BIG DATA ANALYTICS IMPLEMENTATION IN SMALL AND MEDIUM SIZED ENTERPRISES

BIG DATA ANALYTICS IMPLEMENTATION IN SMALL AND MEDIUM SIZED ENTERPRISES: THE PERSPECTIVES OF MANAGERS AND DATA ANALYSTS

By MOHSEN JAVDAN, M.Sc., B.Sc.

A Thesis Submitted to the School of Graduate Studies in Partial Fulfillment of the Requirements for the Degree

Doctor of Philosophy in Business Administration

McMaster University DOCTOR OF PHILOSOPHY IN BUSINESS ADMINISTRATION (2023) Hamilton, Ontario, Canada

TITLE: Big Data Analytics Implementation in Small and Medium Sized Enterprises: The Perspectives of Managers and Data Analysts

AUTHOR: Mohsen Javdan, M.Sc., B.Sc.

SUPERVISOR: Dr. Maryam Ghasemaghaei

NUMBER OF PAGES: ix, 139

ABSTRACT

While many large firms have implemented Big Data Analytics (BDA), it is unclear whether Small and Medium-sized Enterprises (SMEs) are ready to adopt and use this technology. This study investigates BDA implementation from the perspective of both managers and data analysts. Managers are mostly influenced by factors from the external environment, while data analysts are mostly influenced by technological factors. Hence, in this study, it is contended that managers imitate the behavior of external institutions, while data analysts mostly evaluate technology characteristics in the process of BDA implementation. The present study draws on institutional, organizational change, and diffusion of innovation theories through the lens of an imitation-evaluation perspective to investigate readiness and adoption behaviours. Accordingly, a theoretical research model was developed to explore the salient variables that impact organizational and data analysts' readiness for implementing BDA in SMEs. To test these assertions, two surveys were conducted with 340 responses including 170 managers and 170 data analysts in SMEs in North America. The findings demonstrate that: (1) an imitation perspective plays a significant role in organizational readiness to adopt BDA; (2) uncertainty in big data technologies can intensify the effect of normative pressures on organizational readiness; (3) big data complexity, trialability, and relative advantage impact data analysts' readiness to use big data analytics; and (4) the influence of relative advantage is attenuated by the high level of data analytics skills. These findings provide valuable contributions to the theory and practice of BDA implementation in SMEs in the BDA adoption and use literature.

ACKNOWLEDGMENT

The completion of this journey I have chosen, my PhD degree, would not have been possible without the support of a number of individuals to whom I owe my utmost gratitude.

First and foremost, I would like to express sincere appreciation to my supervisor, Dr. Maryam Ghasemaghaei, for her ongoing guidance, support, and encouragement without which this work would have never been completed. Her insights and feedback have been invaluable in shaping my research and enhancing my understanding of the subject matter. Through her great supervisory and mentorship, I have learned a lot about research and teaching which have been the most significant inspiration for me in pursuing an academic career.

I would also like to express my special appreciation to the other members of my supervisory committee Dr. Khaled Hassanein for his insightful comments and suggestions that significantly improved the quality of this work; and Dr. Brian Detlor who helped me a lot in completing this work. In addition, I would like to thank Dr. Yufei Yuan and Dr. Nicole Wagner for their continuous support these years.

In addition, I would like to express a special thanks to former PhD students at DeGroote, especially Dr. Sepideh Ebrahimi, Dr. Samira Farivar, Dr. Pouyan Eslami, Dr. Kamran Eshghi, Dr. Naim Tajvarpour and Dr. Maarif Sohail who helped me along the way. I also like to thank my dear PhD fellows and friends especially, Mahdi (Amir) and Kimia, Sima and Mohsen, Mehmet, Mojan and Jennifer Ho, for their friendship and creating an enjoyable atmosphere. I would also like to thank Bani Rafeh and Christine McConnell for their tremendous help and support. It was a great pleasure working with all members of the DeGroote Community.

Last but certainly not least, I would like to express the deepest gratitude to my family. Words cannot express my thanks to my parents for their love, care, and understanding. Without their support, I would not be able to pursue my educational goals.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

Big Data Analytics (BDA) is a set of advanced analytic techniques and technologies designed to extract deep understanding from large and complex data (Fisher et al. 2012; Kwon et al. 2014). Globally, organizations increasingly implement BDA technologies to enhance their performance (Dubey et al. 2020; Rana et al. 2021). However, Small and Medium-sized Enterprises (SMEs) – those with fewer than 500 employees (Su et al. 2022) and limited financial resources and technical capabilities - lag behind BDA implementation (Verma and Bhattacharyya 2017). Hence, studying BDA implementation among SMEs warrants further investigation, particularly through different perspectives as the extant literature overlooked some critical points of view, as described below.

BDA implementation in organizations is not a one-phase process, but rather includes two general stages of adoption and post-adoption (continued use) (Karahanna et al. 1999a; Veiga et al. 2014). These stages of adoption and use require consideration of different perspectives at different organizational levels, since various organizational/individual factors influence the initial adoption and subsequent usage of a new technology in organizations (Karahanna et al. 1999a; Mustapa et al. 2022). Much of the literature has reviewed BDA adoption and use in SMEs just at the organizational level (El-Haddadeh et al. 2021; Maroufkhani, Ismail, et al. 2020a; Yadegaridehkordi et al. 2018) without considering factors at the individual level.

This research integrates theories from organizational and individual behavior disciplines with the aim of understanding the adoption and usage of BDA among SMEs. Particularly, the thesis investigates BDA implementation from managerial and data analyst perspectives at organizational and individual levels. To this end, drawing on the Technology, Organization, Environment (TOE) framework (Tornatzky et al. 1990) as well as institutional (DiMaggio and Powell 1983), organizational change and the Diffusion Of Innovation (DOI) theories (Rogers 1995), BDA adoption and usage in SMEs are investigated through the lens of an *imitation-evaluation* perspective (Lai et al. 2016). Through this perspective, the significance of institutional pressures impacting managers' imitation in adopting BDA are compared to the significance of technology characteristics influencing data analysts' evaluation in using BDA in SMEs.

In the process of BDA implementation, studying organizational and individual readiness can be critical (Ali et al. 2016; Ijab et al. 2019). Organizational and individual readiness refers to an organization's and individual's capabilities to manage change (Madsen et al. 2005; Weiner 2009). Implementing BDA in SMEs leads to changes in processes and activities that are supposed to be managed by managers at the organizational level and data analysts at the individual level. Accordingly, two theoretical research models have been developed. The managerial research model is developed to analyze environmental factors including institutional pressures that influence organizational readiness for adopting BDA and data analyst research model is developed to investigate technological factors that impact data analyst's readiness for using BDA in SMEs. Institutional pressures are external forces that may affect the performance of organizations' processes and activities including BDA implementation. *Mimetic pressures* refer to the copying and duplicating of successful organizational behavior by other organizations (DiMaggio and Powell 1983). *Coercive pressures* refer to formal and informal forces imposed by resource rich organizations, such as governments, powerful firms, and dominant customers in the institutional environment (Ke et al. 2009; Teo et al. 2003). *Normative pressures* are shared norms, collective environmental values and standards that will appear to be appropriate within a particular industry context (Abdulaziz et al. 2017). Moreover, technology characteristics can create data analysts' perceptions that may influence their beliefs and behaviors in using BDA. Technological factors in the context of BDA implementation among SMEs are BDA relative advantage, BDA complexity, and BDA trialability. In this thesis, the definitions of BDA characteristics are adapted from Rogers, 2003 as follows. *BDA relative advantage* refers to the degree to which BDA is perceived as being better than the idea it supersedes. *BDA complexity* is defined as the degree to which BDA is perceived as relatively difficult to understand and use. *BDA trialability* is the degree to which BDA application may be experimented with on a limited basis.

Previous studies have generated mixed findings in understanding the effects of antecedents influencing technology adoption in different contexts from the perspective of managers and employees. This study applies a new approach in analyzing the adoption and usage of BDA through both managers and data analysts' points of view and explores the influence of *institutional pressures* and *technology characteristics* on the intention to adopt and use BDA through the understanding of organizations and data analysts' readiness. To this end, a quantitative approach is adopted in the research methodology to empirically test sixteen hypotheses (eight in each research model). The theoretical and empirical foundations of this research are presented in this dissertation, starting from this chapter – "Introduction", which prepares the essential underlying background for my investigation.

In this chapter, at first the reason and importance of conducting this research are explained. Next, the theoretical influence of TOE, institutional pressures, change and DOI theories and the associated factors are described. Then a summary of identified factors of Information Systems (IS) implementation in SMEs from the literature that will be used in the next chapters to determine the antecedents and moderators in the study is presented. After that, a conceptual framework of imitation-evaluation perspective as a foundation for developing research models of the thesis is introduced. Finally, research objectives and two research questions are elaborated, followed by presenting a summary of the contributions to the literature.

1.1. Need for This Research

Firms implement BDA since it helps them to make better decisions and enhance their performance (Dubey et al. 2020; Ghasemaghaei 2018; Rana et al. 2021). Globally, firms increasingly adopt and use BDA tools and technologies to handle large and complex datasets with sizes beyond the capacity of their conventional tools. In recent years, the number of firms spending on big data around the world has increased significantly (Alalawneh and Alkhatib 2021). This trend is expected to continue as the global economy recuperates from the COVID-19 pandemic. The global BDA market size is predicted to reach US$105 billion by 2027 (Brik and Pal 2021). Despite this huge spending on big data, SMEs with fewer human and financial resources lag behind using BDA (Verma and Bhattacharyya 2017). In 2019 the BDA adoption rates of small and medium-size companies across the European Union (EU) were 10% and 19%, respectively compared to 33% for large organizations (Bianchini and Michalkova 2019). Having said that, the global market of using BDA in SMEs has shown a significant annual growth rate of 42% between 2013-2018 and this trend is predicted to continue to 2026 (TechNavio 2014; MarketWatch 2020) particularly due to the increasing demand for cloud-based BDA solutions among SMEs.

SMEs are the dominant form of business organizations in many countries (Robu 2013). For example, in Canada, more than 98% of all employers were small businesses in 2021 (SMEs in Canada Statistics, 2022). SMEs are the engine of economic growth through increasing gross domestic product (GDP), providing more job opportunities, and technological innovation (Meshram and Rawani 2019). It is estimated that SMEs have a considerable contribution to the global gross domestic product (GDP) of 60-70% (Kabanda and Brown 2017). In particular, SMEs are focal to the growth of countries' economies in which data-driven decision-making can increase productivity (Brynjolfsson and McElheran 2016). Mainly, this increase can be strengthened with big data technologies in the process of decision-making for SMEs (Nwankpa and Datta 2017; Provost and Fawcett 2013). SMEs are looking for innovative and disrupting technologies to foster their business and enhance their performance (Akpan et al. 2022). Emerging technologies, such as BDA, can help SMEs to be more innovative, productive and optimized (Liu et al. 2020). SMEs in different industries, such as FinTech, marketing, communication, security, manufacturing, etc. can access BDA applications along with large and complex databases (Liu et al. 2020). These databases include data from the world wide web, social media, public databases, and any other available data sets used by SMEs for different purposes, such as innovation, new products and services development, analyzing the industry, customer segmentation, pricing, marketing, etc. (Maroufkhani et al. 2022; Rauniyar et al. 2021). By applying different BDA applications, like analyzing and predicting market and customer behavior, SMEs can evaluate risks and find pertinent opportunities which are helpful in productivity (Iqbal et al. 2018). In particular, BDA can be leveraged by SMEs to enhance their performance in terms of profitability, agility, financial stability, and innovation (Chuah and Thurusamry 2022).

On the other hand, since 2020, global and national economies have been negatively impacted by the COVID-19 pandemic (Chatterjee et al. 2022). During this crisis, multiple challenges - such as supply chain and transportation disruptions, low customer demand, lack of raw materials, decline in productivity, business closure, and so on - have adversely affected all companies (Akingbade 2021). In particular, SMEs suffered greatly in the crisis and should follow practices that mitigate the negative effects of the pandemic. For instance, SMEs can reduce expenses, admit management crisis responses, and monitor environmental changes, then accordingly alter their response strategy. To this end, SMEs can implement BDA solutions in cloud environments to leverage advance analytics techniques in order to predict and optimize performance metrics.

Despite SMEs being under increasing pressures to innovate faster and enhance their performance, these firms encounter challenges when it comes to embracing emerging technologies such as BDA. Particularly SMEs are currently at the early stages of integrating and utilizing BDA. (Maroufkhani, Ismail, et al. 2020b). Furthermore, it is essential to understand the influencing factors of BDA implementation processes in SMEs. This research investigates the underlying factors in the adoption and use of BDA from managerial and data analyst perspectives.

1.2. Theoretical Influence

The process of implementing a new technology occurs in three general stages of initiation, adoption, and usage (Damanpour and Schneider 2006; Karahanna et al. 1999a; Rogers 2003). As such, BDA implementation is not a one-time decision, but rather a process that consists of a series of actions and decisions occurring at each of these three stages. In this process, initiation consists of multiple activities, such as recognizing a requirement, looking for solutions, identifying proper innovations, and proposing best courses of actions (Rogers 1995). SMEs with limited resources and skills may use external entities, such as consultants to perform these initial activities. Hence it is difficult to claim that managers or employees handle all these activities in SMEs. Due to this limitation, the initiation stage is excluded from the present research in which the target respondents are managers and data analysts who work in SMEs. In the adoption stage, managers decide to adopt BDA in organizations (Damanpour and Schneider 2006). There are multiple activities in this stage including: evaluating the proposed solutions from technical, financial, and strategic perspectives; making decisions to adopt the best solution; and allocating resources (Meyer and Goes 1988) to acquire BDA. In this stage, managers decide to adopt BDA and allocate resources. Finally, events and activities in the usage stage include modifying BDA solutions; preparing SMEs for using BDA; trial use; acceptance of BDA solution by data analysts; and continued use of BDA by the time of routinization. In this stage, BDA is put into use by organizational members including data analysts and managers. Managers and data analysts can be influenced by critical factors in the process of adopting and using BDA in SMEs. Drawing on the TOE framework and institutional and DOI theories, these factors are identified as the antecedents of BDA implementation in SMEs.

The TOE framework has been used for many years to holistically explain the process of adopting and implementing different innovations through investigating various technological, organizational, and environmental factors (Ramdani et al. 2013). The TOE framework has been proposed as a generic theory of technology implementation and applied for evaluating the adoption and usage of IS innovations (Zhu et al. 2003). This framework has been also used to study IS implementation by SMEs and the identified TOE factors show good predictions for adoption and usage of a new technology (Awa et al. 2017; Hao et al. 2020; Ramdani et al. 2013; Setiyani and Rostiani 2021). Hence in this research, the TOE framework is applied as an overarching theory to identify important factors in the context of BDA adoption and usage by SMEs.

Despite the prospective benefits of using big data tools and technologies, the effort of BDA implementation may be considered a failure, due to resistance to change among individuals in organizations (Kwahk and Lee 2008). Thus, the success of implementing BDA may depend on the readiness of organizations and data analysts to utilize such tools. Particularly, in SMEs it is not clear whether managers and data analysts are ready and willing to implement BDA in their organizations. Moreover, the factors that may affect readiness to implement BDA in SMEs are unknown or poorly understood and deserve close research attention. In general, using BDA in SMEs has been considered a complex and multifaceted problem which is required to be investigated from different aspects (Liu et al. 2020).

In particular, the conditions under which organizational and data analysts' readiness and BDA implementation process may be influenced among SMEs have not yet been investigated in the literature. Hence, the purpose of this research is to explore how the readiness of SMEs in using

BDA is influenced by external and internal variables from managers and data analysts' perspectives.

Many researchers focused on big data implementation at the organizational level (Goes 2014). For example, Kwon et al. (2014) and Shin (2016) investigated BDA adoption through the theoretical lens of data quality management, data usage experience, and socio-technical factors. Yadegaridehkordi et al. (2018), Lai et al. (2018) and Salleh and Janczewski (2016) identified significant big data adoption factors in terms of technological, environmental, and organizational dimensions. Verma et al. (2018) also extended the research on BDA adoption by investigating managers' attitude toward using BDA systems. However, most of these studies review factors influencing just the adoption stage of BDA implementation in big companies. Moreover, the results of previous research on BDA adoption cannot be easily applied to SMEs due to SMEs' characteristics such as small organizational structure with limited technological and financial resources and different approaches these companies may follow in adopting a new technology such as outsourcing and using cloud-based services. Although, some recent studies tried to analyze the determinants of BDA adoption in SMEs, such as Maroufkhani et al. (2020) and Loh and Teoh (2021), they just studied the antecedents of BDA adoption particularly technological factors without considering the conditions which may influence the effects of determinants. In addition, Maroufkhani et al. (2020) asked only managers or owners of SMEs to answer about the technical aspects of BDA which may not be their expertise. Hence it is important to conduct a comprehensive empirical study on the process of BDA implementation and relevant conditions for SMEs from both managers' and data analysts' perspectives. Top managers mostly explore external environment to find opportunities for improving the performance of their companies. In contrast, employees (here data analysts) are concerned about technological aspects of using BDA in their organizations.

1.3. Research Objectives

Many studies focused on BDA implementation at the organizational level. In addition, the role of organizational and data analysts' readiness is not sufficiently reviewed in previous research. In the literature, the factors that impact readiness to adopt and use BDA in SMEs are unknown or poorly understood. Hence, it is important to conduct a comprehensive empirical study to investigate factors impacting the process of BDA implementation and pertinent conditions in SMEs from managers' and data analysts' perspectives. To this end and drawing on a mix of TOE framework and institutional and DOI theories, two research models for managers and data analysts in the context of BDA implementation among SMEs are developed mainly to address the following research objectives:

1. To investigate and understand the influence of institutional pressures on the adoption of BDA in SMEs.

2. To investigate and understand the influence of BDA characteristics on BDA usage among SMEs.

In addition to these main objectives, this study also involves the following secondary objectives:

3. To understand the role of SMEs readiness in the process of implementing BDA in SMEs.

4. To study the conditions (e.g., uncertainty, data-driven culture, employees' skills, and thinking style) under which the effects of institutional pressures and BDA characteristics on SMEs readiness and BDA adoption and use may change.

1.4. Document Organization

The remaining part of this thesis manuscript is unfolded as follows. Chapter 2 provides the contextual background needed to understand BDA and SMEs. Chapter 3 provides the theoretical background for this research, specifically institutional and DOI theories. Chapter 4 details the research model and hypotheses which will be tested via the research methodology outlined in Chapter 5. Chapter 6 provides the data analysis of the measurement and structural model, as well as post-hoc analyses. Chapter 7 provides a discussion of the key findings, contributions of this research to academics, practitioners, and society, limitations of this research and planned future work in this area.

2. THEORETICAL BACKGROUND

As discussed in Chapter 1, the objective of this research is to evaluate the institutional pressures and technology characteristics affecting BDA adoption and use in SMEs. To this end, two research questions are addressed: (1) Do institutional pressures affect BDA adoption through SMEs readiness for BDA? (2) Do technology characteristics affect BDA usage through data analysts' readiness for BDA in SMEs? To respond to these two research questions, this study combines the TOE framework with Institutional, DOI, and organizational change theories through the lens of an imitation-evaluation perspective in the context of SMEs. As such a theoretical foundation is developed to propose a research model (shown in Figure 1) and suggest eight main hypotheses. In addition, as a secondary objective, this study examines the effects of BDA uncertainty, data-driven culture, data analytics skills, and analytical thinking style on certain parts of the research model.

2.1. BDA Adoption and Usage in SMEs

Organizations implement BDA tools and techniques to obtain rich insights for better decision making with improved performance. Many large companies may already adopt and use BDA. Previous studies have also investigated the concept of BDA and the factors that affect the implementation of this technology significantly in large companies (Alsadi et al. 2021; Shahbaz et al. 2019). However, it is difficult to extend the results of these studies directly to the context of SMEs with different institutional and organizational conditions. Hence, the TOE framework is applied to gain a better understanding of how external and organizational factors affect the adoption and usage of BDA in SMEs. Table 1 shows TOE variables in recent studies investigating IS adoption by SMEs.

Table 1. TOE factors in recent research about IS adoption by SMEs.

TOE Factors	IS Innovation	Participants	Findings	Reference
Technology: Perceived Simplicity, Compatibility, Perceived values. *Organization*: Management support, Size of the enterprise, Scope of business. *Environment*: Normative pressure, Mimetic pressure.	ICT	373 SMEs in Nigeria	There is a significant relationship between adoption and the factors within the contexts of organization, environment and task.	(Awa et al. 2017)
Technology: Compatibility, Perceived usefulness, Complexity, Security concern, Relative advantage. *Organization*: Cost, Organization readiness, Top management support, Organization size, Organization culture. *Environment*: Government support, Competitive pressure, Environmental uncertainty, Vendor quality.	E-Commerce	301 SMEs in Indonesia	Technology, organizational, and environmental indicators, had a significant effect on an SMEs intention to adopt e-commerce.	(Setiyani and Rostiani 2021)
Technology: Relative advantage, Compatibility, Complexity, Observability, Trialability. *Organization*: Size, Centralization, Formalization.	Social media	400 SMEs in Indonesia	All factors of social media adoption that consist of TOE have a significant effect on SME performance.	(Wulandari et al. 2020)

Environment: Competitive intensity, Competitive preference.				
Technology: Relative advantage, Cost, Security and Privacy, Compatibility, Complexity, Trialability. *Organization*: Size, Top management support, Innovativeness, Prior technological experience. *Environment*: Competitive pressure, Sector (Industry), Market scope; Supplier computing support.	Cloud Computing	139 SMEs in Lebanon	The technological and organizational factors are positively related to the decision to adopt cloud computing services.	(Skafi et al. 2020)
Technology: Technology infrastructure, Technology competence. *Organization*: Perceived benefit of e-HRM, Top Management support. *Environment*: Coercive pressure, Normative pressure.	e-HRM	382 executives SMEs in Bangladesh	The infrastructure, IT competence, top management support, and normative pressure toward e-HRM have significant influences on the adoption of e-HRM.	(Alam and Islam 2021)
Technology: Perceived usefulness, Security concern. *Organization*: Top management support, Organizational readiness. *Environment*: Consumer pressure, Trading partner pressure.	Social Commerce	181 SMEs in Saudi Arabia.	Trading partner pressure in the environmental context, followed by top management support in the organizational context, and perceived usefulness in the technological context, have the most significant influence on	(Abed 2020)

			behavioral intention to use social commerce.	
Technology: Perception of the comparative advantage, Perception of complexity, Compatibility, Key personnel ability. *Organization*: Top management organizational support, Organizational readiness, Data management. Environment: Competitive pressure, Vendor quality.	Business Intelligence	100 SMEs in Croatia	The research did not uncover any notable influence of technological factors associated with the characteristics of the considered technological innovation within the technology dimension.	(Stjepić et al. 2021)
Technology: Relative advantage, Compatibility, Complexity, Risk and Insecurity, Trialability, Observability. *Organization*: Top management support, Organizational readiness. *Environment*: Competitive pressure, External support, Government regulations.	Big Data Analytics	112 SMEs in Iran	Technological and organizational elements are the more significant determinants of BDA adoption in the context of SMEs	(Maroufkhani, Ismail, et al. 2020a)

Technology: Trialability, Complexity, Compatibility, Privacy & Security, IT readiness, System quality, Employee knowledge. *Organization*: Perceived benefits, financial readiness, Cost. *Environment*: Competitive pressure, Government regular, Critical mass.	Cloud ERP	Malaysian SMEs	Developed a conceptual framework to identify factors that influence the intention of cloud ERP adoption in Malaysian SMEs.	(RAZZAQ et al. 2021)
Technology: Relative advantage, Complexity, Compatibility. *Organization*: Top management support, financial resource slack. *Environment*: Vendor support, Competitive pressure, Customer pressure.	Mobile Marketing	201 SMEs in South Africa	The relative importance of the salient determinants of the innovation's adoption varies across industries, suggesting that industry variance plays a significant moderating role in mobile marketing adoption decisions across the two SME sectors that were examined.	(Maduku 2021)
Technology: Perceived usefulness (Efficiency, Perceived service quality, Compatibility), Perceived ease of use (Complexity, Fun to use). *Organization*: Respondent characteristics (Attitude toward technology, Manager support, Level of innovativeness), Current availability of the technology, Perceived financial resources.	InStore Technologies	164 SMEs in Spain	The attitude towards technology is the strongest predictor of the intention to adopt Customer Facing In-store Technologies. (CFIST), highlighting the role of top management in technology decisions in retail SMEs.	(Lorente-Martínez et al. 2020)

Environment: Competitive pressure, Customer Attitude, Perceived national readiness.				

In most of the above literature, technological, organizational, and environmental factors have significant impact on the technology adoption and use among SMEs. However, in some studies environmental and technological factors did not reveal a significant impact on technology implementation in SMEs and showed mixed results. Particularly, in adopting BDA relevant technologies, such as business intelligence, technological factors did not show significant impact. This study examines the implementation process of technology among SMEs by considering technological and environmental factors. Specifically, the research focused on the implementation of BDA because there is still a lack of understanding of the main factors that impact the adoption and usage of it in SMEs. Moreover, in some studies, the size of the enterprise is considered as an important factor in the adoption of new technology in organizations that means organizations with different firm sizes would have different behaviors. Particularly, most previous studies investigated the behavior of SMEs with fewer than 250 employees in Asia, Africa, and Europe, and there is a lack of understanding about North American SMEs with fewer than 500 employees and their behaviors in adopting new technology, such as BDA. Finally, some organizational factors (i.e., organizational culture, data management, etc.) could be considered to investigate their moderating roles on the adoption and use decisions in SMEs.

First and foremost, environmental factors should be considered. While discussing the impact of environmental factors, institutional theory particularly draws attention. Institutional theory has been commonly and successfully applied to show the effects of external factors on organizations' behaviors towards information technology adoption (Li and Wang 2018; Liang et al. 2007). According to this theory, the decision-making process in organizations, including the adoption of new technology, is not solely based on rational actions. Instead, organizations have additional intentions to legitimize their behaviors. (DiMaggio and Powell 1983). Based on this theory, the adoption of a technology in organizations is influenced by three dimensions or institutional pressures including coercive, mimetic, and normative forces which induce homogeneity in organizational processes (Lutfi 2020). Many studies have been published investigating the effects of institutional pressures on technology adoption by SMEs. Table 2 shows a sample of these studies.

Table 2. Applying Institutional Theory in Technology Adoption by SMEs.

