User Adoption of Big Data Analytics in the Public Sector

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Date: 2019-05-29
Course Code: 4IK00E, 15 credits
Subject: Information Systems
Level: Graduate
Department of Informatics
Abstract

The goal of this thesis was to investigate the factors that influence the adoption of big data analytics by public sector employees based on the adapted Unified Theory of Acceptance and Use of Technology (UTAUT) model. A mixed method of survey and interviews were used to collect data from employees of a Canadian provincial government ministry.

The results show that performance expectancy and facilitating conditions have significant positive effects on the adoption intention of big data analytics, while effort expectancy has a significant negative effect on the adoption intention of big data analytics. The result shows that social influence does not have a significant effect on adoption intention. In terms of moderating variables, the results show that gender moderates the effects of effort expectancy, social influence and facilitating condition; data experience moderates the effects of performance expectancy, effort expectancy and facilitating condition; and leadership moderates the effect of social influence. The moderation effects of age on performance expectancy, effort expectancy is significant for only employees in the 40 to 49 age group while the moderation effects of age on social influence is significant for employees that are 40 years and more. Based on the results, implications for public sector organizations planning to implement big data analytics were discussed and suggestions for further research were made. This research contributes to existing studies on the user adoption of big data analytics.

Key words: adoption intention, big data, big data analytics, Cronbach’s alpha, probit regression, public sector, public policy, statistical significance, and unified theory of acceptance and use of technology (UTAUT).
I appreciate the constructive feedback and comments of the examiner, Professor Paivi Jokela. The comments helped to redefine and focus the research objectives. I will also like to thank Professor Anita Mirijamdotter for allowing me to join the term and complete the thesis.

I also want to thank anonymous individuals for their assistance and facilitating access to the participants of the research. I say thank you. If you read this, you know yourselves.

Importantly, my utmost thanks go to my lovely wife and my son for allowing me to focus on the thesis. I will like to thank my parents for instilling in me the love for knowledge.

- Abayomi Akintola

- “Every cloud has a silver lining” – Yoruba proverb
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1.0 INTRODUCTION

This section introduces the themes of the thesis, followed by the research objective and research question, justification of the research was discussed, followed by scope and limitations, and the structure of the thesis.

1.1 INTRODUCTION

The volume of data available is growing at an exponential rate. It is estimated that 16 trillion gigabytes of useful data will be available by 2020 (Curry 2016; Turner et al. 2014). The sources of these data include private organizations, government and the citizens. Private organizations generate large amount of data through business transactions with customers and clients; governments generate large data by delivering services to the citizens and businesses, for example, taxation systems, social welfare programs, national statistics and etc. Citizens also generate large amount of data through the use of smart devices such as smartphones, geographic positioning systems and through social media networks. The data generated by these sources are examples of big data (Mueller et al. 2016; Lycett 2013).

Big data is defined as high volume datasets with extensive variety, generated and processed at high velocity (Gartner, 2001). The high volume relates to the size of big data. As more data is generated, so the volume of big data increases. The variety nature of big data means that big data is generated from multiple sources, for example, business transactions, government transactions, citizens’ use of social media. The multiple sources contribute to the structured and unstructured nature of big data. Structured data are data collected in a specific format, for example, a citizen’s social insurance number can only be in a specific format. On the other hand, unstructured data can be in any format, for example numbers, texts, email, media, imaging, audio and etc. The high velocity characteristic of big data is related to the rapid speed at which big data is generated. The characteristics of big data such as high volume, variety and velocity imply that big data is complex (Lycett 2013).

