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# Assessment of Factors Influencing Intent-to-Use Big Data Analytics in an Organization: A Survey Study

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# Assessment of Factors Influencing Intent-to-Use Big Data Analytics in an Organization: A Survey Study

By

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A dissertation submitted in partial fulfillment of the requirements
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In
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An Abstract of a Dissertation Submitted to Nova Southeastern University in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy

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The central question was how the relationship between trust-in-technology and intent-to-use Big Data Analytics in an organization is mediated by both Perceived Risk and Perceived Usefulness. Big Data Analytics is quickly becoming a critically important driver for business success. Many organizations are increasing their Information Technology budgets on Big Data Analytics capabilities. Technology Acceptance Model stands out as a critical theoretical lens primarily due to its assessment approach and predictive explanatory capacity to explain individual behaviors in the adoption of technology. Big Data Analytics use in this study was considered a voluntary act, therefore, well aligned with the Theory of Reasoned Action and the Technology Acceptance Model. Both theories have validated the relationships between beliefs, attitudes, intentions and usage behavior.

Predicting intent-to-use Big Data Analytics is a broad phenomenon covering multiple disciplines in literature. Therefore, a robust methodology was employed to explore the richness of the topic. A deterministic philosophical approach was applied using a survey method approach as an exploratory study which is a variant of the mixed methods sequential exploratory design. The research approach consisted of two phases: instrument development and quantitative. The instrument development phase was anchored with a systemic literature review to develop an instrument and ended with a pilot study. The pilot study was instrumental in improving the tool and switching from a planned covariance-based SEM approach to PLS-SEM for data analysis.

A total of 277 valid observations were collected. PLS-SEM was leveraged for data analysis because of the prediction focus of the study and the requirement to assess both reflective and formative measures in the same research model. The measurement and structural models were tested using the PLS algorithm. $R^2$, $f^{2,}$ and $Q^2$ were used as the basis for the acceptable fit measurement. Based on the valid structural model and after running the bootstrapping procedure, Perceived Risk has no mediating effect on Trust-in-Technology on Intent-to-Use. Perceived Usefulness has a full mediating effect. Level of education, training, experience and the perceived capability of analytics within an organization are good predictors of Trust-in-Technology.

We hereby certify that this dissertation, submitted by Wayne Madhlangobe, conforms to acceptable standards and is fully adequate in scope and quality to fulfill the dissertation requirements for the degree of Doctor of Philosophy.

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# Chapter 1

# Introduction

Today, organizations depend on sophisticated business processes and analytics to be competitive in the global market (Abbasi, Sarker, & Chiang, 2016). The amount of data produced by various business activities and functions is estimated to be growing at an exponential rate (Verschiedene, 2014). Big Data is large quantities of data consisting of different data types and accumulating at a rapid velocity (McAfee & Brynjolfsson, 2012; Provost & Fawcett, 2013; Verschiedene, 2014). Organizations that can harness Big Data can gain useful insights and increase the quality of their decisions. The transformation of data into information and information into knowledge is part of a traditional information value chain as illustrated by Abbasi, Sarker, and Chiang (2016).

A value chain, as defined by Porter (1985), is a series of activities that create value at each step of the chain. Data provides the building blocks that lead to insights; business users can turn those insights into decisions and actions. Information value chain is a systematic process where data is transformed into information, information into knowledge, and the knowledge into decisions that result in specific actions (Sarvary, 2011). To realize the benefits of an information value chain, a business capability composed of technology, processes, and people is imperative.

A capability to handle big data sets to uncover insights, correlations, and useful information is Big Data Analytics (BDA). BDA plays a significant role in the transformation of data into information however to barge into desired results, intent-to-use BDA is essential. The researcher viewed BDA as a capability that requires technology, skilled resources, and structured business processes. Figure 1 is a depiction of the information value chain as defined by Abbasi, Sarker, and Chiang (2016) overlaid with the information systems supporting the analytical steps.

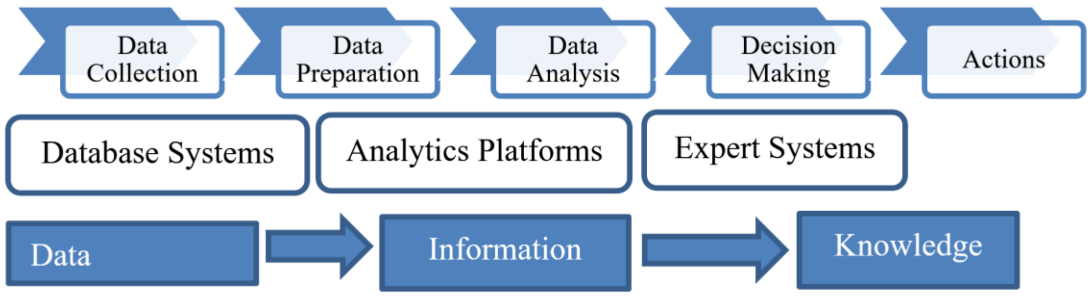


*Figure 1:* Information Value Chain

Other studies refer to the same capability as "Data Mining" or "Data Science" (Loukides, 2010; Provost & Fawcett, 2013).

**Background**

Discussing visualization techniques of how to deal with individual simulations with large datasets, Bryson, Kenwright, Cox, Ellsworth, and Haimes coined the term Big Data. At the time, large datasets were considered a significant disruption to the computational capabilities and data analysis techniques. Even with current advances in computational capabilities, Big Data is a dominant, disruptive force in how organizations process data and use information. An organization needs a business capability with technology, people, and processes to uncover insights, correlations, and useful information from Big Data.

In 2004, as the approaching hurricane Sandy was threatening the eastern seaboard of the continental US, Walmart using BDA was able to stock stores on the path of the storm with items like strawberry Pop-Tarts in addition to the traditional emergency supplies (Marr, 2016). After the hurricane, Walmart posted record sales on nontraditional emergency items. Walmart's case is an excellent example of the timely use of significant real-time data to generate insights for an organization. BDA has the potential to help organizations harness their data and identify new opportunities (Osuszek, Stanek, & Twardowski, 2016).

In 2008 Google launched the Flu Trends (GFT) website based on its search engine queries to predict outbreaks of flu (Lazer, Kennedy, King, & Vespignani, 2014). In 2009 the predictive service was heralded as a fantastic early warning system helping the Center for Disease Control and Prevention (CDC) to implement preventative measures ten days in advance (Cook, Conrad, Fowlkes, & Mohebbi, 2011). In February 2013, GFT was reported to have fitting errors and therefore not as accurate in the later years (Lazer et al., 2014). GFT is an excellent example of pitfalls in BDA that might lead to inferior quality decisions resulting in disastrous business actions.

Big Data is reshaping and changing how organizations function and operate from technology, business processes, and people perspective. Traditional information systems are drastically changing, and this is impacting how organizations make decisions and process data (Mayer-Schönberger & Cukier., 2014). New business roles like Data Scientists are emerging reshaping the traditional information value chains. Timely decision-making is now a critical requirement that needs BDA technologies (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016).

**Problem Statement**

Organizations are accelerating the adoption of BDA due to the perceived benefits. It is essential for organizations to understand factors that will increase the intent-to-use BDA. Understanding factors that influence intent-to-use can help an organization to implement appropriate measures to improve usage. In this study, the researcher was looking to estimate how work Experience (XP), Level of Education (LE), the Perceived Capability (PC), and Training (TRG) influences Trust-in-Technology (TT). TT is a well-studied construct on its influence on Intent-to-Use (IU) however this study explored how Perceived Usefulness (PU) and Perceived Risk (PR) mediates the relationship between TT and IU in a voluntary setting.

In the era of Big Data, Chang, Kauffman, and Kwon (2014) noted a significant paradigm shift towards an interdisciplinary social research agenda in information processing and analytics. The last decade has produced useful tools and techniques for handling massive datasets. Generation and acquisition of data have more than quadrupled (Aye & Thandar, 2015). Abbasi, Sarker, and Chiang (2016) point out that BDA is introducing new lines of data in organizations, therefore, “These emerging data sources, decision-making processes, and IT artifacts present an opportunity to revisit questions related to constructs, such as trust, leadership, knowledge transfer, and decision-making.” (p.11)

Critical questions like “how big data four V’s impact user perceptions and intentions to use big data IT artifacts?” can be posed (Abbasi, Sarker, & Chiang, 2016, p.11). Velocity, Volume, Veracity, and Variety of big data are driving organizations into unchartered territories and disrupting established information value chain processes and systems (Akter et al., 2016). Technology, people, and processes are changing. Therefore, research in BDA might yield new insights based on the existing IS constructs (Young et al., 2016).

If the traditional information systems and processes are changing in organizations, Abbasi, Sarker, and Chiang (2016) argue for revisiting traditional IS constructs. This viewpoint is fueled and emphasized by the increase in Big Data adoption by organizations. A report by IDC (Goepfert & Vesset, 2015) estimates a 23% growth in Big Data Investment per year leading into 2019. Gartner also says three-quarters of organizations are investing or planning to spend in big data in the next biennium (Heudecker & Kart, 2015). Increased investments in BDA is a good indicator of the value placed on BDA by different organizations.

Advances in Big Data Analytics (BDA) technologies such as Deep Learning is introducing information systems with capabilities to automate cognitive tasks (The Economist, 2016). A study by Frey and Osborne (2015) identified 702 occupations at high risk of potential automation. Most of the professions classified by Frey and Osborne required cognitive abilities and decision-making skills. This capability to automate cognitive tasks can introduce anxiety and resistance from the user community within an organization (Liu, Li, Li, & Wu, 2016). User behavioral issues are essential in Information Systems (IS) with some studies focusing on what causes users to accept or resist the use of new information systems (Joshi, 2005).

The rise of BDA and related technologies are changing organizations information value chains hence a call by Abbasi, Sarker, and Chiang (2016) to revisit the traditional IS constructs. Traditional IS theories such as the Technology Acceptance Model (TAM) (Davis, 1989) based on the theory of planned behavior are pivotal in predicting user behavior (Ajzen & Fishbein, 1980) and can shed new insights in the intent-to-use BDA in organizations.

Introduction of new BDA technologies is forcing organizations to re-engineer their business processes (Mayer-Schönberger & Cukier., 2014) due to the automation of cognitive and manual tasks. Automation can introduce anxiety to business users (Frey & Osborne, 2015). The clash between business users and technology is not new to IS. However, increased adoption of BDA presents an exciting opportunity to revisit existing IS concepts. In a Big Data editorial paper, Abbasi et al., (2016) call for an exploratory research agenda of factors influencing behavioral intentions to use BDA in organizations. It is essential for an organization to understand the factors that affect intent-to-use BDA so that they can adopt appropriate measures to promote usage.

**Dissertation Goal**

The primary aim of this research was to understand and explain the factors influencing intent-to-use BDA in an organization. Adoption of BDA can introduce some challenges in organizations such as where to store the amount of data collected, privacy concerns, how to deal with bias and false positives (Janssen, van der Voort, & Wahyudi, 2017). These challenges can be overwhelming and might influence intentions to use BDA. The Economist (2016) reported that advances in deep learning and machine learning are increasing the probability of automation of many US jobs thereby growing workers' anxiety and resistance to using (Liu et al., 2016; Najafabadi et al., 2015).

Using traditional IS theories on behavioral intentions, the researcher explored the interaction of trust in BDA and intent-to-use BDA in an organization. The use of BDA is considered a voluntary act, therefore well aligned with the Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1980) and the Technology Acceptance Model (TAM) (Davis, 1989; Joshi, 2005). These studies have found relationships between beliefs, attitudes, intentions and usage behavior. Information Systems (IS) theories on technology acceptance are pivotal in predicting user behavior and understanding relationships between behavioral intentions, perceived risks, perceived usefulness, usage, and resistance to implementation of an information sys

Cognitive misperceptions, loss aversion, and net benefits as some of the critical factors causing user resistance to technology acceptance. Focusing on the business users and their behavioral intent-to-use BDA, the researcher examined how trust in technology, perceived risks, and usefulness can influence intent-to-use BDA. The goal of this study was to estimate how work experience (XP), level of education (LE), the perceived capability of BDA (PC), and training (TRG) influence trust-in-technology (TT). Based on well-studied IS concepts, the researcher explored how Perceived Usefulness (PU) and Perceived Risk (PR) mediates the relations between TT and IU in a voluntary setting.

**Research Question**

It is essential for an organization to realize the benefits of its BDA investments through the utilization of the capability to drive decision-making. The central research question for this study is “what factors influence intent-to-use Big Data Analytics in an organization.” IS research has developed different models explaining a range of factors that affect technology usage. BDA is technology-driven, therefore, IS constructs can help to predict intent-to-use and use of BDA (Lytras, Raghavan, & Damiani, 2017). TAM stands out primarily due to its assessment approach and its predictive explanatory capacity to explain individual behaviors in the adoption of technology. TAM’s supremacy is about the relationships between four fundamental constructs explaining the adoption of technology: attitude, perceived usefulness, perceived ease-of-use, and intent-to-use.

Intent-to-use (IU) represents an individual's willingness to perform a behavior and therefore a reliable signal to technology usage. Intent and actual behaviors are highly correlated (Venkatesh & Davis, 2000). In a post-adoptive environment, the researcher believes Trust-in-Technology plays a leading role in influencing intent-to-use BDA in an organization. The concept of trust is studied in various scientific disciplines and accepted as a fundamental component of human social relations (Mou, Shin, & Cohen, 2016). Mcknight (2009) introduced Trust-in-Technology (TT), then it was operationalized by Mcknight, Carter, Thatcher, and Clay in 2011 with the development of an instrument consisting of several trust dimensions contributing to Trusting Belief in Specific Technology (TBST). The researcher extended Mcknight, Carter, Thatcher, and Clay's model since their study validated a significant relationship between TT and UI.

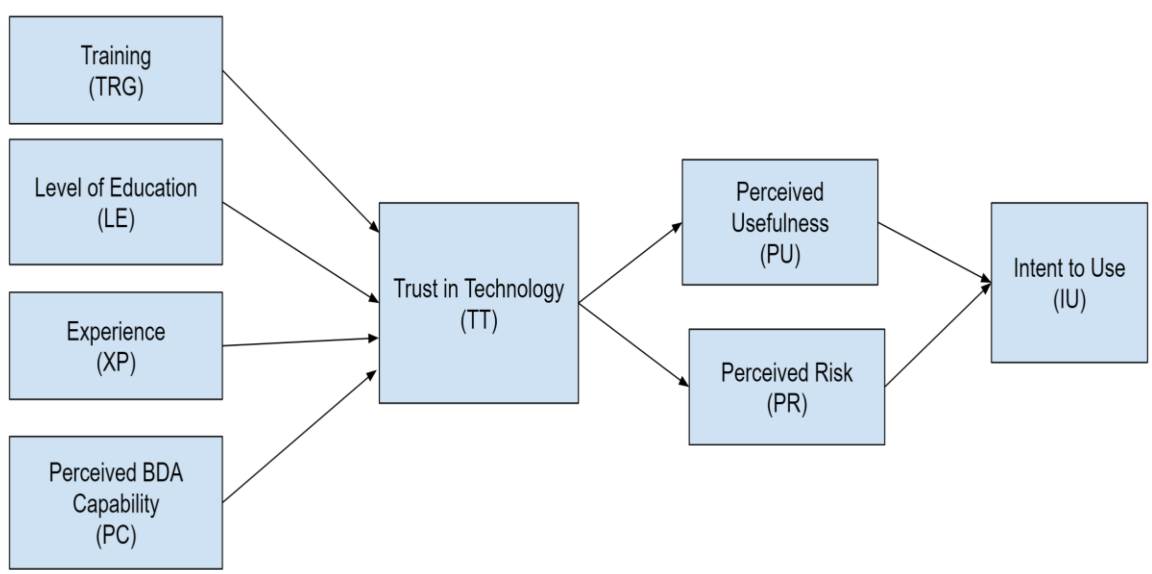


*Figure 2.* Conceptual Research Model

Perceived Usefulness (PU) and Perceived Risks (PR) are mediating variables to explain the relationship between TT and IU better. Rooted in Perceived Risk Theory, PR is the idea that business users' perceptions of risk impact their decisions and choices (Slovic, 2016). The aim was to explore the cognitive misperceptions and loss aversion positions of the business users towards the use of BDA. PU in IS research is defined as the degree that a user believes the use of a system will increase their performance (Davis, 1989; Mou et al., 2016).

The specific research questions addressed are:

RQ1: To what extent does TT influence IU?

RQ2: To what extent do PU and PR mediate the relationship between TT and IU?

RQ3: To what extent do factors such as training, education level, experience, and perceived capability influence TT?

The objective of this study was to understand the degree of influence TT has on IU considering the mediating and independent variables identified.

**Relevance and Significance**

The conducted research is relevant since the assessment was anchored in the Technology Acceptance Model (TAM) and Trust-in-Technology (TT). The aim was to explore the impact of TT on IU mediated by PU and PR. Trust is a multidimensional concept, therefore, plays a pivotal role in shaping trusting intentions to use technology. The work by McKnight on the TT construct was foundational and validated the close relationship between TT and IU.

The goal of adoption is the successful use of technology to achieve desired outcomes. Adoption and usage are positively correlated (King & He, 2006; Mou et al., 2016). However measuring IS success is an elusive endeavor due to the multidimensional definition of the key dependent variable "success" (Petter, DeLone, & McLean, 2008). Some studies concentrated their research on understanding systems use for instance TAM which is very useful explaining usage behavior but still comes short on explaining other phenomena (Karahanna, Agarwal, & Angst, 2006). The research was significant since its results will provide guidelines on how to improve behavioral intentions to use BDA in organizations.

**Barriers and Issues**

A significant obstacle in this study is the identification of subject matter experts on BDA. Big Data is such a "hot" topic. Therefore, the process of qualifying an expert can be challenging given the different definitions of what big data is in the industry. Creswell (2012) and Sadkhan Al Maliky and Jawad (2015) present approaches to criteria, selection, and sizing of expert panels, however, the primary challenge is on identification on potential panelists. The study leveraged professional networks and connections in the study organization to identify thought leaders.

**Limitations, and Delimitations**

*Limitations*

Studies in technology innovation adoption suggest that the organization's size and technological resources competency both play a significant role in the adoption of BDA (Agrawal, 2015). The research focused on an organization within North America because it is not possible to sample all organizations due to budget, time and feasibility. The researcher made use of an industry focused TDWI Big Data Maturity Model to assess the organization's Big Data Analytics maturity. The model provides a proven benchmark on various dimensions of Big Data adoption (Halper & Krish, 2014).