Institutional Pressures	**Moderator/ Mediator**	**Context**	**Findings**	**Reference**
Mimetic, Coercive, Normative	Environment Uncertainty	ERP	All pressures had significant direct effects on ERP adoption.	(Lutfi 2020)

Mimetic, Coercive, Normative	Top Management	M-commerce	All pressures affect intention to adopt m-commerce. But just coercive and normative pressures positively affect top management support.	(Li and Wang 2018)
Mimetic, Coercive, Normative	Top Management & Absorptive Capacity	Social Media	Institutional pressures were found to have no direct effect on social media assimilation.	(Bharati et al. 2014)
Coercive Pressure (Customers) Mimetic Pressure (Competitors)	-	Electronic Trading Systems	All pressures had significant effects on intention to adopt ETS.	(Khalifa and Davison 2006)
Mimetic, Coercive, Normative	-	Cloud-based accounting IS	The intention to adopt a cloud-based accounting information system was significantly influenced by all the pressures examined in the study.	(Alshirah et al. 2021)
Institutional perspective: Government support; Legal and regulatory system; Market forces; Social awareness	-	E-commerce	Government support and legal and regulations (coercive pressures) had the most significant effects on the adoption of e-commerce followed by market forces and social awareness (normative pressures).	(Miao and Tran 2018)

Mimetic, Coercive, Normative	Trust	Cloud services	Developed a conceptual model to assess the critical factors that influences South African SMEs cloud services adoption.	(Ayong and Naidoo 2019)
Mimetic, Coercive, Normative	Top Management Belief, Top Management Participation	Enterprise Information Systems (ERP)	Mimetic & Normative pressures significantly influence the adoption of ERP.	(Saraf et al. 2013)
Mimetic, Coercive, Normative	-	Grid Computing	Mimetic pressures play major roles in adoption processes, which differentiates grid computing from other inter-organizational systems.	(Messerschmidt and Hinz 2013)
Mimetic, Coercive, Normative	-	VoIP	Coercive pressures had a significant impact on the intention to adopt VoIP. But the impact of mimetic pressures on VoIP adoption was not significant.	(Basaglia et al. 2009)
Mimetic, Coercive, Normative	Top Management, Absorptive Capacity	Web 2.0.	Mimetic and Coercive pressures had significant impact on Web 2.0 adoption, but Normative pressures had no impact on Web 2.0 adoption.	(Bharati and Chaudhury 2011)
Mimetic, Coercive, Normative	-	EDI	Normative pressures have a significant impact on the adoption of and EDI.	(Teo et al. 2003)

These studies on adopting new technologies among SMEs, show mixed results regarding the impact of institutional pressures. For instance, while Lutfi (2020), Alshirah et al. (2021) and Khalifa and Davison (2006) found that institutional pressures are significantly associated with the adoption of technology among SMEs, Bharati et al. (2014) did not find any evidence for the direct influence of these pressures on SMEs' adoption of technology. Moreover, the impact of institutional pressures on each IT technology varies and the findings cannot be extended to the context of using any new technology with unique features. Hence, the effects of these pressures on BDA adoption deserves further investigation.

In this thesis, three institutional pressures are identified as the antecedents for the adoption of BDA in SMEs. Moreover, previous studies showed the importance of *uncertainty* along with the institutional perspective in providing greater explanatory power than institutional pressures alone (Chu et al. 2018; Jalaludin et al. 2011; Lutfi 2020). Uncertainty, as a situation in which managers cannot predict changes, is often a concern when organizations want to use new technologies. Hence, this study combines the factor of uncertainty with the institutional perspective and adds the uncertainty of using BDA among SMEs as a moderator for the effects of institutional pressures. To date a limited number of studies have considered the uncertainty of using a technology as a moderator for all the institutional pressures. Uncertainty in using BDA is significant since the volume, variety, and velocity of data increments which could result in a lack of confidence in the decisions made based on pertinent analytics (Hariri et al. 2019). A recent call was made for studying using BDA in different environments to incorporate the factor of uncertainty (Wang et al. 2022). By adding uncertainty to a model, this thesis is an attempt to address that call.

Particularly, as managers play a pivotal role in adopting IT systems (Mehrtens et al. 2001), in this research, the adoption of BDA from a managerial perspective is reviewed. Moreover BDA usage refers to the degree to which data analysts are willing to use an advanced analytical tool to accomplish their tasks (Drnevich et al. 2011; Marotta 2022). Hence, in this thesis, external and internal determinants that influence BDA adoption and use from both managerial and data analysts' perspectives are investigated to comprehensively understand the critical factors that affect adopting and using BDA in SMEs.

2.2. Organizational and Data Analysts' Readiness for BDA Adoption and Usage

Recent research proposes readiness as a relevant factor to technology adoption such that organizations with higher readiness are more likely to adopt and use new technology (Parasuraman and Colby 2015). Readiness for adopting and using new technology has been investigated from different perspectives, such as technology characteristics (Rogers 1983), theory of reasoned action (Fishbein and Ajzen 1977), or technology acceptance model (TAM) (Davis 1989). However, previous studies review the effect of readiness on the process of technology implementation at either individual level or organizational level. To date, no study in the literature has investigated readiness at both organizational and individual levels. Table 3 summarizes the seminal studies on BDA adoption and usage within organizations. These papers have been carried out mostly in the context of adopting BDA in SMEs. As shown in this table, studies overlooked the perspective of individuals toward using BDA as most of the publications investigated factors at the organizational level. Moreover, most of these studies reviewed factors influencing mainly the adoption stage of BDA implementation in big companies and there is a lack of understanding of the factors that affect the usage of BDA by employees, such as data analysts in small and medium size companies. Particularly, the results of previous research on BDA adoption cannot be easily applied to SMEs due to SMEs' characteristics and different approaches these companies may follow in adopting new technology. For instance, in large organizations with a broad range of internal financial and technical assistance, some internal factors such as organizational readiness may not be considered as a critical issue in adopting and using a new technology. Therefore, future studies can be directed towards examining factors specific to SMEs that influence the adoption and usage of BDA.

Table 3. Summary of the studies on BDA implementation in SMEs

Source	Context	Theory	Objective	Findings
(Maroufkhani et al. 2022)	171 manufacturing SMEs, at the organizational level	TOE Framework	This paper reviewed the influence of TOE factors on BDA adoption.	The findings confirmed the interrelationships among the TOE factors. The effects of compatibility, competitiveness and organizational readiness on BDA adoption were mediated by top management support. Furthermore, environmental factors moderate the influences of compatibility and organizational readiness on top management support.

(Yadegaridehkordi et al. 2020)	418 hospitality SMEs, at the organizational level	Human-organization-technology fit & Technology-organization-environment framework	This study proposes a theoretical model to identify the key factors affecting big data adoption and its consequent impact on the firm performance.	Relative advantage, management support, IT expertise, and external pressure are the most important factors in the technological, organizational, human, and environmental dimensions. The results further revealed that technology is the most important influential dimension.
(El-Haddadeh et al. 2021)	320 SMEs & larger firms, at the organizational level	TOE	This study utilizes the TOE framework to examine the role of top management support in facilitating value creation from BDA adoption for the realization Sustainable Development Goals.	The technological driver of BDA coupled with top management support, can significantly help in the adoption process.
(Lai et al. 2018)	210 Small to large organizations, at the organizational level	TOE Framework	This study addresses the factors determining firms' intention to adopt BDA in their daily operations.	Perceived benefits and top management support can significantly influence the adoption intention. And environmental factors, such as competitors' adoption, government policy, and Supply Chain connectivity, can significantly moderate the direct relationships between driving factors and the adoption intention.
(Mangla et al. 2020)	106 Manufacturing SMEs, at the organizational level	BDA and project management literature	This study aims to investigate the mediating role of BDA played between project performance and nine different factors.	Project knowledge management, green purchasing and project operational capabilities require the mediating support of big data analytics. The adoption of big data analytics has a positive influence on project performance in the manufacturing sector.

Hence, it is important to conduct a comprehensive empirical study on the process of BDA implementation and relevant conditions in SMEs from both managers' and data analysts' perspectives. Top managers mostly explore external environment to find opportunities for improving the performance of their companies. In contrast, employees (here data analysts) are mostly concerned about technological aspects of using BDA in their organizations. The purpose of this thesis is to study how SMEs are influenced at both organizational and individual levels to implement BDA. To that end, I will explore the factors that impact organizational and data analysts' readiness in adopting and using BDA in SMEs. Specifically, the impact of institutional pressures and technology characteristics on organizational and data analysts' readiness are investigated respectively. As such, organizational change theory is applied to explain the relationships between the antecedents of BDA adoption/use and organizational/data analysts' readiness. Lewin (1951) suggested that there are external factors (i.e., environmental forces) for change in organizational settings. Organizations changes to adapt these forces and remain effective. For instance, organizations manage their resources to use a new technology. Moreover, it is argued that technology is an external factor for change in organizations (Jacobs et al. 2013). In this sense, organizational readiness is related to Lewin's (1951) suggestion of organizations' adaptation to change factors (Nordin 2011). As such, in this study, readiness is considered as an important factor in the process of adopting and using BDA as a change in SMEs due to external factors and technology characteristics.

2.3. Technology Imitation from a Managerial Perspective – Institutional Pressures

The external environment has a significant contribution in the process of adopting new complex technologies, such as BDA (Wen et al. 2009). While discussing the influence of external factors, the institutional theory primarily draws attention (Liang et al. 2007). The institutional approach helps to advance our knowledge about external pressures and how firms react to these factors (Levanti et al. 2021). Based on this theory, the primary purpose when managers make decisions is to attain greater legitimacy from the stakeholders in the environment by imitating successful actions (DiMaggio and Powell 1983). Institutional pressures (i.e., mimetic, coercive, and normative pressures) can drive organizations to conform to other organizations' specific practices and actions. *Mimetic pressures* come from a reaction to ambiguity and uncertainty, which is a compelling force that motivates organizations to emulate new practices (Liang et al. 2007). *Coercive pressures* stem from both formal and informal forces enforced on firms by other organizations upon which firms are dependent through cultural prospects in their society (Teo et al. 2003). *Normative pressures* stem primarily from professionalization (Berrone et al. 2013). Professionalization means the collective endeavor of counterparts in organizations to specify the underlying conditions and approaches of their work to control the production process and institute a cognitive foundation and legitimation for their professional autonomy. This study considers the effects of institutional pressures on BDA adoption in SMEs from a managerial perspective.

Prior studies on assessing the influence of institutional pressures have been carried out on the adoption of different IT innovations (Bharati et al. 2014; Messerschmidt and Hinz 2013; Saraf et al. 2013; Yigitbasioglu 2015). These articles' findings show mixed results regarding the impact of institutional pressures on technology adoption. For example, Saraf et al. (2013) and Messerschmidt and Hinz (2013) found mimetic pressures significantly influence the adoption of ERP and Grid Computing, while Basaglia et al. (2009) found that the impact of mimetic pressures on VoIP adoption is not significant. As another example, Bharati and Chaudhury (2011) found that normative pressures have no effect on Web 2.0 adoption, while Saraf et al. (2013) argue that normative pressures significantly impact the adoption of ERP and EDI. As such, the effects of institutional pressures on each IT innovation vary and the results cannot be extended to the context of new technology with unique characteristics. Hence, an empirical study about the effects of these pressures on BDA adoption warrants a separate study.

2.4. Technology Evaluation from Data Analyst's Perspective – Technology Characteristics

Despite managers, employees try to investigate an intended IT system by analyzing its characteristics in a logical manner (Lai et al. 2010). The rational evaluation of IT characteristics creates users' perceptions that could affect their beliefs and behaviours when an organization has decided to use an IT system (Moore and Benbasat 1991). In the context of this study, data analysts would more likely be ready to use a system that has been evaluated as useful in conducting their job tasks. To this end, the present study relies on DOI theory to study data analysts' behaviours of using BDA in SMEs.

The DOI theory advocators concentrate on analyzing the relationship between technology characteristics and its usage by end-users (e.g., data analysts) (Premkumar et al. 1994). According to this, Rogers, (2003) specified five critical technological factors to the widespread use of IT in organizations including *relative advantage*, *complexity*, *trialability*, *compatibility*, and *observability*. Previous studies have also found these factors important in implementing innovation among SMEs (Abdollahzadegan et al. 2013; Al Mamun 2018; Maroufkhani, Tseng, et al. 2020). These characteristics are defined by Rogers (2003) as follows. *Relative advantage* refers to "the degree to which an innovation is perceived as being better than the idea it supersedes" (p. 229). SMEs intend to adopt an innovative technology if its benefits surpass the benefits of the old technology (Gu et al. 2012). *Complexity* is defined as "the degree to which an innovation is perceived as relatively difficult to understand and use" (p. 257). Accordingly, SMEs will more quickly adopt new technologies which are easily understood (Premkumar et al. 1994). *Trialability* refers to "the degree to which an innovation may be experimented with on a limited basis" (p. 258). Trialability can reduce uncertainty levels for SMEs that intend to adopt new and unfamiliar technology (Weiss and Dale 1998).

Compatibility is "the degree to which an innovation is perceived as being consistent with previously adopted innovations, past experiences, existing norms or values, and needs of potential adopters" (Rogers 2003). SMEs may look for a critical mass of their partners adopted new technology. In this research, compatibility for investigating BDA intention to use in SMEs is not considered. This is due to the fact that SMEs partners are in the external environment and normally are investigated by managers who are not the target participants of this part of the research and data analysts may not have enough information to properly evaluate this factor. Finally, *observability* is defined as “the degree to which the results of an innovation are visible to others” (Rogers 1995, p.244). Previous research showed that SMEs mostly use a new technology when the possible risks and rewards can be understood (Duckworth 2014). In this research, I do not also consider observability for investigating BDA intention to use in SMEs because understanding the risks and rewards of BDA as an advanced technology before the usage stage is highly unlikely among SMEs that are mostly willing to take risks and innovate to succeed. As such, it could not be possible to evaluate the effects of observability on BDA usage. Hence, in this study, the DOI is used to explore the impact of technology characteristics (i.e., relative advantage, complexity, and trialability) on data analysts’ readiness to use BDA in SMEs. The DOI is an appropriate choice for the logical evaluation of BDA by individual users in organizations (Karahanna et al. 1999a), due to its maturity, comprehensiveness, and ability to explore an innovation implementation.

Thus, the underlying philosophical assumption of this research follows the lens of imitation-evaluation perspective between managers and data analysts to investigate the adoption and usage of BDA in SMEs. According to this perspective, a conceptual framework to study the behaviors and attitudes of managers and data analysts by considering institutional pressures and BDA characteristics is developed and shown in Figure 1.

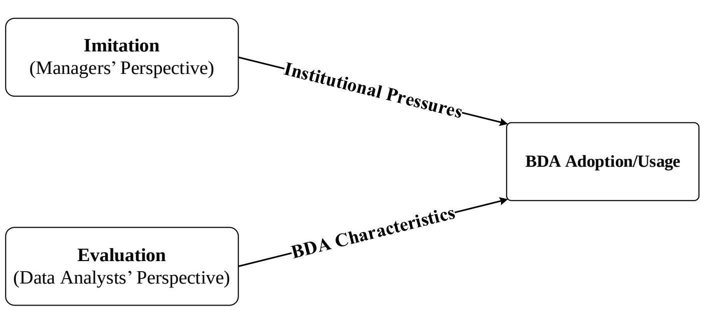


Figure 1. Research Conceptual Framework

To explain how SME implement BDA technology, I rely on diffusion of innovation theory (DOI) (Rogers 2003). DOI theory has been applied in multiple studies and explains the process of implementing a new technology. The process of implementing an Information Technology (IT) system in an organization includes two main phases of adoption and usage (Cooper and Zmud 1990). Based on the DOI, adoption is the initial decision for technology use in an organization (Rogers 2003). Particularly, adoption, as the first step of implementing technology in organizations, is typically reviewed by top management. In addition, top management attitude, support, and commitment are influenced by external factors that could make managers imitating adoption behavior of other organizations (Menguc et al. 2010). Particularly, in uncertain situations due to the advent of a complex technology, managers try to collect information about other organizations for possible imitation (Villadsen et al. 2010). Managers may also experience *bounded rationality* which specifies the inability of humans to consider all potential factors for decision making due to the limitations of human brain (Felin et al. 2014). Hence, in this research, an imitation perspective is applied to investigate SMEs managers' attitudes and behaviors in adopting complex BDA applications.

Another determinant of technology implementation alongside the imitation is technology evaluation (Lai et al. 2016). Technology evaluation considers rational assessment of the characteristics of technology that could facilitate users' attitudes and behavior. Users are key players in the *technology usage* phase which is the next step of implementation process after the adoption. In organizations, employees, despite managers, try to investigate an intended IT system by analyzing its characteristics in a logical manner (Lai et al. 2010). The logical evaluation of IT features creates users' perceptions that could influence their beliefs and behaviors when an organization has decided to use an IT system (Moore and Benbasat 1991). In the context of this thesis, data analysts would more likely be ready to use a new system that has been evaluated as useful in conducting their jab tasks. To this end, the present research relies on DOI theory to study data analysts' behaviors of using BDA in SMEs.

The DOI theory advocators focus on analyzing the relationship between technology characteristics and its usage by end users (e.g., data analysts) (Premkumar et al. 1994). According to this theory, five critical technological factors have been identified to the widespread use of IT in organizations including *relative advantage*, *complexity*, *trialability*, *compatibility*, and *observability*. Previous studies have also found these factors important in implementing innovation among SMEs (Abdollahzadegan et al. 2013; Al Mamun 2018; Maroufkhani, Tseng, et al. 2020). In this research, I do not consider compatibility for investigating BDA intention to use in SMEs. This is due to the fact that SMEs partners are in the external environment and normally are investigated by managers who are not the target participants of this part of the research. I do not also consider observability for investigating BDA intention to use in SMEs because understanding the risks and rewards of BDA as an advanced technology before the usage stage is highly unlikely. As such, it could not be possible to evaluate the effects of observability on BDA intention to use. In this thesis, the DOI theory is applied to explore the impact of technology characteristics (i.e., relative advantage, complexity, and trialability) on data analysts' readiness to use BDA in SMEs. The DOI is an appropriate choice for the logical evaluation of BDA by individual users in organizations (Karahanna et al. 1999a), due to its maturity, comprehensiveness, and ability to explore an innovation implementation.

2.5. Research Model and Hypotheses

According to the imitation-evaluation perspective and drawing on the TOE framework, institutional and DOI theories, two research models are developed and shown in Figure 2 and Figure 3. The routes of the models provide a way to explore the antecedents of organizational and data analysts' readiness in SMEs in terms of institutional pressures and BDA characteristics, respectively. Drawing on the institutional and TOE frameworks (DiMaggio and Powell 1983; Rogers 2003), the first part of the research model is proposed to explore the role of external pressures on BDA adoption mediated by organizational readiness from a managerial perspective. Likewise, the second part of the model is developed to investigate the effects of BDA technology characteristics on BDA usage mediated by data analysts' readiness from the perspective of individual data analysts working in SMEs. This model can also help to investigate the relative importance of external factors against technology characteristics. As such, SMEs can focus on the most important antecedents in the process of BDA implementation. Hence, It is contended that: (1) the influences of *institutional pressures* including mimetic, coercive, and normative forces on BDA adoption in SMEs are mediated by organizational readiness for BDA; and (2) the effects of *technology characteristics* including BDA relative advantage, BDA complexity, and BDA trialability on BDA usage in SMEs are mediated by data analysts' readiness for BDA.

The definitions of all the constructs for the 1st part and 2nd part of the model are provided in Tables 4 and 5. In the following sections, all the hypotheses in the research model are described and justified with relevant sources.

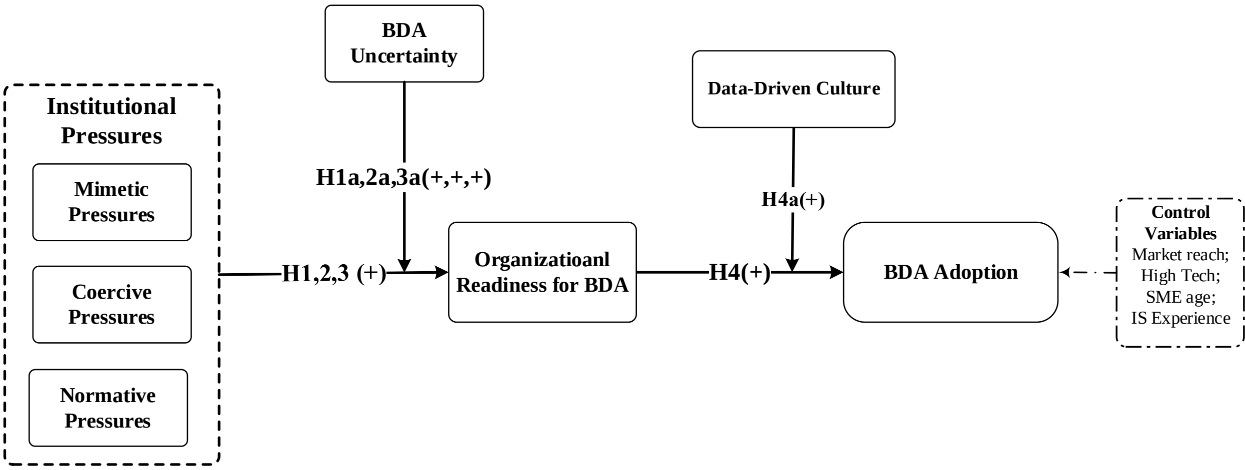


Figure 2. Proposed Managerial Research Model

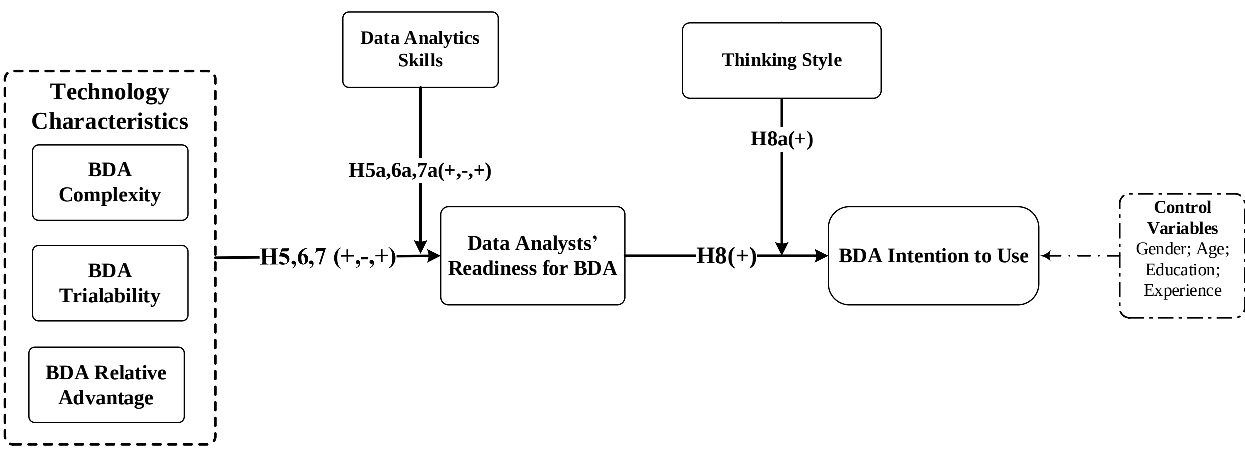


Figure 3. Proposed Data Analyst Research Model

Table 4. Construct Definition – Managers' Perspective at the Organizational Level

Construct	Definition
Mimetic Pressures	Mimetic pressures cause an organization to change over time to become more like other organizations in its environment (Teo et al. 2003).
Coercive Pressures	Formal and informal pressures exerted on organizations by other organizations upon which they are dependent (Zheng et al. 2013).

Normative Pressures	Normative pressures stem from a variety of sources, including business partners and trade and professional associations with practices that are viewed appropriate among organizations (Cavusoglu et al. 2015).
Organizational Readiness	The availability of resources required to manage change in an organization (Tsai and Tang 2012).
BDA Adoption	The first stage of the process of implementing analytical techniques in which potential organizational adopters become aware and initiate gathering of knowledge about BDA (See et al. 2019).
BDA Uncertainty	A situation in which it is difficult to predict the changes associated with big data tools and technologies (Heydari et al. 2020).
Data-Driven Culture	An organizational culture where firms prefer data extracted insights over top management intuition" (McAfee et al. 2012).

Table 5. Construct Definition – Data Analysts' Perspective at the Individual Level

Construct	Definition
BDA Relative Advantage	The degree to which BDA is perceived as being better than the idea it supersedes (Rogers 2003).
BDA Complexity	The degree to which BDA is perceived as relatively difficult to understand and use (Rogers 1995).
BDA Trialability	The degree to which BDA application may be experimented with on a limited basis (Rogers 1995).
Data Analysts' Readiness	The extent to which data analysts have positive perspectives towards the need for a change and its implications.
Data Analytics Skills	Knowledge and capabilities which enhance data analysts' task performance through using analytical applications and user-driven systems (Draganidis and Mentzas 2006).
Analytical Thinking Style	A conscious, analytical, intentional, and comparatively affect free information processing mode (Pacini and Epstein 1999).

