our organization are good at analytical problem solving 4. Employees in our organization have deep knowledge about our business processes 5. Our organization has the ability to use information faster than our competitors **Analytics Culture** 1. It is our organization's policy to incorporate available information within any decision-making process 2. We rely on all relevant information regardless of the type of decision to be taken 3. In our organization, decision- making is often based on experience and intuition rather than information (reverse coded) 4. We have the right facts before making decisions 5. We make decisions in a logical and systematic way 6. When making decisions, we consider various options in terms of a specific goal **Data and IT resources** 1. We have a state-of-art IT infrastructure 2. We use IT to gain a competitive advantage 3. In general, we collect more data than our competitors	**Items 4-5: Davenport et al., 2001** **Items 1-2: Popovic et al., 2012** **Item 3: Watson, 2012** **Items 4-6: Scott and Bruce, 1995** **Germann et al., 2013** **Lu and Ramamurthy, 2014**
Personal Characteristics (1= strongly disagree vs. 7= strongly agree)	
Business Change Orientation 1. I am an achievement oriented person 2. I am socially oriented 3. I frequently try new ideas/ products 4. I am competitive by nature 5. I consider myself a creative person **Personal Risk Orientation**	**Peltier et al., 2012** **Kitchell, 1997**

1. I have often been described as a risk-taker by people who know me 2. If the possible reward was high, I would not hesitate putting my money into a new business that could fail 3. I rarely, if ever, take risks when there is another alternative (reverse coded) 4. I enjoy risk taking, that's what business is all about 5. I would participate only in business undertakings that are relatively certain (reverse coded) 6. I see risk taking as an integral part of a challenging career **Owner-mangers BA related knowledge** 1. I am familiar with BA related tools 2. I am comfortable using BA tools 3. I have formal qualifications in BA related tools	**Thong and Yap, 1995**
Dependent Variable	
Willingness: An organization's willingness to adopt an innovation. **(1= Strongly disagree; 7 = Strongly agree)**	
1. We are contemplating to adopt newer innovations i n Advanced Analytics in near future 2. We are likely to adopt newer innovations in Advan ced Analytics in near future 3. We are expecting to adopt newer innovations in A dvanced Analytics in near future	**Teo et al., 2003** **Liu et al., 2010**
Control Variable	
Competitive Intensity **Please indicate the extent to which your organization:** 1. tracks new initiatives of competitors 2. monitors competitor moves 3. considers competitor information important for firm's decisions	**Ranganathan et al., 2004**
Marker Variable	
Social media use **How often do you use Internet to access:** 1. Social networking websites (e.g. Facebook)	**Kim et al., 2014**

2. Microblogs (e.g. Twitter) 3. Video-sharing websites (e.g. YouTube) 4. News websites 5. Blogs 6. Social Q&A websites (e.g. Yahoo! Answers)	