Due to the complexity of big data, advanced computational techniques are required for processing big data (Gunther et al. 2017). Processing of big data includes merging the data, analyzing the data, identifying important information, generating reports and etc. Big data analytics is the use of advanced techniques to process big data by examining big data to determine useful information and presenting the information in formats that can be used by decision makers in an organization to make decisions such as improving services to clients and allocating resources (Mueller et al. 2016). For example, big data analytics was used for infectious disease surveillance by Public Health Agency of Canada (PHAC) by linking historical datasets on flu incidents and hospital visits to Google’s search engine to project flu outbreaks. Big data is used in this example to forecast and project potential flu outbreaks. The PHAC will not be caught unaware and they can plan adequately for flu outbreak by taking actions and allocating the right amount of resources to where they are mostly needed. This is an example of an application of big data analytics in the public sector (Waldner 2017).
Similar to the application of big data analytics in the health sector, Tsoukas et al. (2013) opined that big data analytics is applicable to public policy; it can improve public policy. Dye (1972 cited in Howlett & Cashore 2014) defined public policy as “anything a government chooses to do or not to do”. Islam (2007) opined that public policy must be able to accurately define the public problems to address, describe the objectives to be accomplished, identify the courses of actions to be undertaken, and identify the resources required. Public policy problems are the issues the government intends to address such as reducing homelessness, reducing crime, increasing post-secondary enrolment rates and etc. Big data analytics is applicable to public policy because it can help the government to identify and define a public policy problem quicker than conventional methods. This is one of the potential benefits of big data analytics to the public sector (Longo & Dobell 2018; Tomer et al. 2016).

Further benefits of big data analytics to the public sector were outlined by Munne (2016), it can improve the forecasting ability of the public sector, prioritization of public programs and services, prevention of crimes, and better planning. For example, if the public policy issue the government wants to address is reducing incarceration rate, data from multiple ministries and government agencies such as social services, justice, police, education, Statistics Canada can be merged. Historical data can be analyzed, clients’ profiles can be created, factors that impact incarceration rates can be identified. By doing so, the government will be able to identify the causes of incarceration, determine factors that influence or cause incarceration, and develop an effective policy to address it. Big data analytics can enable the government to quickly identify urgent and emerging public issues and address these issues in a faster and targeted manner (Tomer et al. 2016).

The benefits of big data analytics to the public sector have been discussed, however, some studies have mentioned that achieving the benefits of big data analytics by an organization depends on the adoption by the users (Brunink 2016; Kwon et al. 2014; Shahbaz et al. 2019). Understanding the factors that influence the adoption of big data analytics from the users’ perspective is important because big data analytics may change the way employees perform their routine tasks. By determining the factors that impact users’ adoption, the organization will know the factors that positively impact the adoption of big data analytics and the factors that negatively impact the adoption of big data analytics. The organization can then focus on the factors that will promote the implementation and avoid factors that can reduce the adoption of big data analytics by the end users (Brunink 2016).

This thesis investigates the factors that influence the adoption of big data analytics by public sector employees. The thesis is carried out by conducting a survey and interviewing employees of a Canadian provincial government ministry. The ministry is at the planning stage of implementing big data analytics corporately.

1.2 Research Objectives and Research Question

The objective of this thesis is to determine the important factors that influence the adoption of big data analytics by public sector employees. This is an effort to contribute to existing academic studies on big data analytics in the public sector. Based on the researcher’s review of
existing literatures, there is no study that attempts to empirically determine the user adoption of big data analytics in the public sector. Hence, this is the first research to investigate user adoption of big data analytics in the public sector. The following research question is examined:

- What are the most important factors that influence the adoption of big data analytics by public sector employees?

1.3 Topic Justification

A review of existing research on big data analytics show that research on the public sector is at the infancy stage. Majority of the studies on the public sector studies focused on understanding the characteristics of big data analytics and the potential challenges and opportunities (Daniell, Morton & Rios Insua 2016; Giest 2017; Munne 2016; Longo & Dobell 2018; Longo & McNutt 2018). These studies did not empirically investigate the factors that impact big data analytics by public employees. Till date, there is no study that attempts to investigate the user acceptance of big data analytics in the public sector. This creates an opportunity for a research in this area. Furthermore, studies such as Giest (2017) and Munne (2016) have emphasized the need for more empirical research on big data analytics in the public sector.