2.5.1. Institutional pressures as the antecedents of organizational readiness for BDA

Institutional pressures including mimetic, coercive, and normative can positively affect the organizational readiness of SMEs for adopting BDA. Mimetic pressures may drive an organization to change over time to become more similar to others in its environment (e.g., competitors in the same industry) (DiMaggio and Powell 1983). Mimetic pressures present in processes, including the prevalence of adoption among organizations operating in a common environment and the number of successful adopters (Haveman 1993). Managers would mimic the actions of other structurally similar organizations because those counterparts are active in the common business network and share common economic targets, provide similar products and services, and are confined to the same restrictions (Teo et al. 2003). Given the uncertainty embedded in the outcomes of BDA initiatives (Michael and Miller 2013), managers submit to model the structures and processes of successful organizational counterparts or competitors because this helps managers preserve legitimacy and receive support against possible harm and loss of organizational image. According to organizational change theories (Armenakis et al. 1993), the BDA adoption of successful firms or leaders in the industry could also drive managers to react to their counterpart's actions for a change of making the organization ready particularly in uncertain situations. When uncertainty is high, successful organizations provide trust and positive attitudes for managers who most probably avoid change or risk behavior especially in SMEs with fewer slack resources (Bouckenooghe et al. 2009; Mikalef and Krogstie 2020). As such, managers intentionally put energy into the process of BDA adoption which is perceived as legitimate practice. Based on institutional theory, adopters and potential adopters of BDA in SMEs may keep track of their environment to be ready for change and make the organizations similar to other SMEs have already adopted BDA. Thus:

H1. *Mimetic pressures are positively associated with organizational readiness for BDA.*

Coercive pressures emerge when an organization dominates other firms in its business network, such that it is able to force others to change their structures or enforce certain practices (DiMaggio and Powell 1983). Pressures from dominant actors mostly stem from the ability to direct scarce resources critical to the influenced organizations (Pfeffer and Gerald 1978). This ability of dominant organizations is defined as the coercive pressures by stakeholders, including suppliers, customers, parent corporations, or any other superior organizations (Teo et al. 2003; Zheng et al. 2013). In the context of BDA adoption, significant coercive pressures may come from business partners or superior organizations (Teo et al. 2003; Zheng et al. 2013). Generally, business partners may use common infrastructure for their transactions and communications. Hence, these organizations would rely heavily on shared networks and common datasets of their partners. Especially, for SMEs these common infrastructures can provide value and benefits at lower expenses (e.g., through cloud computing) (Alshamaila et al. 2013a; Fahmideh et al. 2019). Moreover, the more organizations apply shared data and infrastructure, the more they adopt the activities and processes of their dominant partners (Lai et al. 2006). Accordingly, superior organizations may lead managers to imitate and deliberately make the SMEs ready and intentionally assign resources to associated processes and activities. Hence, based on the institutional theory, superior organizations that have adopted BDA may ask their partners to get ready and deploy BDA technology. Consequently, dependent SMEs may comply and imitate because they rely significantly on a dominant firm's virtual infrastructure and datasets. Thus:

H2. *Coercive pressures are positively associated with organizational readiness for BDA.*

Normative pressures have different sources related to business partners and professional associations (Cavusoglu et al. 2015). SMEs can learn about the innovation that has been adopted and used by their organizational partners with direct or indirect linkages and may be convinced to behave in a similar way (Burt 1982). Normative pressures are associated with the process of giving these accepted norms and values through relational channels among members of their social and business networks (Khalifa and Davison 2006). In particular, business partners' behaviours about new technologies (here BDA) and practices may influence managers' decision to adopt a technology (Liang et al. 2007; Teo et al. 2003). Another normative pressure originates from participation in professional and industry associations (Teo et al. 2003). Especially, participating in associations managed by BDA pioneers and major vendors, such as IBM, SAP, SAS, Alteryx, etc., especially provides SMEs with recent technological innovations and practices, which are significant sources of BDA adoption. Hence, managers as the target audience of these events can learn about big data and find using BDA refreshing. Based on the institutional and organizational change theories, normative pressure is a powerful source of learning that can make managers ready and drive SMEs' needs regarding the adoption of BDA. Therefore:

H3. *Normative pressures are positively associated with organizational readiness for BDA.*

2.5.2. Moderating effects of BDA uncertainty

Uncertainty of new technology can play a significant role in the process of technology adoption in organizations (Chen et al. 2021; Lutfi 2020). BDA uncertainty is a situation in which managers cannot predict the changes associated with big data tools and technologies. Past literature suggests that a higher level of uncertainty may intensify the effect of imitation on organizational behaviour (Sun 2013). Organizations mostly experience uncertainty regarding the performance of applying new tools and practices (March and Olsen 1976). On one hand, organizations should be quick in addressing changes in the environment and keep up with the competitors. They look for imitating other organizations' behaviours to enhance the importance of institutional factors rather than technological characteristics (Meyer 1980). Particularly, in adopting new technology with a high level of uncertainty, SMEs with limited access to resources and skilled employees have difficulties evaluating the quality of the technology. Hence, given the uncertainty in BDA (Bendler et al. 2014), SMEs may find assessing the benefits of big data-related tools and techniques, expensive or complicated. These firms try to decrease the evaluation expenses and more conform to mimetic pressures for applying resources and adopt BDA. As also previously shown in the literature, SMEs perceive higher pressure and conform to other similar organizations applying new promising technology, such as BDA (Gao and Yang 2022). In the context of BDA, SMEs need to use data in the framework of rules and regulations. Coercive pressure supports SMEs to develop resources, such as data connectivity, cloud computing, and technology. SMEs should also follow national or international level policies to obtain these resources for advanced technological applications, such as BDA (Dubey et al. 2019). Particularly, SMEs would rely more on government regulations and policies from industry and professional networks when they have limited amount of knowledge of using advanced technology to become ready for adopting BDA.

BDA uncertainty can also intensify the effect of normative pressures originating from professional and trade associations on SMEs' organizational readiness. When there is a high degree of uncertainty associated with using BDA, the behaviours of SMEs' partners, such as suppliers and customers, have a stronger impact on the allocation of financial and technological resources for BDA adoption. Drawing on institutional theory and the information presented above, it is posited that the actions of other SMEs in uncertain circumstances have a more pronounced influence on the readiness and resource allocation of SMEs when it comes to adopting BDA. Institutional theory suggests that organizations are changed due to their environment and become ready for imitating the behaviours of successful organizations. Therefore, it is logical to expect that in uncertain circumstances, the influence of institutional pressures on organizational readiness could be fortified. Hence:

H1a: *BDA uncertainty positively moderates the association between mimetic pressures and organizational readiness for BDA.*

H2a: *BDA uncertainty positively moderates the association between coercive pressures and organizational readiness for BDA.*

H3a: *BDA uncertainty positively moderates the association between normative pressures and organizational readiness for BDA.*

2.5.3. Organizational readiness for BDA and BDA adoption

Organizational readiness refers to the managing change capabilities of organizations' members, particularly how much they appreciate the determinants of implementing change, such as resource availability (Weiner 2009). Financial, technological, and organizational resources are evaluated for organizational readiness to adopt a technology (Tsai and Tang 2012). When these resources are available, organizational members are more willing to commence changes, such as adopting new technology. For instance, in adopting BDA, the high levels of technical and human resources would be a critical success factor (Sun et al. 2018). Particularly for SMEs, adequate resources are necessary for BDA adoption (Maroufkhani et al. 2019). According to organizational change theory, allocating resources could be a driver for change initiative which expedites the implementation of favorable technology, here BDA. BDA as a new technology in the external environment can trigger change in organizations. Organizational change theory can explain the process of change from different approaches. For instance, Lewin's change management model denotes the step by step stages of unfreezing, changing, and refreezing (Lewin 1947). In the unfreezing step, organizations become ready for implementing change which could be initiated by adopting the change. Thus, SMEs readiness for BDA, can facilitate BDA adoption. Hence it is hypothesized that:

H4. *Organizational readiness for BDA is positively associated with BDA adoption.*

Organizations with a data-driven culture would be more likely to adopt BDA once they are willing to apply resources for BDA implementation. A data-driven culture is "an organizational culture where firms prefer data extracted insights over top management intuition" (McAfee et al. 2012). Previous studies argue that when the culture of decision making in organizations is based on insights that come from data, this culture motivates the organizations to try and use analytical tools (Kiron et al. 2012). Particularly, SMEs with fewer employees generally operate under common practices and values that facilitate regulating culture more easily than large organizations (Hoque 2018). Moreover, SMEs with data-driven culture are constantly learning from data insights and applying them to ameliorate performance and drive innovation. Given that SMEs are willing to innovate to succeed, SMEs can improve their performance and adopt to a change through continuous learning and innovation (Backmann et al. 2015). Furthermore, data driven culture can increase the possibility of adopting BDA for those organizations that are prepared for BDA. Hence:

H4a: *Data-driven culture positively moderates the association between organizational readiness for BDA and BDA adoption.*

2.5.4. Technology characteristics as the antecedents of data analysts' readiness for BDA

Technology characteristics can affect data analysts' readiness in SMEs to use BDA. As described in the theoretical background, the three critical characteristics of using BDA by data analysts are relative advantage, complexity, and trialability. Companies take the relative advantage and the benefits of using new technology into account (Rogers 2003). SMEs and their employees would be more likely to adopt and use an innovation if they perceive the advantage of new technology over the existing one (Hsu et al. 2014). Accordingly, once BDA is perceived as being better than any conventional database management system (DBMS) by data analysts, they may be inclined to try using BDA. Hence, based on the theory of diffusions of innovations and innovations characteristics, data analysts' positive evaluation and perception can provide an incentive for them to be ready and support using BDA in SMEs. Hence:

H5. *BDA relative advantage is positively associated with data analysts' readiness for BDA.*

The chance of using a new technology would decrease if the new technology is relatively complex and hard to understand (Alshamaila et al. 2013b). As the technology is more advanced, employees need to learn more knowledge and skills, which could increase the uncertainty in the usage process (Maroufkhani, Ismail, et al. 2020b). This enhanced uncertainty can make employees reluctant to support using the new technology (Effendi et al. 2020). Recent studies also show that complexity can impede the use of new technology among employees (Pan et al. 2021; Wong et al. 2020). In the context of big data, technological complexity also has a negative impact on BDA adoption (Gangwar 2018). In particular, using BDA by data analysts in companies could be hampered by the complexity of big data methodologies, which need processing large volumes of various types of data in almost real-time. (Loh and Teoh 2021). For SMEs, BDA is possibly challenging to change their processes for further interactions (Alshamaila et al. 2013a). Data analysts in SMEs may not trust BDA since this technology is relatively new to them and hard to understand (Agrawal 2015). Based on DOI theory, if data analysts find BDA a complex tool, they may not support using it in their organizations. Hence:

H6. *BDA complexity is negatively associated with data analysts' readiness for BDA.*

Trialability is one of the key determinant in using a new technology among SMEs (Ramdani and Kawalek 2007). Moreover, trying a new technology among employees can decrease the uncertainty level for early adopters (Rogers 2003). Early adopters, such as SMEs, intend to use innovation when they understand it as effective from the earlier stages (Alshamaila et al. 2013b). Employees in these companies would use the innovation technology if they could try the technology beforehand. In particular, data analysts with the opportunity to try various BDA technologies' functionalities would find using these technologies to be pleasing and, thus, support using them. Data analysts can learn by trying out different BDA uses, which may decrease the uncertainty level of intention to use (Ahmad et al. 2016). Hence, BDA trialability can have a positive influence on the readiness of data analysts for using BDA.

H7. *BDA trialability is positively associated with data analysts' readiness for BDA.*

2.5.5. Moderating effects of data analytics skills

Data analytics skills are knowledge and experiences that improve employees' performance in doing their tasks with the help of analytical applications, such as ad-hoc reports, online analytical processing (OLAP), data mining techniques and programming languages

(Ghasemaghaei 2018). Data analysts who believe BDA improves the quality of work and enhance their job effectiveness with data analytics skills may be more interested in using BDA technologies. Moreover, data analysts with these skills can better understand and use BDA and may perceive BDA to be less complex. Hence, data analytics skills can attenuate the negative effect of BDA complexity on data analysts' readiness for BDA. Moreover, skilled data analysts who have the opportunity to try BDA on a trial basis can better test various BDA functionalities and more quickly check what it could do. Based on the literature, data analytics skills can provide possibility for organizations to improve their performance, particularly for SMEs to innovate (Timothy 2022). Hence the effects of BDA relative advantage and BDA trialability in the presence of data analytics skills in SMEs can be strengthen. Moreover, data analytics skills can increase the knowledge of employees and consequently decrease the uncertainty and the negative effect of BDA complexity in preparing SMEs for BDA adoption. Thus:

H5a: *Data analytics skills positively moderate the association between BDA relative advantage and data analysts' readiness for BDA*.

H6a: *Data analytics skills negatively moderate the association between BDA complexity and data analysts' readiness for BDA.*

H7a: *Data analytics skills positively moderate the association between BDA trialability and data analysts' readiness for BDA.*

2.5.6. Data analysts' readiness for BDA and BDA use

Readiness plays a significant role in the perceptions of employees who intend to use innovative technology (Chiu and Cho 2020). However, most previous studies rely on TAM as the theoretical lens to investigate users' intentions and disregard people's perceptions regarding the technology. Employees who hold a positive perception regarding technology may also intend to use that technology. For instance, data analysts who support using BDA in SMEs would most probably use BDA. Previous studies have shown that individuals' intention to use IT is greatly affected by their readiness for an IT system (Kwahk and Kim 2008; Zolait 2010). As such, based on DOI theory data analysts, who perceive benefits from implementing BDA, may look forward to using big data applications. DOI theory classified individuals into different groups based on their willingness and perceptions to use a new technology (Rogers 2003). In SMEs, data analysts who are familiar with BDA and IT technology are the innovators who would like to use BDA for innovation purposes. Hence:

H8. *Data analysts' readiness for BDA is positively associated with BDA intention to use.*

Analytical thinking style refers to the tendency of data analysts to deliberately analyze the information and spend time scrutinizing the details (Shiloh et al. 2002). Data analysts with analytical thinking styles enjoy learning new methods to solve complex problems requiring a lot of thinking. Data analysts with analytical thinking styles would like intellectual challenges, such as working with new BDA tools and techniques, particularly in SMEs with less or no advanced technological support (Somohano-Rodríguez et al. 2022). As such, data analysts who have an analytical thinking style are motivated to use BDA, especially once they find using BDA to be pleasing.

H8a: *Analytical thinking style positively moderates the association between data analysts' readiness for BDA and BDA intention to use.*

2.6. Summary

In this chapter, a theoretical research model was developed to address the research questions drawing on institutional, organisational change, and diffusion of innovation theories. The model was designed in two parts to measure the significance of institutional pressures and technological characteristics on BDA adoption and use from the perspectives of managers and data analysts. In the following chapter, the methodology applied to investigate the proposed research model is discussed.

3. RESEARCH METHODOLOGY

3.1. Study Design, Context, and Subjects

As the research methodology, a quantitative (deductive) approach (Creswell and Clark 2017) is designed to address the research objectives and test the hypotheses developed in the previous chapter. The advantage of the quantitative method is providing data to draw generalized conclusion over the perceptions, attitudes, and behaviors of a sample through a set of structured questions (Ahmad 2021). Moreover, the empirical results from quantitative analysis of data make it possible to evaluate large sets of data in a short period of time (Sekaran and Bougie 2016). Hence different perspectives and reactions can be quickly integrated to provide a profound understanding of a phenomenon of interest, here BDA implementation among SMEs. To that end, a market research company was hired to send two separate surveys to managers and data analysts (one survey to each group) working in companies with employees fewer than 500 in North America. Participants for this research were invited for a pilot and main study through Dynata (a market research firm). The invitations to participants were sent via email. Participants in the Dynata panel were encouraged to fill out the surveys by providing participants with the ability to accumulate points that can be redeemed later for a prize.

Data collection for this study thus involved two online surveys, one at the organizational level and one at the individual level. For the organizational-level survey, managers who make strategic decisions in SMEs were recruited. For the individual-level survey, data analysts who clean, transform, organize, summarize, and analyze data were invited. The goal was to collect 170 valid responses for managers and 170 valid responses for data analysts to ensure a sufficient number of responses were collected from each group. SMEs used in this study were from different industries including manufacturing, services, finance, communication, etc. As such, the results of the study can be applicable to any SME in North America. Moreover, a small sample size of each group, 30 managers and 30 data analysts, was selected to gather pilot data. Analyzing pilot data helped to revise the questionnaires and measurement items. The surveys were modified based on the feedback from the pilot studies to ensure the clarity of the instructions and questions. More details about the pilot study are provided in the next section. The revised surveys were sent to approximately 3,200 email addresses over a span of two months, resulting in 340 valid responses. The valid and usable responses, including 170 managers and 170 data analysts, were left for further investigation after excluding (1) uninformed responses, (2) incomplete responses, (3) completed surveys in less than 5 minutes; the estimated time to answer the questions was about 15 minutes, and (4) responses who did not answer the attention check question correctly; attention check question was added to find out randomly filled surveys.

3.2. Measurement Instrument

In this research, previously validated instruments were adapted from the literature to ensure content validity. These instruments are applied to measure all the constructs in the proposed research model. The instruments were operationalized using 7-point Likert scales (i.e., 1 = “Strongly disagree” – 7 = “Strongly agree”) in form of online questionnaires created in Qualtrics. The measurement instruments for the managers’ survey are as follows. BDA Adoption was measured using a three-item scale adapted from Hossain et al. (2016) (e.g., “It is critical for our firm to adopt BDA”). The study of Hossain et al. (2016) measured the adoption of a new technology as one stage in the process of technology implementation at the organizational level, hence, making the scales applicable to this thesis. In the Hossain et al. (2016) study, the adoption items achieved composite reliability (CR) score of 0.820 which is at the acceptable level (Campbell and Fiske 1959). The items were modified slightly to reflect the context of BDA. Organizational readiness was measured with three-item scale (e.g., “Our firm is willing or open to applying organizational resources to adopt BDA”) adapted from Tsai and Tang (2012). Mimetic, coercive, and normative pressures were all assessed using Y. Xu et al.'s (2014) four-item scale (e.g., “With regard to our main competitors that have adopted BDA, they have benefited greatly”), four-item scale (e.g., “With regard to our main trading partners (e.g., collaborators, suppliers, customers, etc.) that have adopted BDA, my firm’s well-being depends on their transactions”), and two-item scale (e.g., “My perceptions of BDA usefulness are influenced by the views of other BDA users”) respectively. BDA uncertainty was measured by adapting Pavlou et al.'s (2007) four-item scale (e.g., “We feel that using BDA involves a high degree of uncertainty”). Data-driven culture was assessed using Gupta and George's (2016) five-item scale (e.g., “In our firm, decisions are based on data rather than intuition”). The measurement instruments for the data analysts’ survey are as follows. BDA intention to use was measured using Jaklič et al.'s (2018) three-item scale (e.g., “I would intend to use BDA as a routine part of my job”). Data analysts’ readiness was evaluated using Kwahk and Lee's (2008) seven-item scale (e.g., “I support using BDA”). BDA relative advantage and BDA trialability were assessed by adapting a six-item scale (e.g., “Using BDA improves the quality of work I do”) and a five-item scale (e.g., “I have had a great deal of opportunity to try different BDA functionalities.") respectively developed by Moore and Benbasat (1991). BDA complexity was measured by adapting Morgeson and Humphrey's (2006) four-item scale (e.g., "In using BDA in our firm, we feel that it requires doing different tasks or activities at a time"). The construct of data analytics skills was assessed using Ghasemaghaei et al.'s (2018) three-item scale (e.g., "I possess a high degree of data analytics expertise"). Analytical thinking style was measured by a ten-item scale developed by Pacini and Epstein (1999) (e.g., "I like situations that require thinking in depth about something"). More details of the measurement instruments for both surveys including scale items with sources are presented in Appendix A. A series of control variables were included in the study to control for their potential impact on the endogenous constructs in the proposed research model. According to the literature (Mangla et al. 2020; Nasrollahi et al. 2021), this research controlled for the potential confounding effects of market reach, organization age, revenue, technology level, and IS experience on BDA adoption at the organizational level. For example, Goode and Stevens (2000) suggest that organization age has been identified with direct effect on IT innovation adoption within organizations. Organization revenue and experience of adopting similar technologies have also been considered as control variables due to their potential impact on BDA adoption as highlighted by previous studies (Bai and Cheng 2010; Liang et al. 2007).

In addition, at the individual level for data analyst model, some demographic control variables, such as gender, age, educational level, and experience are considered as control variables. Previous research controlled these variables for their effects on IT usage (Davis and Davis 1990; Gallivan et al. 2005; Harrison and Rainer Jr 1992). These factors can potentially affect managers and data analysts' intention to adopt and use BDA. The results of the effects of controls variables for both models are discussed in Chapter 4.

3.3. Pilot Study

Administering a pilot study is an important step in the research process as lessons learned from the pilot improve the quality of the main study (Boudreau et al. 2001). In quantitative studies, scholars should pre-test or pilot the measurement instrument in a subset of the sample population before finalizing the instrument for the main data collection (Goldin et al. 2011). The main reason of the pilot study in this research was to attest the reliabilities of the measures used in the survey. Moreover, the pilot study was used to refine the measurement instruments and review the clarity of questions in the surveys. This thesis included a pilot study, consisting of a sample of 30 managers and 30 data analysts (i.e., approximately 18% of the estimated sample size of the main study for each group of respondents). Prior to distributing the surveys to the groups of participants for the pilot study, a few scholars, primarily consisting of Ph.D. students and junior faculty members specializing in the field of Information Systems (IS) across different Canadian universities, were requested to review the survey questions and assess their clarity. These scholars did not answer the questions and they just read the questions to see if the questions were clear enough to respond. Their feedback confirmed the clarity of the surveys for both groups of respondents. Then the survey questions were finalized for the pilot study and data collection started. The respondents of the pilot study were recruited by the market research organization. After collecting data for the pilot study, the reliability of the measurement instruments was reviewed by employing Cronbach's alpha. The results showed that in the managers' survey the

Cronbach's alpha of normative pressures was a bit lower than 0.7 which is a general cut-off criterion for a reliability test (Hair 2009). Hence, the scales for this construct were replaced with new ones in the literature. For the data analysts' instruments, all the Cronbach's alpha values are at the acceptable level. In addition, a measurement of discriminant validity for each survey has been done through cross-loading and average variance extracted (AVE) roots. Discriminant validity, as indicated by cross-loading, suggests that the loadings of all scale items should exceed 0.7 and higher than any other constructs items loadings (Joseph et al. 2010). After conducting an analysis of the outer model, some adjustments were made to the online questionnaire, primarily involving the removal of certain items to prevent high correlations between the constructs. Then, the surveys were finalized for main data collection. The pilot study data was kept separate from the main study data and solely used to evaluate the reliability and validity of the measurement scales.

3.4. Main Study

After completing the pilot study and finalizing the measurement instruments, the main stage of the research took place. For the main study, two cross sectional surveys that evaluated BDA adoption and BDA usage and the relationships between their antecedent variables were completed by participants including managers and data analysts of SMEs in North America.

Participants for both pilot and main studies progressed through the surveys as follows.

1. As per McMaster Research Ethics Board (MREB) requirements, approved for this research, before completing both surveys, managers and data analysts were asked to

accept/decline a consent form explaining the purpose and procedure of the study (See Table B1.1 in Appendix B for more details).

2. After accepting the consent form, the respondents were permitted to move forward and answer the questions of the associated online survey.
3. At the very beginning of the online questionnaire, there were two screening questions to check if the respondents are aware of data analytics utilization in their firms and if their jobs involve using data analytics tools.
4. Those respondents who were not aware of data analytics utilization or did not work with data analytics tools were not allowed to continue progressing through the surveys.
5. Then respondents were asked for their roles in their organizations.
6. Next, respondents answered a few questions regarding their familiarities with BDA applications and the dimensions (volume, variety, velocity, veracity) of data they worked with in their organizations.
7. In the next step, participants filled out a questionnaire that included the measures of the dependent, antecedents, and control variables as well as the manipulation check.
8. At the end, respondents were thanked for their participation.

3.5. Model Validation

This research study applied Structural Equation Modelling (SEM) Partial Least Squares (PLS) to validate and test the hypotheses proposed in the research model. The model evaluation in PLS follows two phases. First, the measurement attributes including reliability and convergent/discriminant validity were evaluated. Table 6 illustrates a summary of the tests used to assess the measurement model. Convergent validity for all constructs was evaluated based on item reliability, while discriminant validity was assessed using Average Variance Extracted (AVE). (Fornell 1994). The AVE investigated the Convergent validity for each construct to ensure it goes beyond the variance because of measurement error (Au et al. 2008). The reliability of the reflective constructs was checked by calculating Cronbach's alpha coefficients and composite reliability (Werts et al. 1974). Additionally, to address common method variance, the data from a single source was tested using Harman's single-factor test (Podsakoff et al. 2003). A two-step data analysis was applied to examine the measurement model, and then the proposed hypotheses were tested. The research questions were addressed by validating the models shown in Figure 2 and Figure 3 using SEM techniques. In particular, PLS was used. Finally, the goodness of fit indices was assessed to measure the PLS model and to see how well the model fits the data.

Table 6. Summary of measurement model tests

Analysis	Test	Acceptance criterion	Source
Item reliability	Item loading	Value > 0.50	(Gefen et al. 2000)
Measurement Instruments Reliability	Cronbach's alpha	Value > 0.70	(Nunnally 1967)
	Composite reliability	Value > 0.60	(Bagozzi and Lee 2002)
Discriminant Validity	Fornell-Larcker Criterion	The square root of the AVE of a construct should be larger than the correlation between that construct and any other construct in the model.	(Barclay et al. 1995)
	Item cross-loading	Item loadings on their corresponding construct must be larger than their loadings on any other construct, and the difference should be at least 0.1	(Chin 2010, pp. 655–690)
Convergent validity	Average Variance	Value > 0.50	(Au et al. 2008)

	Extracted (AVE)		
Multicollinearity	Bivariate Correlations	Bivariate correlations greater than 0.8 can indicate traces of multicollinearity	(Meyers et al. 2016)
	VIF	Variance Inflation Factors (VIFs) greater than 3.3 may indicate potential multicollinearity issues	(Petter et al. 2007)

After assessing the appropriateness of the measurement model, the structural model was evaluated to confirm if the proposed research model is supported by the data (Chin 2010). Table 7 shows a summary of the results of evaluating the structural model.

Table 7. Summary of Tests – Structural Model

Analysis	Calculation	Note
Path Coefficients Significance	Obtained from SmartPLS software.	Bootstrap procedure with 500 samples was applied to assess the significance of path coefficients (Chin 1998).
Variance Explained: R^2 for dependent variables	Obtained from SmartPLS software.	No specific acceptable threshold value has been set for R^2, a large enough R^2 values to achieve adequate explanatory power. (Gefen et al. 2000; Urbach and Ahlemann 2010)
Effect Sizes	Obtained from SmartPLS software.	For each path, the magnitude of the effect sizes was assessed following these values: f^2_{small} (.02), f^2_{medium} (.15), and f^2_{large} (.35) (Chin 2010)
Goodness of Fit (GoF) index	Calculated using SmartPLS output as the geometric mean of the average communality index and the average R^2. $GOF = \sqrt{Communality \times R^2}$	Absolute GoF can be applied to evaluate the PLS model in terms of overall (both measurement and structural levels) prediction performance. The suggested baseline values of GoF_{small} (.10), GoF_{medium} (.25), and GoF_{large} (.36) were used to evaluate fit of the model (TENENHAUS 2005, p. 48).

3.6. Post Hoc Analyses

Subsequent to the main analysis of evaluating the structural model, an evaluation of non-hypothesized relationships was performed for both managers and data analysts' models. For instance, in the managers' research model the direct influences of institutional pressures on BDA adoption were evaluated. I considered the possibility that mimetic, coercive, and normative pressures impact BDA adoption in SMEs. To do so, the direct relationships between these pressures and BDA adoption without the presence of mediator were checked. These relationships were positive but nonsignificant. However, with the presence of the mediator, these relationships became significant. Moreover, for data analysts' model, the direct relationships between technology characteristics and BDA usage were examined. I considered the possibility that BDA complexity, BDA trialability, and BDA relative advantage influence BDA usage. As such, the direct relationships between these characteristics and BDA usage without the presents of mediator were investigated. Two relationships including the effects of BDA trialability and BDA relative advantage were positive and significant. However, the direct effect of BDA complexity was negative and nonsignificant. Some other direct relationships between the moderators and the outcome of the models were also checked and more details are presented in chapter 4.

3.7. Summary

In this chapter, the research methodologies applied in the study were explained. In particular, the process of data collection in the pilot and main studies as well as the details of the measurement instrument were discussed. In addition, the procedure for validating the research model was also explained. In the next chapter, performed data analyses and obtained results will be presented and explained.