*Delimitations*

Given the generalization limitation mentioned above, the study focused on an Oil and Gas organization based in both the United States and Canada. The organization has just adopted a data-driven decision-making strategy and making data an organizational asset. Written consent of access was granted, and the survey was administered within the organization. The study was conducted under the study organization's transformation activities therefore well aligned with some of the business objectives. This environment was ideal for support and assistance from the leadership.

**Definition of Terms**

For this study the following items are defined for the study participants:

1. Analytics – is the process of discovery, communication, and interpretation of meaningful patterns in data (Braganza et al., 2016)
2. Big Data – is data that is complex, consisting of different data types and accumulating at a rapid velocity (McAfee & Brynjolfsson, 2012; Provost & Fawcett, 2013; Verschiedene, 2014). These datasets are defined by four dimensions of volume, velocity, veracity, and variety.
3. Big Data Analytics - incorporates advanced analytical techniques to create models using structured modeling processes over big data sets (Abbasi, Sarker, & Chiang, 2016; Ebach et al., 2016). It is a cross-section between Modeling Process, Machine Learning, and Big Data.

4. Information Value Chain - a systematic process where data is transformed into information, information into knowledge, and the knowledge into decisions that result in specific actions (Sarvary, 2011).
5. Institutional-Based Trust - is the belief that success is likely due to the supportive situations and structure within an organization or institution.
6. Intent-to-Use - represents an individual's willingness to perform a behavior (Mcknight et al., 2011).
7. Perceived Risk - is the quantification of uncertainty based on the individual's perceptions of risk associated with the use of specific technology (Gifford, 2010; Stalker, Levy, & Parrish, 2012).
8. Perceived Usefulness – is the degree to which an individual believes that using a particular technology would enhance his job performance in one organizational context (Davis, 1989; King & He, 2006; Zabadi, 2016)
9. Propensity-to-Trust – is the tendency to trust technology (Mcknight et al., 2011).
10. Trust-in-Technology – Is the willingness to depend on technology as the trustee because of its perceived characteristics (Mcknight et al., 2011).
11. Trusting Beliefs in Specific Technology – is the conviction that the trustee has the favorable attributes to induce trusting intentions (Mcknight et al., 2011).

**List of Acronyms**

1. BDA - Big Data Analytics
2. IBT - Institutional-Based Trust

3. IS - Information Systems
4. IU - Intent-to-Use
5. IT - Information Technology
6. ML - Machine Learning
7. PR - Perceived Risk
8. PTT - Propensity-to-Trust
9. PU - Perceived Usefulness
10. TAM - Technology Acceptance Model
11. TDWI - The Data Warehouse Institute
12. TRA - Theory of Reasoned Action
13. TT - Trust in Technology

**Summary**

Increased adoption of BDA technologies by organizations is disrupting existing business processes due to automation of cognitive and manual tasks. This trend is introducing yet another frontier in the clash between business users and technology. This study leveraging existing IS constructs will explore this frontier and consider assessing the factors influencing intent-to-use BDA in an organization. The researcher will focus on trust in technology and its impact on intent-to-use. The researcher will also introduce perceived risks and usefulness as mediating variables to explore the nature of the relationship between TT and IU. To better explain TT within an organizational context, independent variables were examined such as experience, perceived capability, training, and level of education (LE).

# Chapter 2

# Review of the Literature

## Introduction

The literature review was conducted to provide a theoretical foundation for this research. Extensive research is available on behavioral intentions and use of technology in IS. This study was instead focused on the disruptive phenomena of Big Data Analytics and how trust-in-technology (TT) influences intent-to-use (IU) in an organization. Trust is a complex concept studied in various disciplines however in the decision-making context of BDA; trust is an essential pre-condition for assessing risks and alternatives (Delibašić et al., 2015; Schrage, 2016).

Trust can influence the level of confidence in any relationship and interaction. Rotter (1967) referred to trust as primarily the optional dependency on others' behavior instead of controlling it. Rousseau, Sitkin, Burt, and Camerer (1998) defined trust as a psychological state to be vulnerability accompanied by positive expectations from another party. Both definitions reflect a dependency relationship between the trustor and the trustee. Literature supports a link between TT and IU; however, this study will also explore how Perceived Risk (PR) and Perceived Usefulness (PU) mediates the relationship.

In an organizational setting, the researcher posited training (TRG), experience (XP), perceived capability (PC),  and educational level (LE) influenced trust-in-technology (TT) in  BDA. These independent variables can better explain TT which in turn can be used to estimate IU as mediated by PR and PU. BDA is changing organizations' information value chains. Therefore, technology, people, and processes are also changing. This research focused on leveraging existing IS constructs on BDA consequently yielding new insights.

**Big Data Analytics**

A "Big Data Analytics" search on Google Scholar returns thousands of search results. An indication of increased activity in this research area. A quick scan of over 300+ journal articles and conferences papers reveal a focus on tools and technologies that deal with the four characteristics of big data: volume, velocity, veracity, and variety. Big Data Analytics (BDA) incorporates advanced analytical techniques to create models using structured modeling processes over big data sets (Abbasi, Sarker, & Chiang, 2016; Ebach et al., 2016). This definition is a cross-section between Modeling Process, Machine Learning, and Big Data. The development lifecycle of BDA applications involves data ingestion, data processing, analytical modeling of the data, and preparation of insights and data egestion. Sophisticated big data technologies in commercial and open-source domains support the organization's Big Data Analytics adoption journey

As defined by Chen, Chiang, and Storey (2012), BDA is related to Business Intelligence and makes use of data mining and statistical analysis. The definition by Côrte-Real, Oliveira, and Ruivo (2016) seems to summarize how literature defines BDA in general. BDA is " a new generation of technologies and architectures, designed to economically extract value from massive volumes of a wide variety of data, by enabling high-velocity capture, discovery, and analysis (p 380)." The definition describes a group of components working together to produce useful information. The researcher defines BDA as a capability (people, processes, and technology) to process big data sets to uncover insights, correlations, and useful information. A capability is business processes, technology, and people working together to produce useful information hence BDA regarded as an Information System (IS) in this study (Kroenke, 2014).

The business value of technology in many IS research studies however the focus seems to be on cost and benefits assessments. Focusing on IS spending alone can be misleading because the spend on BDA has been expanding and expected to reach more than 180 Billion Dollars by 2019 (Columbus, 2016). The promise of BDA to provide competitive advantages and business agility to changing market conditions is the primary driver of spending growth (Barton & Court, 2012; Côrte-Real et al., 2016) however does not drive usage once BDA adopted in an organization.

The impact of BDA is massive if leveraged and used accordingly (Arora, 2016; Chen et al., 2012; Duan & Xiong, 2015). This fact highlights the importance of BDA in organizations to improve operational efficiencies and market positions. Increased investments in BDA does not necessarily translate into intent-to-use and usage (Agrawal, 2015).

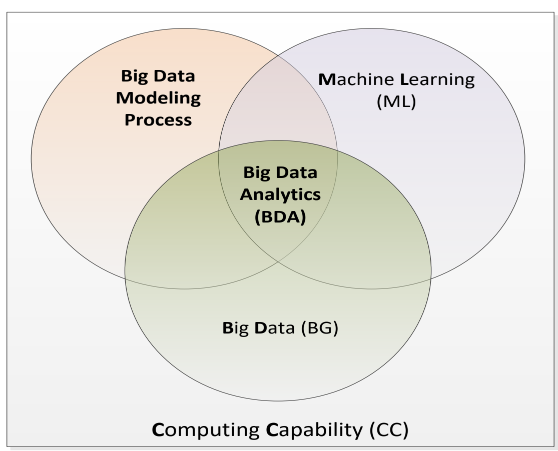


*Figure 3.* Big Data Analytics Definition (Agrawal, 2015)

It is essential to understand what factors can influence intent-to-use and future usage of BDA to improve decision-making processes.

The availability of Big Data and BDA is driving organizations to be data-driven, therefore, changing their decision-making frameworks entirely (Schrage, 2016). This transformation is leading to many organizations investing heavily in Big Data technologies thereby increasing pressure on the decision makers to leverage these new capabilities (Mandinach, Honey, & Light, 2014; McAfee & Brynjolfsson, 2012). The process of understanding data is critical to the decision-making process. Without a structured process of collecting, storing and performing analysis of the data, the decision process can be flawed (Poleto, De Carvalho, & Seixas Costa, 2015). BDA is a disruptive capability. Therefore, it is essential to understand how decision-makers view this capability and how factors such as trust (Agarwal & Dhar, 2014), perceived capability within the organization, training and educational levels of users play a role in the intent-to-use this new capability.

The use of BDA can be insightful to inform and evaluate alternatives in decision-making due to the use of data mining and statistical analysis (Schrage, 2016). A good example is a case study on how Reviewer a cloud-based guest intelligence solution makes use of guest reviews to generate insights for its hotel clients to use in making pricing decisions and services (Mcguire, 2017). These actionable insights from raw guest reviews can help hotels to prioritize their service and operational improvements. BDA insights are input to the decision-making process, and it is imperative for these ideas to be trusted by the decision-maker.

**Technology Acceptance**

To understand technology acceptance models, it essential to have a quick review of some foundational IS models and theories such as the Theory of Reasoned Action (TRA). In 1975, Ajzen and Fishbein proposed TRA. The theory was updated in 1980. TRA is based on studies in social psychology aimed at predicting individual’s behaviors on intention and process of persuasion. The focus was on predicting attitudes however explicitly concerned with behavior. TRA separated behavioral intention from the behavior. Therefore, it centered on the factors that limit the influence of attitudes (behavioral intention) on behavior. TRA is viewed as one of the early prediction models of adoption suggesting a direct relationship between behavioral intent and action (Mou et al., 2016). The theory proposed that behavioral attitudes were facilitated through behavioral intent and normative beliefs (Ajzen & Fishbein, 1980).

The model uses the underlying assumption of a direct effect of attitude toward intent-to-use which is referred to as the behavioral intention (Belanche, Casaló, & Flavián, 2012). TRA has been adopted in several studies, and it is a foundational theory for the Technology Acceptance Model (TAM). To link beliefs and behavior, Ajzen and Fishbein (1980) introduced the Theory of Planned Behavior (TPB) to address the limitations of TRA by presenting the concept of perceived behavior (Knabe, 2012; Mathieson, 1991). Ajzen and Fishbein (1980) examined relationships of norms, attitudes, perceived behavioral factors to the intent and actual behavior. TPB focused on the individual’s control and abilities to perform on their intentions when there is an opportunity (Abbasi, Sarker, Chiang, et al., 2016; Mathieson, 1991)

To better predict user behavior on technology acceptance, Davis (1989) developed a Technology Acceptance Model (TAM) based on adopting the Theory of Reasoned Action (TRA) by Ajzen and Fishbein (1980). Many are researchers have used TAM to predict intention to use technology (Gefen, Karahanna, & Straub, 2003; Mathieson, 1991; Moqbel & Bartelt, 2015; Zabadi, 2016) however some researchers such as Chuttur (2009) argued the model was not flexible and generalizable. TAM's foundation on TRA depended on two beliefs of perceived usefulness (PU) and perceived ease of use. Use of technology is believed to start with perceived usefulness by the user of the technology (Davis, 1989).

Perceived Usefulness (PU) was defined by Davis (1989, p. 320) as "the degree to which a person believes that using a particular system would enhance his or her job performance." In the context of BDA, this concept can be viewed as the degree that a decision maker believes a BDA information system will facilitate the decision-making process, especially in uncertainty conditions. Even with an active PU, it is essential to understand the actual intent-to-use. This study is focusing on the intent-to-use because it is believed to be a single high predictor of actual usage (Venkatesh, Thong, & Xu, 2016).

Venkatesh and Davis (2000) introduced the extension of TAM based on the conclusion that perceived usefulness is directly proportional to the usage intentions. They concluded that perceived usefulness construct drives usage intentions and this influence will change over time with an increase in usage. The essential contribution of TAM2 is understanding usage intentions with continued use of over time. Within an organization context, TAM2 added theoretical constructs on social influences processes (as such as voluntariness and image), job relevance, output quality and perceived ease of use

(Belanche et al., 2012; King & He, 2006). In TAM2, voluntariness is considered a moderating variable, suggesting that in mandatory settings good intentions to use weakens from the time of implementation (Venkatesh & Davis, 2000).

A Unified Theory of Acceptance and Use of Technology (UTAUT) was introduced in 2003 as an attempt to incorporate all the theories on technology acceptance such as TRA, TAM, Motivation Model (MM), Theory of Planned Behavior and the Model of PC Utilization (Venkatesh et al., 2016; Williams, Rana, & Dwivedi, 2015; Zuiderwijk, Janssen, & Dwivedi, 2015). UTAUT considered several moderating variables such as gender and experience to predict user behavior and behavioral intentions. UTAUT focused on four constructs of performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh et al., 2016).

UTAUT does not include the Task-Technology Fit (TTF). TTF is defined as the likelihood of an information system to have a positive impact on an individual’s performance (Goodhue & Thompson, 1995). Later in 2012, UTUAT2 was introduced to focus mainly on employees and organizations (Williams et al., 2015). Both models have been criticized for the number of independent variables and also the fact that voluntariness has been ignored (Seuwou, Banissi, & Ubakanma, 2016). Several extensions have been proposed, and a good example is a study by Alharbi (2014) extending UTAUT Model with a Trust construct in the acceptance of cloud computing.

**Trust in Technology**

In an organizational setting, trust is critical: frontline workers must trust that data collected is complete; information workers must trust that the data provided is accurate for logical analysis and processes, and decision-maker must trust that the information is timely and precise. Uncertainty and undesirable outcomes are both consequences of decision-making. Therefore, trust becomes a crucial aspect of the decision process.

A study on Trust-Based analysis on Air Force Collision Avoidance System concluded that trust is heavily influenced by "high reliability, transparency, familiarity, and anthropomorphic features" (Lyons et al., 2016, p 9). These factors support cognitive and emotional trust as a necessary trust-in-technology antecedent. Organizational norms and social beliefs are also additional viewpoints that need to be considered for an increase in technology adoption (X. Li, Hess, & Valacich, 2008). Trust as to be seen in its full spectrum (Lyons, Ho, Koltai, et al., 2016) to understand how users perceive risks and usefulness of technology.

Trying to predict organizational factors that will influence intent-to-use technology, TAM comes short because the theory is based cost and benefit assessment of its constructs. This study is going to explore the work by Mcknight, Carter, Thatcher, and Clay (2011) who developed a trust-in-technology (TT) measurement broken into two components of initial trust and knowledge-based trust. Initial trust is defined as the trustor's perspective and judgments before experiencing the trustee. After experiencing the trustee, the trustor will then have enough information to predict the trustee's behavior. Based on behavioral predictability that comes with experience and interaction this called knowledge-based trust.

Technology acceptance is correlated to usage and trust can be a crucial driver for adoption (Belanche et al., 2012) as portrayed in the online shopping study by Gefen, Karahanna, and Straub (2003). In an IS context, recent studies view technology as the other party required to be dependable and reliable hence the trust-in-technology construct

(Lankton, Mcknight, & Tripp, 2015; H. McKnight, Carter, & Clay, 2009; Pak, Rovira, McLaughlin, & Baldwin, 2016).

## Perceived Usefulness and Risk

### *Perceived Usefulness*

Perceived usefulness is defined as the degree to which an individual believes that using a particular technology would enhance his job performance in one organizational context (Davis, 1989; King & He, 2006; Zabadi, 2016). In TAM, perceived usefulness is a crucial measure of attitude and influence on the recent technology. In the BDA context, use of big data has enabled the automated use of algorithms and models supporting decision-making processes in organizations promptly (Abbasi, Sarker, & Chiang, 2016). Harvard Business Review published an article promoting the use of BDA to improve operational efficiency (cost, revenue, and risk) in organizations (Schrage, 2016). In this study, perceived usefulness will be applied to the individual perception and belief that BDA increases the quality of decision-making, therefore, lowering the perceived risks of intent-to-use of BDA.

When studying consumer risk-taking behaviors, Bauer (1960) introduced the Perceived Risk Theory to explain how consumers perceive risk when faced with uncertainty. Past studies in IS have shown that technology users seeing greater risks will limit or avoid the use of the technology (Im, Kim, & Han, 2008; Y. Li & Huang, 2009). Some studies have concluded that perceived risk is a moderating variable to technology acceptance (Im et al., 2008). The core constructs of the Perceived Risk Theory are conceptualized into six dimensions of performance, financial, time, safety, social, and psychological (Carroll, Connaughton, Spengler, & Byon, 2014).

*Perceived Risk*

In a nutshell, perceived risk is a critical aspect of decision-making in various settings and levels. For instance, a business manager must evaluate the benefits and costs of action by evaluating as many possible alternatives and information. The process of risk analysis is critical is making significant decisions in the face of uncertainty (Poleto et al., 2015) therefore this demands careful evaluation of data to balance undesired consequences and expected outcomes. Gifford (2010) defines the notion of risk to be linked to the concept of uncertainty. The degree of uncertainty in an outcome is closely related to the risk of undesirable consequences. In a simplified version, perceived risk can be viewed as the quantification of uncertainty based on the individual's perceptions (Gifford, 2010; Stalker et al., 2012).

In the BDA context, decision-making quality is adversely influenced by Big Data volatility, noise in the data and inherent errors which can result in incorrect outcomes (Janssen et al., 2017). For each decision driven by BDA, a decision-maker may perceive a financial risk if there is a potential for a monetary loss. Performance risk if there is the likelihood of the action not to derive the expected outcomes. Physical risk if the decision is related to a safety problem that can result in a health or safety consequence. Psychological risk if there is a possibility self-image damage from the decision. Social risk if there is a possibility of adverse perceptions of others. Perceived Risk in this study is the measure of perceived situations and uncertainty defined from the perspective of the decision-maker (Dowling & Staelin, 1994).

## Research Model

The primary goal was to understand the degree of influence of Training (TRG), Level of Education (LE), Experience (XP), Perceived Capability (PC), and Trust-in-Technology (TT) on Intent-to-Use (UI) of BDA in an organization. Perceived Usefulness (PU) and Perceived Risks (PR) are mediating variables to explain the causal effect of TT to IU better.

### *Intent-to-Use (IU)*

Intent-to-use (IU) represents an individual's willingness to perform a behavior and therefore a reliable signal to usage. Intent and actual behaviors are highly correlated (Venkatesh & Davis, 2000) thus IU is deemed as the best predictor of actual usage. As previously stated, it is essential for an organization to realize the benefits of its BDA investments through the utilization of the capability to drive decision-making. IS research has developed different models explaining numerous factors influencing technology usage. BDA is technology-driven. Therefore, IS constructs can help to predict intent-to-use BDA (Lytras et al., 2017).