The findings of this thesis is useful for public sector organization that wants to implement big data analytics. If a public sector organization wants to implement big data analytics, understanding the user adoption is important. According to Brunink (2016), understanding user adoption enables an organization to anticipate potential problems that are associated with the implementation of big data analytics from the users’ perspective. This implies that the organization will be able to identify factors that promote the adoption of big data analytics and also plan for factors that inhibit the adoption of big data analytics. Understanding the factors that influence user adoption of big data analytics will enable a public sector that wants to implement big data analytics to design a proper implementation plan that mitigates potential problems during the implementation of big data analytics.

1.4 Scope and Limitations

Though big data analytics can be adopted by senior management, this thesis focused on the adoption by employees that are not in senior management positions. Hence, it is important to note that the focus of this thesis is to investigate the factors that influence big data analytics from the users’ perspective and not from the senior management’s perspective.

Generalization of the results is limited. The thesis is conducted on a public sector in a Canadian provincial jurisdiction. The results may not be wholly generalized to all provincial governments in Canada because each provincial government may be at different stages of either planning to implement big data analytics or have implemented big data analytics. Post implementation of big data analytics is out of scope of this thesis as the research setting is at the pre-implementation stage of big data analytics. Therefore, the focus of the thesis is at the pre-implementation of big data analytics by a public sector.
1.5 Structure of Thesis

The remaining sections of the thesis are organized into five sections:

- Literature review and theories: this section includes the definition of big data and big data analytics, discussion of relevant literatures, explanation of the Unified Theory of Acceptance and Use of Technology UTAUT Model, followed by studies that have used the UTAUT model in the public sector. Lastly, the conceptual framework and the hypotheses are presented.
- Methodology: this section discusses the research methodology, research worldview and research design, followed by the quantitative methods, qualitative methods, and lastly research quality and limitations.
- Results and Findings: this section includes the results and findings from the survey and the interviews.
- Discussion: this section includes the discussions of the results and findings.
- Conclusions and future research: this section includes the conclusion of the thesis, contribution of the thesis and suggestions for future research.
2.0 LITERATURE REVIEW AND THEORIES

This section starts by presenting the definition of big data and big data analytics, followed by relevant literatures on big data and big data analytics in the public sector, followed by explanation of the Unified Theory of Acceptance and Use of Technology model (UTAUT), followed by relevant UTAUT studies in the public sector, and the conceptual framework and hypothesis.

2.1 Definition of Big Data and Big Data Analytics

The term big data has been used synonymously with business intelligence, business analytics and there is no consensus about its definition. Big data was first defined as data that is too big, too fast, or too difficult to be analyzed or processed using existing tools (Hadi et al. 2014). The default popular definition was by Gartner (2012) who defined big data “as high-volume, high-velocity and/or high variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation”. This has been extended further to the 5V model, that is volume, velocity, variety, veracity, and value.

The 5V model of big data is used to describe the characteristics of big data in terms of volume, velocity, variety, veracity, and value. Volume is related to the size and scalability of the data (Hadi et al. 2014; Longo & Dobell 2018). Velocity refers to the frequency of data, that is, the speed the data is generated and the time available to make decision (Hadi et al. 2014). Big data are generated in real time and high speed. Variety is the third characteristics which refer to the diversity of the data types. Veracity refers to maintaining the quality and accuracy of the raw data since big data may come from multiple sources that are either related or unrelated and the data can be messy or unorganized. The last characteristics of big data is value. This refers to how the data can be used to create value, meaningfulness or benefits both observable and unobservable (Hadi et al. 2014; Longo & Dobell 2018). Due to the complex nature of big data in terms of volume, velocity, variety, it is not possible to analyze big data using conventional analytical tools. Analyzing big data requires the use of advanced computational techniques that can manage the volume, variety, veracity and velocity of big data. Big data analytics is the application of advanced analytical techniques to big data to identify data trends, patterns, inferences and insights in a manner that can be used for decision making (Mueller et al. 2016).