4. DATA ANALYSIS AND RESULTS

In the previous chapter, the process of collecting and analyzing data was briefly discussed. This chapter explains more details about subjects, data collection and analyzing data. Moreover, the proposed hypotheses were tested by employing structural equation modeling. SEM allowed specifying and testing both the measurement model and the structural model of latent variables (Bollen 1989; Kline 2015). SEM has also shown more effectiveness compared to traditional regression analyses in finding relationships among latent variables (Schreiber et al. 2006). Particularly, for data analysis, SEM- PLS was used due to the relatively small sample size of the research (Hair et al. 2017). To test the hypotheses of the proposed research model, SEM analyses were conducted by using SmartPLS3.2.9. After hypotheses testing, associated results were explained. Before testing the structural model, the quality of the measurements was investigated with a set of preliminary data analyses.

4.1. Data Collection

The subjects of this study were 340 participants (170 managers and 170 data analysts) working in SMEs in North America. Data samples were collected through two cross-sectional online surveys hosted on Qualtrics, one for managers and the other for data analysts. All participants, including managers and data analysts for both surveys in the pilot and main studies were invited by the research company. Participants in the surveys accumulate points that can be redeemed for a prize to incentivize maximum collaboration. The pilot study was carried out and 30 valid responses were collected. After collecting data for the pilot study, a few changes to the measurement scales of the managers' survey were made. In the managers' survey, one scale item of the five items measuring the latent variable "data-driven culture" had a low loading (0.514). As a result, the associated item question was removed from the survey, while the remaining four question items with loadings above 0.7 were retained. After revising the survey, the research company started to send invitation emails to managers and data analysts, and 340 valid responses were collected for both managers and data analysts surveys.

4.2. Data Screening

A set of data screening was conducted after the data collection to make sure that no statistical and methodological issues affect the measurements, analyses, and results of the study. There are five main issues that can negatively affect the quality of measurements and analyses of this study: (i) presence of outliers (e.g., Barnett and Lewis 1994), (ii) low reliability of factors measurements (e.g., Nunally and Bernstein 1978), (iii) low validity of factors (e.g., Straub et al. 2004), (iv) multicollinearity among the factors (e.g., Meyers et al. 2016), and (v) common method bias (e.g., (Straub et al. 2004).

During data collection, survey responses were reviewed and some of them were screened out to find valid responses. The data screening analyses were performed using IBM SPSS Statistics, Version 27, and MS Excel.

In the first step of data screening, participants who were not familiar with data analytics tools or their work did not involve using data analytics tools, or participants that clearly declared their roles not manager or not data analyst, were not allowed to complete the surveys. Screening questions are provided in Appendix D. Next, invalid responses were filtered out from all the responses during the data collection to reach 170 valid responses for each survey. To that end, there was a "quality control" question in each survey. This question (see Appendix D) was integrated in a measurement scale in the middle of the surveys before demographic questions and called "attention check". As such participants were asked to select a specific response (e.g., "Strongly agree") from a Likert scale to indicate they carefully read the questions. Those participants who did not select "Strongly agree" for attention check question were dropped for further analysis. In addition to attention check, some other quality control measures were applied to discard (i) participants took less than 5 minutes to answer all the questions in each survey, and (ii) participants selected the same answer for most of the questions. These participants most probably completed the surveys just for collecting point rewards. Finally, from managers and data analysts' surveys 1107 and 2390 data cases were removed respectively.

4.2.1. Outliers and Missing Values

Finding outliers and missing values was also performed during the data collection process. Outliers are defined as "cases with extreme or unusual values on a single variable (univariate) or on a combination of variables (multivariate)" (Meyers et al. 2016). To find univariate outliers for each construct, composite scores were calculated, and box and whisker plots were provided using IBM SPSS Statistics 27. Overall, 24 unique cases were found as outliers including 7 and 17 cases for managers and data analysts respectively during the process of data collection. These 24 outliers were deleted since no known explanation was available (Meyers et al. 2016). Table 8 illustrates the univariate outliers for each construct in the research models for managers and data analysts.

The box plots of all the outliers found in SPSS were presented in the Appendix D.

Table 8. Univariate Outliers

Model	Construct	Outlier Case IDs	Number of Outliers	Number of new Outliers
Managers	Mimetic Pressures	64	1	0
	Coercive Pressures	None	0	0
	Normative Pressures	None	0	0
	Organizational Readiness	16, 26, 46, 50, 114	5	2
	BDA Adoption	50	1	0
	Data-driven Culture	102	1	0
	BDA Uncertainty	None	0	0
Data Analysts	BDA Relative Advantage	20, 21, 42, 96, 120, 142, 145	7	5
	BDA Complexity	42, 95	2	2
	BDA Trialability	20, 29, 32, 169	4	3
	Data Analysts Readiness	20, 71, 96, 120, 142, 145, 166	7	5
	BDA Usage	None	0	0
	Data Analytics Skills	20, 28, 71	3	0
	Analytical Thinking Style	9, 20, 68, 120, 137, 145	6	5

Moreover, to find multivariate outliers, a Mahalanobis distance analysis was performed. In this analysis, the multivariate distance between each data item and the group multivariate mean (known as centroid) is measured. Mahalanobis distance for each data item was measured and compared with the chi-square distribution (alpha level = 0.001). If Mahalanobis distance of a data item is more than the threshold, the item can be categorized as a multivariate outlier (Meyers et al. 2016). After the analysis, 5 new multivariate outliers were found and removed from the data set. Finally for a few missed data points in some items, the mean value of the item was imputed.

4.3. Demographics

In the surveys, managers and data analysts answered some demographic questions. Tables

9 and 10 demonstrate the demographic information of the final samples used for this research. Most managers are male (73%) between 25-34 (40%) with a 2-year degree educational level (40%) working in companies with the number of employees between 100 to 250 (39%). For data analysts the demographic is similar to managers except the educational level and the size of the companies. Most data analysts had a 4-year degree (45%) and worked in SMEs with 350 to 500 employees (43%). It is logical as most data analysts educated at university and do not usually work in very small companies. The participation in my study was voluntary and a consent form (Appendix B) at the very beginning of the surveys was shown to participants. Participants who agreed to cooperate in data collection (i.e., select "I agree to participate) were allowed to continue filling the surveys after the consent form. All the final participants were familiar with the concept of BDA according to their declarations. There are also some other questions related to control variables, such as industry type and firm revenue. The results of these questions are presented in Tables 9 and 10.

Table 9. Sample characteristics of managers

Dimension	Category	Percentage
Age	18-24	10%
	25-34	40%
	35-44	16%
	45-54	24%
	55-64	10%
Gender	Female	27%
	Male	73%
Education	High school	12%
	Some college	11%
	2-year degree	40%
	4-year degree	29%
	Professional degree	3%
	Doctorate	5%
Firm Size	Fewer than 10	5%

	10-49 50-99 100-249 250-349 350-499	8% 6% 39% 11% 31%
Industry Type	Communication Finance Health care Manufacturing Retail Technology Others	5% 11% 6% 16% 6% 15% 41%
Firm Revenue	Less than 500,000 $ 5K-2.5 million $ 2.5-5 million $ 5-15 million $ 15-20 million $ 20-25 million $ More than 25 million $ No answer	4% 15% 9% 22% 10% 9% 26% 5%

Table 10. Sample characteristics of data analysts

Dimension	Category	Percentage
Age	18-24 25-34 35-44 45-54 55-64	19% 50% 13% 13% 5%
Gender	Female Male	18% 82%
Education	High school Some college 2-year degree 4-year degree Professional degree Doctorate	8% 3% 37% 45% 3% 4%
Firm Size	Fewer than 10 10-49 50-99 100-249 250-349 350-499	1% 3% 8% 24% 21% 43%
Industry Type	IT/Communication Finance	38% 12%

	Health care Manufacturing Retail Others	5% 14% 7% 34%
Firm Revenue	Less than 500,000 \$ 5K-2.5 million \$ 2.5-5 million \$ 5-15 million \$ 15-20 million \$ 20-25 million \$ More than 25 million \$ No answer	2% 7% 9% 17% 23% 10% 22% 10%

4.4. Research Model Validation

In this section, the results of evaluating measurement model, common method bias, the structural model, the model goodness of fit, and effect sizes are presented. To validate the research model, SmartPLS version 3.2.9 is applied.

4.4.1. Measurement Model

Before evaluating the research model, the validity and reliability of each variable were measured employing PLS. Since all the constructs of this research are reflective in nature, the validity and reliability were measured by examining the internal consistency and discriminant validity. In this section, the measurement model is evaluated, and the results are explained. It is worthwhile to mention that all the constructs in this research are reflective and there is no formative construct.

Relying on the PLS approach used by Götz et al. (2009), all the constructs in the research were assessed. First, to investigate the measurement item reliability of the reflective variables, the loading of each item on its intended variable was measured and compared with the recommended tolerance of 0.70 (e.g., Barclay et al., 1995). Any items with the potential loading or cross-loading issues would be removed, in the process of convergent and discriminant validity test. To this end, items were evaluated to check if their loadings on their assigned latent variables are highly more than any other latent variable.

As shown in Table 11, all measurement items loaded at a minimum threshold of 0.70 and most highly on their theoretically assigned variable. It is also argued that "loadings of the measurement items on their assigned latent variables should be an order of magnitude larger than any other loading" and the difference must be at least 0.10 (Gefen and Straub 2005). As can be seen in Tables 12 and 13 this criterion was also met for both managers' and data analysts' data sets.

To examine the variables' internal consistency, the Cronbach's alpha and composite reliability were measured for each construct. As shown in Tables 12 and 13, all variables met the recommended tolerance of being higher than 0.70 for both managers and data analysts' data sets. In these tables, the diagonal numbers are the square root of average variance extracted (AVE) of variables, and the off-diagonal elements show the correlation between them. The findings show the square root of the AVE of a variable is higher than the correlation between that construct and any other variable. This exhibits sufficient discriminant validity in the data.

Table 11. Internal consistency and discriminant validity

Construct	**Reflective Indicator**	**Loadings (>0.7)**	**Cronbach's Alpha (>0.7)**	**AVE (>0.5)**
Mimetic Pressures	Mim1	0.903	0.920	0.806
	Mim2	0.909		
	Mim3	0.880		
	Mim4	0.899		

Coercive Pressures	Coerc1	0.826	0.887	0.748
	Coerc2	0.850		
	Coerc3	0.892		
	Coerc4	0.890		
Normative Pressures	Norm1	0.912	0.798	0.832
	Norm2	0.913		
Organizational Readiness	Org_Ready1	0.907	0.915	0.855
	Org_Ready2	0.935		
	Org_Ready3	0.931		
BDA Uncertainty	Uncertainty1	0.948	0.935	0.803
	Uncertainty2	0.942		
	Uncertainty3	0.837		
	Uncertainty4	0.852		
Data-Driven Culture	Culture1	0.785	0.865	0.650
	Culture2	0.775		
	Culture3	0.810		
	Culture4	0.832		
	Culture5	0.827		
BDA Adoption	Adoption1	0.816	0.864	0.787
	Adoption2	0.927		
	Adoption3	0.915		
Data Analytics Skills	Analytic_Skills1	0.889	0.769	0.812
	Analytic_Skills2	0.913		
BDA Complexity	Complexity1	0.850	0.866	0.707
	Complexity2	0.736		
	Complexity3	0.882		
	Complexity4	0.887		
BDA Trialability	Trialability1	0.844	0.891	0.697
	Trialability2	0.822		
	Trialability3	0.854		
	Trialability4	0.850		
	Trialability5	0.802		
BDA Relative Advantage	Advantage1	0.836	0.825	0.740
	Advantage2	0.872		
	Advantage3	0.873		
Data Analyst Readiness	Readiness1	0.899	0.740	0.793
	Readiness2	0.882		
Thinking Style	Think_Style1	0.878	0.769	0.684
	Think_Style2	0.752		
	Think_Style3	0.846		
BDA Intention to use	Intent_Use1	0.908	0.759	0.806
	Intent_Use2	0.887		

Table 12. Loading and cross loading of measures for manager's model

	BDA Adoption	Coercive Pressures	Data Driven Culture	Mimetic Pressures	Normative Pressures	Organizational Readiness	BDA Uncertainty
Adoption1	**0.816**	0.49	0.512	0.498	0.443	0.531	-0.027
Adoption2	**0.927**	0.54	0.474	0.541	0.538	0.745	0.052
Adoption3	**0.915**	0.512	0.462	0.609	0.539	0.732	0.061
Coerc1	0.497	**0.826**	0.5	0.57	0.548	0.481	0.107
Coerc2	0.483	**0.85**	0.541	0.587	0.515	0.519	0.057
Coerc3	0.505	**0.892**	0.476	0.587	0.58	0.607	0.208
Coerc4	0.52	**0.89**	0.527	0.684	0.631	0.564	0.238
Culture1	0.417	0.445	**0.785**	0.406	0.325	0.401	-0.065
Culture2	0.391	0.439	**0.775**	0.395	0.261	0.357	-0.001
Culture3	0.441	0.412	**0.81**	0.413	0.328	0.367	0.018
Culture4	0.469	0.478	**0.832**	0.425	0.276	0.491	-0.202
Culture5	0.453	0.592	**0.827**	0.516	0.5	0.502	0.047
Mim1	0.552	0.652	0.476	**0.903**	0.635	0.591	0.236
Mim2	0.546	0.633	0.52	**0.909**	0.629	0.595	0.183
Mim3	0.547	0.611	0.478	**0.88**	0.592	0.52	0.123
Mim4	0.584	0.623	0.449	**0.899**	0.589	0.569	0.189
Norm1	0.52	0.613	0.393	0.617	**0.912**	0.561	0.297
Norm2	0.527	0.588	0.376	0.627	**0.913**	0.564	0.224
Org_Ready1	0.727	0.548	0.458	0.562	0.546	**0.908**	0.086
Org_Ready2	0.707	0.651	0.574	0.623	0.597	**0.935**	0.071
Org_Ready3	0.679	0.546	0.427	0.573	0.565	**0.93**	0.039
Uncertainty1	0.059	0.192	-0.069	0.192	0.288	0.075	**0.948**
Uncertainty2	0.03	0.165	-0.012	0.199	0.255	0.072	**0.942**
Uncertainty3	-0.037	0.108	-0.096	0.168	0.229	0.021	**0.837**
Uncertainty4	-0.064	0.065	-0.152	0.103	0.192	0.002	**0.852**

Table 13. Loading and cross loading of measures for data analysts' model

	Analytics Skills	BDA Relative Advantage	BDA Intention to Use	BDA Complexity	Data Analyst Readiness for BDA	Thinking Style	BDA Trialability
Analytic_Skills1	**0.889**	0.500	0.475	0.233	0.576	0.469	0.573
Analytic_Skills2	**0.913**	0.522	0.603	0.320	0.647	0.534	0.686
Advantage1	0.541	**0.836**	0.488	0.298	0.534	0.458	0.556
Advantage2	0.491	**0.872**	0.545	0.204	0.501	0.410	0.458
Advantage3	0.439	**0.873**	0.605	0.253	0.613	0.497	0.525
Intent_Use1	0.598	0.592	**0.908**	0.231	0.613	0.568	0.460

Intent_Use2	0.477	0.551	**0.887**	0.181	0.527	0.542	0.456
Complexity1	0.423	0.315	0.239	**0.850**	0.445	0.426	0.418
Complexity2	0.031	0.115	0.083	**0.736**	0.206	0.150	0.102
Complexity3	0.173	0.200	0.147	**0.882**	0.284	0.270	0.252
Complexity4	0.267	0.286	0.249	**0.887**	0.334	0.297	0.323
Readiness1	0.657	0.602	0.537	0.367	**0.899**	0.558	0.670
Readiness2	0.551	0.541	0.601	0.349	**0.882**	0.557	0.600
Think_Style1	0.551	0.440	0.568	0.330	0.517	**0.878**	0.447
Think_Style2	0.390	0.448	0.437	0.130	0.581	**0.752**	0.393
Think_Style3	0.432	0.441	0.521	0.429	0.474	**0.846**	0.379
Trialability1	0.619	0.476	0.419	0.332	0.609	0.456	**0.844**
Trialability2	0.537	0.532	0.489	0.220	0.592	0.378	**0.822**
Trialability3	0.616	0.542	0.496	0.286	0.611	0.390	**0.854**
Trialability4	0.642	0.532	0.445	0.379	0.610	0.447	**0.850**
Trialability5	0.510	0.408	0.270	0.278	0.558	0.375	**0.802**

Table 14. Internal consistency and discriminant validity for manager's model

Construct	CR	CA	1	2	3	4	5	6	7
1. Mimetic Pressures	0.943	0.922	0.898						
2. Coercive Pressures	0.922	0.887	0.702	0.865					
3. Normative Pressures	0.908	0.789	0.682	0.658	0.912				
4. BDA Uncertainty	0.942	0.935	0.205	0.182	0.286	0.896			
5. Org. Readiness	0.946	0.915	0.635	0.631	0.617	0.071	0.924		
6. BDA Adoption	0.917	0.864	0.620	0.579	0.574	0.036	0.762	0.887	
7. Data-driven culture	0.903	0.868	0.536	0.589	0.421	-0.053	0.529	0.540	0.806

Table 15. Internal consistency and discriminant validity for data analyst's model

Construct	CR	CA	1	2	3	4	5	6	7
1. BDA Relative Advantage	0.895	0.825	0.567						
2. BDA Complexity	0.906	0.866	0.294	0.841					
3. BDA Trialability	0.920	0.891	0.598	0.359	0.835				
4. Data Analytics Skills	0.896	0.769	0.567	0.310	0.702	0.901			
5. Data Analyst Readiness	0.885	0.740	0.643	0.402	0.714	0.680	0.891		
6. BDA Intention to Use	0.764	0.759	0.638	0.231	0.511	0.602	0.637	0898	
7. Analytical Thinking Style	0.866	0.769	0.532	0.368	0.491	0.558	0.626	0.619	0.827

As shown in Tables 14 and 15, some constructs in each part of the research model are highly correlated with each other. In Table 12 for managers, the constructs coercive pressures and normative pressures are highly correlated with mimetic pressures. Additionally, coercive pressures are moderately correlated with normative pressures. These high and moderate correlations among mimetic, coercive, and normative pressures are consistent with the institutional pressure's theory. This theory suggests that mimetic, coercive and normative pressures are related in conforming organizations to appropriate forms (DiMaggio and Powell 1983) and therefore high correlations are expected among them. All the institutional pressures in the analysis were kept to compare their effects on the organizational readiness and BDA adoption. Moreover, organizational readiness and BDA adoption are highly correlated. This high correlation between these two variables may be a result of the measurement instrument used in the data collection process. The measurement scales used to evaluate the constructs are highly related, since the organizational readiness was measured in the context of BDA adoption, there were questions about organizations resources to adopt BDA that are very similar to the questions to assess BDA adoption in organizations including organization's commitments or plans. Hence, this relation could result in high correlation between these constructs in the research model.

In Table 15, for data analysts, there is a high correlation between BDA trialability and data analytics skills and data analyst readiness. This high correlation is expected as most probably data analysts with data analytics skills and readiness would like to try BDA tools and applications and organizations may first ask these types of data analysts to try and test BDA functionalities for further decisions. It is also the case between data analytics skills and data analyst readiness. The high correlation among the other constructs may indicate the complexity of the understudied concept of BDA for SMEs and their employees. Hence, it would be challenging to easily capture the intricacy of each construct with one single measure and consequently the constructs in the research model may be related to each other.

4.4.2. Common Method Bias (CMB)

Common method bias (CMB) is the "potential variance that is attributable to the measurement method rather than to the constructs the measures represent" (Podsakoff et al. 2003). This variance, in the self-report factors, can be a threat to the validity of the results of an empirical study. Hence, after evaluating the reliability and validity of the research constructs, the possibility of CMB was assessed by using two techniques including (i) Full collinearity assessment proposed by Kock (2015) through checking Variance Inflation Factors (VIFs) in the inner model and (ii) adding unmeasured latent -method construct (ULMC) in the model (Liang et al. 2007).

In the first technique, to check the method bias a full collinearity assessment can be used (Kock 2015). As such, VIFs of all paths in the inner (Structural) model are calculated and if the VIFs are less than or equal to 3.3, it is argued that the model can be considered free of common method bias. In table 16 all VIFs of paths for both managers and data analysts' models are depicted. As can be seen there is no VIF more than 3.3, hence no evidence for possible common method bias was found.

Table 16. Common Method Bias – Full Collinearity Assessment

Paths	VIF of Inner (Structural) Model
Mimetic pressures-Organizational readiness	2.683
Coercive pressures-Organizational readiness	2.376
Normative pressures-Organizational readiness	2.533
Organizational readiness for BDA – BDA adoption	1.387
BDA relative advantage-Data Analysts' readiness	2.626
BDA complexity-Data Analysts' readiness	1.229
BDA trialability-Data Analysts' readiness	2.785
Data Analysts' readiness-BDA Use	2.684

In ULMC method, the presence of CMB was also evaluated. This method was used by Liang et al.(2007) and followed in this research. Based on the ULMC technique, three following steps were performed: (1) each measurement item was applied to generate a single-item construct, (2) each original construct in the research models (e.g., mimetic pressures of institutional pressures in the research model for managers) was linked to its associated single-item constructs (e.g., Mim1), and (3) a method construct with all the items was added to each research model, by connecting it to each single-item construct. Then research models were analyzed using SmartPLS 4 and the coefficients of the paths from the substantive (i.e., theoretical) constructs and the method factor to each single-item construct were investigated.

Following Liang et al. (2007), the results are presented as shown in Tables 17 and 18. The squared values of the method factor loadings were interpreted as the method created the percent of indicator variance. While the squared loadings of theoretical or substantive constructs were interpreted as the substantive constructs created the percent of indicator variance. CMS is unlikely a major issue when the method factor loadings are nonsignificant, and the indicators' substantive variance are significantly greater than their method variance. Consequently, as shown in Tables 17 and 18 no track of CMB was identified in the research using the ULMC because (1) no items had a significant method factor loading (at $P<0.05$), while all substantive construct loadings were significant ($p<0.001$), (2) the average substantive variances 0.798 and 0.685 were significantly larger than the average method variances.

Table 17. ULMC Common Method Bias – Managers Model

Construct	Item	Substantive Construct			Method Factor		
		Loading (L1)	Sig.	$(L1)^2$	Loading (L2)	Sig.	$(L2)^2$
Mimetic Pressures	Mim1	0.903	p < 0.001	0.815	0.064	n.s.	0.004
	Mim2	0.909	p < 0.001	0.826	0.001	n.s.	0.000
	Mim3	0.880	p < 0.001	0.744	-0.080	n.s.	0.006
	Mim4	0.898	p < 0.001	0.806	0.076	n.s.	0.005
Coercive Pressures	Coerc1	0.826	p < 0.001	0.682	0.133	n.s.	0.018
	Coerc2	0.849	p < 0.001	0.720	0.048	n.s.	0.002
	Coerc3	0.892	p < 0.001	0.795	0.018	n.s.	0.000
	Coerc4	0.890	p < 0.001	0.792	0.074	n.s.	0.005
Normative Pressures	Norm1	0.912	p < 0.001	0.832	-0.011	n.s.	0.000
	Norm2	0.913	p < 0.001	0.833	0.053	n.s.	0.003
Org. Readiness	Org.Ready1	0.909	p < 0.001	0.826	-0.199	n.s.	0.039
	Org.Ready1	0.934	p < 0.001	0.872	0.009	n.s.	0.000
	Org.Ready1	0.930	p < 0.001	0.865	-0.087	n.s.	0.008
BDA Adoption	Adopt1	0.811	p < 0.001	0.657	0.081	n.s.	0.000
	Adopt2	0.929	p < 0.001	0.863	-0.054	n.s.	0.003
	Adopt3	0.917	p < 0.001	0.841	-0.063	n.s.	0.004
Average		**0.894**		**0.798**	**0.004**		**0.006**

Table 18. ULMC Common Method Bias – Data Analysts Model

Construct	Item	Substantive Construct			Method Factor		
		Loading (L1)	Sig.	$(L1)^2$	Loading (L2)	Sig.	$(L2)^2$
BDA rel. advantage	Adv1	0.809	p < 0.001	0.654	-0.031	n.s.	0.001
	Adv2	0.813	p < 0.001	0.660	-0.015	n.s.	0.000
	Adv3	0.848	p < 0.001	0.719	-0.063	n.s.	0.004
	Adv4	0.875	p < 0.001	0.766	-0.046	n.s.	0.002
	Adv5	0.819	p < 0.001	0.670	0.008	n.s.	0.000
	Adv6	0.863	p < 0.001	0.745	-0.181	n.s.	0.033
BDA Complexity	Complex1	0.852	p < 0.001	0.726	-0.080	n.s.	0.006
	Complex2	0.709	p < 0.001	0.503	0.125	p<0.1	0.016
	Complex3	0.882	p < 0.001	0.778	-0.045	n.s.	0.002
	Complex4	0.897	p < 0.001	0.805	0.009	n.s.	0.000
BDA Trialability	Trial1	0.841	p < 0.001	0.707	0.064	n.s.	0.004
	Trial2	0.823	p < 0.001	0.677	0.074	n.s.	0.005
	Trial3	0.856	p < 0.001	0.732	-0.149	n.s.	0.022
	Trial4	0.851	p < 0.001	0.724	0.021	n.s.	0.000
	Trial5	0.803	p < 0.001	0.645	-0.132	n.s.	0.017
	Readiness1	0.831	p < 0.001	0.690	-0.026	n.s.	0.001
	Readiness2	0.827	p < 0.001	0.684	0.081	n.s.	0.006

Data Analysts Readiness	Readiness3	0.787	$p < 0.001$	0.619	0.032	n.*s*.	0.001
	Readiness4	0.735	$p < 0.001$	0.540	0.014	n.*s*.	0.000
	Readiness5	0.751	$p < 0.001$	0.564	-0.057	n.*s*.	0.003
	Readiness6	0.783	$p < 0.001$	0.613	-0.031	n.*s*.	0.000
	Readiness7	0.836	$p < 0.001$	0.699	0.107	n.*s*.	0.011
BDA Use	Use1	0.871	$p < 0.001$	0.759	0.027	n.*s*.	0.000
	Use1	0.853	$p < 0.001$	0.728	-0.009	n.*s*.	0.000
	Use1	0.850	$p < 0.001$	0.723	-0.158	n.*s*.	0.025
Average		**0.827**		**0.685**	**-0.018**		**0.006**

4.4.3. Structural model

After ensuring the adequacy of the measurement model, SmartPLS version 3.2.9 with bootstrapping employing 1000 re-samples was used to assess the significance levels of the relationships in the research model. For managers, as shown in Figure 4, the results indicated that all institutional pressures significantly influence organizational readiness for BDA, providing sufficient support to H1, H2 and H3. Results also showed that organizational readiness for BDA significantly affects BDA adoption by managers, proving support for H4. In terms of moderators, BDA uncertainty intensifies the relationship between normative pressures and organizational readiness, providing support for H3a. However, BDA uncertainty did not moderate the influence of mimetic and coercive pressures on organizational readiness, which did not support H1a and H2a. Finally, data-driven culture strengthened the relationship between organizational readiness and BDA adoption, providing support for H4a. As shown in Figure 4, the variety of institutional pressures explain about 52% (= R^2) of the variety in organizational readiness for BDA. Likewise, organizational readiness explains about 62% (= R^2) of BDA adoption behaviours among managers.