TAM stands out primarily due to its assessment and predictive explanatory capacity to explain individual behaviors in the adoption of technology. TAM supremacy is anchored in the relationships between four fundamental constructs explaining the adoption of technology: attitude, perceived usefulness, perceived ease-of-use, and intent-to-use. Theory of Reasoned Action (TRA) separated behavioral intention from the behavior. Therefore, it centered on the factors that limit the influence of attitudes (behavioral intention) on behavior. IU is the dependent variable in this model.

*Perceived Risk (PR) and Perceived Usefulness (PU)*

Rooted in Perceived Risk Theory, PR is the idea that business users' perceptions of risk impact their decisions and choices (Slovic, 2016). The cognitive misperceptions and loss aversion positions of business-users towards the use of BDA can weaken the relationship between TT and IU. Another argument is less TT can lead to increased PR and eventually a reduction in IU. On the other hand, PU in IS Research has been defined as the degree that a user believes the use of a system will increase their performance (Davis, 1989; Mou et al., 2016). The researcher is introducing PR and PU as mediating variables to explain the causal effect of TT on IU accurately. The causal and mediating relationships are presented in Figure 4 an extension of Mcknight, Carter, Thatcher, and Clay's model.

*Trust-in-Technology (TT)*

Söderström (2009) presents trust into three categories of institution, person, and technology. Each category is divided into knowledge-based and cognitive-based trust as experienced by the trustor. Institution-based trust focuses on relying on an institution or third party to build trust. Person trust refers to individual personalities that influence trust building. Technology trust relates to an individual's willingness to be vulnerable to an information technology based on expectations of technology predictability, reliability, and utility (Lippert & Davis, 2006). Mcknight et al. (2009) introduced TT based on these ideas and later operationalized by Mcknight, Carter, Thatcher, and Clay in 2011 with the development of an instrument measure TT.

The research model presented in Figure 4 is an extension of Mcknight, Carter, Thatcher, and Clay's model.

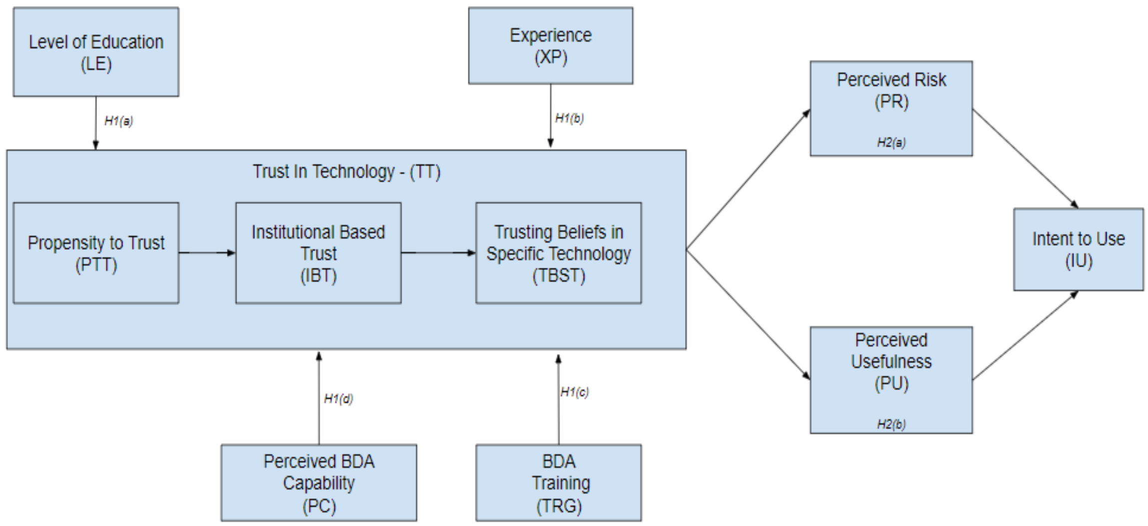


*Figure 4.* Research Model

The operationalized TT construct is composed of a) Propensity-to-Trust (PTT), b) Institutional-Based Trust (IBT), and c) Trusting Beliefs in Specific Technology (TBST). Table 1 shows the indicators variables combined to define the TT composite variable. Based on Mcknight, Carter, Thatcher, and Clay's (2011) work, positive PTT and IBT will positively influence TBST. This study focused on composite variable TT based on the aggregation of the PTT, IBT, and TBST.

The study expanded the work by Mcknight, Carter, Thatcher, and Clay (2011) by examing the influence of a) Level of Education (LE) to PTT, b) Perceived Capability (PC) to IBT, and c) Training (TRG) and Experience (XP) to TBST. LE, PC, XP, and TRG are part demographic information and represent the levers an organization can manage to influence TT and IU.

Table 1

*Indicators for TT*

| Indicator Variable | Description |
|---|---|
| PTT | PTT is the tendency to trust technology |
| IBT | The belief that success is likely due to supportive situations and structures |
| TBST | The conviction that the trustee has the favorable attributes to induce trusting intentions |

Note. Information from Mcknight, Carter, Thatcher, and Clay (2011)

**Hypotheses**

*Demographics and Perceived Capability*

Building TT may help in increasing IU if users believe the technology has the necessary ability, integrity, and benevolence to deliver the desired outcomes. As already stated, trust has three categories of institutional, personal, and technology. LE, XP, and TRG impact trust categories in varying degrees. The following research hypotheses were presented:

H1 (a): Level of Education will positively influence Trust-in-Technology.

H1 (b): Experience will positively influence Trust-in-Technology.

H1(c): Training will positively influence Trust-in-Technology.

The researcher posited positive influence of LE, XP, and TRG on TT. Increased adoption of BDA is an indicator of the perceived value. However, the perceived capability of business users can influence their trust. Positive perception of the BDA capability within the organization may influence TT. Therefore, the following hypothesis statements:

H1 (d): Perceived Capability will positively influence Trust-in-Technology.

*Perceived Risk (PR) and Perceived Usefulness (PU)*

Trust provides assurances to the users. Therefore, it can impact both perceived risk and usefulness. The degree of influence of TT, PR, and PU to IU is well established in IS literature. Mcknight, Carter, Thatcher, and Clay (2011) proved there is a strong influence of TT to IU. As people's trust in specific technology increase, it is also a good indicator of their growth in intent to use that technology. The researcher investigated the type of mediation between TT and IU with PR and PU as parallel mediators.

Under conditions of uncertainty, risk can be defined as a situation where the outcome of a particular decision is unknown to the decision-maker (Riabacke, 2006). The uncertainty of results leads to wrong choices, and worst still is incorrect expected results based on false assumptions and insights. Perceived risk is a measure encapsulated in perceived usefulness and perceived ease of use, however in this study perceived risk is defined as the probability of loss due to subjective feelings of unfavorable consequences (Davis, 1989; Slovic, 2016; Stalker et al., 2012). Rooted in Perceived Risk Theory, this study hypothesizes:

> H2 (a): Perceived Risk partially / fully mediates the effect of Trust-in-Technology on Intent-to-Use.

Perceived usefulness of technology is a fundamental determinant of user acceptance (Davis, 1989; Joshi et al., 2005; Mathieson, 1991). In a BDA context, this study focused on user's beliefs and trust in their intention to use BDA for decision-making. This approach is a recommendation by Venkatesh, Thong, and Xu (2016) as the path forward for a multi-level framework for the Unified Theory of Acceptance and Use of Technology (UTAUT). The researcher proposed the following hypothesis statement:

H2 (b): Perceived Usefulness partially / fully mediates the effect of Trust-in-Technology on Intent-to-Use

For completeness, the researcher validated the TT instrument and research model by Mcknight, Carter, Thatcher, and Clay, (2011) in the context of BDA in an organization.

**Summary**

The literature review has been helpful in identifying the need for a refocused IS research agenda in the Big Data Analytics space. Big Data Analytics is reshaping organization information value chains. Given the volume, variety, veracity, and velocity of data, there is enough evidence to suggest a need to understand how trust-in-technology can influence intent-to-use in an organization. This study explored the existing IS constructs in predicting factors affecting intent-to-use.

The study expanded the work by Mcknight, Carter, Thatcher, and Clay (2011) by examing the influence of a) Level of Education (LE), b) Perceived Capability (PC), Training (TRG) and Experience (XP) on Trust in Technology (TT). LE, PC, XP, and TRG are part of the demographic information and represent the levers an organization can manage to influence TT. As discussed previously, building TT may help in increasing IU if users believe the technology has the necessary ability, integrity, and benevolence to deliver the desired outcomes. The researcher posited positive associations between LE, XP, PC, and TRG on TT.

Trust provides assurances to the users. Therefore, it can impact both perceived risk and usefulness. As people's trust in specific technology increase, it is also a good indicator of their growth in intent to use that technology. The researcher investigated the mediation effects of  PR and PU on the relationship of TT on IU.

# Chapter 3

# Methodology

## Introduction

This section describes the approach and steps employed to conduct this research: survey development, pilot study, data collection, and data analysis. As stated previously, the research questions for this study are:

RQ1: To what extent does TT influence IU?

RQ2: To what extent do PU and PR mediate the relationship between TT and IU?

RQ3: To what extent does factor such as training, education level, experience, and perceived capability influence TT?

## Approach

Predicting intent-to-use (IU) technology is a broad phenomenon covering multiple disciplines in literature. Therefore, a robust methodology to explore the richness of the topic and the complexity of human behavior from different viewpoints was necessary. A deterministic philosophical approach was employed to understand the factors influencing intent-to-use BDA. The aim was to generalize the results because BDA is a disruptive technology in many organizations (Wamba et al., 2016). The goal was to have this study reproducible across different organizations and industries. Using a survey method approach allowed for an in-depth exploration of the phenomenon and then measured its prevalence in an organization.

Exploratory Design is a variant of the mixed methods sequential exploratory design that consists of two phases: qualitative followed by a quantitative phase (Bryman, 2011). The voluntary use of BDA in the study organization was the default assumption in this study, and this assumption was confirmed during the senior leadership interview.

Table 2

*Instrument Development Model Steps*

| **Step** | **Description** | **Purpose and Mechanism** |
|---|---|---|
| 1 | Analytics Maturity Assessment | Interviewed the study organization leadership and facilitated the completion of the TDWI's Analytics Maturity Assessment. |
| 2 | Systemic Literature Review | Focusing on the theoretical study constructs, the researcher conducted a systematic literature review as recommended by Maxwell (2006) to find connections and relevance. |
| 3 | Instrument Development | Developed an anonymous web-based survey instrument to measure the study constructs based on the proposed research model using existing IS measures. The tool has all items as closed questions with answers on a 7-point Likert scale. |
| 4 | Pilot Study | Participants of the focused group were recruited via email and invited to a private Yammer group. A web-based survey was opened, and participants collaborated in the private Yammer group. Participants were encouraged to provide feedback about the instrument. |
| 5 | Pilot Data Analysis | Applied advanced multi-variant statistical methods to analyze pilot data. Given the small sample in the Pilot Study, PLS-SEM was employed to validate the measurement and structural models. |
| 6 | Pilot Study Results | Based on the pilot study results and feedback, the instrument was adjusted to reflect the findings. Given the combination of formative and reflective measures, the data analysis was switched from a covariance-based SEM to a PLS-SEM. |

Note. Information from Cresswell (2014)

Given the complexity of the phenomena, a survey methodology to quantitatively estimate and measure causation factors influencing intent-to-use BDA was employed as planned (Cresswell, 2014; Creswell, 2012). Table 2 and Figure 4 outlined the research approach. The Instrument Development Model approach is a variant of the Exploratory Design (Bryman, 2011; Cresswell, 2014). Figure 5 is an outline of the two phases: a) Instrument Development and b) Data Collection and Analysis.

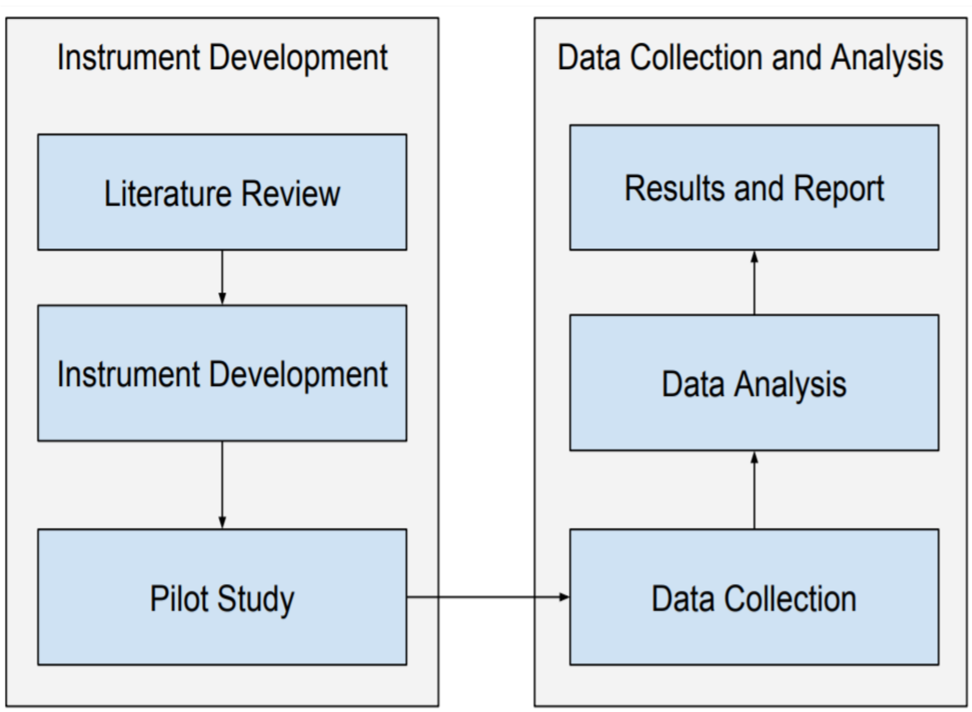


*Figure 5.* Research Approach

*Literature Review and Instrument Development Phase*

In the first phase, the focus was a literature review, and survey development based on validated IS constructs. The objective was to develop an instrument supported by literature to measure and estimate intent-to-use (IU) Big Data Analytics in an organization. Validated instruments existed in IS to measure all the constructs in this study. The researcher conducted a systemic literature review to situate and justify decisions in the study (Siddaway, 2014). Beile and Boote (2005) presented an argument that a literature review should be thorough and comprehensive. In response to Beile and Boote (2005), Maxwell (2006) argued for relevance rather than comprehensiveness. A systematic literature review was conducted as recommended by Maxwell (2006) to find connections and relevance.

An anonymous web-based survey instrument to measure the critical constructs based on the research model was developed leveraging existing IS constructs. The tool had all items as closed questions with answers on a 7-point Likert scale. Before the tool was finalized for the study, the researcher conducted a pilot within the same organization. The pilot participants were recruited from the population of the established online focus group to test the validity of the instrument. Validity tests were carried out before the instrument was finalized. The instrument was based on the study constructs, and each criterion reliability was verified using Cronbach's alpha, a measure of internal consistency (Cronbach, 1951; Levy & Green, 2009).

*Measures*

Trust-in-Technology (TT) construct was operationalized with three sets of concepts. McKnight and others (2011) defined the TT construct as composed of a) Propensity-to-Trust (PTT), b) Institutional-Based Trust (IBT), and c) Trusting Beliefs in Specific Technology (TBST). McKnight and others (2011) developed the instrument with measures outlined in Table 3 showing their reliability results. In summary, PTT is the tendency to trust technology. IBT is the belief that success is likely due to supportive situations and structure. TBST is the conviction that the trustee has the favorable attributes to induce trusting intentions.

Table 3

*Trust-in-Technology Measures and Reliability of Constructs*

| **Construct** | **Measure** | **Items** | **Cronbach's Alpha** |
|---|---|---|---|
| Trust-in-Specific Technology | Trusting Intention-Specific Technology | 4 | .97 |
| | Trusting Belief-Specific Technology – Reliability | 6 | .95 |
| | Trusting Belief-Specific Technology – Capability | 4 | .94 |
| | Trusting Belief-Specific Technology – Helpfulness | 5 | .97 |
| Institution-Based Trust-in-Technology | Situational Normality – Technology | 4 | .95 |
| | Structural Assurance – Technology | 4 | .95 |
| The Propensity to Trust General Technology | Faith in General Technology | 4 | .95 |
| | Trusting Stance – General Technology | 3 | .91 |

Note. Information from Mcknight, Carter, Thatcher, and Clay (2011)

Perceived Risk (PR) was conceptualized into six dimensions of performance, financial, time, safety, social, and psychological by Carroll and others, (2014). Based on the work by Carroll and others (2014), the Perceived risk was assessed using a 7-item measure. The majority of items were adapted from Dowling and Staelin (1994), and Y. Li and Huang (2009). For this study, all the items were modified to reflect the perceived risk associated with BDA. In summary, the items covered performance risk as the likelihood that technology does not perform as expected. Financial risk as the potential monetary loss from the use of technology. The psychological risk as the possibility that the selected technology will be consistent with the user's self-image. Social risk as the perception of significant others towards the technology. Time as the perception of wasted effort or loss of time due to the use of technology and finally safety is the perceived personal risk of using the technology. The seventh item measured the overall perception of risk from using Big Data Analytics for decision-making.

Perceived Usefulness (PU) was a 6-item measure with all the items adopted from Davis (1989). Mcknight and others, (2011) adopted the same measure but changed the items to fit their study. In this study, the PU (6 items, $\alpha$=.98) validated by Davis (1989) was well suited for the study. As stated in Chapter 2, PU is defined as the degree to which an individual believes that using a particular technology would enhance his job performance in one organizational context (Davis, 1989; King & He, 2006; Zabadi, 2016). Items measuring PU are available in Appendix C.

Perceived Capability (PC) was derived from BDA Capability defined by Gupta and George (2016) as "a firm's ability to assemble, integrate, and deploy its big data-specific resources" (p. 1049). BDA Capability construct was based on resource-based theory (RBT) and IT capability literature. The construct was composed of three concepts: a) tangible resources, b) human skills, and c) intangible resources.

Tangible resources were measured with three constructs: a) Data (3 items), b) Basic Resources (2 items) and c) Technology (5 items). Human skills were measured with two constructs: Managerial Skills ( 6 items, $\alpha$=.92) and Technical Skills (6 items, $\alpha$=.93). Finally, the Intangible Resources was measured by the Data-driven Culture (5 items, $\alpha$=.90) and Organizational Learning (5 items, $\alpha$=.94) constructs.