2.2 Big Data Analytics and Public Sector

Though the studies presented in this section did not discuss user adoption of big data analytics or empirically investigate big data analytics adoption, they are relevant to the thesis because they discussed the potential benefits and challenges of using big data analytics in the public sector.

To show the relationship between big data and public policy analysis, Shi, Ai and Cao (2017) carried out a systematic analysis of existing literature to present the impact of big data on public policy. One of the objectives of the research is to determine how big data affects public policy
analysis. Shi, Ai and Cao (2017) concluded that big data have the potential to accelerate the innovation in public policy. The authors noted that big data analysis can be beneficial to public policy analysis, however, there are risks of privacy, bias, data misuse, and others, associated with the process; and big data can be applied in public policy analysis in a number of ways by data management and data analysis. Also, big data can be used to determine public performance indexes (Shi, Ai, & Cao 2017).

Longo and McNutt (2018) discussed how big data can change the traditional policy analysis. Policy analysis is the evaluation of solutions to solve public policy issues. The traditional policy analysis is characterized with conventional quantitative analysis methods used in the 70s and 80s (Longo & McNutt 2018). However, big data, supported with the modern day technology can enhance public policy. Longo and McNutt (2018) concluded by highlighting some of the issues associated with adopting big data, one notably that government has to build enough capacity to accommodate the proper usage of big data in public policy. This can be accomplished by providing training to the public employees (Longo & McNutt 2018).

Similarly, Schintler and Kulkarni (2014) identified some benefits and challenges of using big data in the public sector. The benefit includes provision of useful information, detailed, accurate and timely data for decision making. However, using big data comes with some notable challenges. The fact that big data are usually skewed, too complex, and tend to be missing some relevant information; in brevity, big data tend to be biased in some cases. A set of big data might have lost its contextual value when they are being processed, reshuffled, repurposed and reinterpreted going through the phase of being supplied to the end users (Schintler & Kulkarni 2014).

In terms of the theoretical and practical use of big data in policy making, Giest (2017) concluded that big data serves as a solid foundation for public policies and public administration. Therefore, there is a need to incorporate big data analytic tools into studying public policies. One of the challenges identified by Giest (2017) is limited institutional support for big data management and capacity within the government. According to Giest (2017), when government has low level of analytical capacity, they would have to source for additional stakeholders with the right skill sets. Giest (2017) opined that the issue of capacity can be solved by training government workers in data analytics or simplifying the ambiguities involved in analyzing big data for policy decision making. According to Giest (2017) using big data in policy making should be at the problem identification stage, where data serves as an evidence to gauge the severity of a social problem. Big data should also serve as the basis for policy makers in setting their priorities. Big data should be considered at the root cause analysis stage for social problems (Giest 2017).

### 2.3 Studies on Adoption of Big Data Analytics

The studies presented in this section studied the adoption of big data analytics in the private sector and health care sector. While none of the papers carried their research in the public sector, they are relevant to this thesis because of the commonalities in the research topic of big data analytics adoption.
Brunink (2016) conducted a research on the adoption of big data analytics in a Franco-Dutch company using the adapted (UTAUT) model. In essence, the writer explored the factors that drive big data acceptance across different cross functional levels. Results show that irrespective of the gender; performance expectancy, business value expectancy, and social influence have significant positive impact on big data adoption intention. However, high levels of data usage experience and data driven decision making behaviour have a negative effect on big data adoption intention. Brunink (2016) found that the UTAUT model is useful in identifying factors positively impacting big data adoption intention. However, the author opined that the UTAUT model must be adapted to fit the big data analytics context.