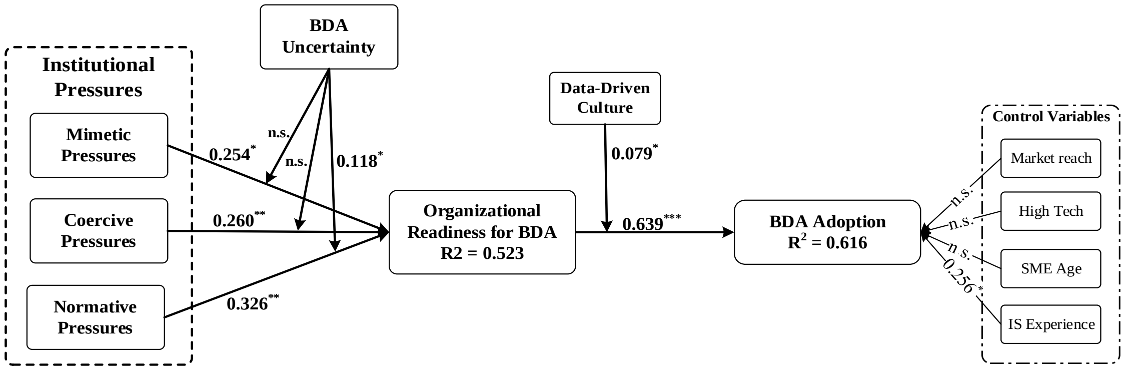


Figure 4. Results of the Managers' Research Model

Notes: *p < 0.05; **p < 0.01; ***p < 0.001

For data analysts, as shown in Figure 5, results indicated that all technology characteristics significantly influence data analysts' readiness for BDA, providing support for H5, H6, and H7. However, interestingly BDA complexity positively affects data analysts' readiness, which is in contrast to the associated hypothesis with suggested negative effects. These results provide sufficient support for H6 and H7. The Results also showed that data analysts' readiness for BDA significantly influences BDA intention to use, providing support for H8. In terms of moderators, data analytics skills weakened the relationship between BDA relative advantage and data analysts' readiness, which did not provide support for H5a.

Additionally, analytical thinking style did not moderate the influence of data analysts' readiness on BDA intention to use, which did not support H8a. As shown in Figure 5, the variety of technology characteristics explain about 65% (= R^2) of the variety in data analysts' readiness for BDA. Likewise, data analysts' readiness explains about 49% (= R^2) of BDA intention to use behaviours among data analysts. As shown in Figures 3 and 4, for both managers and data analysts, control variables do not have significant effects on the models' endogenous variables.

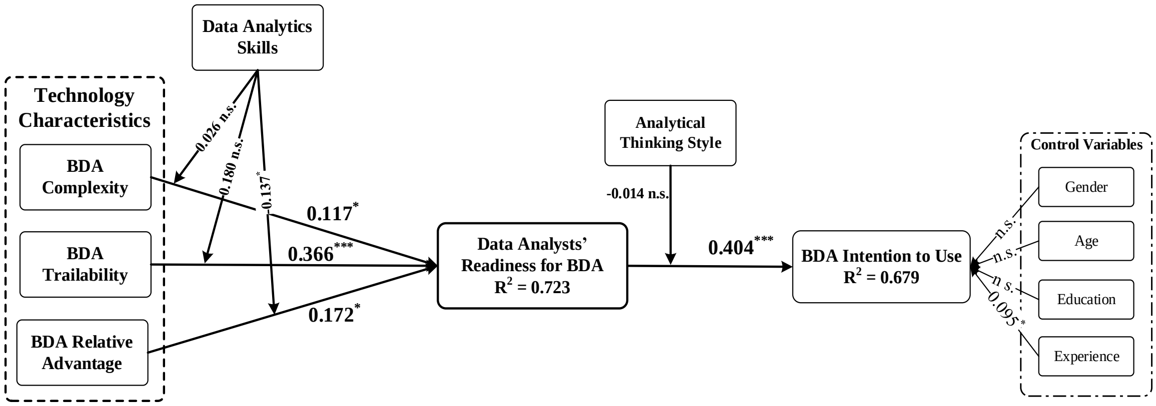


Figure 5. Results of the Data Analysts' Research Model

Notes: *p < 0.05; **p < 0.01; ***p < 0.001

As can be seen in the Table 19, all the hypotheses except the relationship between complexity and readiness are supported. A discussion on the findings is presented in Chapter 5.

Table 19. Validation of the Study Hypotheses

Hypothesis	Path	Path Coefficient	t-Statistic	Sig. Level	Validation Result
H1	Mim-->Readiness	0.254	2.402	0.016	Supported
H2	Coerc-->Readiness	0.260	2.651	0.008	Supported
H3	Norm-->Readiness	0.326	3.022	0.003	Supported
H4	Readiness-->Adop	0.639	10.198	0.000	Supported
H5	Adv-->Readiness	0.172	2.262	0.024	Supported
H6	Complex-->Readiness	0.117	1.325	0.185	Not supported
H7	Trial-->Readiness	0.366	3.707	0.000	Supported
H8	Readiness-->Use	0.404	6.254	0.000	Supported
H1a	BDA uncertainty --> H1	-0.001	0.012	0.990	Non-significant
H2a	BDA uncertainty --> H2	-0.036	0.361	0.718	Non-significant
H3a	BDA uncertainty --> H3	0.118	2.538	0.012	Supported
H5a	Data Analytics Skills --> H5	0.026	0.268	0.789	Non-significant
H6a	Data Analytics Skills --> H6	0.180	1.576	0.115	Non-significant
H7a	Data Analytics Skills --> H7	-0.137	1.942	0.050	Supported

4.4.4. Goodness of Fit of the Model (GoF)

To investigate the quality of structural model, the Goodness of Fit (GoF) index was applied. The GoF index is the “geometric mean of the average communality and average R^2 for all endogenous constructs” (Akter et al. 2011). According to Wetzels et al. (2009) approach, in this research GoF index is calculated as follows:

$$GoF = \sqrt{\frac{\sum_n AVE_n}{n} \times \frac{\sum_m R_m^2}{m}}$$

In the above GoF formula, n is the number of total constructs and m is the number of endogenous constructs. Hence, relying on the GoF formula, for managers and data analysts proposed research models two GoF values are calculated as 0.668 and 0.693 respectively. These values are far exceed suggested threshold of 0.36 (Wetzels et al. 2009) and consequently indicate a good performance of both models.

4.4.5. Analyses of R-squared and effect sizes

After analyzing the strength and significant levels of the hypotheses, the R-Squared (R^2) or the coefficient of determination of the endogenous variables of the research models were measured with SmartPLS 4. R^2 is used to calculate the proportion variation of the dependent variable that is explained by independent variable (s) (Gefen et al. 2000). There is no cutoff value for R^2, however higher values of R-squared show a better fit of the model that can explain more variations in the dependent variable. It is argued that R^2 of all dependent variables should be more than 0.10 (Falk and Miller 1992). Other scholars, such as Chin (1998) and Urbach and Ahlemann (2010) proposed that R^2 values of around 0.670, 0.333, and 0.190 are considered substantial, moderate, and weak. As shown in Figures 3 and 4 all the calculated R^2 are higher than the proposed moderate value of 0.333. Particularly, the R^2 values of the constructs including organizational readiness, data analysts' readiness, BDA adoption and BDA use are 0.523, 0.650, 0.616, and 0.486 respectively.

Effect size (f^2) is calculated to investigate the impact of an antecedent (independent) construct on a dependent construct (Cohen 2013). The thresholds for small, medium, and large f^2 are <= 0.02, 0.15, and 0.35 respectively that indicate different levels of predictor (independent) construct's effect on the dependent construct (Roldán and Sánchez-Franco 2012). To calculate the effect size of each hypothesis, SmartPLS 4 was used, and the findings are shown in Table 20. As can be seen in the table the effect sizes are varied (1 small, 9 medium and 2 large).

Table 20. Effect Sizes Analysis

Dependent Construct	Independent Construct	f^2	Effect Size
BDA Adoption	Data=driven culture	0.086	Medium
	Org. Readiness	0.827	Large
Org. Readiness	BDA Uncertainty	0.037	Medium
	Coercive Pressures	0.057	Medium
	Mimetic Pressures	0.050	Medium
	Normative Pressures	0.092	Medium
BDA Use	Analytical Thinking Style	0.047	Medium
	Data Analysts Readiness	0.486	Large
Data Analyst Readiness	BDA complexity	0.017	Small
	BDA Trialability	0.145	Medium
	BDA Rel. Advantage	0.059	Medium
	Data Analytics Skills	0.120	Medium

4.5. Post-hoc Analyses

Several post-hoc analyses were also conducted to deliver a complete control variable analysis and to examine saturated model analysis including the relevance of non-hypothesized relationships in both managers and data analysts research models.

4.5.1. Control Variables

As discussed before in chapter three, a set of control variables were included in the surveys along with the measurement items in both research models. In manager's model, organizational characteristics, such as organization age, revenue, and IS experience are included to ensure that the observed variances can be assigned to the theoretical constructs of the research.

The potential impact of these variables on the endogenous constructs were investigated to control their effects in the research models. For managers research model, in total 5 control variables were evaluated including: Market reach, High-tech company, organizations' age, revenue, and IS experience. To evaluate the impact of these control variables, each was added to the managers model one at a time. Then each of them was linked to each endogenous construct and the strength and significance of those links were calculated by employing SmartPLS 4. The findings are shown in Table 21 which indicate none of these control variables except IS experience significantly impacted the endogenous construct, organizational readiness for BDA, of the managers model.

Table 21. Results of Control Variable Analysis for Managers Research Model

Control Variable	Endogenous Construct	Path Coefficient	Significance
Market reach (Local = 1 Regional = 2 National = 3 International = 4)	BDA Adoption	-0.088	n.s.
	Organizational Readiness	0.085	n.s.
High tech company (Low Tech = 1 High Tech = 2)	BDA Adoption	-0.050	n.s.
	Organizational Readiness	0.095	n.s.
Organization's Age (Less than 5 years = 1 5-10 years = 2 10+ = 3)	BDA Adoption	0.001	n.s.
	Organizational Readiness	-0.088	n.s.
Revenue (Less than 500K = 1 500K-5M = 2 5M-12.5M = 3 12.5M-25M = 4 More than 25M = 5)	BDA Adoption	-.042	n.s.
	Organizational Readiness	0.134	p <0.05
IS experience (Low IS users = 1 Medium IS users = 2 High IS users = 3)	BDA Adoption	0.073	n.s.
	Organizational Readiness	0.256	p <0.001

Despite the significant impact of revenue and IS experience on organizational readiness for BDA when added to the managers model, none of the hypothesized links in the model changed in terms of either their sign or significance level. Hence, it can be concluded that the control variables did not modify the inferences coming from the hypotheses of the managers' model.

Moreover, for data analysts research model, in total 4 control variables were evaluated including data analyst's gender, age, education, and experience. The same approach was followed for data analysts and the results are shown in Table 22.

Table 22. Results of Control Variable Analysis for Data Analysts Research Model

Control Variable	Endogenous Construct	Path Coefficient	Significance
Data Analysts Gender (Male = 1, Female = 2).	BDA Use	-0.034	n.s.
	Data Analysts' Readiness	0.143	n.s.
Age (Under 18 = 1, 18-24 = 2, 25-34 = 3, 35-44 = 4, 45-54 = 5, 55-64 = 6, 65-74 = 7, 75-84 = 8, 85 or older = 9)	BDA Use	0.085	n.s.
	Data Analysts' Readiness	0.088	n.s.
Education (Less than high school =1 High school graduate = 2 Some college = 3 2-year degree = 4 4-year degree = 5 Professional degree = 6 Doctorate = 7).	BDA Use	-0.050	n.s.
	Data Analysts' Readiness	-0.007	n.s.
Experience (less than one year = 1 1-3 = 2, 3-5 = 3, 5-10 = 4, 10+ = 5).	BDA Use	0.095	$p < 0.05$
	Data Analysts' Readiness	-0.018	n.s.

Table 22 indicates that none of the control variables except "Experience" significantly impacted any of the endogenous constructs of the data analysts' model. Despite the significant impact of experience of data analysts on their BDA use, when added to the data analysts' model, none of the hypothesized links modified in terms of neither their sign nor significance level. Hence, it can be concluded that the control variables did not modify the inferences coming from the hypotheses of the data analysts' model.

4.5.2. Saturated Model Analysis

To investigate any possible non-hypothesized relationships among the variables of the two proposed research models, a saturated model was generated through considering all possible hypotheses among the variables in both originally proposed research models. As such, SmartPLS 4 was applied to perform path analysis and the results are shown in Table 23.

Table 23. PLS Results on Non-Hypothesized Paths-Saturated Model Analysis

Path Number	Non-Hypothesized Path	Path Coefficient	Significance	Validation
1	Mimetic→BDA Adoption	0.129	0.131	Rejected
2	Coercive→BDA Adoption	0.010	0.906	Rejected
3	Normative→BDA Adoption	0.081	0.330	Rejected
4	Data-driven Culture→BDA Adoption	0.167	0.023	Supported
5	BDA Uncertainty→BDA Adoption	-0.020	0.740	Rejected
6	BDA Complexity→BDA Use	-0.096	0.051	Rejected
7	BDA Trialability→BDA Use	-0.222	0.011	Supported
8	BDA Relative Advantage→BDA Use	0.249	0.001	Supported
9	Analytical thinking style→BDA Use	0.163	0.109	Rejected
10	Data Analytics Skills→BDA Use	0.185	0.049	Supported

As illustrated in Table 23, for the managers research model just the direct relationship between data-driven culture and BDA adoption is significant and all other relationships (Paths: 1,2,3, and 5) are insignificant. It is logical to investigate whether paths 1,2, & 3 including the relationships between institutional pressures and BDA adoption are fully mediated by organizational readiness for BDA. Moreover, although there is theoretical justification for the effect of data-driven culture on BDA adoption, in this study the moderating role of data-drive culture is considered to evaluate the effect of organizational readiness on BDA adoption under the existence of data-driven culture. For other significant paths particularly 7 and 8 there is a theoretical justification (Karahanna et al. 1999b). In order to evaluate the possible influences of these paths on the explanatory power of the data analysts research model, changes in the R-squared of the model as a result of adding these non-hypothesized paths were compared across the original model and the saturated model. Table 24 illustrates the R^2 values for the variables before and after adding the non-hypothesized paths. Thus, the changes in R^2 of data analysts' readiness and BDA use are considered small.

Table 24. Changes in R^2 of the data analysts model variables – Saturated Model Analysis

Model	Data Analysts Readiness	BDA Use
Original Model of data analyst study	0.723	0.679
Saturated Model	0.723	0.731
R^2 Changes	.00	0.052

4.6. Summary

This chapter described the procedures and statistical methodologies used to collect, screen, and analyse data from managers and data analysts' surveys and provided an overview of the key findings. Particularly a detailed explanation of the procedures and results of validating the proposed research models were presented. Moreover, post-hoc analyses including a thorough control variables analysis and a saturated model analysis were explained. In the following chapter, the contributions of the findings will be explained.

5. DISCUSSION

In this chapter, the findings presented in chapter 4 are examined in more detail. In section 5.1 the results for each research question are summarized. Section 5.2 describes the contributions of this research in terms of theoretical and practical implications. Moreover, the limitations and future research are presented in Sections 5.3 and 5.4 respectively. Finally, this chapter is summarized in section 5.5.

5.1. Answers to Research Questions

5.1.1. Research Question 1

RQ1: Do institutional pressures affect BDA adoption through SMEs readiness for BDA?

Related Hypotheses:

H1: Mimetic pressures are positively associated with organizational readiness for BDA.

H2: Coercive pressures are positively associated with organizational readiness for BDA.

H3: Normative pressures are positively associated with organizational readiness for BDA.

H4: Organizational readiness for BDA is positively associated with BDA adoption.

According to the findings explained in the previous chapter, mimetic pressures significantly impact organizational readiness for BDA. This relation had a statistically significant beta coefficient of 0.254 ($p\text{-value} < 0.05$). The direction and significance of the path coefficient supported hypothesis H1. Organizational readiness for BDA was also hypothesized as an antecedent of BDA adoption. The results in the previous chapter show organizational readiness significantly impacts BDA adoption. This relation had a statistically significant beta coefficient of 0.639 (p-value < 0.001). The direction and significance of the path coefficient supported H4. The findings also confirm hypotheses H2 and H3 for coercive and normative pressures. According to the institutional and organization change theories, it is logical to expect that institutional pressures can impact BDA adoption in SMEs. As such, managers encountered more institutional pressures more likely decide to adopt BDA for their organizations.

5.1.2. Research Question 2

RQ2: Do technology characteristics affect BDA usage through data analysts' readiness for BDA in SMEs?

Related Hypotheses:

H5: BDA relative advantage is positively associated with data analysts' readiness for BDA.

H6: BDA complexity is negatively associated with data analysts' readiness for BDA.

H7: BDA trialability is positively associated with data analysts' readiness for BDA.

H8: Data analysts' readiness for BDA is positively associated with BDA intention to use.

Based to the results described in the previous chapter, relative advantage significantly impacts data analysts' readiness for BDA. This relation had a statistically significant beta coefficient of 0.172 (p-value < 0.05). The direction and significance of the path coefficient supported hypothesis H5. Data analysts' readiness for BDA was also hypothesized as an antecedent of BDA use. The results in the previous chapter show data analysts readiness significantly impacts BDA use. This relation had a statistically significant beta coefficient of 0.404 (p-value < 0.001). The direction and significance of the path coefficient supported H8. The findings also confirm hypothesis H7 for trialability but not H6 for complexity. According to the diffusion of innovation and organization change theories, it is logical to expect that most technological characteristics can impact BDA use by data analysts in SMEs.

5.2. Contributions

This research investigates the dichotomy of imitation-evaluation in SMEs by asking both managers and data analysts about adopting and using big data analytics tools and technologies at organizational and individual levels. Based on this dichotomy, this research suggests that institutional pressures and technology characteristics can influence organizational and data analysts' readiness and consequently affect the adoption and intention to use BDA in SMEs. Accordingly, it is argued that managers of SMEs imitate the behaviour of other organizations for adopting BDA due to institutional pressures. Still, data analysts evaluate the characteristics of technology when they want to use BDA tools. Then the research considered conditions under which the effects of these factors can be empowered or attenuated. It is suggested that BDA uncertainty, data-driven culture, data analytics skills, and analytical thinking style can moderate the relationships in the research models. This approach is a unique perspective, as the extant studies have mainly investigated the effects of institutional pressures and technology characteristics in separate studies ignoring company and employee-related factors. The positive effects of institutional pressures on organizational readiness for BDA are significant because managers in SMEs imitate the behaviour of other organizations, particularly the actions of professional associations, to exhibit conformity and obtain legitimacy. These findings show the relative importance of technology imitation once SMEs implement BDA. In particular, technology imitation has a relatively significant positive effect on organizational readiness for BDA. Compared to the evaluation perspective, the results indicate a more significant effect of technology imitation on BDA implementation in SMEs.

Moreover, managers are more likely to intend to apply SMEs' resources for adopting BDA when they experience a higher level of uncertainty in using BDA. In uncertain situations associated with using BDA, normative forces from SMEs environment put more pressures on firms to apply resources to adopt BDA than other institutional pressures. This is an interesting finding since previous studies (e.g., Teo et al. 2003) on adopting a new information technology system suggest that the effect of mimetic pressures would be more significant when there is greater uncertainty. This difference may be due to the fact that in SMEs, managers rely more on community or professional associations and groups to adopt a new technology rather than copying the behaviour of their small and medium counterparts with limited experience in using BDA. Some papers also analyzed the effects of institutional pressures on the technology implementation process in SMEs (Agrawal 2015; Lutfi 2020); however, no study has highlighted the influence of firms' characteristics on this process. The present research provides a novel contribution that data-driven culture in SMEs can intensify the effect of SMEs readiness on BDA adoption. SMEs with appropriate resources will adopt BDA if they consider data as a tangible asset.

Following the second aspect of the imitation-evaluation dichotomy, the results demonstrate that technology characteristics can indirectly increase the intention to use BDA among data analysts in SMEs. These characteristics provide the knowledge of the varying effects of each technological feature on data analysts' behaviour. BDA trialability and BDA relative advantage, as hypothesized, positively affect BDA intention to use. Interestingly, BDA complexity has also shown a positive effect on data analysts' intention to use BDA. Previous studies suggested the inhibiting impact of complexity on technology adoption (e.g., Choi et al. 2010). These studies argue that complex technologies require a significant amount of time and effort to lead users to understand technology implementation (Lim 2009). In SMEs with limited organizational and technical resources for implementing BDA tools, complexity was supposed to exacerbate the situation. However, the results show complexity with a positive impact on data analysts' intention to use BDA. One possible explanation is those data analysts who find BDA complex try to apply new approaches to BDA. In SMEs with limited IT experience, when employees encounter a complex tool essential for their work, they are more likely to have an increased intention to learn and utilize it promptly. Contrary in large organizations, employees may avoid using the tool and look for help from IT department which would be well structured. Hence, in SMEs data analysts look forward to using BDA at work when they feel BDA includes performing complicated tasks.

Findings from this research have critical implications for theory and practice that are explained in the following sections.

5.2.1. Contributions to the Theory

The findings extend several theoretical foundations on BDA, imitation-evaluation perspective, and diffusion of innovation theory in the context of technology implementation in SMEs.

First, this study provides an important contextualized model of BDA implementation in SMEs that predicts factors that result in adoption and intention to use. A prominent aspect of the research is that in the context of SMEs, it makes sense to suppose that both managers and data analysts' attitudes and behaviors are at play, and it is required to empirically investigate how technology imitation and evaluation at organizational and individual levels complement each other and where these perspectives differ.

Moreover, the findings extend technology implementation literature by demonstrating the similarity among institutional pressures for managers and technology characteristics for data analysts in SMEs, which can treat forces and characteristics as two separate holistic factors. Present research indicates that all institutional pressures and BDA characteristics are significant to SMEs for BDA adoption and intention to use. The findings show the direct effect of each institutional pressure and BDA characteristic on organizations' and data analysts' readiness for BDA and the indirect effect on BDA adoption and intention to use. For example, under uncertain conditions, normative pressures on SMEs' readiness to adopt BDA will be empowered. This finding is novel and unique since previous studies showed companies would be more affected by mimetic pressures in complex uncertain situations, no matter how big or small.

Furthermore, the results indicate that when research is narrowed down to small-medium-sized companies, technology adoption would comprise different behaviors in uncertain situations. Further studies can evaluate this assertion in uncertain situations for SMEs adopting other technologies.

Moreover, the results highlight the potential of different BDA characteristics to generate various theory-driven impacts in SMEs. In particular, although the positive effect of BDA relative advantage and BDA trialability on BDA intention to use empowers diffusion of innovation theory considerations, the positive effect of BDA complexity on BDA intention to use may require distinct theory building. These results indicate that perhaps in SMEs, BDA complexity makes data analysts ready for using relevant tools and techniques. In SMEs with limited resources, employees have to learn to work with complex technologies mostly by their own efforts, which might be appealing, particularly for those willing to learn (Hamburg 2020, p. 4). These results extend the diffusion of innovation theory in SMEs by indicating that although complexity is mostly considered an impediment for using new technologies, employees in working environments with limited resources may intend to use complex technologies comprised of relatively complicated tasks. The behavior of employees, here data analysts, with higher levels of knowledge and skills in SMEs could be different from typical employees. For example, a data analyst with an analytical thinking style enjoys intellectual challenges in using advanced complex BDA technology when they work in environments with inadequate training, education, and employee development. Here this research makes a step forward towards the perception of BDA characteristics effects on BDA intention to use and call for further analysis to investigate the specific conditions under which complexity of technology has a positive effect on adoption and intention to use. All in all, the results propose an opportunity to study the impact of different technology characteristics in SMEs under various conditions.

The findings also extend the big data literature through theorizing and assessing the role of readiness in BDA adoption and intention to use at two different organizational and individual levels. These perspectives represent a unique integration of institutional and diffusion of innovation theories with organizational change theory in the context of SMEs. These perspectives can resolve the inconsistency in the literature of technology implementation about different perceptions of managers and employees when they both asked in a single study about using new technology. The findings indicate that managers in SMEs evaluate the effects of all institutional pressures significant and positive on BDA adoption.

Moreover, results demonstrate that data analysts working in SMEs consider all BDA technology characteristics important and evaluate their impacts positively on BDA intention to use. This shows that further research should focus not only on the important positive impact of technology characteristics, including complexity but also on the conditions that can influence the impact of these characteristics in SMEs. While most researchers consider the negative effect of complexity on intention to use new technology, the results point out the possible positive impact of complexity on intention to use in SMEs. Hence, researchers should also investigate the conditions or moderators under which the effect of complexity might be reversed. Future research can apply the approach presented in this study to analyze the possible effect of moderators on complexity, such as the characteristics of employees or workplaces.

To sum, the results extend the understanding of institutional pressures and technology characteristics implications from organizational, individual, and information systems perspectives by indicating how institutional pressures and BDA characteristics can affect BDA adoption and intention to use in SMEs.

5.2.2. Implications for Practice

The findings of this research have various significant implications for practitioners who want to use BDA in SMEs. They provide knowledge for adopting and using BDA at both organizational and individual levels. First and foremost, the results show the relative importance of technology imitation in SMEs for implementing BDA. Managers pay significant attention to the behaviours of their counterparts in other corporations when they want to adopt BDA.

Moreover, the effects of institutional pressures are significant on adopting BDA; particularly normative pressures show higher effects under uncertain conditions than mimetic and coercive forces. Hence, it is recommended that product developers, particularly cloud-based application providers, to promote their BDA services in professional associations and affiliated unions for SMEs. In addition, the findings recommend that managers should consider participating in BDA promotion events for SMEs rather than copying the behaviours of their competitors and partners. Particularly, participating in professional networks and associations would decrease the uncertainty of using advanced technology and help managers make decisions. Furthermore, such considerations should also take into account the uncertainties about using BDA or the information managers receive from BDA.

Second, the results regarding the moderating effects assist top management in determining specific BDA strategies according to the culture and different levels of data analytics skills in SMEs. For instance, the research shows that managers or owners may be required to continuously evaluate and improve their business policies based on insights extracted from data. Hence, they can advance data-driven culture, which would speed up the adoption of BDA. Particularly in SMEs with a lack of learning disciplines, it is the responsibility of managers for a radical change coming from using advanced technology. Moreover, IT managers can explain the value of BDA for employees with lower levels of data analytics skills since this group of individuals was found to be more inclined to be ready for using BDA.