Intent-to-use (IU) represents an individual's willingness to perform a behavior and therefore a reliable signal to usage. McKnight and others (2011) called it Intention-to-Explore in their study. In this study, IU was based on the Intention-to-Explore (6 items, $\alpha$=.98) validated by McKnight and others (2011).

*Survey Method Strengths and Limitations*

The study objective was to understand people's attitudes, perceptions, trust, and intentions to use BDA. Therefore, a survey method was ideal. The survey method provides a faster and cheaper approach to data collection, especially if compared to observational techniques. Data collected using a survey method is often simple to analyze, aggregate and interrelate. Unwillingness or inability of respondents to provide accurate information was a significant issue with survey method. It was difficult to identify these issues because respondents found it challenging to understand survey questions based on their perspectives and background.

A pilot study was conducted with 50 participants in the focus group to address the issue of respondents not understanding the survey questions and context. The focus group was tasked with responding to the survey and identifying any potential concerns with the questions. A private Yammer site was created as a collaboration platform to allow participants to post comments, feedback, and questions concerning the survey questions. Based on this approach, several items were rephrased and addressed without compromising the theoretical foundation of the problem.

Another major limitation of the survey method was the issues connected with self-reported data such as selective memory, telescoping, attribution, and exaggeration. It was difficult to prove if these problems existed because of the lack of other sources to compare. Selective memory is when participants remember or do not remember events from the past, and this can impact a participant's understanding of the question and context. Telescoping is recalling events that occurred however with wrong timing. On the other hand, attribution is the act of attributing positive outcomes to one's own and adverse consequences to external forces. Both these biases might have influenced how participants responded to questions about their perception of specific subjects.

No incentives were offered for survey participation to preserve anonymity and the voluntary nature of the study. As anticipated, this was going to be a limitation influencing response rate. To encourage participation recruitment notifications were precise and articulated the goals of the study. During the data collection, weekly reminders were sent out via email and announcements on Yammer.

*Pilot Study*

An online focus group was recruited to join an interactive Yammer group comprising of randomly selected individuals. Each participant had to sign a consent form. Some researchers such as Stancanelli (2010) have claimed that online tools provide the same detail and focus just like the traditional focus group groups. A study by Chai et al.,

(2017) showcase the use of Twitter-based chats in their health-related research based on structured tweets. The study provides useful references for dealing with privacy and ethical concerns of online platforms for research. Results of the pilot study are presented in Chapter 4 and contributions to the primary study.

To better understand the level of adoption of BDA in the study organization, a self-assessment on Analytics Maturity based on The Data Warehousing Institute's (TDWI) Analytics Maturity Model was conducted within the pilot study phase. The model provided a high-level benchmark of an analytics program of the study organization and provided a sound basis for comparing results across different organizations in future studies. The Analytics Model is a benchmark assessment with 35 questions across the five categories a) Organizational Structure, b) Infrastructure, c) Data Management, d) Analytics and e) Governance (Halper & Stodder, 2014).

The self-assessment was an interview with the Chief Information Officer (CIO) of the organization. The assessment was a combination of the TDWI Analytics Model and a face-to-face meeting with the leadership of the organization to better understand the problem space in the context of the organization.  Assessment results were reviewed and shared with the organization's Information Management leadership. Responses to the 35 questions TDWI Analytics Maturity Model Assessment survey were captured in the web-based TDWI survey tool. Table 4 outlines the TDWI Analytics Maturity Model stages of maturity within an organization.

Table 4

*TDWI Analytics Maturity Model – Stages of Maturity*

| Stage | Name | Description |
|---|---|---|
| 1 | Nascent | Pre-analytics stage and the organization is not utilizing analytics fully except perhaps use of spreadsheet programs. |
| 2 | Pre-Adoption | The organization has moved past the Nascent stage, and its staff are aware or playing around with Analytics tools. |
| 3 | Early Adoption | The organization is putting analytics tools and methodologies in place. |
| 4 | The Chasm | The organization is trying to move from early adoption to corporate adoption and extend the value of analytics to more users and departments; enterprises must overcome a series of hurdles. |
| 5 | Corporate Adoption | Corporate Adoption Corporate adoption is the primary crossover phase in any organization's analytics journey. During corporate adoption, end users typically get involved, and the analytics transforms how they do business. |
| 6 | Mature/Visionary | The organization is executing analytics programs smoothly using well-tuned technology infrastructure and business process. |

Note. Information based on the work by Halper and Stodder (2014)

*Data Collection*

The goal of a quantitative inquiry is to seek explanation or causation (Bryman, 2011). Therefore, the primary objective of this phase was collecting useful data for the construction of an estimation model. Table 5 outlines the data collection approaches employed in the study. For the self-assessment on Big Data Analytics Maturity, data was collected using a 35 questions TDWI web-based questionnaire. A face-to-face interview was conducted with the researcher responding to the questions based on the responses from the analytics leader of the organization. In both the primary and pilot phases of the study, an anonymous web-based survey instrument was leveraged. In the pilot study, the participants were part of a focus group that provided feedback and asked questions using a Yammer group. The qualitative data collected in the pilot study was instrumental in improving the instrument and the quantitative data in proving out the data analysis approach.

Table 5

*Data Collection*

| | **Data Collection** | **Tools** |
|---|---|---|
| Self-Assessment on Analytics Maturity | Corporate Leader – Chief Information Officer (CIO) or Analytics Leader | TDWI Analytics Maturity Model Assessment (Survey) and Face-to-Face Interview. |
| Pilot Study | Survey instrument within the study organization. An online focus group will be established. | Anonymous Online Survey Instrument and Invitation only Yammer group. |
| Survey | Survey instrument within the study organization. | Anonymous Online Survey Instrument |

*Pilot Study Sample Size*

The estimate for the pilot study sample size was based on a Rule-of-10 as recommended by Van Belle (2008). The rule suggests at least ten observations for each predictor in the model. In medical research using the same statistical parameters defined in Table 6, a pilot size treatment of between 25 and 75 is recommended (Whitehead, Julious, Cooper, & Campbell, 2016). The primary focus of the pilot study was to estimate feasibility and acceptability, as well as outcome variability that will add to the execution of the primary research. A sample size between 25 and 40 was defined as relatively precise to meet the feasibility outcomes.

The pilot study recruited 50 random participants. Participants were recruited via email and had to register for the study. The pilot study needed 40 participants however due to a high response rate the researcher added an additional 10 participants as a contingency for the desired sample size. A private Yammer group was created as an online discussion forum to allow the participants to discuss and ask questions about the study. The Yammer forum served as an ideal platform to gather feedback on the survey questions and for the researcher to respond to any specific questions.

Table 6

*Statistical Study Parameters*

| **Parameter** | **Value** | |
|---|---|---|
| Anticipated Effect Size | 0.5 | Minimum anticipated absolute effect value for SEM |
| Desired Power Level | 0.9 | Literature defaults to 0.8 |
| Number of Latent Variables | 2 | |
| Number of Observed Variables | 14 | |
| Significance | 0.05 | Also known as the p-value |

Note. Based on the information by Soper (2016)

*Main Study Sample Size*

Initially, the sample size calculation was based on a co-variance-based SEM approach using the parameter values in Table 6. Structural Equation Modeling (SEM) is documented in the literature as an ideal statistical modeling technique for understanding causation and mediation (Monecke & Leisch, 2012). In a study by Levy and Green (2009), SEM was leveraged for model fit examination over multiple regression analysis. SEM is a series of statistical methods that allow for complex multivariate relationships and variables to be examined.

In literature, SEM is considered a hybrid approach between some form of analysis of variance (ANOVA)/regression and factor analysis. It can be remarked that SEM allows for multilevel regression/ANOVA therefore ideal for multivariate analysis. A calculator developed by Soper (2016) provides a perfect tool to calculate the sample size required for SEM. Using the values in Table 6, the minimum recommended sample was set at 400 and a minimum of 30 to detect an effect. Given the size of the study organization and the recommended minimum size, the study initially aimed for a sample size of 500.

In the pilot study, a PLS-SEM approach was leveraged due to the small pilot sample size and the requirement to evaluate both informative and reflective measures in the same model. For PLS-SEM sample size, Hair, Hult, Ringle, and Sarstedt (2014) proposed an alternate method to the Rule-of-10 based on a minimum $R^2$, effect size and a maximum number of arrows pointing to the endogenous variable. This method is ideal because $R^2$ and effect size are excellent measures for model fit in PLS-SEM (Gefen & Straub, 2005). Based on the table by Kock and Hadaya (2018) with five maximum arrows pointing at endogenous variable and targeting a minimum $R^2$ value of 0.1, the recommended sample size was set at 147.

## Data Analysis

The goal of a quantitative inquiry is to seek explanation or causation (Bryman, 2011). SEM is a better approach to understanding mediation and causation in this study. This study has a defined model based on literature. Therefore, SEM provides a better mechanism to conduct a confirmatory factor analysis using model fit analysis. In SEM, a model implies a covariance matrix of the measures therefore once the model parameters are estimated the resulting covariance matrix can be compared for validity (Monecke & Leisch, 2012). Table 7 shows the SEM assumptions for the approach to be valid.

Table 7

*Structural Equation Modeling Assumptions*

| **Assumptions** |
| --- |
| 1. The research model accurately reflects the causal relationship based on theory. |
| 2. The relationship between the variables is assumed to be linear, additive and casual. |
| 3. All exogenous variables are measured without errors |
| 4. There is a one-way causal flow in the model |

Note. Based on the information by Mertler and Vannatta (2013).

### *Data Screening and Processing*

Data collected from the instrument underwent different statistical and multivariate analysis using SPSS and SmartPLS 3.0. Raw files from Google Forms were transformed and exported to CSV format for SPSS. A descriptive study of the data was conducted to summarize and understand the collected data. Missing data analysis was undertaken to examine missing data for each variable. Mahalanobis distance analysis as outlined by Mertler and Vannatta (2013), was leveraged to identify any multivariate outliers. A secondary study calculating the probability of the Mahalanobis distance using SPSS was conducted to flag any cases where the likelihood was less than 0.001 as an outlier. Normality and linearity tests were performed to test SEM assumptions in Table 7.

*Covariance-based SEM*

Levy and Green (2009) identified SEM as a valid approach for confirmatory factor analysis and examining model fit testing better than a multiple regression modeling. The Goodness-of-Fit (GoF) index is a fundamental measurement for projection and reliability of the model. It is understood as the geometric mean of the average commonality and the average $R^2$ (Geoffrey & Ray, 2016). GoF was calculated based on the on the square root of the product of average AVE and average $R^2$ (Becker, Klein, & Wetzels, 2012). A large GoF is considered ideal. However, others argue that GoF does not indicate the reliability of the model, therefore, says nothing about the model (Geoffrey & Ray, 2016; Henseler & Sarstedt, 2013).

The conceptual model presented in this study has both reflective and formative measures. Perceived Capability (PC) is a third-order construct with two first-order constructs (Technology and Basic Resources) with formative measures. Level of Education (LE), Experience (XP), and Training (TRG) are predictors pointing to Trust-in-Technology (TT), but these variables are categorical. Dummy variables were created in SPSS for each construct to capture the appropriate latent scores for each construct. Dummy variables became formative measures pointing to their respective emergent construct in the model. The requirement to assess and evaluate both reflective and formative measures in the measurement and structural model led to the exploration of using Partial Least Squares (PLS) SEM approach.

*Partial Least Squares (PLS) Structural Equation Modeling*

In IS research, the use of OLS regression-based PLS-SEM has become a critical multivariate analysis method to estimate complex models with relationships between latent variables (Gefen & Straub, 2005; Levy & Danet, 2010). The goal of a nonparametric PLS-SEM method is to maximize the explained variance of endogenous variables. The purpose of the study was estimating factors influence intent-to-use (IU). Therefore, the prediction focus was ideal for PLS-SEM (Garson, 2016).

PLS is primarily intended for causal-predictive analysis. The approach is also ideal if the goal is evaluating both formative and reflective measures in the same model. The research model had constructed with both informative and reflective measures. Multivariate normality is a requirement in a traditional SEM approach. However, in PLS-SEM this requirement is relaxed. PLS-SEM approach is deal if a) the target is predicting a construct, b) model has a mix of formative and reflective measures, c) the structural model is complicated, and d) the sample size is small, or the data is non-normally distributed (Garson, 2016).

PLS-SEM models consist of the three main components: a) Inner Model (*Structural*), b) Outer Model (*Measurement*), and c) Weighting Scheme. The PLS Algorithm initially manifest all variables in a data matrix that is scaled to have a zero mean and unit variance. The next step is the estimation of factor scores for the latent constructs using an iterative process. The first step in the iterative process is to construct each latent variable by the weighted sum of its manifest variables. The second step is to reconstruct each latent construct using its associated latent construct as a weighted sum of the neighboring latent constructs. The outer approximation procedure then attempts to locate the best linear combination to express each latent construct by its manifest variables as the third step in the process. In the last step, the latent constructs are put together again as the weighted sum or linear combination of their corresponding manifest variables to arrive at factor scores. The algorithm terminates when the relative change for the outer weights is less than a pre-specified tolerance (Garson, 2016).

The iterative process results in latent variable scores, reflective loadings, formative weights for the measurement model, estimations of path coefficients in the structural model, and $R$-squared values of endogenous latent variables. SmartPLS 3.0 then calculates addition quality measures such as Cronbach's alpha, the composite reliability, the $Q^2$ value of predictive relevance, and $f^2$ effect size. These results make the PL-SEM algorithm a powerful tool, especially when dealing with both formative and reflective measure with a small data sample.

**Summary**

The approach and methodology consisted of instrument development based on a literature review, and data collection and analysis. A web-based anonymous instrument was developed on validated measures in literature. Most of the survey items were rephrased to the context of the study. A pilot study was conducted with a primary goal to estimate feasibility and acceptability. A sample size between 25 and 40 was deemed relatively precise to meet the feasibility outcomes. The pilot study collected 40 observations. Therefore, it was within an acceptable range.

One of the goals was to generalize the results across different organizations. Therefore, the researcher conducted an Analytics Maturity Assessment to benchmark the study organization. The goal of the assessment was to better understand the level of adoption of BDA in the study organization. A TDWI's Analytics Maturity Model Assessment was conducted which is composed of 35 questions across the five categories a) Organizational Structure, b) Infrastructure, c) Data Management, d) Analytics and e) Governance. Based on the assessment, the organization's maturity level was determined based on its peers of the same size in the industry. This information will become important in future studies across different organizations and industries.

In the primary study, respondents to the web-based anonymous instrument were recruited via email. The traditional covariance-based SEM approach required a minimum sample size of 400. For the PLS-SEM approach, Hair, Hult, Ringle, and Sarstedt (2014) proposed an alternate method to calculate a sample size based on minimum $R^2$, effect size and a maximum number of arrows pointing to the endogenous variable. Based on the table by Kock and Hadaya (2018) with five maximum arrows pointing at endogenous variable and targeting a minimum $R^2$ value of 0.1, the recommended sample size was 147.

Data analysis was performed using SPSS and SmartPLS 3.0. In the pilot study, given the small sample size, the estimation focus of the study, non-normal data and a sophisticated research model with formative and reflective measures, PLS-SEM approach was selected as the ideal approach. Based on the significant and relevant data analysis results in the pilot study, PLS-SEM was also leveraged as the approach in the primary research. Chapter 4 presents the results of the measurement and structural models.

# Chapter 4

# Results

## Introduction

Given the complexity of the phenomena, as previously stated, the researcher employed an exploratory design approach which is a variant of mixed methods sequential design that consists of two phases. Phase I included a literature review, instrument development, and a pilot study. Phase II is the primary study consisting of data collection, data analysis and reporting of results. The primary goal of the pilot study was to do a dry-run of the instrument and make corrections in the subsequent study. This chapter presents the results from both the pilot and the primary study.

## Pilot Study

### *Introduction*

The pilot study was initiated on February 26$^{th}$, 2018 by asking for volunteers to sign-up to join the focus group. A total of 50 participants were randomly selected for the volunteer pool, and the participants were enrolled in the private Yammer group. The recruitment message for the study was posted in the Yammer group including a PDF with the Participant Letter for Anonymous Surveys in Appendix D and E respectively. Participants were encouraged to ask questions through the private Yammer group and reminded the study is voluntary. On February 28$^{th}$, 2018 a conference call with the focus group was conducted to address any concerns and questions. During this call, the researcher elaborated on the research background and purpose. This section is reporting the results and findings of the pilot study.

*Analysis of Instrument Reliability*

On February 28th, 2018 after the conference call, the Google Forms survey was opened. The survey consisted of multiple choice questions on a 7-point Likert-scale and demographic information. The survey had two open-ended questions for feedback at the end. However, participants in the pilot study were encouraged to post their feedback in the Yammer group. The survey was closed on March 9th, 2018 with 40 responses out of the 50 participants in the focus group an 80% response rate. The sample size was at the upper limit of the targeted pilot study sample size.

Multivariate data analysis and data screening were conducted. From the data analysis, five cases were removed due to missing data and the instrument was updated to enforce the required responses. Responses were further analyzed resulting in one case being eliminated because all the responses were either neutral (4) or strongly agree (7). A total of six observations were removed leaving a total of 34 valid observations. Table 8 provides the results of the analysis for the instrument reliability. Perceived Risk Cronbach's alpha is at moderate 0.65 and the composite reliability at the same level. Based on IS literature, a Cronbach's alpha between 0.60 and 0.75 is considered to be acceptable (Levy & Green, 2009). These results provide a strong indication that the survey instrument is reliable in its measurements and consistent with prior research that developed the measures.

*Model Testing Results*

Given the small sample size and the combination of formative and reflective measures that make up the Perceived Capability (PC) construct, a PLS-SEM approach was used as an alternative to covariance-based structural equation modeling (traditional

SEM). Data were analyzed using Partial Least Square (PLS) and bootstrapping with SmartPLS 3.0. Consistent PLS algorithm was used because it is well calibrated and can produce actual parameter value for the model as proposed by Dijkstra and Schermelleh-Engel (2014).