Shabaz et. al. (2019) investigated the adoption of big data analytics in the healthcare sector. This study explores the adoption mechanism of big data analytics in healthcare organization to test the elements correlated to behavioural intention using the technology acceptance model and task technology fit paradigm. The results show that the elements of the technology acceptance model together with task technology fit highly contribute to the enhancement of behavioural intentions to use big data analytics system in health care, leading towards actual use. Shabaz et. al. (2019) found that the trust in and security of the information system also positively influenced the behavioural intention of use. However, employee resistance to change negatively moderates the relationship between intention to use and the actual use of big data analytics in health care sector. Shabaz et. al. (2019) concluded that combining technology acceptance model and task technology fit theories on behavioural intentions to adopt big data analytics gives more effective results than using the models individually.

Lai et. al. (2017) studied the determinants of big data analytics adoption in logistics and supply chain management. The main purpose of this research is to address factors determining firm’s intention to adopt big data in their daily operations. Lai et. al. (2017) classified the potential factors into four categories: technological, organizational, environmental factors, and supply chain characteristics. The innovation diffusion theory was used in this research, a model that consisted the direct technological and organizational factors; moderators were also proposed. The results show that perceived benefits and top management support can greatly influence the adoption intention of big data analytics. However, environmental factors such as competitor’s adoption, government policies, and supply chain connectivity can highly moderate the direct relationship between the driving factors and the user adoption intention (Lai et. al. 2017).

### 2.4 Unified Theory of Acceptance and Use of Technology (UTAUT)

According to Venkatesh et al. (2003) the basic concept underlying user acceptance of information system/information technology are individual’s reactions to using information technology, the intentions to use information technology, and actual use of information technology. Venkatesh et al. (2003) formulated the Unified Theory of Acceptance and Use of Technology (UTAUT) by unifying eight models of user technology acceptance. These models include the Technology Acceptance Model (TAM), the Theory of Planned Behaviour (TPB), Theory of Reasoned Action (TRA), Motivational Model (MM), Model of PC Utilization (MPCU), Innovation Diffusion Model (IDM), Social Cognitive Theory (SCT), and the Combined model of Technology Acceptance Model and Theory of Planned Behaviour.
Figure 2.1: Original UTAUT Model Adapted from Venkatesh et al. (2003)

Figure 2.1 above is the UTAUT model adapted from Venkatesh et al. (2003). It shows the determinants of Use Behavior, that is, the actual use of a new system (Venkatesh et al. 2003). These determinants are Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Behavioral Intention. The determinants are adapted from the eight user adoption models (Venkatesh et al. 2003). The first four determinants are moderated by the following key variables: gender; age; experience; and voluntariness of use (Venkatesh et al. 2003).

Performance expectancy is the degree to which individuals believe that using a system will improve their job performances (Venkatesh et al. 2003). Performance expectancy is close to perceived usefulness in TAM, extrinsic motivation in MM, relative advantage in IDT, job fit in the MPCU model, and outcome expectation in the SCT model (Venkatesh et al. 2003). According to Venkatesh et al. (2003), perceived expectancy is the strongest predictor of an individual intention to use a new system.

Effort expectancy is the perceived ease of use of a system (Venkatesh et al. 2003). It is the degree in which an individual believes a system is easy to use. Effort expectancy pertains to three constructs, that is, perceived ease of use in TAM, complexity of system in MPCU, and ease of use in the IDT models (Venkatesh et al. 2003).

Social influence is the degree to which individuals think important people in their organization believes they should use the new system (Venkatesh et al. 2003). Social influence pertains to social factors presented in the MPCU model, image in the IDT model, and subjective norm in the TRA, TAMTRP models (Venkatesh et al. 2003). Social influence pertains to how an individual’s behaviour is influenced by the way individuals think others will perceive them if they use or decide not to use a new system (Venkatesh et al. 2003). It is interesting to note that social influence can impact an individual’s behaviour depending on if the use of the new system is a compliance to set decisions or if it is voluntary (Venkatesh et al. 2003).
Facilitating condition is the extent an individual believes that an organizational and technical infrastructure exist to support the use of the system (Venkatesh et al. 2003). Facilitating conditions construct pertains to the perceived behavioral control in TPB and TAM models, facilitating conditions in MPCU model, and compatibility in the IDT model.