The results also indicate that technology characteristics do not have significant effects on BDA implementation in SMEs. Since SMEs mostly use standard off the shelf BDA solutions that do not need advance knowledge and skill sets, data analysts may not consider technology characteristics critical. Therefore, technology consultants can help SMEs to implement standard BDA solutions rather than custom or open-source software.

5.3. Limitations

This research also has some limitations that need to be considered. First, the theoretical discussions might not be generalized to organizations with different institutional and economic conditions. Second, the present research was carried out in North America among managers and data analysts working in small and medium-sized firms with the number of employees fewer than 500. As such, the perceptions of managers and employees about adopting and using BDA could be influenced by economic, cultural, and social factors. Third, similar to every complex system, BDA has unique characteristics that bring unique challenges. Fourth, theories are applied that explain the relationships with causal phrases in both managers' and data analysts' research models; however cross-sectional methodology of the present research does not fully confirm the causality between variables. Fifth, since identifiable information were not collected from respondents, it is impossible to confirm if the respondents were from the same organizations. This is one of the limitations of my research. Sixth, a limited set of organizational and individual behaviors were considered. Seventh, participants in the data collection process might have a limited knowledge and experience of using BDA and developed perceptions and intentions according to heuristics rather than on actual experience. The ninth limitation pertains to the absence of open-ended questions in the surveys, which could have allowed for qualitative analysis. This qualitative analysis could have provided explanations and interpretations to further understand the findings.

Despite the mentioned limitations, this study possesses notable merits that warrant recognition. One strength lies in the robustness of the methodology employed. The research utilized a rigorous approach involving surveys administered to managers and data analysts in SMEs. This methodological rigor enhances the reliability and validity of the study's findings. Additionally, the study's focus on firms in North America provides valuable insights into the perceptions and behaviors related to BDA adoption and use within this specific context. While the generalizability to organizations with different institutional and economic conditions may be limited, the findings offer valuable insights that can inform decision-making and practices within the studied region. Furthermore, the study's application of relevant theories helps to establish a solid theoretical foundation for understanding the relationships and dynamics examined. Despite the cross-sectional nature of the research design, which does not establish causal relationships definitively, the inclusion of theoretical frameworks aids in generating plausible explanations and providing a strong basis for further investigation. Finally, while open-ended questions were not included in the surveys, which is acknowledged as a limitation, the study still offers meaningful findings through the utilized quantitative analysis. Future research could consider incorporating qualitative analysis to provide additional depth and context to the findings. In conclusion, despite the outlined limitations, the study's robust methodology, theoretical foundations, and valuable insights contribute to its merit and make it a valuable contribution to the field of BDA research.

5.4. Future Research

The above-mentioned limitations imply multiple opportunities to do further research. First future research should explore any effect of institutional and economic differences. For instance, organizational readiness can be influenced by factors other than institutional pressures, such as policies and procedures, professional growth and training, and organizational resources and structure. Second, the impact of other external and internal factors on organizational readiness warrants future studies. Third. future studies need to be conducted in a similar manner to economically, culturally, or socially different geographical areas. Fourth, future studies can be extended for an extensive understanding of the adoption and use of complex systems. Fifth, a longitudinal study as an additional confirmation for causal relationships is required. Sixth, future research can compare the attitudes and behaviors of managers and data analysts from the same organizations particularly by adopting a qualitative methodology. The findings of such an approach can develop valuable understanding about the adoption and usage of BDA in SMEs. Seventh, the research models in this dissertation focused on a limited set of antecedents and outcomes of organizational and individual behaviors. Future research may consider more antecedents and outcomes. For instance, continued use of BDA can be considered by extending the research models developed in this dissertation. Lastly, for future research, there is potential for conducting qualitative research such as case studies or employing mixed methods approaches. These approaches would offer a deeper understanding of BDA adoption and use and provide enhanced insights into the factors that influence the adoption and usage of BDA tools.

5.5. Conclusion

This research challenges the assumption of technology imitation-evaluation among managers and data analysts in SMEs. It is proposed that managers are influenced by institutional pressures when they want to adopt BDA at the organizational level. Moreover, at the individual level, it is assumed that technology characteristics can affect data analysts' intention to use BDA. The research utilizes institutional, organizational change, and DOI theories to explore the effects of institutional pressures and technology characteristics on BDA adoption and intention to use. The findings suggest that all institutional pressures have positive effects on organizational readiness for BDA. However, from technology evaluation perspective data analysts did not identify significant effects for all technology characteristics. Hence, the effect of technology imitation is more significant than technology evaluation for SMEs to adopt and use BDA. This research also highlights the importance of BDA uncertainty in facilitating BDA adoption by complying with normative pressures. It confirms that BDA trialability and BDA complexity positively affect data analysts' readiness for BDA. One of the interesting contributions of the present study is that it demonstrates how the influence of BDA relative advantage on data analysts' readiness varies when data analysts have different levels of data analytics skills.

REFERENCES

Abdollahzadegan, A., Hussin, C., Razak, A., Moshfegh Gohary, M., and Amini, M. 2013. "The Organizational Critical Success Factors for Adopting Cloud Computing in SMEs," *Journal of Information Systems Research and Innovation (JISRI)* (4:1), pp. 67–74.

ABDULAZIZ, N. A., SENIK, R., YAU, F. S., SAN, O. T., and ATTAN, H. 2017. "Influence of Institutional Pressures on the Adoption of Green Initiatives.," *International Journal of Economics & Management* (11).

Abed, S. S. 2020. "Social Commerce Adoption Using TOE Framework: An Empirical Investigation of Saudi Arabian SMEs," *International Journal of Information Management* (53), Elsevier, p. 102118.

Agrawal, K. 2015. *Investigating the Determinants of Big Data Analytics (BDA) Adoption in Asian Emerging Economies*, Citeseer.

Ahmad, A., Ahmad, R., and Hashim, K. F. 2016. "Innovation Traits for Business Intelligence Successful Deployment," *Journal of Theoretical and Applied Information Technology* (89:1), Journal of Theoretical and Applied Information, p. 96.

Ahmad, N. L. 2021. "Exploring Factors That Influence the Use and Acceptanceof Virtual Learning Environment OnTeaching and Learning Accounting," *Turkish Journal of Computer and Mathematics Education (TURCOMAT)* (12:3), pp. 476–488.

Akingbade, W. A. 2021. "COVID-19 Pandemic Challenges to Micro, Small and Medium Enterprises in Nigeria: Strategic Options for Survival," *Acta Economica* (19:34), pp. 153–167.

Akpan, I. J., Udoh, E. A. P., and Adebisi, B. 2022. "Small Business Awareness and Adoption of State-of-the-Art Technologies in Emerging and Developing Markets, and Lessons from the COVID-19 Pandemic," *Journal of Small Business & Entrepreneurship* (34:2), Taylor & Francis, pp. 123–140.

Akter, S., D'ambra, J., and Ray, P. 2011. *An Evaluation of PLS Based Complex Models: The Roles of Power Analysis, Predictive Relevance and GoF Index*.

Al Mamun, A. 2018. "Diffusion of Innovation among Malaysian Manufacturing SMEs," *European Journal of Innovation Management*, Emerald Publishing Limited.

Alalawneh, A. A., and Alkhatib, S. F. 2021. "The Barriers to Big Data Adoption in Developing Economies," *The Electronic Journal of Information Systems in Developing Countries* (87:1), Wiley Online Library, p. e12151.

Alam, S. S., and Islam, K. Z. 2021. "Examining Adoption of Electronic Human Resource Management from the Perspective of Technology Organization Environment Framework," *IEEE Engineering Management Review*, IEEE.

Ali, R. H. R. M., Mohamad, R., and Sudin, S. 2016. "A Proposed Framework of Big Data Readiness in Public Sectors," in *AIP Conference Proceedings* (Vol. 1761), AIP Publishing LLC, p. 020089.

Alsadi, A. K., Alaskar, T. H., and Mezghani, K. 2021. "Adoption of Big Data Analytics in Supply Chain Management: Combining Organizational Factors With Supply Chain Connectivity," *International Journal of Information Systems and Supply Chain Management (IJISSCM)* (14:2), IGI Global, pp. 88–107.

Alshamaila, Y., Papagiannidis, S., and Li, F. 2013a. "Cloud Computing Adoption by SMEs in the North East of England," *Journal of Enterprise Information Management*.

Alshamaila, Y., Papagiannidis, S., and Li, F. 2013b. "Cloud Computing Adoption by SMEs in the North East of England: A Multi-Perspective Framework," *Journal of Enterprise Information Management*, Emerald Group Publishing Limited.

Alshirah, M., Lutfi, A., Alshirah, A., Saad, M., Ibrahim, N., and Mohammed, F. 2021. "Influences of the Environmental Factors on the Intention to Adopt Cloud Based Accounting Information System among SMEs in Jordan," *Accounting* (7:3), pp. 645–654.

Armenakis, A. A., Harris, S. G., and Mossholder, K. W. 1993. "Creating Readiness for Organizational Change," *Human Relations* (46:6), pp. 681–703.

Au, N., Ngai, E. W., and Cheng, T. E. 2008. "Extending the Understanding of End User Information Systems Satisfaction Formation: An Equitable Needs Fulfillment Model Approach," *MIS Quarterly*, pp. 43–66.

Awa, H. O., Ojiabo, O. U., and Orokor, L. E. 2017. "Integrated Technology-Organization-Environment (TOE) Taxonomies for Technology Adoption," *Journal of Enterprise Information Management*, Emerald Publishing Limited.

Ayong, K. T., and Naidoo, R. 2019. "Modeling the Adoption of Cloud Computing to Assess South African SMEs: An Integrated Perspective," *Kalpa Publications in Computing* (12), EasyChair, pp. 43–56.

Backmann, J., Hoegl, M., and Cordery, J. L. 2015. "Soaking It up: Absorptive Capacity in Interorganizational New Product Development Teams," *Journal of Product Innovation Management* (32:6), Wiley Online Library, pp. 861–877.

Bagozzi, R. P., and Lee, K.-H. 2002. "Multiple Routes for Social Influence: The Role of Compliance, Internalization, and Social Identity," *Social Psychology Quarterly*, JSTOR, pp. 226–247.

Bai, H., and Cheng, J. 2010. "The Impact of Organizational Culture on ERP Assimilation: The Mediating Role of User Participation," in *2010 2nd International Workshop on Database Technology and Applications*, IEEE, pp. 1–5.

Barclay, D., Higgins, C., and Thompson, R. 1995. *The Partial Least Squares (PLS) Approach to Casual Modeling: Personal Computer Adoption Ans Use as an Illustration*.

Barnett, V., and Lewis, T. 1994. *Outliers in Statistical Data*, (Vol. 3), Wiley New York.

Basaglia, S., Caporarello, L., Magni, M., and Pennarola, F. 2009. "Environmental and Organizational Drivers Influencing the Adoption of VoIP," *Information Systems and E-Business Management* (7:1), pp. 103–118. (https://doi.org/10.1007/s10257-008-0077-1).

Bendler, J., Wagner, S., Brandt, T., and Neumann, D. 2014. "Taming Uncertainty in Big Data," *Business & Information Systems Engineering* (6:5), Springer, pp. 279–288.

Berrone, P., Fosfuri, A., Gelabert, L., and Gomez-Mejia, L. R. 2013. "Necessity as the Mother of 'Green'Inventions: Institutional Pressures and Environmental Innovations," *Strategic Management Journal* (34:8), Wiley Online Library, pp. 891–909.

Bharati, P., and Chaudhury, A. 2011. *Impact of Institutional Pressures on Absorptive Capacity of a Firm and Web 2.0 Assimilation*, p. 15.

Bharati, P., Zhang, C., and Chaudhury, A. 2014. "Social Media Assimilation in Firms: Investigating the Roles of Absorptive Capacity and Institutional Pressures," *Information Systems Frontiers* (16:2), pp. 257–272. (https://doi.org/10.1007/s10796-013-9433-x).

Bianchini, M., and Michalkova, V. 2019. *Data Analytics in SMEs*.

Bollen, K. A. 1989. *Structural Equations with Latent Variables*, (Vol. 210), John Wiley & Sons.

Bouckenooghe, D., Devos, G., and Van den Broeck, H. 2009. "Organizational Change Questionnaire–Climate of Change, Processes, and Readiness: Development of a New Instrument," *The Journal of Psychology* (143:6), pp. 559–599.

Boudreau, M.-C., Gefen, D., and Straub, D. W. 2001. "Validation in Information Systems Research: A State-of-the-Art Assessment," *MIS Quarterly*, JSTOR, pp. 1–16.

Brik, A. B., and Pal, L. A. 2021. "Introduction: Futures, Now and Then," in *The Future of the Policy Sciences*, Edward Elgar Publishing.

Brynjolfsson, E., and McElheran, K. 2016. "The Rapid Adoption of Data-Driven Decision-Making," *American Economic Review* (106:5), pp. 133–39.

Burt, R. S. 1982. *Toward a Structural Theory of Action: Network Models of Social Structure, Perception, and Action.*

Campbell, D. T., and Fiske, D. W. 1959. "Convergent and Discriminant Validation by the Multitrait-Multimethod Matrix.," *Psychological Bulletin* (56:2), American Psychological Association, p. 81.

Cavusoglu, Huseyin, Cavusoglu, Hasan, Son, J.-Y., and Benbasat, I. 2015. "Institutional Pressures in Security Management: Direct and Indirect Influences on Organizational Investment in Information Security Control Resources," *Information & Management* (52:4), pp. 385–400.

Chatterjee, S., Chaudhuri, R., Shah, M., and Maheshwari, P. 2022. “Big Data Driven Innovation for Sustaining SME Supply Chain Operation in Post COVID-19 Scenario: Moderating Role of SME Technology Leadership,” *Computers & Industrial Engineering* (168), Elsevier, p. 108058.

Chen, X., Li, Y., Davison, R. M., and Liu, Y. 2021. “The Impact of Imitation on Chinese Social Commerce Buyers’ Purchase Behavior: The Moderating Role of Uncertainty,” *International Journal of Information Management* (56), Elsevier, p. 102262.

Chin, W. W. 1998. “The Partial Least Squares Approach to Structural Equation Modeling,” *Modern Methods for Business Research* (295:2), Mahwah, NJ, pp. 295–336.

Chin, W. W. 2010. *How to Write up and Report PLS Analyses. In ‘Handbook of Partial Least Squares’.(Eds VV Esposito, WW Chin, J Henseler and H Wang) Pp. 655–690*, Springer: Heidelberg, Berlin.

Chiu, W., and Cho, H. 2020. “The Role of Technology Readiness in Individuals’ Intention to Use Health and Fitness Applications: A Comparison between Users and Non-Users,” *Asia Pacific Journal of Marketing and Logistics*, Emerald Publishing Limited.

Choi, J., Nazareth, D. L., and Jain, H. K. 2010. “Implementing Service-Oriented Architecture in Organizations,” *Journal of Management Information Systems* (26:4), Taylor & Francis, pp. 253–286.

Chu, Z., Xu, J., Lai, F., and Collins, B. J. 2018. “Institutional Theory and Environmental Pressures: The Moderating Effect of Market Uncertainty on Innovation and Firm Performance,” *IEEE Transactions on Engineering Management* (65:3), IEEE, pp. 392–403.

Chuah, M.-H., and Thurusamry, R. 2022. “The Relationship between Architecture, Social, Law and Market in Determine Challenges of Big Data Analysis for Malaysia SMEs,” *Cogent Business & Management* (9:1), Taylor & Francis, p. 2021835.

Cohen, J. 2013. *Statistical Power Analysis for the Behavioral Sciences*, Academic press.

Cooper, R. B., and Zmud, R. W. 1990. “Information Technology Implementation Research: A Technological Diffusion Approach,” *Management Science* (36:2), pp. 123–139.

Creswell, J. W., and Clark, V. L. P. 2017. *Designing and Conducting Mixed Methods Research*, Sage publications.

Damanpour, F., and Schneider, M. 2006. “Phases of the Adoption of Innovation in Organizations: Effects of Environment, Organization and Top Managers,” *British Journal of Management* (17:3), pp. 215–236.

Davis, D. L., and Davis, D. F. 1990. “The Effect of Training Techniques and Personal Characteristics on Training End Users of Information Systems,” *Journal of Management Information Systems* (7:2), Taylor & Francis, pp. 93–110.

Davis, F. D. 1989. "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," *MIS Quarterly*, pp. 319–340.

DiMaggio, P. J., and Powell, W. W. 1983. "The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields," *American Sociological Review* (48:2), pp. 147–160. (https://doi.org/10.2307/2095101).

Draganidis, F., and Mentzas, G. 2006. "Competency Based Management: A Review of Systems and Approaches," *Information Management & Computer Security* (14:1), pp. 51–64.

Drnevich, P., Marino, L., and Withers, M. 2011. "Technological Drivers of Innovation," in *Babson College Entrepreneurship Research Conference*.

Dubey, R., Gunasekaran, A., Childe, S. J., Blome, C., and Papadopoulos, T. 2019. "Big Data and Predictive Analytics and Manufacturing Performance: Integrating Institutional Theory, Resource-Based View and Big Data Culture," *British Journal of Management* (30:2), Wiley Online Library, pp. 341–361.

Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Giannakis, M., Foropon, C., Roubaud, D., and Hazen, B. T. 2020. "Big Data Analytics and Artificial Intelligence Pathway to Operational Performance under the Effects of Entrepreneurial Orientation and Environmental Dynamism: A Study of Manufacturing Organisations," *International Journal of Production Economics* (226), Elsevier, p. 107599.

Duckworth, R. 2014. *Examining Relationships between Perceived Characteristics of Innovation and Adoption Intentions of Small and Medium Enterprises*, Northcentral University.

Effendi, M. I., Sugandini, D., and Istanto, Y. 2020. "Social Media Adoption in SMEs Impacted by COVID-19: The TOE Model," *The Journal of Asian Finance, Economics, and Business* (7:11), Korea Distribution Science Association, pp. 915–925.

El-Haddadeh, R., Osmani, M., Hindi, N., and Fadlalla, A. 2021. "Value Creation for Realising the Sustainable Development Goals: Fostering Organisational Adoption of Big Data Analytics," *Journal of Business Research* (131), Elsevier, pp. 402–410.

Fahmideh, M., Daneshgar, F., Rabhi, F., and Beydoun, G. 2019. "A Generic Cloud Migration Process Model," *European Journal of Information Systems* (28:3), Taylor & Francis, pp. 233–255.

Falk, R. F., and Miller, N. B. 1992. *A Primer for Soft Modeling.*, University of Akron Press.

Felin, T., Kauffman, S., Koppl, R., and Longo, G. 2014. "Economic Opportunity and Evolution: Beyond Landscapes and Bounded Rationality," *Strategic Entrepreneurship Journal* (8:4), Wiley Online Library, pp. 269–282.

Fishbein, M., and Ajzen, I. 1977. *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research*.

Fisher, D., DeLine, R., Czerwinski, M., and Drucker, S. 2012. “Interactions with Big Data Analytics,” *Interactions* (19:3), ACM New York, NY, USA, pp. 50–59.

Fornell, C. 1994. “Partial Least Squares,” *Advanced Methods of Marketing Research*.

Gallivan, M. J., Spitler, V. K., and Koufaris, M. 2005. “Does Information Technology Training Really Matter? A Social Information Processing Analysis of Coworkers’ Influence on IT Usage in the Workplace,” *Journal of Management Information Systems* (22:1), Taylor & Francis, pp. 153–192.

Gangwar, H. 2018. “Understanding the Determinants of Big Data Adoption in India: An Analysis of the Manufacturing and Services Sectors,” *Information Resources Management Journal (IRMJ)* (31:4), IGI Global, pp. 1–22.

Gao, L., and Yang, F. 2022. “Do Resource Slack and Green Organizational Climate Moderate the Relationships between Institutional Pressures and Corporate Environmental Responsibility Practices of SMEs in China?,” *Environment, Development and Sustainability*, Springer, pp. 1–26.

Gefen, D., and Straub, D. 2005. “A Practical Guide to Factorial Validity Using PLS-Graph: Tutorial and Annotated Example,” *Communications of the Association for Information Systems* (16:1), p. 5.

Gefen, D., Straub, D., and Boudreau, M.-C. 2000. *Structural Equation Modeling and Regression: Guidelines for Research Practice*, (4), p. 78.

Ghasemaghaei, M. 2018. “Improving Organizational Performance Through the Use of Big Data,” *Journal of Computer Information Systems*, pp. 1–14.

Ghasemaghaei, M., Ebrahimi, S., and Hassanein, K. 2018. “Data Analytics Competency for Improving Firm Decision Making Performance,” *The Journal of Strategic Information Systems* (27:1), pp. 101–113.

Goes, P. B. 2014. “Editor’s Comments: Big Data and IS Research,” *Mis Quarterly* (38:3), pp. iii–viii.

Goldin, A. B., LaRiviere, C., Arca, M. J., Cassidy, L., Abdullah, F., Lee, S. L., Islam, S., Huang, E. Y., Downard, C. D., and Cowles, R. A. 2011. “Guidelines for Surveys of the American Pediatric Surgical Association,” *Journal of Pediatric Surgery* (46:10), Elsevier, pp. 2012–2017.

Goode, S., and Stevens, K. 2000. “An Analysis of the Business Characteristics of Adopters and Non-Adopters of World Wide Web Technology,” *Information Technology and Management* (1), Springer, pp. 129–154.

Götz, O., Liehr-Gobbers, K., and Krafft, M. 2009. “Evaluation of Structural Equation Models Using the Partial Least Squares (PLS) Approach,” in *Handbook of Partial Least Squares: Concepts, Methods and Applications*, Springer, pp. 691–711.

Gu, V. C., Cao, Q., and Duan, W. 2012. “Unified Modeling Language (UML) IT Adoption—A Holistic Model of Organizational Capabilities Perspective,” *Decision Support Systems* (54:1), Elsevier, pp. 257–269.

Gupta, M., and George, J. F. 2016. "Toward the Development of a Big Data Analytics Capability," *Information & Management* (53:8), pp. 1049–1064.

Hair, J. F. 2009. *Multivariate Data Analysis*.

Hair, J., Hollingsworth, C. L., Randolph, A. B., and Chong, A. Y. L. 2017. "An Updated and Expanded Assessment of PLS-SEM in Information Systems Research," *Industrial Management & Data Systems*, Emerald Publishing Limited.

Hamburg, I. 2020. "Facilitating Lifelong Learning in SMEs towards SDG4," *Advances in Social Sciences Research Journal* (7:9), pp. 262–272.

Hao, J., Shi, H., Shi, V., and Yang, C. 2020. "Adoption of Automatic Warehousing Systems in Logistics Firms: A Technology–Organization–Environment Framework," *Sustainability* (12:12), Multidisciplinary Digital Publishing Institute, p. 5185.

Hariri, R. H., Fredericks, E. M., and Bowers, K. M. 2019. "Uncertainty in Big Data Analytics: Survey, Opportunities, and Challenges," *Journal of Big Data* (6:1), SpringerOpen, pp. 1–16.

Harrison, A. W., and Rainer Jr, R. K. 1992. "The Influence of Individual Differences on Skill in End-User Computing," *Journal of Management Information Systems* (9:1), Taylor & Francis, pp. 93–111.

Haveman, H. A. 1993. "Follow the Leader: Mimetic Isomorphism and Entry Into New Markets," *Administrative Science Quarterly* (38:4), pp. 593–627. (https://doi.org/10.2307/2393338).

Heydari, M., Mylonas, A., Tafreshi, V. H. F., Benkhelifa, E., and Singh, S. 2020. "Known Unknowns: Indeterminacy in Authentication in IoT," *Future Generation Computer Systems* (111), Elsevier, pp. 278–287.

Hoque, A. 2018. "The Effect of Entrepreneurial Orientation on Bangladeshi SME Performance: Role of Organizational Culture," *International Journal of Data and Network Science* (2:1), pp. 1–14.

Hossain, M., Quaddus, M., and Islam, N. 2016. "Developing and Validating a Model Explaining the Assimilation Process of RFID: An Empirical Study," *Information Systems Frontiers* (18:4), pp. 645–663. (https://doi.org/10.1007/s10796-014-9537-y).

Hsu, P.-F., Ray, S., and Li-Hsieh, Y.-Y. 2014. "Examining Cloud Computing Adoption Intention, Pricing Mechanism, and Deployment Model," *International Journal of Information Management* (34:4), Elsevier, pp. 474–488.

Ijab, M. T., Wahab, S. M. A., Salleh, M. A. M., and Bakar, A. A. 2019. "Investigating Big Data Analytics Readiness in Higher Education Using the Technology-Organisation-Environment (TOE) Framework," in *2019 6th International Conference on Research and Innovation in Information Systems (ICRIIS)*, IEEE, pp. 1–7.

Iqbal, M., Kazmi, S. H. A., Manzoor, A., Soomrani, A. R., Butt, S. H., and Shaikh, K. A. 2018. "A Study of Big Data for Business Growth in SMEs: Opportunities & Challenges," in *2018 International*

Conference on Computing, Mathematics and Engineering Technologies (ICoMET), IEEE, pp. 1–7.

Jacobs, G., Van Witteloostuijn, A., and Christe-Zeyse, J. 2013. “A Theoretical Framework of Organizational Change,” *Journal of Organizational Change Management*, Emerald Group Publishing Limited.

Jaklič, J., Grublješič, T., and Popovič, A. 2018. “The Role of Compatibility in Predicting Business Intelligence and Analytics Use Intentions,” *International Journal of Information Management* (43), pp. 305–318.

Jalaludin, D., Sulaiman, M., and Ahmad, N. N. N. 2011. “Understanding Environmental Management Accounting (EMA) Adoption: A New Institutional Sociology Perspective,” *Social Responsibility Journal*, Emerald Group Publishing Limited.

Joseph, F., Barry, J. B., Rolph, E. Ander, and Rolph, E. Anderson. 2010. *Multivariate Data Analysis*, Pearson Prentice Hall.

Kabanda, S., and Brown, I. 2017. “A Structuration Analysis of Small and Medium Enterprise (SME) Adoption of E-Commerce: The Case of Tanzania,” *Telematics and Informatics* (34:4), pp. 118–132.

Karahanna, E., Straub, D. W., and Chervany, N. L. 1999a. “Information Technology Adoption across Time: A Cross-Sectional Comparison of Pre-Adoption and Post-Adoption Beliefs,” *MIS Quarterly*, pp. 183–213.

Karahanna, E., Straub, D. W., and Chervany, N. L. 1999b. “Information Technology Adoption across Time: A Cross-Sectional Comparison of Pre-Adoption and Post-Adoption Beliefs,” *MIS Quarterly*, JSTOR, pp. 183–213.

Ke, W., Liu, H., Wei, K. K., Gu, J., and Chen, H. 2009. “How Do Mediated and Non-Mediated Power Affect Electronic Supply Chain Management System Adoption? The Mediating Effects of Trust and Institutional Pressures,” *Decision Support Systems* (46:4), pp. 839–851. (https://doi.org/10.1016/j.dss.2008.11.008).