Table 8

*Pilot Study: Summary of Measurement Scales*

| **Summary of Measurement Scales** *(n=34)* | | | | |
|---|---|---|---|---|
| **Latent Variable** | **Cronbach's Alpha** | **rho_A** | **Composite Reliability** | **AVE** |
| IBT | 0.84 | 0.855 | 0.843 | 0.409 |
| IU | 0.938 | 0.948 | 0.938 | 0.793 |
| PC | 0.904 | 0.926 | 0.909 | 0.284 |
| PR | 0.645 | 0.699 | 0.653 | 0.399 |
| PU | 0.934 | 0.938 | 0.935 | 0.782 |
| PTT | 0.827 | 0.84 | 0.833 | 0.42 |
| TT | 0.9 | 0.916 | 0.9 | 0.276 |
| TBST | 0.818 | 0.887 | 0.834 | 0.349 |

*Quality Criteria*

The Goodness-of-Fit (GoF) index is the critical measurement for projection and reliability of the model. It is understood as the geometric mean of the average commonality and the average $R^2$ (Geoffrey & Ray, 2016). The calculated GoF based on the square root of the product of average AVE and average $R^2$ is.707 which is considered significant (Becker et al., 2012). However, others argue that GoF does not indicate the reliability of the model, therefore, says nothing about the model (Geoffrey & Ray, 2016; Henseler & Sarstedt, 2013). Instead of GoF, quality measures as the coefficient of determination ($R^2$), predictive relevance ($Q^2$) and importance of an exogenous variable ($f^2$) were leveraged to measure the model quality for an acceptable fit.

Reporting Goodness-of-Fit (GoF) quality measures using PLS-SEM does make not make sense since the measures are based on the comparison of covariance matrices of the saturated versus the estimated model (Garson, 2016). However, all the three measures of GoF outlined in Table 9 are within acceptable ranges. A major setback of GoF is its inability to distinguish valid from invalid models. Therefore, researchers are recommended to avoid its use (Garson, 2016) except for PLS multi-group analysis (PLS-MGA) this quality measure is reported to be ideal (Sarstedt, Hair, Ringle, Thiele, & Gudergan, 2016).

The coefficient of determination, $R^2$ for the endogenous variable IU is at 0.500 indicating the three exogenous constructs TT ($\beta_{TT \rightarrow IU} = -0.098, Q^2 = -0.182, p = .573, R^2 = 0.139$), PU ($\beta_{PU \rightarrow IU} = .685, f^2 = .812, Q^2 = .157, p = .000, R^2 = 0.202$) and PR ($\beta_{PR \rightarrow IU} = .239, f^2 = .071, Q^2 = .225, p = .170, R^2 = 0.291$) can explain the variation.

Table 9

*Pilot Study: Analysis of Overall Goodness-of-fit*

| GoF | Recommended Values | Study Value |
|---|---|---|
| Chi-square | < 3.00 | 0.855 |
| SRMSR | < 0.10 | 0.036 |
| NFI | > 0.90 | 0.986 |

Predictive relevance, $Q^2$ is obtained by the sample re-use technique called ‘Blindfolding’ in SmartPLS 3.0 using the default omission distance set to 7. The recommended setting is between 5 to 10 where the number of observations divided by the omission distance is not an integer (Garson, 2016). A value greater zero is indicative of the path model’s predictive relevance in the context of the endogenous construct and the corresponding measures. $Q^2$ value for TT is below zero indicating the non-predictive significance of TT → IU. This result is not consistent with the findings of Mcknight and others, (2011) in which their study showed a significant predictive relevance of TT → IU.

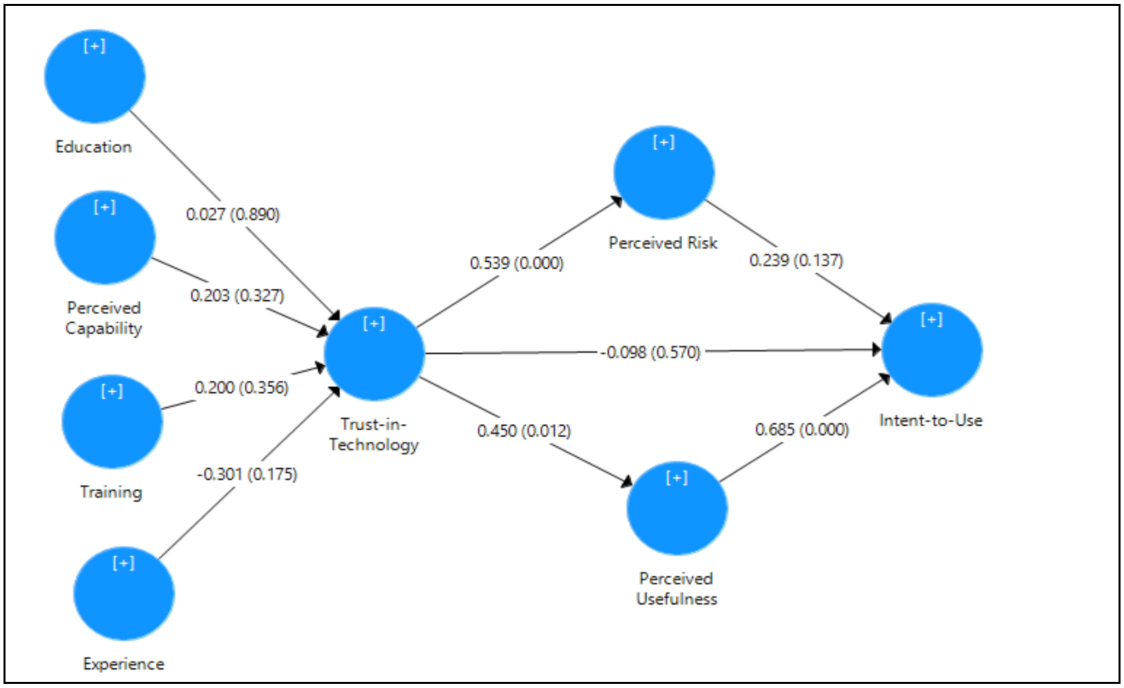


*Figure 6.* Pilot Study: Research Model (Path Coefficients and P-Values)

To measure the importance of an exogenous variable in explaining the endogenous, $f^2$ is an excellent quality measure based on the recalculation of $R^2$ by omitting one exogenous construct at a time. This measure showed consistency with the path significance values as displayed in Figure 6, indicating the importance of PU influencing IU. All the quality measures as indicated in Table 10 are within acceptable thresholds indicating a good fit except for the predictive relevance of TT on IU. The value is negative, and in this case, can be explained by the small sample size of the pilot study.

Table 10

*Pilot Study: Quality Criteria*

| **Measure** | **$R^2$** | **$Q^2$** | **$f^2$** |
|---|---|---|---|
| IU | 0.500 | | |
| TT ($\beta_{TT \rightarrow IU} = -0.098$) | 0.139 | -0.182 | |
| PU ($\beta_{PU \rightarrow IU} = .685$ | 0.202 | 0.157 | 0.812 |
| PR ($\beta_{PR \rightarrow IU} = .239$ | 0.291 | 0.225 | 0.071 |

*Level of Big Data Analytics Adoption*

The TDWI Analytics Maturity Model was a benchmark assessment with 35 questions across the five categories a) Organizational Structure, b) Infrastructure, c) Data Management, d) Analytics and e) Governance (Halper & Stodder, 2014). The assessment interview was conducted on February 27th, 2018 by completing the assessment questions with a senior leader. As stated before, the goal of the assessment was to benchmark the maturity stage of the analytics program within the organization for future use when comparing with other organizations. The organization is in a pre-adoption stage however aware of the benefits of Big Data Analytics. In the interview, the senior leader expressed commitment to continue investments in Analytics as a business necessity. Based on the company size and industry, the organization is in the same stage as most of its peers.

Organizations in a pre-adoption stage are not exploiting data as expected (Halper & Stodder, 2014). In this level, the organization is either planning to adopt Big Data Analytics or in the initial stages of adoption. The study organization has pockets of adoption especially in departments that heavily rely on analytics such as Information

Technology, Finance, and Human Resources. Data is managed in silos and with different versions of truth on critical datasets. In most cases, analytics is mainly on spreadsheets and various tools within the organization.

*Pilot Study Results*

After running a consistent PLS bootstrapping with a thousand sub-samples, Figure 5 outlines the path coefficient of each relationship with the associated p-value. Level of Education (LE), Perceived Capability (PC), Training (TRG), and Experience (XP) have some effects on TT. However, their contributions are not significant.

The negative path coefficient between TT and IU was surprising since the study by Mcknight, Carter, Thatcher, and Clay (2011) has shown a positive coefficient and also significant. A summary of hypothesis statements is presented in Table 11. The results of this study show Perceived Usefulness to have a mediating effect of Trust-in-Technology on Intent-to-Use. Perceived Risk does not have the same mediating effect.

Table 11

*Pilot Study: Summary of Hypothesis Results*

| **Hypothesis** | **Relationship** | **Sig.** |
|---|---|---|
| H1(a) | LE will positively influence TT | No |
| H1(b) | XP will positively influence TT | No |
| H1(c) | TRG will positively influence TT | No |
| H1(d) | PC will positively influence TT | No |
| H2(a) | PR mediates the effect of TT on IU | No |
| H2(b) | PU mediates the effect of TT on IU | Yes |

*Pilot Study Summary*

The pilot study made several contributions to improve the data collection and analysis. The first contribution was the refinement of the instrument based on the focus group feedback. Multiple corrections were made to the instrument to address grammar and structure of the questions without changing the theoretical concept of the problem. Some participants were slightly confused about 7-point Likert scale used because the not-applicable option was not available. Based on the feedback from the participants, if the question was not applicable to them, by default, the participant selected the neutral (4) answer on the 7-point Likert scale. The study 7-point Likert scale did not cover all the viable options. Therefore, not-applicable and neutral options were grouped. The impact of this grouping was deemed insignificant to affect the study results since not-applicability, and a neutral response did not indicate the direction of the response.

The second contribution is using PLS-SEM versus using traditional co-variance-based SEM. The conceptual model presented in this study has both reflective and formative measures. Perceived Capability (PC) is a third-order construct with two first-order constructs (Technology and Basic Resources) with formative measures. Level of Education (LE), Experience (XP), and Training (TRG) are predictors pointing to Trust-in-Technology (TT), but these variables are categorical. Dummy variables were created in SPSS for each construct to capture the appropriate latent scores for these constructs. Dummy variables became formative measures pointing to their respective emergent construct in the model. The capability to evaluate both formative and reflective measures in the same model makes PLS-SEM ideal.

## Main Study: Data Collection

### *Introduction*

The data collection began by addressing the grammatical issues identified by the focus group without compromising the theoretical basis of the instrument. As previously stated in Chapter 3, the instrument is based on existing and validated IS constructs. An anonymous Google Forms survey instrument to measure the constructs based on the research model was refined, and the instrument had all items as closed questions with answers on a 7-point Likert scale.

The survey was emailed to the entire organization consisting of more than ten thousand employees in both Canada and the United States of America. The corporate communications team of the study organization were concerned about mass emailing the entire organization. Therefore, the recruitment message was changed to reflect the survey is strictly voluntary, and the message was sent without senior leadership persuading as initially planned. The organization has ten thousand employees and contractors; however, the study was looking for participants currently using or looking to use Big Data Analytics. It was difficult to estimate the population planning or using Big Data Analytics within the study organization.

With consideration that the organization is a pre-adoptive phase of Big Data Analytics, a low participation rate 3% makes sense when viewed from an organizational perspective. The response rate is good and sufficient evidence to judge the quality of data collection because the population is a subset of all the potential participants in the organization. Some employees and contractors will never use or intend to use BDA. With only 282 respondents reflecting a 3% response rate, the researcher focused on the reliability measures to judge the quality and validity of the study.

*Demographics*

A few demographic characteristics relevant to the study are shown in Table 12. Approximately 66.5 percent of the respondents were male, 31 percent were female, and 1.4 percent were transgender. Analytics training among the respondents is split between 44.8 percent for those trained and 54.1 percent not trained. Among the participants, 33.5 percent have analytics experience between 1-5 years and 29.5 percent between 6-10 years.

Table 12

*Key Demographics*

| | | **Frequency** | **Percentage** |
|---|---|---|---|
| Gender | Male | 187 | 66.5% |
| | Female | 87 | 31.0% |
| | Transgender | 4 | 1.4% |
| Training (TNG) | Yes | 126 | 44.8% |
| | No | 152 | 54.1% |
| Experience (XP) | None | 34 | 12.1% |
| | 1-5 | 94 | 33.5% |
| | 6-10 | 83 | 29.5% |
| | 11-15 | 27 | 9.6% |
| | Over 15 | 40 | 14.2% |
| Level of Education (LE) | Associate degree | 17 | 6.0% |
| | Bachelor’s degree | 130 | 46.3% |
| | Doctorate degree | 7 | 2.5% |
| | High school graduate | 8 | 2.8% |
| | Master’s degree | 74 | 26.3% |
| | Professional degree | 4 | 1.4% |
| | Some college credits | 8 | 2.8% |
| | Trade/Technical/Vocational | 30 | 10.7% |

Only 12.1 percent of participants did not have working experience with analytics tools meaning most of the participants had some working knowledge. Most of the participants have a degree with only 2.8% with some college credits without a degree.

In PLS-SEM, categorical variables such as LE, XP, and TRG can be handled as moderating or predictor variables. All the other measures are on a 7-point Likert scale therefore primarily the PLS Algorithm will process them as categorical since they are ordinal variables. Using SPSS software, LE and XP were coded in an ordinal fashion by assigning a higher numerical value to more experience or elevated level of education gained. It was difficult to conclude the variables are ordinal therefore measures were regarded as nominal. According to Garson (2016), nominal variables must be implemented as a series of dummy variables in PLS-SEM. Thus, dummy variables were created for each category of the variable to reflect the measures using the SPSS algorithm. Training had two possible values. Therefore, the coding was merely one = *No* and two = *Yes*.

After coding a multivariate data analysis was conducted on the resulting dataset. From the study, 2 cases were removed due to missing system data caused by Google Forms' error in writing the results to file. The two cases could not be recovered therefore deleted from the dataset. Responses were further visually analyzed to identify instances where participants just provided the same answer. Three cases were then removed after the response set analysis. A total of 5 cases were excluded resulting in 277 valid cases to be used for data analysis. After calculating Mahalanobis distance as part of the outlier analysis, no extreme cases were identified and removed.

Normality test was conducted on the dataset even though PLS-SEM ignores the distribution of the data. Variables with a Shairo-Wilk significance of less than 0.005 showed enough evidence to reject normality. Normal Q-Q plots and associated histograms for each variable shows non-normality and indicating a negative skewness of data. The conclusion is the dataset is non-normal and negatively skewed in general.

*Data Collection and Pre-Processing Summary*

Based on the results of the pilot study, a PLS-SEM approach suitable for estimation and small sample sizes was leveraged as the data analysis approach. A total of 282 cases were reported after the data collection exercise. For a covariance-based SEM approach, the study target was 400 observations; however, for a PLS-SEM approach, the target was 147 observations. The sample size was calculated based a) effect size of 0.5, b) desired power level of 0.9, and c) significance of 0.05. Regardless of the low response rate, the desired effect size and significance after pre-screening data was deemed to be valid. After pre-screening, a total of 277 cases were deemed valid, and the sample size was deemed acceptable to continue with data analysis.

When compared with the pilot study response rate, the main study participation was low, and this was attributed to several factors. First, in the pilot study, the participants were very engaged, and there was much collaboration via the Yammer group, however, in the primary research phase, the collaboration aspect was absent. Engagement of participants was made via email communication and participants were asked to follow-up with the researcher if they need further information about the study. This was rather a one-directional approach compared to the collaborative pilot study. It is possible that some participants started and abandoned the survey due to lack of clarification information about the study.

The second point was the fact the survey study was voluntary. Therefore, no incentives or leadership push for participation was employed.  The target population was for business users looking to use or using Big Data Analytics. It was difficult to estimate the target population because of limited literature on the usage of Big Data Analytics. The researcher estimated the target population to be way below the ten thousand since the study organization was in the pre-adoption phase of its analytics maturity according to the TDWI Analytics Maturity Model. This meant the reported response rate was lower than the actual response rate. This is an area that needs further research to understand the target population intending to use or using Big Data Analytics in an organization.

Lastly, the organization was going through a significant cybersecurity awareness program. More than 400 mail messages for this study were flagged by employees as possible phishing emails. The recruitment message was sent via the study organization's internal communications team email account. The attachment and the survey link pointing to an external site were possible features why the email was flagged that way by many business users. When using email for study recruitment, it is critical to factor cybersecurity programs within the study organization and other security measures such as spam filters.

These challenges can explain the low response rate for the primary study. The response rate in the pilot study was exceptional maybe because the participants were efficiently engaged with a Yammer group as a collaborative tool. Participants were able to ask questions and engage the researcher in the pilot study. It seems like more information about the survey helped volunteers to be more active in the research.

## Model Evaluation: Measurement Model Results

*Model Estimation*

All the variables and factor loadings of the measurement model are shown in Table 13. The model has a PC, LE, TRG, and XP as exogenous variables influencing TT. At the same time, TT is also an exogenous variable influencing IU. PU and PR are both mediating variables to the relationship between TT and IU. In a sense, both PU and PR can be viewed as exogenous variables influencing IU. Each indicator's outer weight in the model was examined for its relative contribution to the assigned construct an outer loading value for its total contribution to the assigned construct. Used bootstrapping to assess their contribution significance. All the indicators were observed to be significant except for all 3 PR indicators include several indicators for LE, XP, and PR with outer loadings of less than 0.5.

As of rule of thumb, if the indicator's outer weight is not significant but its outer loading is higher than 0.5, then it is recommended to retain that indicator (Hair et al., 2014). In the case of PR2 with a factor loading of -0.145, the rule of thumb could not be applied therefore the indicator was removed that improved PR1 and PR3 to be significant and higher than 0.5. Indicators for LE and XP are represented by dummy variables, meaning each variable will take a value 0 or 1 to indicate the absence or presence of the categorical effect expected to shift the outcome. The dummy variables are modeled as formative measures in the measurement model. Negative formative indicators (outer weight) could be the effect of multicollinearity between the indicators (Hair et al., 2014).

The collinearity issues are because the VIF values of LE and XP are higher than 5. In multiple regression models, if one predictor can be linearly predicted from others with substantial accuracy, this is called collinearity (Chin, 2010). Since the goal of the model is a prediction, and each measure represents a category therefore for that reason that all bad indicators for LE and XP were not removed from the model. Another reason was the cause indicators representing LE and XP were not interchangeable therefore removing indicators was not recommended because deleting an indicator might change the latent variable meaning.