Performance expectancy, effort expectancy, social influence, and facilitating conditions are moderated by gender, age, experience and voluntariness of use. Moderating variable gender impacts performance expectancy, effort expectancy and social influence. Age moderates all the four constructs. Experience impacts effort expectancy, social influence, and facilitating conditions while voluntariness of use impacts only social influence (Venkatesh et al. 2003).

Facilitating conditions directly impacts an individual’s use behaviour of a new system (Venkatesh et al. 2003). Venkatesh et al. (2003) posit that three constructs, that is performance expectancy, effort expectancy and social influence directly impact behavioral intention to use a new system and behavioral intention impacts the use behavior. According to Venkatesh et al. (2003), behavioral intention has a significant positive influence on an individual use of a technology.

2.5 Some Applications of the UTAUT Model and Adoption of Technology in the Public Sector

The studies presented in this section used the UTAUT model to investigate the adoption of technology in the public sector. Although these studies investigated different types of technologies, they are relevant to this thesis because they use the UTAUT theory and the studies were conducted in a similar research setting which is the public sector.

Gupta, Dasgupta, and Gupta (2008) did an empirical study using the Unified Theory of Acceptance and Use of Technology to show the factors that impact the adoption of internet applications by government employees. The authors found that performance and effort expectancy, peer influence and suitability conditions positively impact the adoption of ICT by the employees. Using the UTAUT model they concluded that UTAUT is applicable to studying the adoption and successful use of ICT in a government organization. The authors opined that providing training for employees is a prerequisite for successful implementation of ICT to government employees and that training reinforces the adoption of a new technology (Gupta et al. 2008).

Similar to the studies of Gupta et al. (2008), Wang and Feeney (2014) investigated the adoption of intranet and e-services by employees of municipalities. Using data collected from random survey of managers in 500 municipalities, the authors found that centralization of organization, work routines, and personnel constraints are linked to the adoption of intranet and e-services, but these relationships are moderated by organization’s risk taking culture. Wang and Feeney (2014) also found that stakeholder’s influence is positively correlated to user acceptance of e-services and intranet. The authors concluded that organization’s risk taking culture mediates
the relationship between constraints and ICT adoption in municipal governments (Wang & Feeney 2014).

Dwivedi et al. (2015) used the UTAUT model to empirically determine the predictors influencing the acceptance and use of open data technologies. Dwivedi et al. (2015) found that performance expectancy, effort expectancy, social influence and voluntariness of use all account for 45% of the variability in people’s intention to use open data technologies which is very significant, except for facilitating conditions. Dwivedi et al. (2015) concluded that policy makers can encourage the use of open data technologies by presenting the benefits of open data use, by creating awareness to users that already use open data, by creating social strategy platform to encourage people to trigger each other to use open data, by integrating open data use in daily operations, and by making the use of open data technologies very easy for people (Dwivedi et al. 2015).

2.6.0 Conceptual Framework: Adapted UTAUT model

The UTAUT model has been slightly adapted to suit the objectives of this thesis. The objective of this thesis is to investigate factors that influence the intention to use big data analytics by public sector employees. Since the focus of this thesis is on intention to use and not the actual use of the new system, some of the determinants in the original model of Venkatesh et al. (2003) have been removed.

In the original UTAUT model, Use Behaviour refers to the actual use of the new system after its implementation (Venkatesh et al. 2003). This variable is not relevant to this thesis because of three reasons. First, the unit of analysis in this thesis is at the early stage of implementing big data analytics. This implies that Use Behavior is a big data analytics post implementation variable and cannot be measured until it is fully implemented by the ministry. Second, development of policy especially operational policies is decentralized in the unit of analysis. It is likely that some unit within the organization may be ahead of others in terms of use of analytics in policy development. Lastly, one of the objectives of the thesis is to identify factors that can influence the adoption of big data analytics at the individual level. So, it is important to determine the factors that significantly stimulate or demotivate the public employees’ adoption of big data analytics intention prior to the actual implementation. This will enable the organization to identify how to promote the acceptance of big data analytics among the users and mitigate issues that may lead to the resistance of some of the employees. Therefore, the dependent variable Use Behaviour is not included in the adapted model.