Khalifa, M., and Davison, M. 2006. “SME Adoption of IT: The Case of Electronic Trading Systems,” *IEEE Transactions on Engineering Management* (53:2), pp. 275–284.

Kiron, D., Prentice, P. K., and Ferguson, R. B. 2012. “Innovating with Analytics,” *MIT Sloan Management Review* (54:1), Massachusetts Institute of Technology, Cambridge, MA, p. 47.

Kline, R. B. 2015. *Principles and Practice of Structural Equation Modeling*, Guilford publications.

Kock, N. 2015. “Common Method Bias in PLS-SEM: A Full Collinearity Assessment Approach,” *International Journal of E-Collaboration (Ijec)* (11:4), IGI Global, pp. 1–10.

Kwahk, K.-Y., and Kim, H.-W. 2008. “Managing Readiness in Enterprise Systems-Driven Organizational Change,” *Behaviour & Information Technology* (27:1), Taylor & Francis, pp. 79–87.

Kwahk, K.-Y., and Lee, J.-N. 2008. "The Role of Readiness for Change in ERP Implementation: Theoretical Bases and Empirical Validation," *Information & Management* (45:7), Elsevier, pp. 474–481.

Kwon, O., Lee, N., and Shin, B. 2014. "Data Quality Management, Data Usage Experience and Acquisition Intention of Big Data Analytics," *International Journal of Information Management* (34:3), pp. 387–394. (https://doi.org/10.1016/j.ijinfomgt.2014.02.002).

Lai, K., Wong, C. W., and Cheng, T. E. 2006. "Institutional Isomorphism and the Adoption of Information Technology for Supply Chain Management," *Computers in Industry* (57:1), pp. 93–98.

Lai, V. S., Lai, F., and Lowry, P. B. 2016. "Technology Evaluation and Imitation: Do They Have Differential or Dichotomous Effects on ERP Adoption and Assimilation in China?," *Journal of Management Information Systems* (33:4), Taylor & Francis, pp. 1209–1251.

Lai, V. S., Liu, C. K., Lai, F., and Wang, J. 2010. "What Influences ERP Beliefs—Logical Evaluation or Imitation?," *Decision Support Systems* (50:1), Elsevier, pp. 203–212.

Lai, Y., Sun, H., and Ren, J. 2018. "Understanding the Determinants of Big Data Analytics (BDA) Adoption in Logistics and Supply Chain Management: An Empirical Investigation," *The International Journal of Logistics Management* (29:2), pp. 676–703.

Levanti, D., Pitulice, I. C., and Stefanescu, A. 2021. "Accounting Harmonization Measurement: The Case of Non-Banking Financial Institutions in Romania," *Journal of Accounting and Management Information Systems* (20:1), Faculty of Accounting and Management Information Systems, The Bucharest …, pp. 111–131.

Lewin, K. 1947. "Lewin's Change Management Model: Understanding the Three Stages of Change," *Retrieved on March* (9), p. 2019.

Lewin, K. 1951. *Field Theory in Social Science: Selected Theoretical Papers (Edited by Dorwin Cartwright.).*, Harpers.

Li, L., and Wang, X. 2018. "M-Commerce Adoption in SMEs of China: The Effect of Institutional Pressures and the Mediating Role of Top Management," *Journal of Electronic Commerce in Organizations (JECO)* (16:2), IGI Global, pp. 48–63.

Liang, H., Saraf, N., Hu, Q., and Xue, Y. 2007. "Assimilation of Enterprise Systems: The Effect of Institutional Pressures and the Mediating Role of Top Management," *MIS Quarterly* (31:1), pp. 59–87. (https://doi.org/10.2307/25148781).

Lim, K. H. 2009. "Knowledge Management Systems Diffusion in Chinese Enterprises: A Multistage Approach Using the Technology-Organization-Environment Framework," *Journal of Global Information Management (JGIM)* (17:1), IGI Global, pp. 70–84.

Liu, Y., Soroka, A., Han, L., Jian, J., and Tang, M. 2020. “Cloud-Based Big Data Analytics for Customer Insight-Driven Design Innovation in SMEs,” *International Journal of Information Management* (51), Elsevier, p. 102034.

Loh, C.-H., and Teoh, A.-P. 2021. “The Adoption of Big Data Analytics Among Manufacturing Small and Medium Enterprises During Covid-19 Crisis in Malaysia,” in *Ninth International Conference on Entrepreneurship and Business Management (ICEBM 2020)*, Atlantis Press, pp. 95–100.

Lorente-Martínez, J., Navío-Marco, J., and Rodrigo-Moya, B. 2020. “Analysis of the Adoption of Customer Facing InStore Technologies in Retail SMEs,” *Journal of Retailing and Consumer Services* (57), Elsevier, p. 102225.

Lutfi, A. 2020. “Investigating the Moderating Role of Environmental Uncertainty between Institutional Pressures and ERP Adoption in Jordanian SMEs,” *Journal of Open Innovation: Technology, Market, and Complexity* (6:3), Multidisciplinary Digital Publishing Institute, p. 91.

Madsen, S. R., Miller, D., and John, C. R. 2005. “Readiness for Organizational Change: Do Organizational Commitment and Social Relationships in the Workplace Make a Difference?,” *Human Resource Development Quarterly* (16:2), Wiley Online Library, pp. 213–234.

Maduku, D. K. 2021. “Antecedents of Mobile Marketing Adoption by SMEs: Does Industry Variance Matter?,” *Journal of Organizational Computing and Electronic Commerce*, Taylor & Francis, pp. 1–28.

Mangla, S. K., Raut, R., Narwane, V. S., and Zhang, Z. J. 2020. “Mediating Effect of Big Data Analytics on Project Performance of Small and Medium Enterprises,” *Journal of Enterprise Information Management*, Emerald Publishing Limited.

March, J. G., and Olsen, J. P. 1976. “Ambiguity and Choice in Organizations (Bergen: Universitetsforlaget, 1976),” *The Same Point Is Stressed in Wilson, Bureaucracy*, pp. 55–59.

Marotta, A. 2022. “When AI Is Wrong: Addressing Liability Challenges in Women’s Healthcare,” *Journal of Computer Information Systems* (62:6), Taylor & Francis, pp. 1310–1319.

Maroufkhani, P., Iranmanesh, M., and Ghobakhloo, M. 2022. “Determinants of Big Data Analytics Adoption in Small and Medium-Sized Enterprises (SMEs),” *Industrial Management & Data Systems*, Emerald Publishing Limited.

Maroufkhani, P., Ismail, W. K. W., and Ghobakhloo, M. 2020a. “Big Data Analytics Adoption Model for Small and Medium Enterprises,” *Journal of Science and Technology Policy Management*, Emerald Publishing Limited.

Maroufkhani, P., Ismail, W. K. W., and Ghobakhloo, M. 2020b. “Big Data Analytics Adoption Model for Small and Medium Enterprises,” *Journal of Science and Technology Policy Management*, Emerald Publishing Limited.

Maroufkhani, P., Tseng, M.-L., Iranmanesh, M., Ismail, W. K. W., and Khalid, H. 2020. "Big Data Analytics Adoption: Determinants and Performances among Small to Medium-Sized Enterprises," *International Journal of Information Management* (54), Elsevier, p. 102190.

Maroufkhani, P., Wagner, R., Wan Ismail, W. K., Baroto, M. B., and Nourani, M. 2019. "Big Data Analytics and Firm Performance: A Systematic Review," *Information* (10:7), Multidisciplinary Digital Publishing Institute, p. 226.

McAfee, A., Brynjolfsson, E., Davenport, T. H., Patil, D. J., and Barton, D. 2012. "Big Data: The Management Revolution," *Harvard Business Review* (90:10), pp. 60–68.

Mehrtens, J., Cragg, P. B., and Mills, A. M. 2001. "A Model of Internet Adoption by SMEs," *Information & Management* (39:3), pp. 165–176.

Menguc, B., Auh, S., and Ozanne, L. 2010. "The Interactive Effect of Internal and External Factors on a Proactive Environmental Strategy and Its Influence on a Firm's Performance," *Journal of Business Ethics* (94:2), pp. 279–298.

Meshram, S., and Rawani, A. M. 2019. "Analyzing Success Factors of Small and Medium Enterprises (SMEs): A Study in Indian Context," in *Advances in Industrial and Production Engineering*, Springer, pp. 843–851.

Messerschmidt, C. M., and Hinz, O. 2013. "Explaining the Adoption of Grid Computing: An Integrated Institutional Theory and Organizational Capability Approach," *The Journal of Strategic Information Systems* (22:2), pp. 137–156. (https://doi.org/10.1016/j.jsis.2012.10.005).

Meyer, A. D., and Goes, J. B. 1988. "Organizational Assimilation of Innovations: A Multilevel Contextual Analysis," *Academy of Management Journal* (31:4), pp. 897–923. (https://doi.org/10.2307/256344).

Meyer, J. W. 1980. *Institutional and Technical Sources of Organizational Structure Explaining the Structure of Educational Organizations.*, ERIC.

Meyers, L. S., Gamst, G., and Guarino, A. J. 2016. *Applied Multivariate Research: Design and Interpretation*, Sage publications.

Miao, J.-J., and Tran, Q. D. 2018. "Study on E-Commerce Adoption in SMEs under the Institutional Perspective: The Case of Saudi Arabia," *International Journal of E-Adoption (IJEA)* (10:1), IGI Global, pp. 53–72.

Michael, K., and Miller, K. W. 2013. "Big Data: New Opportunities and New Challenges," *Computer* (46:6), pp. 22–24. (https://doi.org/10.1109/MC.2013.196).

Mikalef, P., and Krogstie, J. 2020. "Examining the Interplay between Big Data Analytics and Contextual Factors in Driving Process Innovation Capabilities," *European Journal of Information Systems* (29:3), Taylor & Francis, pp. 260–287.

Moore, G. C., and Benbasat, I. 1991. “Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation,” *Information Systems Research* (2:3), pp. 192–222.

Morgeson, F. P., and Humphrey, S. E. 2006. “The Work Design Questionnaire (WDQ): Developing and Validating a Comprehensive Measure for Assessing Job Design and the Nature of Work.,” *Journal of Applied Psychology* (91:6), p. 1321.

Mustapa, M. N., Hamid, S., and Md Nasaruddin, F. H. 2022. “Factors Influencing Open Government Data Post-Adoption in the Public Sector: The Perspective of Data Providers,” *PloS One* (17:11), Public Library of Science San Francisco, CA USA, p. e0276860.

Nasrollahi, M., Ramezani, J., and Sadraei, M. 2021. “The Impact of Big Data Adoption on SMEs’ Performance,” *Big Data and Cognitive Computing* (5:4), MDPI, p. 68.

Nordin, N. 2011. “The Influence of Emotional Intelligence, Leadership Behaviour and Organizational Commitment on Organizational Readiness for Change in Higher Learning Institution,” *Procedia-Social and Behavioral Sciences* (29), Elsevier, pp. 129–138.

Nunally, J. C., and Bernstein, I. H. 1978. *Psychometric Theory*, New York: McGraw-Hill.

Nunnally, J. C. (n.d.). *Psychometric Theory. New York 1967*, McGraw-Hill.

Nwankpa, J. K., and Datta, P. 2017. “Balancing Exploration and Exploitation of IT Resources: The Influence of Digital Business Intensity on Perceived Organizational Performance,” *European Journal of Information Systems* (26:5), pp. 469–488.

Pacini, R., and Epstein, S. 1999. “The Relation of Rational and Experiential Information Processing Styles to Personality, Basic Beliefs, and the Ratio-Bias Phenomenon.,” *Journal of Personality and Social Psychology* (76:6), p. 972.

Pan, Y., Froese, F., Liu, N., Hu, Y., and Ye, M. 2021. “The Adoption of Artificial Intelligence in Employee Recruitment: The Influence of Contextual Factors,” *The International Journal of Human Resource Management*, Taylor & Francis, pp. 1–23.

Parasuraman, A., and Colby, C. L. 2015. “An Updated and Streamlined Technology Readiness Index: TRI 2.0,” *Journal of Service Research* (18:1), SAGE Publications Sage CA: Los Angeles, CA, pp. 59–74.

Pavlou, P. A., Liang, H., and Xue, Y. 2007. “Understanding and Mitigating Uncertainty in Online Exchange Relationships: A Principal-Agent Perspective,” *MIS Quarterly*, JSTOR, pp. 105–136.

Petter, S., Straub, D., and Rai, A. 2007. “Specifying Formative Constructs in Information Systems Research,” *MIS Quarterly* (31:4), pp. 623–656. (https://doi.org/10.2307/25148814).

Pfeffer, J., and Gerald, R. 1978. *Salancik. 1978. The External Control of Organizations: A Resource Dependence Perspective*, New York: Harper & Row.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., and Podsakoff, N. P. 2003. “Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies.,” *Journal of Applied Psychology* (88:5), pp. 879–903. (https://doi.org/10.1037/0021-9010.88.5.879).

Premkumar, G., Ramamurthy, K., and Nilakanta, S. 1994. “Implementation of Electronic Data Interchange: An Innovation Diffusion Perspective,” *Journal of Management Information Systems* (11:2), pp. 157–186.

Provost, F., and Fawcett, T. 2013. “Data Science and Its Relationship to Big Data and Data-Driven Decision Making,” *Big Data* (1:1), Mary Ann Liebert, Inc. 140 Huguenot Street, 3rd Floor New Rochelle, NY 10801 USA, pp. 51–59.

Ramdani, B., Chevers, D., and Williams, D. A. 2013. “SMEs’ Adoption of Enterprise Applications: A Technology-Organisation-Environment Model,” *Journal of Small Business and Enterprise Development*, Emerald Group Publishing Limited.

Ramdani, B., and Kawalek, P. 2007. “SME Adoption of Enterprise Systems in the Northwest of England,” in *IFIP International Working Conference on Organizational Dynamics of Technology-Based Innovation*, Springer, pp. 409–429.

Rana, N. P., Chatterjee, S., Dwivedi, Y. K., and Akter, S. 2021. “Understanding Dark Side of Artificial Intelligence (AI) Integrated Business Analytics: Assessing Firm’s Operational Inefficiency and Competitiveness,” *European Journal of Information Systems*, Taylor & Francis, pp. 1–24.

Rauniyar, Kanchan, Rauniyar, Komal, and Sah, D. K. 2021. “Role of FinTech and Innovations for Improvising Digital Financial Inclusion,” *International Journal of Innovative Science and Research Technology* (6:5), pp. 1419–1424.

RAZZAQ, A., ASMAI, S. A., ABIDIN, Z. Z., TALIB, M. S., ALI, M. F., and MOHAMMED, A. 2021. “PROPOSE A CONCEPTUAL FRAMEWORK FOR THE CLOUD ERP ADOPTION AMONG MALAYSIAN SMES,” *Journal of Engineering Science and Technology* (16:4), pp. 3387–3406.

Robu, M. 2013. “The Dynamic and Importance of SMEs in Economy,” *The USV Annals of Economics and Public Administration* (13:1 (17)), pp. 84–89.

Rogers, E. M. 1983. *Diffusion of Innovations*, (3rd ed.), New York : London: Free Press ; Collier Macmillan.

Rogers, E. M. 1995. *Diffusion of Innovations*, New York: Free Press.

Rogers, E. M. 2003. *Diffusion of Innovations, 5th Edition*, Simon and Schuster.

Roldán, J. L., and Sánchez-Franco, M. J. 2012. “Variance-Based Structural Equation Modeling: Guidelines for Using Partial Least Squares in Information Systems Research,” in *Research Methodologies, Innovations and Philosophies in Software Systems Engineering and Information Systems*, IGI global, pp. 193–221.

Salleh, K. A., and Janczewski, L. J. 2016. "Adoption of Big Data Solutions: A Study on Its Security Determinants Using Sec-TOE Framework.," in *CONF-IRM*, p. 66.

Saraf, N., Liang, H., Xue, Y., and Hu, Q. 2013. "How Does Organisational Absorptive Capacity Matter in the Assimilation of Enterprise Information Systems?," *Information Systems Journal* (23:3), pp. 245–267. (https://doi.org/10.1111/j.1365-2575.2011.00397.x).

Schreiber, J. B., Nora, A., Stage, F. K., Barlow, E. A., and King, J. 2006. "Reporting Structural Equation Modeling and Confirmatory Factor Analysis Results: A Review," *The Journal of Educational Research* (99:6), Taylor & Francis, pp. 323–338.

See, B. P., Yap, C. S., and Ahmad, R. 2019. "Antecedents of Continued Use and Extended Use of Enterprise Systems," *Behaviour & Information Technology* (38:4), pp. 384–400.

Sekaran, U., and Bougie, R. 2016. *Research Methods for Business: A Skill Building Approach*, john wiley & sons.

Setiyani, L., and Rostiani, Y. 2021. "Analysis of E-Commerce Adoption by SMEs Using the Technology-Organization-Environment (TOE) Model: A Case Study in Karawang, Indonesia," *International Journal of Science, Technology & Management* (2:4), pp. 1113–1132.

Shahbaz, M., Gao, C., Zhai, L., Shahzad, F., and Hu, Y. 2019. "Investigating the Adoption of Big Data Analytics in Healthcare: The Moderating Role of Resistance to Change," *Journal of Big Data* (6:1), p. 6.

Shiloh, S., Salton, E., and Sharabi, D. 2002. "Individual Differences in Rational and Intuitive Thinking Styles as Predictors of Heuristic Responses and Framing Effects," *Personality and Individual Differences* (32:3), pp. 415–429.

Shin, D.-H. 2016. "Demystifying Big Data: Anatomy of Big Data Developmental Process," *Telecommunications Policy* (40:9), pp. 837–854. (https://doi.org/10.1016/j.telpol.2015.03.007).

Skafi, M., Yunis, M. M., and Zekri, A. 2020. "Factors Influencing SMEs' Adoption of Cloud Computing Services in Lebanon: An Empirical Analysis Using Toe and Contextual Theory," *IEEE Access* (8), IEEE, pp. 79169–79181.

"Smes in Canada Statistics - Google Search." (n.d.). (https://www.google.com/search?q=smes+in+canada+statistics&oq=SMEs+in+canada&aqs=chrome.1.0i512j0i22i30l5j0i15i22i30j0i22i30l2j0i390.6470j0j7&sourceid=chrome&ie=UTF-8, accessed December 29, 2022).

Somohano-Rodríguez, F. M., Madrid-Guijarro, A., and López-Fernández, J. M. 2022. "Does Industry 4.0 Really Matter for SME Innovation?," *Journal of Small Business Management* (60:4), Taylor & Francis, pp. 1001–1028.

Stjepić, A.-M., Pejić Bach, M., and Bosilj Vukšić, V. 2021. "Exploring Risks in the Adoption of Business Intelligence in SMEs Using the TOE Framework," *Journal of Risk and Financial Management* (14:2), Multidisciplinary Digital Publishing Institute, p. 58.

Straub, D., Boudreau, M.-C., and Gefen, D. 2004. “Validation Guidelines for IS Positivist Research,” *Communications of the Association for Information Systems* (13:1), p. 24.

Su, L., Cui, A. P., Samiee, S., and Zou, S. 2022. “Exploration, Exploitation, Ambidexterity and the Performance of International SMEs,” *European Journal of Marketing* (ahead-of-print), Emerald Publishing Limited.

Sun, H. 2013. “A Longitudinal Study of Herd Behavior in the Adoption and Continued Use of Technology,” *Mis Quarterly*, JSTOR, pp. 1013–1041.

Sun, S., Cegielski, C. G., Jia, L., and Hall, D. J. 2018. “Understanding the Factors Affecting the Organizational Adoption of Big Data,” *Journal of Computer Information Systems* (58:3), pp. 193–203.

TENENHAUS, M. 2005. *PLS Path Modeling Computational Statistics & Data Analysis, v. 48*.

Teo, H. H., Wei, K. K., and Benbasat, I. 2003. “Predicting Intention to Adopt Interorganizational Linkages: An Institutional Perspective,” *MIS Quarterly* (27:1), pp. 19–49. (https://doi.org/10.2307/30036518).

Timothy, V. L. 2022. “The Effect of Top Managers’ Human Capital on SME Productivity: The Mediating Role of Innovation,” *Heliyon* (8:4), Elsevier, p. e09330.

Tornatzky, L. G., Fleischer, M., and Chakrabarti, A. K. 1990. *Processes of Technological Innovation*, Lexington books.

Tsai, W.-C., and Tang, L.-L. 2012. “A Model of the Adoption of Radio Frequency Identification Technology: The Case of Logistics Service Firms,” *Journal of Engineering and Technology Management* (29:1), Elsevier, pp. 131–151.

Urbach, N., and Ahlemann, F. 2010. “Structural Equation Modeling in Information Systems Research Using Partial Least Squares,” *Journal of Information Technology Theory and Application (JITTA)* (11:2), p. 2.

Veiga, J. F., Keupp, M. M., Floyd, S. W., and Kellermanns, F. W. 2014. “The Longitudinal Impact of Enterprise System Users’ Pre-Adoption Expectations and Organizational Support on Post-Adoption Proficient Usage,” *European Journal of Information Systems* (23:6), Springer, pp. 691–707.

Verma, S., and Bhattacharyya, S. S. 2017. “Perceived Strategic Value-Based Adoption of Big Data Analytics in Emerging Economy: A Qualitative Approach for Indian Firms,” *Journal of Enterprise Information Management* (30:3), pp. 354–382.

Verma, S., Bhattacharyya, S. S., and Kumar, S. 2018. “An Extension of the Technology Acceptance Model in the Big Data Analytics System Implementation Environment,” *Information Processing & Management* (54:5), pp. 791–806.

Villadsen, A. R., Hansen, J. R., and Mols, N. P. 2010. "When Do Public Managers Imitate Each Other? Mimetic Decision Making in Contracting Decisions of Danish Municipalities," *Public Organization Review* (10:4), Springer, pp. 357–376.

Wang, X., Kumar, V., Kumari, A., and Kuzmin, E. 2022. "Impact of Digital Technology on Supply Chain Efficiency in Manufacturing Industry," *Digital Transformation in Industry: Digital Twins and New Business Models*, Springer Nature, p. 347.

Weiner, B. J. 2009. "A Theory of Organizational Readiness for Change," *Implementation Science* (4:1), Springer, pp. 1–9.

Weiss, J. A., and Dale, B. C. 1998. "Diffusing against Mature Technology: Issues and Strategy," *Industrial Marketing Management* (27:4), Elsevier, pp. 293–304.

Wen, L., Zailani, S., and Fernando, Y. 2009. "Determinants of RFID Adoption in Supply Chain among Manufacturing Companies in China: A Discriminant Analysis," *Journal of Technology Management & Innovation* (4:1), pp. 22–32. (https://doi.org/10.4067/S0718-27242009000100003).

Werts, C. E., Linn, R. L., and Jöreskog, K. G. 1974. "Intraclass Reliability Estimates: Testing Structural Assumptions," *Educational and Psychological Measurement* (34:1), pp. 25–33. (https://doi.org/10.1177/001316447403400104).

Wetzels, M., Odekerken-Schröder, G., and Van Oppen, C. 2009. "Using PLS Path Modeling for Assessing Hierarchical Construct Models: Guidelines and Empirical Illustration," *MIS Quarterly*, JSTOR, pp. 177–195.

Wong, L.-W., Leong, L.-Y., Hew, J.-J., Tan, G. W.-H., and Ooi, K.-B. 2020. "Time to Seize the Digital Evolution: Adoption of Blockchain in Operations and Supply Chain Management among Malaysian SMEs," *International Journal of Information Management* (52), Elsevier, p. 101997.

Wulandari, A., Suryawardani, B., and Marcelino, D. 2020. "Social Media Technology Adoption for Improving MSMEs Performance in Bandung: A Technology-Organization-Environment (TOE) Framework," in *2020 8th International Conference on Cyber and IT Service Management (CITSM)*, IEEE, pp. 1–7.

Xu, Y., Boh, W. F., and Soh, C. 2014. "Vertical IS Standards Deployment and Integration: A Study of Antecedents and Benefits," *Information & Management* (51:2), Elsevier, pp. 206–216.

Yadegaridehkordi, E., Hourmand, M., Nilashi, M., Shuib, L., Ahani, A., and Ibrahim, O. 2018. "Influence of Big Data Adoption on Manufacturing Companies' Performance: An Integrated DEMATEL-ANFIS Approach," *Technological Forecasting and Social Change* (137), pp. 199–210.

Yadegaridehkordi, E., Nilashi, M., Shuib, L., Nasir, M. H. N. B. M., Asadi, S., Samad, S., and Awang, N. F. 2020. "The Impact of Big Data on Firm Performance in Hotel Industry," *Electronic Commerce Research and Applications* (40), Elsevier, p. 100921.

Yigitbasioglu, O. M. 2015. "The Role of Institutional Pressures and Top Management Support in the Intention to Adopt Cloud Computing Solutions," *Journal of Enterprise Information Management* (28:4), pp. 579–594. (https://doi.org/10.1108/JEIM-09-2014-0087).

Zheng, D., Chen, J., Huang, L., and Zhang, C. 2013. "E-Government Adoption in Public Administration Organizations: Integrating Institutional Theory Perspective and Resource-Based View," *European Journal of Information Systems* (22:2), pp. 221–234.

Zhu, K., Kraemer, K., and Xu, S. 2003. "Electronic Business Adoption by European Firms: A Cross-Country Assessment of the Facilitators and Inhibitors," *European Journal of Information Systems* (12:4), pp. 251–268. (https://doi.org/10.1057/palgrave.ejis.3000475).

Zolait, A. H. S. 2010. "An Examination of the Factors Influencing Yemeni Bank Users' Behavioural Intention to Use Internet Banking Services," *Journal of Financial Services Marketing* (15:1), Springer, pp. 76–94.