Table 13

*Measurement Model: Factor Loadings*

| *n = 277* | **LE** | **XP** | **IU** | **PC** | **PR** | **PU** | **TT** |
|---|---|---|---|---|---|---|---|
| EDU_1 | -0.332 | | | | | | |
| EDU_2 | 0.495 | | | | | | |
| EDU_3 | 0.628 | | | | | | |
| EDU_4 | 0.322 | | | | | | |
| EDU_5 | -0.278 | | | | | | |
| EDU_6 | -0.195 | | | | | | |
| EDU_7 | -0.187 | | | | | | |
| EDU_8 | -0.324 | | | | | | |
| XP_1 | | -0.389 | | | | | |
| XP_2 | | 0.447 | | | | | |
| XP_3 | | -0.768 | | | | | |
| XP_4 | | 0.48 | | | | | |
| XP_5 | | 0.364 | | | | | |
| IU1 | | | 0.930 | | | | |
| IU2 | | | 0.906 | | | | |
| IU3 | | | 0.929 | | | | |
| IU4 | | | 0.906 | | | | |
| PCBR1 | | | | 0.686 | | | |
| PCBR2 | | | | 0.675 | | | |
| PCDDC1 | | | | 0.401 | | | |
| PCDDC2 | | | | 0.328 | | | |
| PCDDC3 | | | | 0.359 | | | |
| PCDDC4 | | | | 0.331 | | | |
| PCDDC5 | | | | 0.315 | | | |
| PCMS1 | | | | 0.705 | | | |

| *n = 277* | **LE** | **XP** | **IU** | **PC** | **PR** | **PU** | **TT** |
|---|---|---|---|---|---|---|---|
| PCMS2 | | | | 0.781 | | | |
| PCMS3 | | | | 0.788 | | | |
| PCMS4 | | | | 0.751 | | | |
| PCMS5 | | | | 0.767 | | | |
| PCMS6 | | | | 0.794 | | | |
| PCOL1 | | | | 0.527 | | | |
| PCOL2 | | | | 0.616 | | | |
| PCOL3 | | | | 0.666 | | | |
| PCOL4 | | | | 0.649 | | | |
| PCOL5 | | | | 0.705 | | | |
| PCT1 | | | | 0.626 | | | |
| PCT2 | | | | 0.628 | | | |
| PCT3 | | | | 0.644 | | | |
| PCT4 | | | | 0.639 | | | |
| PCTS1 | | | | 0.621 | | | |
| PCTS2 | | | | 0.702 | | | |
| PCTS3 | | | | 0.735 | | | |
| PCTS4 | | | | 0.735 | | | |
| PCTS5 | | | | 0.758 | | | |
| PCTS6 | | | | 0.772 | | | |
| PR1 | | | | | 0.397 | | |
| PR2 | | | | | -0.145 | | |
| PR3 | | | | | 0.738 | | |
| PU1 | | | | | | 0.879 | |
| PU2 | | | | | | 0.918 | |
| PU3 | | | | | | 0.896 | |
| PU4 | | | | | | 0.884 | |
| TBST1 | | | | | | | 0.692 |
| TBST10 | | | | | | | 0.686 |
| TBST11 | | | | | | | 0.713 |
| TBST2 | | | | | | | 0.651 |
| TBST3 | | | | | | | 0.671 |
| TBST4 | | | | | | | 0.523 |
| TBST5 | | | | | | | 0.752 |
| TBST6 | | | | | | | 0.765 |
| TBST7 | | | | | | | 0.745 |
| TBST8 | | | | | | | 0.718 |
| TBST9 | | | | | | | 0.692 |
| IBT1 | | | | | | | 0.507 |

| *n = 277* | **LE** | **XP** | **IU** | **PC** | **PR** | **PU** | **TT** |
|---|---|---|---|---|---|---|---|
| IBT2 | | | | | | | 0.745 |
| IBT3 | | | | | | | 0.774 |
| IBT4 | | | | | | | 0.747 |
| IBT5 | | | | | | | 0.685 |
| IBT6 | | | | | | | 0.693 |
| IBT7 | | | | | | | 0.662 |
| IBT8 | | | | | | | 0.649 |
| PTT1 | | | | | | | 0.654 |
| PTT2 | | | | | | | 0.654 |
| PTT3 | | | | | | | 0.675 |
| PTT4 | | | | | | | 0.682 |
| PTT5 | | | | | | | 0.614 |
| PTT6 | | | | | | | 0.58 |
| PTT7 | | | | | | | 0.67 |

*Reliability Measures*

Composite reliability measures of reflective constructs are shown in Table 14. All values are above 0.8, demonstrating high levels of internal consistency reliability.

Table 14

*Construct Reliability and Validity*

**Construct Reliability and Validity**

*n = 277*

| | **Cronbach's Alpha** | **rho_A** | **Composite Reliability** | **Average Variance Extracted (AVE)** |
|---|---|---|---|---|
| Intent-to-Use | 0.938 | 0.949 | 0.937 | 0.789 |
| Perceived Capability | 0.948 | 0.958 | 0.951 | 0.421 |
| Perceived Risk | 0.735 | 0.566 | 0.301 | 0.241 |
| Perceived Usefulness | 0.941 | 0.941 | 0.941 | 0.799 |
| Trust-in-Technology | 0.956 | 0.958 | 0.957 | 0.462 |

Cronbach's alpha values for all the constructs in the measurement model are above 0.75 therefore acceptable. Convergent validity was assessed by AVE value and shown in Table 15. All AVE values for all reflective constructs are above 0.5 except for TT (AVE=0.462, $\alpha$ = .956) and PC (AVE=0.421, $\alpha$ = .948). The values for both TT and PC are very close to 0.5, and their respective Cronbach's alpha values are very high.

Table 15

*Discriminant Validity: Fornell-Larcker criterion*

**Discriminant Validity**

| | **LE** | **XP** | **IU** | **PC** | **PR** | **PU** | **TRG** | **TT** |
|---|---|---|---|---|---|---|---|---|
| Education | 0.138 | | | | | | | |
| Experience | 0.217 | 0.301 | | | | | | |
| Intent-to-Use | 0.481 | 0.172 | 0.889 | | | | | |
| Perceived Capability | 0.175 | 0.151 | 0.224 | 0.649 | | | | |
| Perceived Risk | 0.161 | 0.103 | 0.121 | 0.067 | 0.85 | | | |
| Perceived Usefulness | 0.656 | 0.001 | 0.701 | 0.159 | 0.133 | 0.894 | | |
| Training | 0.654 | -0.082 | 0.247 | 0.126 | 0.048 | 0.256 | 1 | |
| Trust-in-Technology | 0.752 | 0.283 | 0.381 | 0.407 | 0.231 | 0.469 | 0.257 | 0.68 |

Fornell-Larcker criterion and the cross-loadings were checked for discriminant validity. In Table 15 Fornell-Larcker criterion results are shown, and diagonal elements are the square roots of AVE. The values should exceed the inter-construct correlations for adequate discriminant validity.  The cross-loadings were checked for discriminant validity, and the square root of the AVE of each construct was higher than the construct's highest correlation with any other construct in the model.

In PLS, the heterotrait-monotrait ratio of correlations (HTMT) is the unique approach to assessing discriminant validity. The innovative approach is better than Fornell-Larcker criterion and cross-loadings. If discriminant validity is established, then the structural paths in the model are considered significant and within acceptable fit. Values in Table 16 are within acceptable ranges for discriminant validity.

Table 16

*Discriminant Validity: Heterotrait-Monotrait Ratio (HTMT)*

| Heterotrait-Monotrait Ratio (HTMT) | | | | | | |
|---|---|---|---|---|---|---|
| *n = 277* | **IU** | **PC** | **PR** | **PU** | **TRG** | **TT** |
| Intent-to-Use | | | | | | |
| Perceived Capability | 0.292 | | | | | |
| Perceived Risk | 0.147 | 0.230 | | | | |
| Perceived Usefulness | 0.695 | 0.261 | 0.125 | | | |
| Training | 0.249 | 0.142 | 0.043 | 0.256 | | |
| Trust-in-Technology | 0.391 | 0.421 | 0.242 | 0.473 | 0.257 | |

*Measurement Model Summary*

In this section, the measurement fit for the reflective and informative outer model was assessed for an acceptable fit. Both aspects of the measurement model were verified to be an acceptable fit. PR2 was the only indicator dropped after assessing all the factor loadings for all the indicators. Dropping PR2 improved the composite reliability and Cronbach’s alpha for PR. In summary, the measurement model was assessed to have acceptable fit based on different measures outlined above. Using the PLS algorithm, latent variable scores were generated from the measurement model as a method to get values for the third and second-order constructs in the model. The structural model was created based on the latent scores.

**Model Evaluation: Structural Model Results**

*Quality Criteria*

As stated in the pilot study results, measures of goodness-of-fit (GoF) outlined in Table 17 are within acceptable ranges. SRMR as a goodness of fit measure for PLS-SEM was introduced by Henseler and Sarstedt in 2014 (Sarstedt, Ringle, Henseler, & Hair, 2014). SRMR is the difference between the observed correlation and the predicted correlation. It allows assessing the average magnitude of the discrepancies between observed and expected correlations as an absolute measure of model fit. In PLS-SEM, this measurement, however, does not make a lot of sense however reported for completeness.

Instead of GoF measures, the coefficient of determination ($R^2$), predictive relevance ($Q^2$) and importance of an exogenous variable ($f^2$) were leveraged to measure the model quality for acceptable fit. The overall Goodness-of-Fit (GoF) index in PLS-SEM is not easily reportable therefore $R^2$, $f^2$ and $Q^2$ are the ideal model-fit measures (Chin, 2010). The summary of these quality measures is reported in Table 18. The coefficient of determination, $R^2$ for the endogenous variable IU is at 0.439 and $f^2 = 0.425$ indicating the three exogenous constructs TT ($\beta_{TT \rightarrow IU} = 0.082, f^2 = .001, Q^2 = .222, p = .182, R^2 = 0.242$), PU ($\beta_{PU \rightarrow IU} = .623, f^2 = .561, Q^2 = .186, p = .000, R^2 = 0.196$) and PR ($\beta_{PR \rightarrow IU} = .019, f^2 = .001, Q^2 = .048, p = .688, R^2 = 0.047$) can explain the variation.

Predictive relevance, $Q^2$ is obtained by the sample re-use technique called ‘Blindfolding’ in SmartPLS 3.0 using the default omission distance set to 7. The $Q^2$

values for both TT ($Q^2 = 0.222$) and IU ($Q^2 = 0.425$) are greater than zero indicating the path model's predictive relevance in the context of the endogenous construct and the corresponding measures.

Table 17

*Analysis of Overall Goodness-of-fit*

| **GoF** | **Recommended Values** | **Study Value** |
|---|---|---|
| Chi-square | < 3.00 | 22.813 |
| SRMSR | < 0.10 | 0.045 |
| NFI | > 0.90 | 0.938 |

To measure the importance of an exogenous variable in explaining the endogenous, $f^2$ is an excellent quality measure based on the recalculation of $R^2$ by omitting one exogenous construct at a time. The rule of thumb according to Garson (2016) $f^2$ value of 0.02 is considered small, 0.15 is medium, and 0.35 is large. In the model, we had $f^2$ at 0.425 on IU indication of a substantial effect. However, the $f^2$ on TT was at .001which was rather a minimal effect. All the quality measures indicated in Table 18 were within acceptable thresholds indicating a good fit except for $R^2$ and $f^2$ for PR.

Coupled with problematic factor loadings and outer loadings, there was clear evidence that the sample cannot significantly explain the variance in PR. The effect size was also too low to justify a low $R^2$ value. This can be explained by several things like the linearity assumption may not correct and missing important observed variables in the measurement model. In the measurement model, PR was measured by negatively keyed items, and these items were reverse-scored before computing individual total scores. The reliability analysis was conducted after reserve scoring of PR.

Table 18

*Main Study: Quality Criteria*

| **Measure** | **$R^2$** | **$Q^2$** | **$f^2$** |
|---|---|---|---|
| IU | 0.439 | | 0.425 |
| TT ($\beta_{TT \rightarrow IU} = 0.082$) | 0.242 | 0.222 | 0.001 |
| PU ($\beta_{PU \rightarrow IU} = .623$) | 0.196 | 0.186 | 0.561 |
| PR ($\beta_{PR \rightarrow IU} = .019$) | 0.047 | 0.48 | 0.001 |

The researcher expected to see a negative co-efficient PR ($\beta_{PR \rightarrow IU} = .019$). However, the results show a slightly positive co-efficient value. No evidence was found to suggest the PR items were not reverse-coded properly or if the reverse-worded items prevented response bias. Instead, the data suggest scores were contaminated by respondent inattention and confusion. Further research is needed to improve the PR instrument in the context of Big Data Analytics.

*Study Results*

After running a consistent PLS bootstrapping with a thousand sub-samples, Figure 7 outlines the path coefficient of each relationship with the associated p-value. Level of Education (LE), Perceived Capability (PC), Training (TRG), and Experience (XP) have some effects to TT, and their contributions are significant. The positive path coefficient between TT and IU was not significant, and that was surprising since the study by Mcknight, Carter, Thatcher, and Clay (2011) showed a significant relationship. The examination of the hypothesis statements is summarized in Table 19.

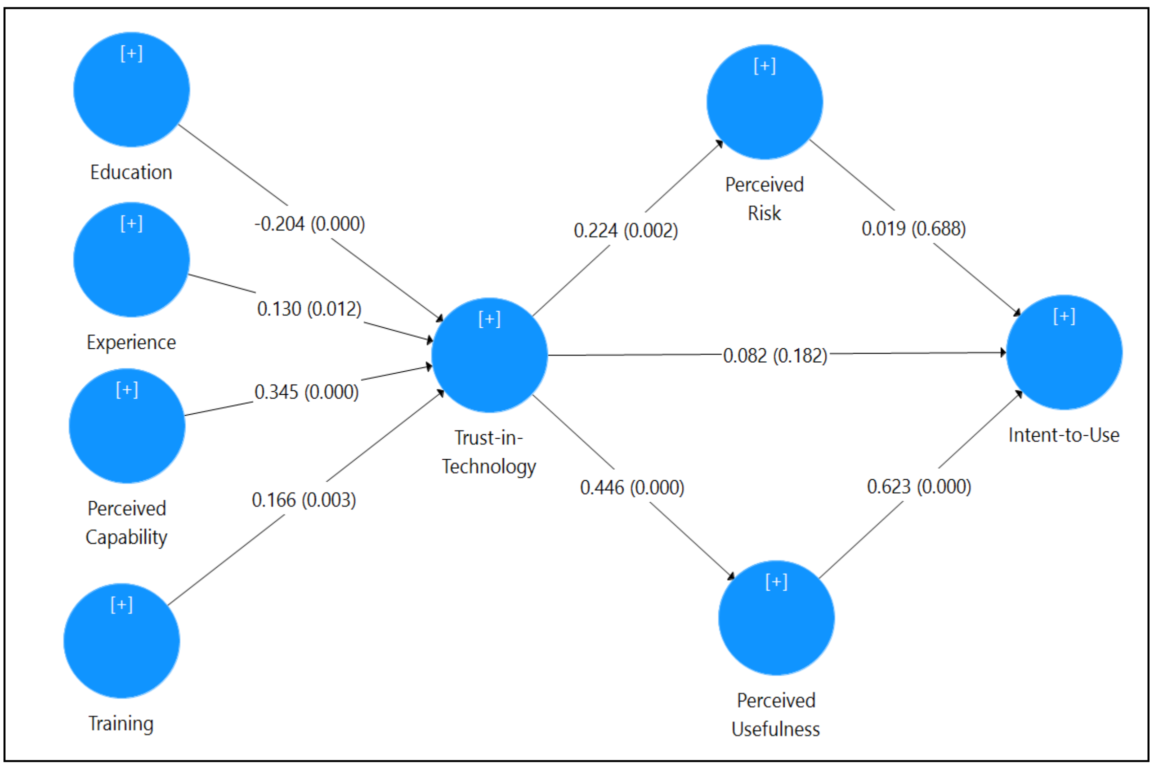


*Figure. 7* Research Model (Path Coefficients and P-Values)

Table 19

*Summary of Hypothesis Results*

| **Hypothesis** | **Relationship** | **Sig** |
|---|---|---|
| H1(a) | LE will positively influence TT | Yes |
| H1(b) | XP will positively influence TT | Yes |
| H1(c) | TRG will positively influence TT | Yes |
| H1(d) | PC will positively influence TT | Yes |
| H2(a) | PR mediates the effect of TT on IU | No |
| H2(b) | PU mediates the effect of TT on IU | Yes |

The research model presents two mediation effects: the influence of Trust-in-Technology on Intent-to-Use was mediated through Perceived Usefulness and Perceived Risk. After running the PLS algorithm and Bootstrapping function, Table 18 shows all the specific indirect effects in the model. Three conditions are required for mediation a) the relationship between the exogenous variable to the mediator must be significant, b) the mediator influence on the endogenous variable should also be significant, and c) the indirect effect must also be significant. If all three conditions are met, then mediation is assumed to present.

Based on the mediation testing rule, the relationship between TT → PU and between PU → IU are both significant. However, the relationship between TT → IU is not significant. The indirect effect TT → PU → IU is significant therefore supporting the hypothesis PU mediates the effect of TT on IU. The indirect effect TT→ PR→IU is not significant therefore PR does not mediate the effect of TT on IU. An examination of the specific indirect effects presented in Table 20, clearly shows paths through Perceived Usefulness to Intent-to-Use are significant.

Table 20

*Specific Indirect Effects*

| **Significant Specific Indirect Effects** | | |
|---|---|---|
| | **T Statistics** | **P Values** |
| Education -> Trust-in-Technology -> Perceived Usefulness -> Intent-to-Use | 2.785 | 0.005 |
| Experience -> Trust-in-Technology -> Perceived Usefulness -> Intent-to-Use | 2.388 | 0.017 |
| Perceived Capability -> Trust-in-Technology -> Perceived Usefulness -> Intent-to-Use | 2.946 | 0.003 |
| Training -> Trust-in-Technology -> Perceived Usefulness -> Intent-to-Use | 2.543 | 0.011 |
| Education -> Trust-in-Technology -> Perceived Risk | 2.268 | 0.024 |
| Experience -> Trust-in-Technology -> Perceived Risk | 2.04 | 0.042 |
| Perceived Capability -> Trust-in-Technology -> Perceived Risk | 2.514 | 0.012 |
| Training -> Trust-in-Technology -> Perceived Risk | 2.208 | 0.027 |
| Education -> Trust-in-Technology -> Perceived Usefulness | 3.181 | 0.002 |
| Experience -> Trust-in-Technology -> Perceived Usefulness | 2.553 | 0.011 |
| Perceived Capability -> Trust-in-Technology -> Perceived Usefulness | 3.402 | 0.001 |
| Training -> Trust-in-Technology -> Perceived Usefulness | 2.718 | 0.007 |

**Summary**

In this chapter, the results of the pilot study were presented and the contributions that influenced how the primary research was conducted. Data screening and pre-processing results were performed in both phases of the study including the description of the sample size, survey completeness, response sets analysis and multivariate outlier analysis. The sample size in the pilot was small therefore conducting SEM using a co-variance approach was not feasible. PLS-SEM was selected as the ideal approach for the pilot study however given other factors such as the complexity of the research model and the combination and reflective and formative measures the plan became the recommend data analysis method for the primary study.