Voluntariness of Use is one of the four moderating variables in the original UTAUT model. Voluntariness of Use is an important moderating variable when the user has the liberty to either use or not use a technology (Venkatesh et al. 2003). Voluntariness of Use is replaced with leadership because decision making in the public sector is different from the private sector. In situation where the decisions are made at the senior management level, this limits the voluntariness of use. However, leadership style may impact adoption intention because it encourages innovation. In some cases, public employees have the liberty to scan for innovative ideas that can improve their tasks and make recommendations on new innovative ideas. The
perceived openness of the top decision makers to new ideas may impact the intention of the public employee to adopt a new technology (Moussa et al. 2018). Therefore, Voluntariness of Use is replaced with Leadership.

In the original model of Venkatesh et al. (2003), *Facilitating Condition* directly impact Use Behavior. Since Use Behavior has been removed, *Facilitating Condition* has been amended to be a factor that will impact *Adoption Intention*, that is the intent of the users to accept the new system. According to Giest (2017), technology and institutional resources are one of the factors that can impact adoption of big data in the public sector. It could be theorized that perceived availability of adequate resources can impact users’ intention to adopt big data analytics. Figure 2.2 below shows the conceptual framework of the thesis including the hypotheses numbers.

![Figure 2.2: Conceptual Framework (Author developed and adapted from the original UTAUT model by Venkatesh et al. 2003).](image)

**2.6.1 Hypotheses**

**Performance Expectancy**

*Performance Expectancy* is the degree to which an individual believes a system will enable him or her to achieve improvements in job performance (Venkatesh et al. 2003). Performance Expectancy is anticipated to impact the intention of users to adopt a new system. The construct is an important determinant of an individual’s intention to use a IS/IT innovation (Dwivedi et al. (2015). According to Giest (2017) using big data analytics in policy formulation will enhance the quality of decisions, options, and can enhance policy outcomes. Also, previous studies such as Rana et al. (2016), Dwivedi et al. (2015), Venkatesh et al. (2003) posited that *Performance Expectancy* have positive impact on the user adoption of new IS/IT system. It can be assumed that the public employees will expect an improvement in performances by using big data analytics. Based on this, the following hypothesis is stated:
H1A: Performance expectancy positively impacts the intention of public employees to adopt big data analytics.

Empirical studies on user adoption have reported differences in results with respect to age and gender of respondents. Ong and Lai (2006) studied gender differences in user acceptance of e-learning. Gender was reported to impact the influences of performance expectancy. Ghalandari (2012) reported that age and gender play a moderating role in performance expectancy. Venkatesh et al. (2003) argued that similar to gender, age also plays a moderating role in performance expectancy. Venkatesh et al. (2003) posited that younger employees value extrinsic rewards more and this will impact their performance expectancy (Venkatesh et al. 2003). It can be theorized that younger public employees will have different performance expectancy than older public employees. The hypotheses are framed thus:

H1B: The impact of performance expectancy on the adoption of big data analytics by public employees is moderated by the gender of the public employees.

H1C: The impact of performance expectancy on the adoption of big data analytics by public employees is moderated by age of the public employees such that the effect will be stronger for younger employees than older employees.

One of the success factors that have been identified and discussed by past studies on big data in the public sector is the expertise and experience of the civil service to utilize big data (Daniell, Morton & Rios Insua 2016; Giest 2017). This includes the knowledge, skills and ability of an individual to meaningfully perform analytics tasks using big data. Banerjee, Bandyopadhyay and Acharya (2013) argued that expertise and skill sets are some of the important facilitators of analytics adoption. Kwon et al. (2014) reported that employees with experience in traditional analytics are likely to adopt big data analytics. It can be assumed that public employees with data experience are likely to adopt big data than those without data experience. Therefore, the following hypothesis is stated:

H1D: The impact of performance expectancy on the adoption of big data will be moderated by data expertise, such that the effect will be stronger for public employees with data expertise than public employees without data expertise.