APPENDIX A – Measurement Items

Table 25. Measurement items and sources

Construct Name	**Measurement Items (7-point scale)** **7-point Likert scales ranging from “strongly disagree” to “strongly agree”**	**Resources**
Managers’ Survey Items		
Mimetic Pressures	With regard to our main competitors that have adopted BDA: • They have benefited greatly. • They are perceived favorably by others in the same industry. • They are perceived favorably by their customers. • BDA is widely adopted by our firm’s competitors.	(Xu et al. 2014)
Coercive Pressures	With regard to our main trading partners (e.g., collaborators, suppliers, customers, etc.) that have adopted BDA: • My firm’s well-being depends on their transactions. • My firm MUST maintain good relationships with them. • They are the largest partners in the industry. • These partners have great influence on our firm’s decision of whether or not to adopt BDA.	
Normative Pressures	To what extent do you agree with the following statements: • My perceptions of BDA usefulness are influenced by the views of other BDA users. • Participating in some BDA promotion events generates some pressures on our firm to adopt BDA.	
Organizational Readiness	Our firm is willing or open to applying: • Financial resources to adopt BDA. • Technological resources to adopt BDA. • Organizational resources to adopt BDA.	(Tsai and Tang 2012)
BDA Uncertainty	• We feel that using BDA involves a high degree of uncertainty. • We feel that the uncertainty associated with the insights provided by BDA is high. • We are exposed to many uncertainties if we use BDA. • There is a high degree of information uncertainty (i.e., the information you receive may not be what you expect) when using BDA.	(Pavlou et al. 2007)
Data-Driven Culture	• In our firm, data is considered a tangible important asset. • In our firm, decisions are based on data rather than intuition. • We are willing to override our own intuition when data contradicts our viewpoints. • We continuously assess and improve our business policies in response to insights extracted from data. • We continuously coach our employees to make decisions based on data.	(Gupta and George 2016)

BDA adoption	• It is critical for our firm to adopt BDA. • We are committed to use BDA. • We have certain plans to use BDA.	(Hossain et al. 2016)
Data Analysts Survey Items		
BDA Complexity	In using BDA in our firm, we feel that: • It requires doing different tasks or activities at a time. • It is complicated. • It is comprised of relatively complicated tasks. • It involves performing relatively complex tasks.	(Morgeson and Humphrey 2006)
BDA Trialability	• I have had a great deal of opportunity to try different BDA functionalities. • I know where I can go to satisfactorily try out different uses of BDA. • BDA was available to me to adequately test different functionalities. • Before deciding whether to use BDA functionalities, I was able to properly try them out. • I was permitted to use BDA on a trial basis long enough to see what it could do.	(Moore and Benbasat 1991)
BDA Relative Advantage	Using BDA: • Enables me to accomplish tasks more quickly. • Improves the quality of work I do. • Makes it easier to do my job. • Enhances my effectiveness on the job. • Gives me greater control over my work. • Increases my productivity.	(Moore and Benbasat 1991)
Data Analysts Readiness	• I look forward to use BDA at work. • I find using BDA to be pleasing. • Other people think that I support BDA. • I am inclined to try using BDA. • I support using BDA. • I suggest new approaches to using BDA. • I intend to do whatever is possible to support using BDA	(Kwahk and Lee 2008)
Data Analytics Skills	• I am knowledgeable when it comes to utilizing such tools. • I possess a high degree of data analytics expertise. • I am skillful at using data analytics tools.	(Ghasemaghaei et al. 2018)
Analytical Thinking Style	• I like situations that require thinking in depth about something. • I enjoy intellectual challenges. • I like to have to do a lot of thinking. • I enjoy solving problems that require hard thinking. • Thinking is an enjoyable activity. • I prefer complex problems to simple problems.	(Pacini and Epstein 1999)

	• Thinking hard and for a long time about something gives me great satisfaction. • I enjoy thinking in abstract terms. • Knowing the answer without having to understand the reasoning behind it is not good enough for me. • Learning new ways to think would be very appealing to me.	
BDA Intention to Use	• I would intend to use BDA as a routine part of my job. • I would intend to use BDA at every opportunity. • I would plan to increase my use of BDA.	(Jaklič et al. 2018)

APPENDIX B – Survey Description and Consent Form

Table 26. Survey Description and Consent Form

Big Data Analytics Use and Organizational Behavior

Purpose of the Study: We are conducting this survey as a part of a research study that aims at investigating internal and external factors influencing the process of big data analytics implementation in organizations.

Procedures involved in the Research: You will be asked to complete an online survey, which will require approximately 10 minutes of your time. In the survey, you will be asked to respond to closed-ended questions about how analytical tools are adopted and used by your organization. After completing the survey, you will be asked to respond to open-ended questions to gather basic background information about you, and your organization.

Potential Harms, Risks or Discomforts: The risks involved in participating in this study are minimal. There are no foreseeable physical or financial risks associated with this study. For demographic questions, you can skip questions that make you feel uncomfortable.
You are participating in this research anonymously. No one, including us, will know that you have participated.Please take this into consideration in answering the survey questions. The information you provide will be kept on the researchers' laptop computers protected by a password. In addition, there are no right or wrong answers in responding to the survey questions.

Potential Benefits: This research will not benefit you directly. The results of this study will help researchers and practitioners understand how internal and external factors impact business analytics adoption and use in organizational settings.

Compensation: You will be compensated by Research Now as outlined in Dynata terms and conditions. You must complete the survey before you can enter your e-mail address into the sweepstakes. Please note that you are still eligible for compensation if you elect not to answer some of the demographic questions in the survey. See http://www.webperspectives.ca/index.php?id=11 for further information about the compensation process.

Confidentiality: You are participating in this research anonymously. All information collected from you will be kept secure and in strict confidence. Only the researchers named above will have access to the data, which will be stored securely on the researchers' password-protected laptop computers. Participants will not be identified individually in any reports or analyses resulting from this study.

Participation and Withdrawal: Your participation in this study is voluntary. If you decide that you do not want to participate in the study, you can withdraw at any time during completion of the survey by clicking on the “exit” button at the top left hand side of the survey header or simply by closing the online survey. Also, if you do not wish to answer a question there is an option “Prefer not to answer” for all questions. Demographic questions (such as your age and gender) are optional. If you decide to withdraw, there will be no consequences to you and none of your survey responses will be collected or stored. Once you have submitted your responses for this anonymous survey, your answers will be put into a database and will not be identifiable to you. This means that once you have submitted your survey, your responses cannot be withdrawn from the study because we will not be able to identify which responses are yours.

Information about the Study Results: We expect to have this study completed by approximately August 2020 and publish the findings in a peer-reviewed journal.

Moreover, the results of the study will be posted on the MeRC website (McMaster eBusiness Research Center): http://merc.mcmaster.ca/

Questions about the Study

If you have questions or need more information about the study itself, please contact us at: javdanm@mcmaster.ca or ext. 26195.

This study has been reviewed by the McMaster University Research Ethics Board and received ethics clearance.

If you have concerns or questions about your rights as a participant or about the way the study is conducted, please contact:

McMaster Research Ethics Secretariat
Telephone: (905) 525-9140 ext. 23142
c/o Research Office for Administrative Development and Support
E-mail: ethicsoffice@mcmaster.ca

CONSENT

I understand the information provided for the study “Big Data Analytics Use and Organizational Behavior” as described herein. My questions have been answered to my satisfaction, and by clicking on the “I agree to participate” button below, I agree to participate in this study. I understand that if I agree to participate in this study, I may withdraw from the study at any time.

- I agree to participate.
- I do not agree to participate.

APPENDIX C – Survey Questions

Big data analytics definition

Big data analytics (BDA) applies processing and analytical techniques and technologies to big data to provide critical insights with the aim of enhancing businesses - BDA enables organizations to efficiently use data and make better decisions.

Page 1 – Screening Questions

(I) To what extent are you familiar with the use of data analytics in your firm (For example: sharing reports, summaries of findings stemming from processing large sizes of different types of data)?
o Not at all familiar*
o Slightly familiar
o Somewhat familiar
o Moderately familiar
o Very familiar
o Highly familiar
o Extremely familiar

(II) Does your work involve using data analytics tools?
o Yes
o No*

* If participants selected at least one of these items, the survey ended and did not allow respondents to continue the survey.

Please indicate your role in the organization:
- Business unit/department manager / Data Manager
- Data Analyst / IT system analyst / Data scientist / Business analyst /
- IT Manager

- Marketing Manager
- Other: please specify

Page 2 – General Big Data Related Questions

1. Which of the following BDA applications are you familiar with?
- IBM Watson
- SAS
- Tableau
- Oracle
- SAP
- Alteryx
- MicroStrategy
- Microsoft
- Qlik
- Salesforce
- Other: Please specify
- Prefer not to answer

2. My firm processes data every day that is: (Provide a best guess if you do not know the amount of data)
- Lower than 100 Megabytes
- Between 100 Megabytes and 100 Gigabytes
- Between 100 Gigabytes and 1 Terabyte
- Between 1 Terabyte and 10 Terabytes
- More than 10 Terabytes
- Prefer not to answer

3. My firm processes the following data format(s) every day:
- Numbers or Dates or Strings
- Sensor data
- Text or Documents or Spreadsheets or Email
- Images
- Social media data
- Audio or Video files
- Other: Please specify.
- Prefer not to answer

4. Please indicate how often you use data analytics tools in your job.
- Not at all
- Not much
- Sometimes
- Quite often

- Often
- Almost always
- Always
- Prefer not to answer

5. Please indicate to what extent you use data analytics tools in your job.

- Not at all
- To a very small extent
- To a small extent
- To a moderate extent
- To a fairly great extent
- To a great extent
- To a very great extent
- Prefer not to answer

6. On average, please specify the estimated proportion of time you use data analytics in your job.

- Never
- Rarely, in less than 10% of the time
- Occasionally, in about 30% of the time
- Sometimes, in about 50% of the time
- Frequently, in about 70% of the time
- Usually, in about 90% of the time
- Almost all the time
- Prefer not to answer

Page 3 – Questionnaire (Managers version)

1.With regard to our MAIN COMPETITORS that have adopted BDA:

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	Prefer not to answer
They have benefited greatly.								
They are perceived favorably by others in the same industry.								
They are perceived favorably by their customers.								
BDA is widely adopted by our firm's competitors.								

2. With regard to our MAIN TRADING PARTNERS (e.g., suppliers, customers, etc.) that have adopted BDA:

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	Prefer not to answer
Our firm's well-being depends on their transactions.								
Our firm MUST maintain good relationships with them.								
They are the largest partners in the industry.								
These partners have a great influence on our firm's decision of whether or not to adopt BDA.								

3.To what extent do you agree with the following statements:

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	Prefer not to answer
My perceptions of BDA usefulness are influenced by the views of other BDA users.	○	○	○	○	○	○	○	○
Participating in some BDA promotion events (e.g., seminars and conferences) generates some pressures on our firm to adopt BDA.	○	○	○	○	○	○	○	○

4. Big Data Analytics (BDA) application is:

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	Prefer not to answer
Conceptually difficult to understand from a BUSINESS perspective.	○	○	○	○	○	○	○	○
Conceptually difficult to understand from a TECHNICAL perspective.	○	○	○	○	○	○	○	○
Difficult to use.	○	○	○	○	○	○	○	○

5. How do you explain data-culture in your firm?

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	Prefer not to answer
We consider data a tangible asset.	○	○	○	○	○	○	○	○
We base our decisions on data rather than on intuition.	○	○	○	○	○	○	○	○
We are willing to override our own intuition when data contradicts our viewpoints.	○	○	○	○	○	○	○	○
We continuously assess and improve our business policies in response to insights extracted from data.	○	○	○	○	○	○	○	○
We continuously coach our employees to make decisions based on data.	○	○	○	○	○	○	○	○

6. What is your firm attitude about adopting BDA?

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	Prefer not to answer
It is critical for our firm to adopt BDA.	○	○	○	○	○	○	○	○
We are committed to use BDA.	○	○	○	○	○	○	○	○
We have certain plans to use BDA.	○	○	○	○	○	○	○	○

7. How uncertain are you in using BDA in your firm?

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	Prefer not to answer
I feel that using BDA involves a high degree of uncertainty.	○	○	○	○	○	○	○	○
I feel that the uncertainty associated with the insights provided by BDA is high.	○	○	○	○	○	○	○	○
I am exposed to many uncertainties if I use BDA.	○	○	○	○	○	○	○	○
There is a high degree of information uncertainty (i.e., the information you receive may not be what you expect) when using BDA.	○	○	○	○	○	○	○	○
Select "Strongly agree" to indicate that you have read the questions carefully. *	○	○	○	○	○	○	○	○

[* Attention Check Question for data analysts.]

8. How do you evaluate the readiness of your firm in using BDA?

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	Prefer not to answer
My firm has the financial resources to adopt BDA.	○	○	○	○	○	○	○	○
My firm has the technological resources to adopt BDA.	○	○	○	○	○	○	○	○

****

The End of Managerial Questions
Please proceed to demographic and background questions.
Thanks!

Page 3 – Questionnaire (Data Analyst version)

1. Using Big Data Analytics (BDA):

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	Prefer not to answer
Enables me to accomplish tasks more quickly.								
Improves the quality of work I do.								
Makes it easier to do my job.								
Enhances my effectiveness on the job.								
Gives me greater control over my work.								
Increases my productivity.								

2. Big Data Analytics (BDA) application is:

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	Prefer not to answer
Conceptually difficult to understand from a BUSINESS perspective.	○	○	○	○	○	○	○	○
Conceptually difficult to understand from a TECHNICAL perspective.	○	○	○	○	○	○	○	○
Difficult to use.	○	○	○	○	○	○	○	○

3. How did you try BDA in your firm?

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	Prefer not to answer
I have had a great deal of opportunity to try different BDA functionalities.	○	○	○	○	○	○	○	○
I know where I can go to satisfactorily try out different uses of BDA.	○	○	○	○	○	○	○	○
BDA was available to me to adequately test different functionalities.	○	○	○	○	○	○	○	○
Before deciding whether to use BDA functionalities, I was able to properly try them out.	○	○	○	○	○	○	○	○
I was permitted to use BDA on a trial basis long enough to see what it could do.	○	○	○	○	○	○	○	○

4. How do you find using DATA ANALYTICS? (Not specifically big data)

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	Prefer not to answer
I find it easy to create new and effective ways of using data analytics.	○	○	○	○	○	○	○	○
I am very creative when using data analytics.	○	○	○	○	○	○	○	○
I make many novel contributions to my work-related tasks through the use of data.	○	○	○	○	○	○	○	○

5. How do you think about different ways of using DATA ANALYTICS? (Not specifically big data)

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	Prefer not to answer
I like to investigate different ways of using data analytics.	○	○	○	○	○	○	○	○
I am very curious about different ways of using data analytics.	○	○	○	○	○	○	○	○
I like to figure out different ways of using data analytics.	○	○	○	○	○	○	○	○

6. What is your orientation in using DATA ANALYTICS? (Not specifically big data)

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	Prefer not to answer
I often notice how other people are using data analytics.	○	○	○	○	○	○	○	○
I attend to the 'big picture' of a project when using data analytics.	○	○	○	○	○	○	○	○
I 'get involved' when using data analytics.	○	○	○	○	○	○	○	○

7. What is your thinking style look like in general?

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	Prefer not to answer
I like situations that require thinking in depth about something.	○	○	○	○	○	○	○	○
I enjoy intellectual challenges.	○	○	○	○	○	○	○	○
I like to have to do a lot of thinking.	○	○	○	○	○	○	○	○
I enjoy solving problems that require hard thinking.	○	○	○	○	○	○	○	○
Thinking is an enjoyable activity.	○	○	○	○	○	○	○	○
I prefer complex problems to simple problems.	○	○	○	○	○	○	○	○
Thinking hard and for a long time about something gives me great satisfaction.	○	○	○	○	○	○	○	○
I enjoy thinking in abstract terms.	○	○	○	○	○	○	○	○
Knowing the answer without having to understand the reasoning behind it is not good enough for me.	○	○	○	○	○	○	○	○
Learning new ways to think would be very appealing to me.	○	○	○	○	○	○	○	○

8. How do you evaluate your data analytics skills?

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	Prefer not to answer
I am knowledgeable when it comes to utilizing data analytics tools.	○	○	○	○	○	○	○	○
I possess a high degree of data analytics expertise.	○	○	○	○	○	○	○	○
I am skilled at using data analytics tools.	○	○	○	○	○	○	○	○

9. How ready are YOU for BDA?

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	Prefer not to answer
I look forward to use BDA at work.	○	○	○	○	○	○	○	○
I find using BDA to be pleasing.	○	○	○	○	○	○	○	○
Other people think that I support BDA.	○	○	○	○	○	○	○	○
I am inclined to try using BDA.	○	○	○	○	○	○	○	○
I support using BDA.	○	○	○	○	○	○	○	○
I suggest new approaches to using BDA.	○	○	○	○	○	○	○	○
I intend to do whatever is possible to support using BDA.	○	○	○	○	○	○	○	○

10. How ready is your FIRM for BDA?

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	Prefer not to answer
We have the resources required for using BDA successfully.	○	○	○	○	○	○	○	○
The effective usage of BDA is well within our control.	○	○	○	○	○	○	○	○
We have all the support we need for using BDA.	○	○	○	○	○	○	○	○
Select “Strongly agree" to indicate that you have read the questions carefully. *	○	○	○	○	○	○	○	○

[* Attention Check Question for data analysts.]

11. Do you intend to use BDA?

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	Prefer not to answer
I am likely to use BDA.	○	○	○	○	○	○	○	○
I predict I will use BDA.	○	○	○	○	○	○	○	○
I plan to use BDA.	○	○	○	○	○	○	○	○

12. In my organization I extensively use:

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	Prefer not to answer
Paper Report	○	○	○	○	○	○	○	○
Interactive Reports (Ad-hoc)	○	○	○	○	○	○	○	○
On-Line Analytical Processing (OLAP)	○	○	○	○	○	○	○	○
Analytical Applications including Trend Analysis and “What-if” scenarios	○	○	○	○	○	○	○	○
Data Mining	○	○	○	○	○	○	○	○
Dashboards, including Metrics, Key Performance Indicators (KPI), and Alerts	○	○	○	○	○	○	○	○

Page 4 - Demographic and Background Questions

Please note that answering demographic questions (Q1, Q2, Q3) is optional.

1. Which of the following describes your gender?

○ Male

○ Female

○ Prefer not to answer

2. Which age group do you belong to:

- Under 18
- 18 - 24
- 25 - 34
- 35 - 44
- 45 - 54
- 55 - 64
- 65 - 74
- 75 - 84
- 85 or older
- Prefer not to answer!

3. What is your highest education level?

- Less than high school
- High school graduate
- Some college
- 2-year degree
- 4-year degree
- Professional degree
- Doctorate
- Prefer not to answer!

4. For how many years, you have been working in your company?

- ○ less than one year
- ○ 1-3
- ○ 3-5
- ○ 5-10
- ○ 10+
- ○ Prefer not to answer

5. How many people are employed in your organization?

- ○ Fewer than 10
- ○ 10-100
- ○ 100-250
- ○ 250-500
- ○ 500+
- ○ Prefer not to answer

6. Which of the following describes the industry group of your organization?

- ○ Manufacturing (producer goods)
- ○ Manufacturing (consumer goods)
- ○ Finance (Banking/Insurance)
- ○ Wholesaling
- ○ Retail

- ○ Utilities/Energy
- ○ Communication
- ○ Health Care
- ○ Pharmaceuticals
- ○ Other services
- ○ Prefer not to answer

6.1. Please specify your industry group:

____

7. How would you classify your organization's market reach?

- ○ Local
- ○ Regional
- ○ National
- ○ International
- ○ Prefer not to answer

8. Is your firm's principal industry commonly considered a high tech industry?
("High-tech" industries are technologically sophisticated industries, while "low-tech" industries are not.)

- ○ Yes
- ○ No
- ○ Prefer not to answer

9. How old is your organization?

- Less than 5 years
- 5-10
- 10+
- Prefer not to answer

10. Which of the following describes the annual sales revenue (USD) of your organization?

- Less than $ 500,000
- $ 500,0000 - $ 5 million
- $ 5 million - $ 12.5 million
- $ 12.5 million - $ 25 million
- More than $ 25 million
- Prefer not to answer

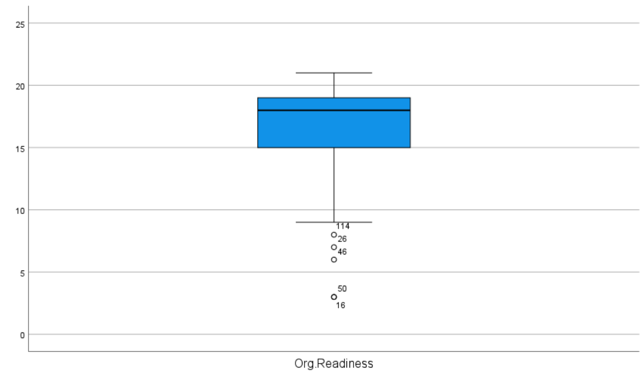
11. How do you rate the IS experience of your organization in terms of the number of IS users?

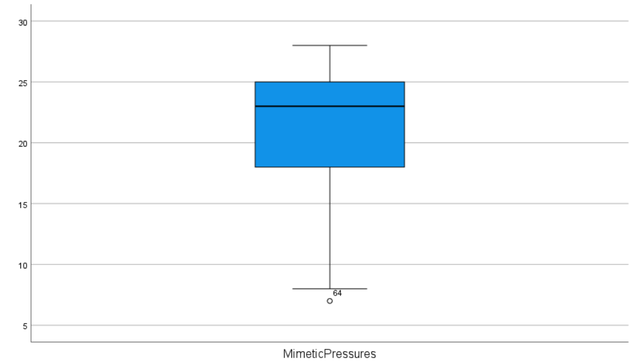
- Low IS users
- Medium IS users
- High IS users
- Prefer not to answer

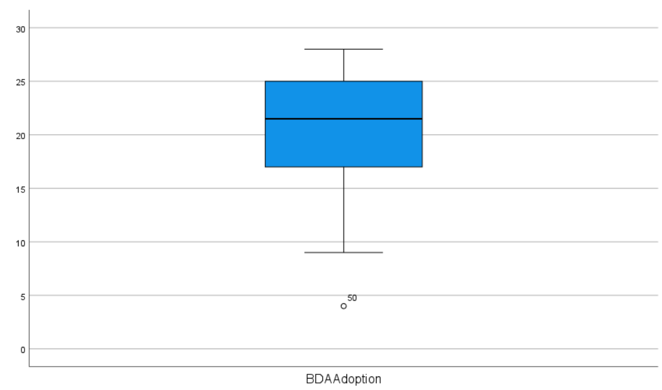
****

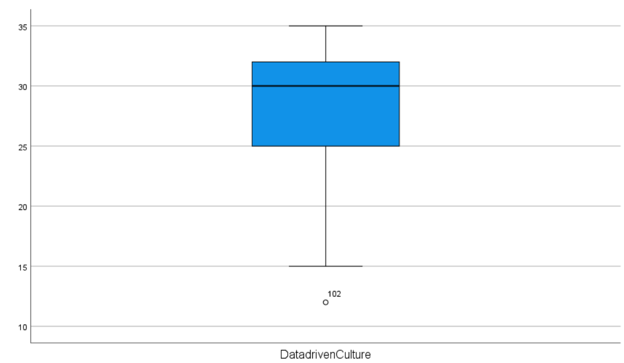
The End of the Questionnaire.

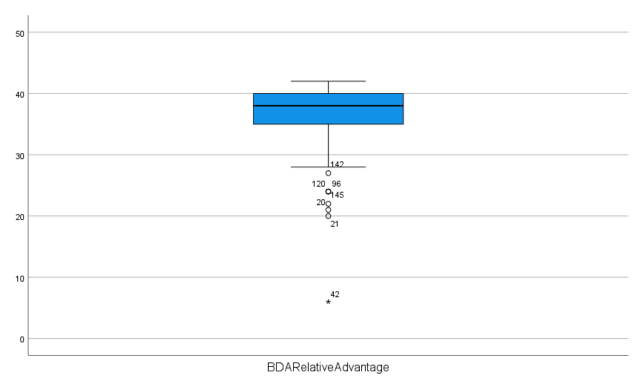
APPENDIX D – Composite/Indicator Box Plots

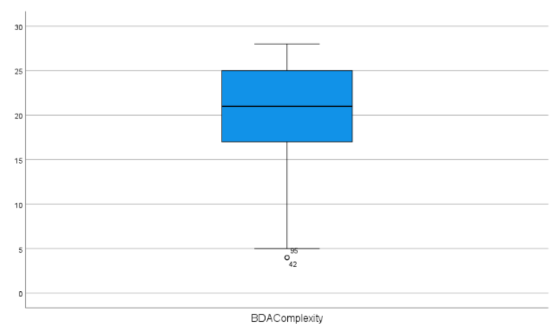


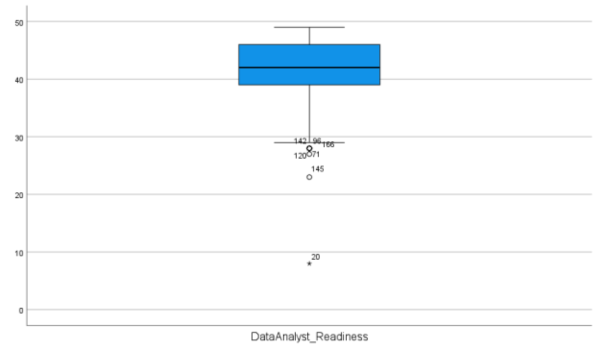


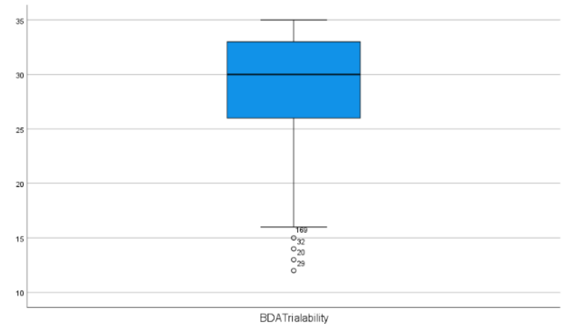


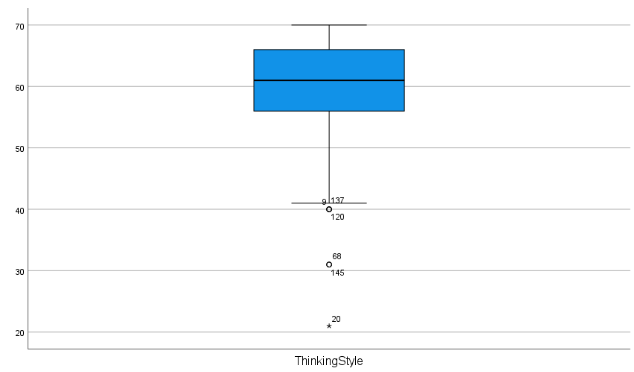


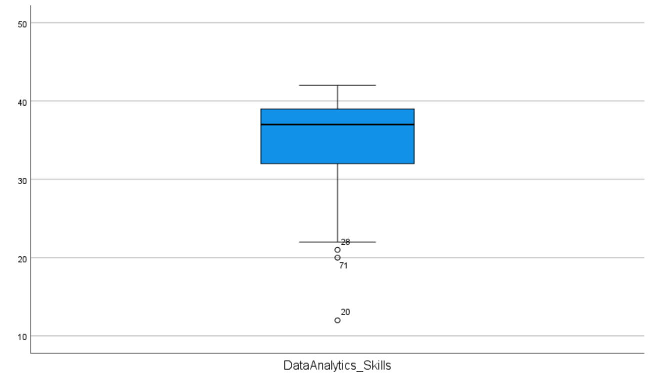





50
40
30
20
10
0
DataAnalyst_Readiness


35
30
25
20
15
10
BDATrialability


70
60
50
40
30
20
ThinkingStyle


50
40
30
20
10
DataAnalytics_Skills