The sample size target in the primary study was 400 observations. Only 282 observations were recorded because most participants in the study organization classified the survey recruitment email message as a phishing attempt. Given the complexity of the research model and using PLS-SEM approach, 147 was the desired minimum sample size. Therefore, data collection was not extended. A note to researchers using email recruitment method is to check for cybersecurity programs within the study organizations that might interfere with the message reaching potential participants or the message being viewed as a potential cybersecurity threat.

Data collected was pre-processed and missing observations removed. After a multivariate analysis of outliers, 277 observations were deemed valid. The measurement model was assessed for acceptable fitness since the outer model had both reflective and informative measures. Both aspects of the measurement model were verified to be an acceptable fit. Using the PLS algorithm, latent variable scores were generated, and the structural model was based on latent variables scores. The overall Goodness-of-Fit (GoF) and acceptable fit are discussed in this section. $R^2$, $f^{2,}$ and $Q^2$ were used as the basis for acceptable fitness of the structural model, and these measures were within acceptable values. Based on the valid structural model and after running the bootstrapping procedure on hypothesis H2 (a) is rejected and the rest can be accepted as significant. Details of these findings and conclusions are discussed in the next chapter.

# Chapter 5

# Conclusion

## Introduction

The objective of this research was to assess factors influencing the relationship of Trust-in-Technology on Intent-to-Use Big Data Analytics. The assessment focused on the mediation effects of Perceived Risk and Perceived Usefulness on the relationship between Trust-in-Technology and Intent-to-Use. Other factors such as Level of Education, Training, Experience, and Perceived Capability were assessed for their predictive influence on Trust-in-Technology. The conclusions derived from this assessment are presented in this chapter. In this chapter, limitations and practical implications of the research are discussed.

## Conclusions

*RQ1: To what extent does TT influence IU?*

Trust-in-Technology ($\beta_{TT \rightarrow IU} = 0.082, f^2 = .001, Q^2 = .222, p = .182, R^2 = 0.242$) has a positive impact on Intent-to-Use however that relationship was not significant. Trust-in-Technology (TT) construct was operationalized with three sets of concepts, a) Propensity-to-Trust (PTT), b) Institutional-Based Trust (IBT), and c) Trusting Beliefs in Specific Technology (TBST). Mcknight, Carter, Thatcher, and Clay (2011) did not the test the significance of the higher order construct of Trust-In-Technology but at the second order construct Trusting Beliefs in Specific Technology (TBST). Following the same approach, TBST ($\beta_{TBST \rightarrow IU} = 0.157, f^2 = .037, Q^2 = .281, p = .011, R^2 = 0.308$)

had a positive influence on IU and the influence was significant. This conclusion was aligned with the work by Mcknight, Carter, Thatcher, and Clay (2011).

*RQ2: To what extent do PU and PR mediate the relationship between TT and IU?*

There was a definite relationship between Trust-in-Technology and Intent-to-Use Big Data Analytics. However, the relationship was not significant. For mediation to be fulfilled, three conditions were tested a) the relationship between the exogenous variable to the mediator must be significant, b) the mediator influence on the endogenous variable should also be significant, and c) the indirect effect must also be significant. If all three conditions are met, then mediation was assumed to be present. Based on the mediation testing rule, the relationship between TT → PU and between PU → IU were both significant. However, the relationship between TT → IU was not significant. The indirect effect TT → PU → IU was significant therefore supported the hypothesis PU mediates the effect of TT on IU. The indirect effect TT→ PR→IU was not significant therefore PR does not mediate the effect of TT on IU.

*RQ3: To what extent do factors such as training, education level, experience, and perceived capability influence TT?*

All factors Level of Education (LE), Perceived Capability (PC), Training (TRG), and Experience (XP) were significant in their effects on TT. The most exciting result was the negative coefficient on the relationship of Level of Education (LE) on Trust-in-Technology. This result indicated as the level of education increased, an individual’s trust in analytics technology decreases. An indication that as the employee gain education, they have more confidence in their capabilities than the analytical tools. This result represented an area that will need further exploration to decompose this relationship further. Of all the predictors to TT, Perceived Capability had the most significant effect on the TT, and its indirect effect on IU was significant.

**Implications**

The first implication of this research in practice was the understanding that factors such as level of education, training, experience and the perceived capability of analytics within an organization can influence trust in analytics technology and tools. Behavioral intentions to use Big Data Analytics are mediated by the perceived usefulness of the tools therefore to promote usage of Big Data Analytics; organizations will need to manage the perceived value and trust-in-technology. On the mediation effects, Perceived Usefulness is significant compared to Perceived Risk indicating that organizations should focus on the usefulness of tools rather than focusing on risks of using analytics tools.

The second implication for practice is the understanding Perceived Capability is a good predictor of Trust-in-Technology, and its indirect effect on Intent-to-Use was significant. Perceived Capability can be viewed as the window to the business users' viewpoint on analytics within the organization while the TDWI Analytics Maturity Model as the leadership perspective. The comparing these two perspectives within an organization can offer an opportunity to identify any gaps and alignment in the organization.

For future research, the study introduced Gap Alignment Quadrant (GAQ) presented in Figure 8 as a method of assessing the Analytics Maturity and Perceived Capability within an organization. GAQ was based on the TDWI Analytics Maturity Model Assessment and the Perceived Capability construct. The maturity stage of TDWI

Analytics Maturity Model was primarily the management's perceived assessment of the maturity of the organization since the results are derived from the self-assessment.

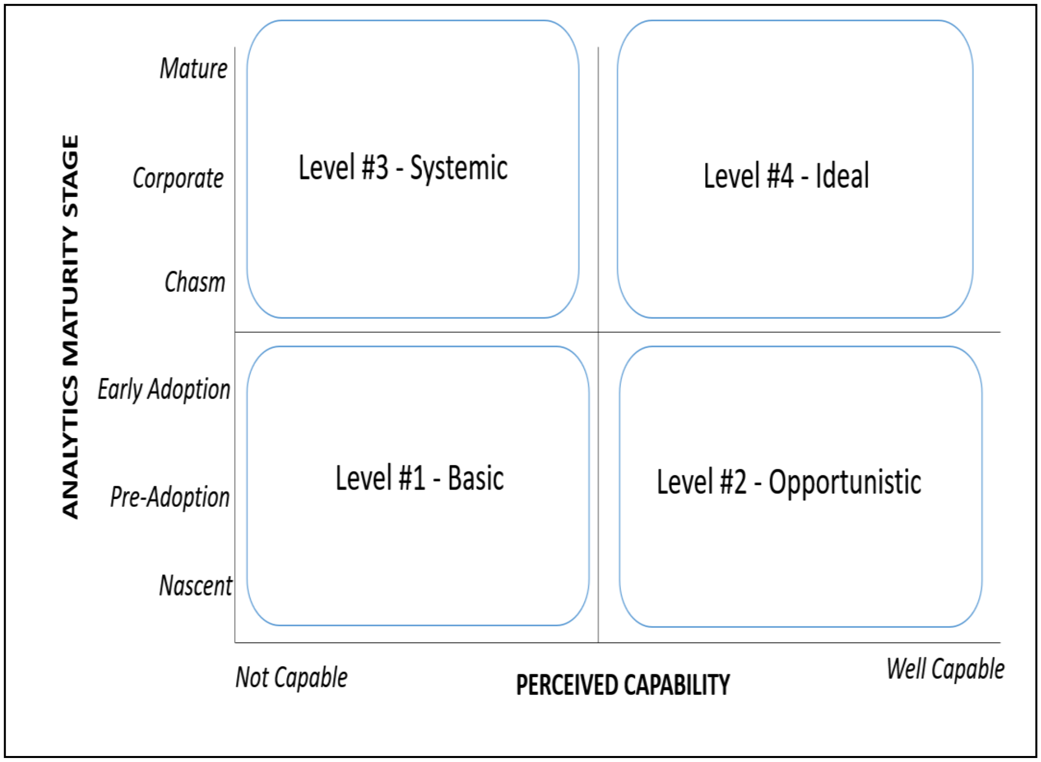


Figure. 8 *Gap Alignment Quadrant*

Future research must look to extend TDWI Analytics Maturity Model Assessment by adding a dimension of Perceived Capability. The Gap Alignment Quadrant (GAQ) showed four quadrants of gaps and alignment between business users and leadership. The bottom left quadrant was considered the primary level where the organization is not exploiting data and analytics as expected. In this level, the organization is either planning to adopt Big Data Analytics or in the initial stages of adoption. Data is managed in silos and with different versions of truth on critical datasets. Analytics is conducted mainly on spreadsheets and various tools within the organization. Lack of a centralized analytics capability can explain the low perceived capability within the organization in this quadrant.

Quadrants of misalignment represented as level 2 and 3 in Figure 8 refers to alignment gaps between analytics maturity as perceived by the organizational leaders and business users' perceived capability. The alignment gap can be a result of many factors, and the future research can look to undercover these factors in detail. The ideal quadrant will be the top right quadrant indicating alignment on the analytics maturity within the organization.

**Limitations**

Studies in technology innovation adoption suggest that the organization's size and technological resources competency both play a significant role in the adoption of BDA (Agrawal, 2015). This research was focused on a single organization in North America because it was not possible to sample all organizations due to budget, time and feasibility. The future study was recommended to be conducted across different organizations to generalize the results better.

The data collected for Perceived Risk was problematic. As stated before, surveys are mainly associated with the unwillingness or inability of respondents to provide accurate information. It was difficult to identify these issues because respondents found it challenging to understand survey questions based on their perspectives and background. Another major limitation of the survey method was the issues connected with self-reported data such as selective memory, telescoping, attribution, and exaggeration. It was difficult to prove if these problems existed because of the lack of other sources to compare. Selective memory is when participants remember or do not remember events from the past, and this can impact a participant's understanding of the question and context. Telescoping is recalling events that occurred however with wrong timing. On the other hand, attribution is the act of attributing positive outcomes to one's own and adverse consequences to external forces. Both these biases might have influenced how participants responded to questions about their perception of specific subjects.

No incentives were offered for survey participation to preserve anonymity and the voluntary nature of the study. As anticipated, this became a limitation influencing response rate. Participation recruitment notifications were precise and articulated the goals of the study as a method of promoting participation. Another cause for the low response rate was the organization was going through a robust cybersecurity awareness program therefore previously reported, more than 400 mail messages for this study were flagged by employees as possible phishing emails. The attachment and the survey link pointing to an external site were possible features why the email was flagged that way by many business users. This was a critical factor and a lesson for future studies conducting surveys by email to consider cybersecurity programs within the study organizations and other security measures such as spam filters.

**Summary**

Over the past years, there is an increase in adoption of BDA technologies in an organization thereby disrupting existing business processes due to automation of cognitive and manual tasks.  Using existing IS theoretical concepts, the study explored predictors (experience, perceived capability, training, and level of education) for trust in technology and its impact on intent-to-use. The study also focused on the mediation effects of perceived risks and usefulness.

A two-phased approached was employed. Phase I was instrument development based on literature and conducted a pilot study to test the instrument and data analysis.

Phase II was data collection and analysis. Data were collected using an anonymous web-based survey over a two-week period. Recruitment was done via email that resulted in several emails classified as spam or phishing in the study organization. Regardless of the security challenges, a total of 282 cases were reported. After pre-screening data and multivariate analysis for outliers and missing data, 277 cases were deemed valid. For PLS-SEM and targeting a minimum $R^2$ value of 0.1, the recommended sample was 147. Therefore, the sample size was acceptable to continue with data analysis.

Using the PLS algorithm, both the measurement and structural models were validated and tested. Both models were acceptable fit. $R^2$, $f^{2,}$ and $Q^2$ were used as the basis for acceptable fitness of the structural model, and these measures were within acceptable values. Based on the valid structural model and after running the bootstrapping procedure on hypothesis, only Perceived Risk has no mediating effect on Trust-in-Technology on Intent-to-Use.  All other hypothesis statements were accepted as significant.

Level of education, training, experience and the perceived capability of analytics within an organization are good predictors of Trust-in-Technology. The influence on intent-in-use by trust-in-technology was not demonstrated however Perceived Usefulness fully mediates the relationship. In summary, for organizations to change behavioral intentions to use Big Data Analytics, it is clear to focus on the perceived usefulness of the technologies and improving predictors to trust-in-technology.

# Appendix A

## Research Questions

Table A1

*Proposed Research Questions*

| | |
|---|---|
| **RQ1:** To what extent does TT influence IU? | **RQ1.1:** To what extent does TBST contribute to IU? |
| **RQ2:** To what extent do PU and PR mediate the relationship between TT and IU? | **RQ2.1:** To what extent is TBST better explained by PU on its influence on IU? |
| | **RQ2.2:** To what extent does TBST contribute to PU? |
| | **RQ2.3:** To what extent is TBST better explained by PR on its influence on IU? |
| | **RQ2.4:** To what extent does TBST contribute to PR? |
| | **RQ2.5:** To what extent does PU contribute to IU? |
| | **RQ2.6:** To what extent does PR contribute to IU? |
| **RQ3:** To what extent does factor such as training, education level, experience, and perceived capability influence TT? | **RQ3.1:** To what extent does LE contribute to PTT in the context of TT? |
| | **RQ3.2:** To what extent does PC contribute to IBT in the context of TT? |
| | **RQ3.3:** To what extent does XP contribute to TBST in the context of TT? |
| | **RQ3.4:** To what extent does TRG contribute to TBST in the context of TT? |

# Appendix B

## Demographics

1. Gender (Male, Female, Transgender)
2. Age
3. Role Level (Individual Contributor, Supervisor, Manager, Director, VP)
4. Function in the organization (Operations, Engineering, Finance, IT, Support Services, HR, Corporate Services)
5. Years of experience using Big Data Analytics (1-5, 6-10, 11-15, over 15)
6. Highest level of education completed and major (bachelor's degree, master's degree, doctoral degree)
7. Big Data Analytics Training (Yes / No)

# Appendix C

## Study Constructs based on Literature Review

Survey Instrument:
https://docs.google.com/forms/d/e/1FAIpQLSeYV3zq1YsvqIjjyaD9BQOezjHUjvPcixTwKRUDtbQlNFp0DA/formResponse

Level of Agreement

1. Strongly disagree
2. Disagree
3. Somewhat disagree
4. Neither agree or disagree
5. Somewhat agree
6. Agree
7. Strongly agree

Trusting Belief-Specific Technology: Reliability (Adapted from Mcknight et al., 2011)

1. Big Data Analytics is very reliable.
2. Big Data Analytics does not fail me.
3. Big Data Analytics is exceptionally dependable.
4. Big Data Analytics does not malfunction for me.

Trusting Belief-Specific Technology: Functionality (Adapted from Mcknight et al., 2011)

1. Big Data Analytics has the functionality I need.
2. Big Data Analytics has the features required for my job tasks.
3. Big Data Analytics can do what I want it to do.

Trusting Belief-Specific Technology: Helpfulness (Adapted from Mcknight et al., 2011)

1. Big Data Analytics supplies my need for help through a support function.
2. Big Data Analytics provides competent guidance (as needed) through a support service.
3. Big Data Analytics provides whatever help I need.
4. Big Data Analytics provides very sensible and useful advice if needed.

Situational Normality: Technology (Adapted from Mcknight et al., 2011)

1. I am comfortable working with Big Data Analytics tools or products.
2. I feel excellent about how things go when I use Big Data Analytics products.

3. I always feel confident that the right things will happen when I use Big Data Analytics products.
4. It appears that things will be okay when I utilize Big Data Analytics products.

Structural Assurance: Technology (Adapted from Mcknight et al., 2011)

1. I feel okay using analytics products because vendor protections back them.
2. Product guarantees make it feel all right to use analytics software.
3. Favorable-to-consumer legal structures help me feel safe working with analytics products.
4. Having the backing of legal statutes and processes makes me feel secure in using analytics products.

Faith in General Technology (Adapted from Mcknight et al., (2011))

1. I believe that most technologies are efficient at what they are designed to do.
2. A clear majority of technologies are excellent.
3. Most technologies have the features needed for their domain.
4. I think most technologies enable me to do what I need to do.

Trusting Stance: General Technology (Adapted from Mcknight et al., 2011)

1. My typical approach is to trust innovative technologies until they prove to me that I should not trust them.
2. I usually trust a technology until it gives me a reason not to trust it.
3. I give technology the benefit of the doubt when I first use it.

Perceived Usefulness (PU) (Adapted from Davis, (1989))

1. Using Big Data Analytics would enable me to accomplish tasks quickly.
2. Using Big Data Analytics would improve my job performance.
3. Using Big Data Analytics would increase my productivity.
4. Using Big Data Analytics would enhance my effectiveness on the job.
5. Using Big Data Analytics would make it easy to do my job.
6. I find Big Data Analytics useful in my job.

Perceived Risk (PR) (Adapted from Y. Li and Huang, (2009))

1. Using Big Data Analytics will introduce risk in my decision-making process.
2. Using Big Data Analytics will increase my dependency on the technology and uncertainty.
3. Using Big Data Analytics leads to loss of privacy.
4. Using Big Data Analytics is costly.
5. Using Big Data Analytics takes time.

6. Using Big Data Analytics introduces a sense of anxiety in decision making.
7. How do you rate your overall perception of risk from using Big Data Analytics for decision-making?

Perceived Capability: Technology (Adapted from Gupta & George, 2016)

1. My organization has adopted parallel computing approaches (e.g., Hadoop) to Big Data processing.
2. My organization has adopted different data visualization tools.
3. My organization has adopted open-source software for Big Data Analytics.
4. My organization has adopted new forms of storing data such as No SQL or Data Lakes.

Perceived Capability: Basic Resources (Adapted from Gupta & George, 2016)

1. Big Data Analytics projects are well funded and supported by my organization.
2. Big Data Analytics projects are given enough time to meet their objectives in the organization.

Perceived Capability: Technical Skills (Adapted from Gupta & George, 2016)

1. My organization provides Big Data Analytics training to its employees.
2. My organization hires new employees that have already have the Big Data Training.
3. My organization has staff with the right skills to accomplish their jobs using Big Data Analytics.
4. My organization big data staff has suitable education to fulfill their jobs.
5. My organization’s Big Data Analytics staff is well-trained and have the appropriate work experience.
6. My organization big data analytics staff is well trained.

Perceived Capability: Managerial Skills (Adapted from Gupta & George, 2016)

1. Our big data analytics managers understand and appreciate the business needs of other functional managers, suppliers, and customers.
2. Our big data analytics managers can work with functional managers, suppliers, and customers to determine opportunities that big data might bring to our business.
3. Our big data analytics managers can coordinate big data-related activities in ways that support other functional managers, suppliers, and customers.
4. Our big data analytics managers can anticipate the future business needs of functional managers, suppliers, and customers.
5. Our big data analytics managers have a good sense of where to apply big data.

6. Our big data analytics managers can understand and evaluate the output extracted from big data

Perceived Capability: Data-Driven Culture (Adapted from Gupta & George, 2016)

1. I consider data a tangible asset.
2. I base my decisions on data rather than instinct.
3. I am willing to override my intuition when data contradicts my viewpoints.
4. I continuously assess and improve business processes and rules in response to insights extracted from data.
5. I continuously coach employees to make decision-based data.

Perceived Capability: Organizational Learning (Adapted from Gupta & George, 2016)

1. We can search for new and relevant organizational knowledge.
2. We can acquire new and relevant knowledge.
3. We can assimilate relevant knowledge.
4. We can apply relevant knowledge.
5. We have made concerted efforts for the exploitation of existing competencies and exploration of new knowledge.

Intent-to-Use: Specific Technology (Adapted from McKnight et al., 2011)

1. I intend to experiment with Big Data Analytics for potential ways of analyzing data.
2. I plan to investigate Big Data Analytics for enhancing my ability to perform calculations on data.
3. I plan to spend considerable time in exploring Big Data Analytics to help me make better decisions.
4. I plan to invest substantial effort in exploring Big Data Analytics.

# Appendix D

## Participants Recruitment Message

Dear Participant,

The Internet of things (IoT), also called the internet of everything, is an innovative technology paradigm whereby everything is exposed through the architecture of the Web. Physical devices (including home appliances) are now capable of interacting with each other through automation and are also able to collect and exchange data with mobile apps. What has previously been considered a science fiction scene that showed our refrigerators ordering us milk and our washing machines messaging us when laundry needs to be done is now a reality. This new reality means new Data is being generated at an exponential rate.

Big Data Analytics is a cross-section of big data, machine learning and modeling processes of examining large data sets to uncover hidden patterns, unknown correlations, trends and other useful information for decision-making. Big Data Analytics is quickly becoming a critically important driver for business success. Many organizations are increasing their Information Technology budgets on Big Data Analytics capabilities. The objective of this study is to assess the factors influencing the intent-to-use of Big Data Analytics by an organization.

We are conducting this survey to obtain a better understanding of your planned intent to use Big Data Analytics in your business processes and activities.

Your participation in this study will consist of answering questions on the topic, which should take approximately 30-45 minutes. Although there is no time limit and you may discontinue the survey at any time; we strongly encourage you to complete the survey and help us in this important research. Your participation is strictly voluntary, and there is no penalty for opting-out from participating in this research.

Your response is anonymous, and only members of the research team will have access to the information you provide. By continuing below, you acknowledge that you have read and understood the above information. You are also aware that you can discontinue your participation in the study at any time.

Thank you for agreeing to take the survey in this study and thank you very much for your time.

Wayne Madhlangobe BSc, MBA, CAP (Certified Analytics Professional)
Ph.D. Student in Information Systems
College of Engineering and Computing
Nova Southeastern University (NSU)

# Appendix E

## Participant Letter for Anonymous Surveys

NSU Consent to be in a Research Study Entitled

**Who is doing this research study?**

This person doing this study is Wayne Madhlangobe with College of Computing and Engineering. They will be helped by Dr. Ling Wang as the Advisor and Dissertation Chair.

**Why are you asking me to be in this research study?**

You are being asked to take part in this research study because you are an adult over the age of 18, currently employed by Enbridge Inc. and based in Canada or the United States.

**Why is this research being done?**

The purpose of this study is to find out the factors influence intent-to-use Big Data Analytics in organizations. We are conducting this research to understand your planned intentions of using Big Data Analytics within your organization.

**What will I be doing if I agree to be in this research study?**

You will be taking a one-time, anonymous survey. The survey will take approximately 20 minutes to complete.

**Are there possible risks and discomforts to me?**

This research study involves minimal risk to you. To the best of our knowledge, the things you will be doing have no more risk of harm than you would have in everyday life.

**What happens if I do not want to be in this research study?**

You can decide not to participate in this research, and it will not be held against you. You can exit the survey at any time.

**Will it cost me anything? Will I get paid for being in the study?**

There is no cost for participation in this study. Participation is voluntary, and no payment will be provided.

**How will you keep my information private?**

Your responses are anonymous. Information we learn about you in this research study will be handled confidentially, within the limits of the law. To ensure the privacy of participants, we are not going to be collecting any personally identifiable information (PII). This data will be available to the researcher, the Institutional Review Board and other representatives of this institution, and any granting agencies (if applicable). All confidential data will be kept securely in an encrypted and secured Google Drive. All data will be kept for 36 months and destroyed after that time by permanently purging the data.

**Whom can I talk to about the study?**

If you have questions, you can contact Wayne Madhlangobe at 403 613 4157 or Dr. Ling Wang at 954 262 2020

If you have questions about the study but want to talk to someone else who is not a part of the study, you can call the Nova Southeastern University Institutional Review Board (IRB) at (954) 262-5369 or toll-free at 1-866-499-0790 or email at IRB@nova.edu.

**Do you understand, and do you want to be in the study?**

If you have read the above information and voluntarily wish to participate in this research study, please complete the survey at this link.

# Appendix F

## Recruitment email for the Main Study

**Subject:** External Research Study | Seeking Participation | Survey Closes April 13

ENBRIDGE

Technology and Information Services

***Sent to all members of Enbridge***

Well-conducted research informs program and policy development all over the world. An external research study from the Nova Southeastern University (NSU) is assessing factors that influence Big Data Analytics here at Enbridge. If you currently use or plan to use Big Data Analytics, please continue reading and participate in the study.

**What is Big Data Analytics?**

Data is growing at an explosive rate in a myriad of formats like social media, spatial coordinates, smart phones, and even smart refrigerators! The result is a lot of data, and we need to think about it in a larger perspective. Hence, it's referred to as 'big data'.

Big Data is a cross-section of machine learning and modeling processes examining large data sets to uncover hidden patterns, unknown correlations, trends, and other useful information for decision-making. Big Data Analytics is quickly becoming a critically important driver for business success.

Enbridge is excited to have been approached to participate in this study; it's an opportunity to influence program development in a highly competitive and fast-moving marketplace. The objective of this study is to assess the factors influencing the intent-to-use Big Data Analytics by an organization.

**How do I participate?**

If you are interested in taking part in this study, click here to fill out the survey. The survey will take approximately 30 minutes to complete, and you will have until **April 13th** to complete it. A Yammer group has also been setup in the event you would like to ask questions.

We thank you in advance for your participation in this unique opportunity!

# Appendix H

# Descriptive Statistics

Table H1

*Descriptive Statistics*

| Construct | Measure | *N* | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|---|
| Trust-in Technology | Trusting Beliefs in Specific Technology 1 | 277 | 1 | 7 | 5.04 | 1.294 |
| | Trusting Beliefs in Specific Technology 2 | 277 | 1 | 7 | 4.32 | 1.430 |
| | Trusting Beliefs in Specific Technology 3 | 277 | 1 | 7 | 4.41 | 1.464 |
| | Trusting Beliefs in Specific Technology 4 | 277 | 1 | 7 | 4.03 | 1.409 |
| | Trusting Beliefs in Specific Technology 5 | 277 | 1 | 7 | 4.49 | 1.483 |
| | Trusting Beliefs in Specific Technology 6 | 277 | 1 | 7 | 4.76 | 1.487 |
| | Trusting Beliefs in Specific Technology 7 | 277 | 1 | 7 | 4.68 | 1.523 |
| | Trusting Beliefs in Specific Technology 8 | 277 | 1 | 7 | 4.40 | 1.514 |
| | Trusting Beliefs in Specific Technology 9 | 277 | 1 | 7 | 4.22 | 1.538 |
| | Trusting Beliefs in Specific Technology 10 | 277 | 1 | 7 | 4.69 | 1.441 |
| | Trusting Beliefs in Specific Technology 11 | 277 | 1 | 7 | 4.47 | 1.398 |
| | Institutional-Based Trust 1 | 277 | 1 | 7 | 5.08 | 1.412 |
| | Institutional-Based Trust 2 | 277 | 1 | 7 | 4.89 | 1.351 |
| | Institutional-Based Trust 3 | 277 | 1 | 7 | 4.55 | 1.350 |
| | Institutional-Based Trust 4 | 277 | 1 | 7 | 4.68 | 1.240 |
| | Institutional-Based Trust 5 | 277 | 1 | 7 | 3.95 | 1.414 |
| | Institutional-Based Trust 6 | 277 | 1 | 7 | 3.84 | 1.549 |
| | Institutional-Based Trust 7 | 277 | 1 | 7 | 4.01 | 1.546 |
| | Institutional-Based Trust 8 | 277 | 1 | 7 | 4.09 | 1.616 |
| | Propensity-to-Trust 1 | 277 | 1 | 7 | 4.88 | 1.373 |
| | Propensity-to-Trust 2 | 277 | 1 | 7 | 4.61 | 1.452 |
| | Propensity-to-Trust 3 | 277 | 1 | 7 | 4.81 | 1.327 |
| | Propensity-to-Trust 4 | 277 | 1 | 7 | 5.12 | 1.180 |
| | Propensity-to-Trust 5 | 277 | 1 | 7 | 4.67 | 1.640 |
| | Propensity-to-Trust 6 | 277 | 1 | 7 | 4.91 | 1.593 |
| | Propensity-to-Trust 7 | 277 | 1 | 7 | 4.99 | 1.484 |
| Perceived Usefulness | Perceived Usefulness 1 | 277 | 1 | 7 | 5.89 | 1.224 |
| | Perceived Usefulness 2 | 277 | 1 | 7 | 6.00 | 1.156 |
| | Perceived Usefulness 3 | 277 | 1 | 7 | 5.96 | 1.130 |
| | Perceived Usefulness 4 | 277 | 1 | 7 | 6.04 | 1.078 |
| Perceived Risk | Perceived Risk 1 | 277 | 1 | 7 | 3.87 | 1.668 |
| | Perceived Risk 2 | 277 | 1 | 7 | 3.97 | 1.552 |
| | Perceived Risk 3 | 277 | 1 | 7 | 3.51 | 1.476 |
| Perceived Capability | Technology 1 | 277 | 1 | 7 | 3.04 | 1.685 |
| | Technology 2 | 277 | 1 | 7 | 4.12 | 1.733 |
| | Technology 3 | 277 | 1 | 7 | 3.21 | 1.589 |
| | Technology 4 | 277 | 1 | 7 | 3.38 | 1.639 |
| | Basic Resources 1 | 277 | 1 | 7 | 3.18 | 1.647 |
| | Basic Resources 2 | 277 | 1 | 7 | 3.21 | 1.501 |
| | Technical Skills 1 | 277 | 1 | 7 | 3.01 | 1.706 |
| | Technical Skills 2 | 277 | 1 | 7 | 3.63 | 1.355 |
| | Technical Skills 3 | 277 | 1 | 7 | 3.64 | 1.564 |
| | Technical Skills 4 | 277 | 1 | 7 | 3.87 | 1.516 |
| | Technical Skills 5 | 277 | 1 | 7 | 3.64 | 1.464 |
| | Technical Skills 6 | 277 | 1 | 7 | 3.72 | 1.499 |
| | Managerial Skills 1 | 277 | 1 | 7 | 3.71 | 1.584 |
| | Managerial Skills 2 | 277 | 1 | 7 | 3.82 | 1.625 |
| | Managerial Skills 3 | 277 | 1 | 7 | 3.66 | 1.590 |
| | Managerial Skills 4 | 277 | 1 | 7 | 3.47 | 1.687 |
| | Managerial Skills 5 | 277 | 1 | 7 | 3.50 | 1.583 |
| | Managerial Skills 6 | 277 | 1 | 7 | 3.83 | 1.580 |
| | Data-Driven Culture 1 | 277 | 1 | 7 | 6.10 | 1.341 |
| | Data-Driven Culture 2 | 277 | 1 | 7 | 5.36 | 1.432 |
| | Data-Driven Culture 3 | 277 | 1 | 7 | 5.56 | 1.281 |
| | Data-Driven Culture 4 | 277 | 1 | 7 | 5.55 | 1.284 |
| | Data-Driven Culture 5 | 277 | 1 | 7 | 5.14 | 1.487 |
| | Organizational Learning 1 | 277 | 1 | 7 | 5.04 | 1.668 |
| | Organizational Learning 2 | 277 | 1 | 7 | 4.87 | 1.560 |
| | Organizational Learning 3 | 277 | 1 | 7 | 4.54 | 1.682 |
| | Organizational Learning 4 | 277 | 1 | 7 | 4.56 | 1.662 |
| | Organizational Learning 5 | 277 | 1 | 7 | 4.08 | 1.664 |
| Intent-to-Use | Intent-to-Use 1 | 277 | 1 | 7 | 5.85 | 1.335 |
| | Intent-to-Use 2 | 277 | 1 | 7 | 5.79 | 1.386 |
| | Intent-to-Use 3 | 277 | 1 | 7 | 5.51 | 1.464 |
| | Intent-to-Use 4 | 277 | 1 | 7 | 5.45 | 1.497 |

# Appendix I

# IRB Approval

NOVA SOUTHEASTERN UNIVERSITY
Institutional Review Board

**MEMORANDUM**

To: **Wayne Madhlangobe**

From: **Wei Li, Ph.D,**
**Center Representative, Institutional Review Board**

Date: **December 13, 2017**

Re: **IRB #: 2017-706; Title, "Assessment of Factors Influencing Intent-to-Use Big Data Analytics in an Organization in a Post-Adoption Context: A Survey Study"**

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I have reviewed the above-referenced research protocol at the center level. Based on the information provided, I have determined that this study is exempt from further IRB review under **45 CFR 46.101(b) ( Exempt Category 5)**. You may proceed with your study as described to the IRB. As principal investigator, you must adhere to the following requirements:

1) CONSENT: If recruitment procedures include consent forms, they must be obtained in such a manner that they are clearly understood by the subjects and the process affords subjects the opportunity to ask questions, obtain detailed answers from those directly involved in the research, and have sufficient time to consider their participation after they have been provided this information. The subjects must be given a copy of the signed consent document, and a copy must be placed in a secure file separate from de-identified participant information. Record of informed consent must be retained for a minimum of three years from the conclusion of the study.

2) ADVERSE EVENTS/UNANTICIPATED PROBLEMS: The principal investigator is required to notify the IRB chair and me (954-262-5369 and Wei Li, Ph.D, respectively) of any adverse reactions or unanticipated events that may develop as a result of this study. Reactions or events may include, but are not limited to, injury, depression as a result of participation in the study, life-threatening situation, death, or loss of confidentiality/anonymity of subject. Approval may be withdrawn if the problem is serious.

3) AMENDMENTS: Any changes in the study (e.g., procedures, number or types of subjects, consent forms, investigators, etc.) must be approved by the IRB prior to implementation. Please be advised that changes in a study may require further review depending on the nature of the change. Please contact me with any questions regarding amendments or changes to your study.

The NSU IRB is in compliance with the requirements for the protection of human subjects prescribed in Part 46 of Title 45 of the Code of Federal Regulations (45 CFR 46) revised June 18, 1991.

Cc: Ling Wang, Ph.D.
Ling Wang, Ph.D.

# Appendix J

## Enbridge Approval Letter

ENBRIDGE

Enbridge Inc.
200, Fifth Avenue Place
425 – 1st Street SW
Calgary, Alberta
Canada T2P 3LB

**Subject:** Enbridge Approval Letter

To whom it may concern:

This letter acknowledges that I have received and reviewed a request by Wayne Madhlangobe to conduct a research project entitled "*Assessment of Factors Influencing Intent-to-Use Big Data Analytics in the Organization in a Post-Adoptive Context: A Survey Study*" at Enbridge and I approve of this research to be conducted at our facility.

When the researcher receives approval for his/her research project from the Nova Southeastern University's Institutional Review Board/NSU IRB, I agree to provide access for the approved research project. If we have any concerns or need additional information, we will contact the Nova Southeastern University's IRB at (954) 262-5369 or irb@nova.edu.

Sincerely,

Mel Crocker
VP, TIS Enterprise Support & Chief Information Security Officer
Enbridge Inc.
Telephone: (403) 767 - 3807
mel.crocker@enbridge.com

# Appendix K

## Construct Reliability and Validity

Table K1

*Construct Reliability and Validity*

| Construct Reliability and Validity | | | | |
|---|---|---|---|---|
| | Cronbach's Alpha | rho_A | Composite Reliability | Average Variance Extracted (AVE) |
| Intangible | 0.891 | 0.897 | 0.891 | 0.453 |
| Data-Driven Culture | 0.892 | 0.893 | 0.892 | 0.624 |
| Faith in General Technology | 0.902 | 0.904 | 0.902 | 0.698 |
| Functionality | 0.937 | 0.937 | 0.937 | 0.832 |
| Helpfulness | 0.927 | 0.928 | 0.927 | 0.761 |
| Human | 0.958 | 0.96 | 0.959 | 0.659 |
| Institutional-Based Trust | 0.913 | 0.921 | 0.916 | 0.58 |
| Intent-to-Use | 0.938 | 0.949 | 0.937 | 0.789 |
| Managerial Skills | 0.958 | 0.959 | 0.959 | 0.794 |
| Org Learning | 0.914 | 0.919 | 0.916 | 0.685 |
| Perceived Capability | 0.948 | 0.958 | 0.951 | 0.421 |
| Perceived Risk | 0.733 | 0.987 | 0.824 | 0.722 |
| Perceived Usefulness | 0.941 | 0.941 | 0.941 | 0.799 |
| Propensity-to-Trust | 0.91 | 0.911 | 0.91 | 0.591 |
| Reliability | 0.882 | 0.886 | 0.882 | 0.652 |
| Situational Normality | 0.881 | 0.904 | 0.886 | 0.665 |
| Structural Assurance | 0.94 | 0.942 | 0.941 | 0.799 |
| Tangible | 0.863 | 0.867 | 0.864 | 0.516 |
| Technical Skills | 0.928 | 0.934 | 0.93 | 0.691 |
| Trust-in-Technology | 0.956 | 0.958 | 0.957 | 0.462 |
| Trusting Beliefs in Specific Technolo | 0.933 | 0.938 | 0.935 | 0.568 |
| Trusting Stance | 0.882 | 0.883 | 0.881 | 0.713 |

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