Borins (2002) argued there is a strong relationship between leadership and innovation in the public sector. Innovation in the public sector can be categorized into two broad categories: top-down and bottom-up innovations. The latter is related to strategic innovations which are mostly reactive innovations to crisis, new visions, priorities or national agenda, while the former are innovations that are routine based and promulgated by the doers in the public sector (Borins 2002). Borins (2002) concluded that bottom-up innovations frequently occur in the public sector than top-down. However, bottom-up innovations depends on the organisational climate created by the politicians and senior public servant. A supportive organizational climate promotes innovations (Borins 2002). This supports the arguments of Hochtel et al. (2016) that attitude of openness and encouraging innovation is required for big data analytics to be applied to policy formulation. It can be assumed that public employees that perceive positive leadership
support for innovation are likely to have a higher intention to adopt big data than public employees that do not perceive positive leadership support. This leads to the following hypothesis:

H1E: The impact of performance expectancy on the adoption of big data analytics by public employees will be moderated by leadership support, such that the effect will be stronger for public employees that perceive positive leadership support for innovation than employees that do not perceive positive leadership support.

Effort Expectancy

Effort Expectancy is the degree of ease associated with using a system, that is the extent a system is perceived to be complicated or easy to use (Venkatesh et al. 2003). Variability and complexity are one of the dimensions of big data. Complexity implies that big data is generated from multiple sources, as a result poses a challenge of cleansing, matching, connecting and transforming data collected from different sources (Gandomi & Haider 2015). With respect to public policy, Hochtel et al. (2016) posited that for public organizations to use big data analytics; there is need to prepare for the speed in terms of data volume and velocity. Based on the effort required to use big data analytics, the following hypothesis was formed.

H2A: Effort expectancy negatively impacts the intention of public employees to adopt big data analytics.

According to the UTAUT model, age and gender moderate the influence of effort expectancy on user adoption (Venkatesh et al. 2003), with the effect more pronounced in females than males. In terms of age, the older the end user, it is theorized that the higher the effort expectancy (Venkatesh et al. 2003). Previous studies on adoption reported that effort expectancy is influenced by age and gender of the end user (Dakduk, Banderalli & Woude 2018; Venkatesh et al. 2012;). The following hypothesis is developed to determine if age and gender moderate effort expectancy.

H2B: The impact of effort expectancy on the intention of public employees to adopt big data will be influenced by gender of the public employees such that the effect will be stronger for females.

H2C: The impact of effort expectancy on the intention of public employees to adopt big data will be influenced by age of the public employees such that the effect will be stronger for older employees.

As a result of the complex, structured and unstructured nature of big data (Lycett 2013), the skills, ability and data expertise of the public employees will alter the user adoption of big data. Gandomi and Haider (2015) proposed a five steps process for extracting insights from big data: acquisition and recording; extraction, cleaning and annotation; integration, aggregation and representation; modelling and analysis; and interpretation. The author argued that due to the unstructured nature of big data, using big data analytics may be complex (Gandomi & Haider 2015). It can be assumed that public employees with data expertise are likely to have different
perspective of big data than public employees with limited expertise in big data analytics. The following hypothesis is developed.

H2D: *The impact of effort expectancy on adoption of big data analytics by public employees will be moderated by data expertise.*

**Social Influence**

Social influence is the degree to which an individual believes people that are important think he or she should use a new system (Venkatesh et al. 2003). According to Venkatesh et al. (2003), social influence impacts usage adoption. Venkatesh et al. (2012) and Dakduk, Banderalli and Woude (2018) argued that social influence is subjective. How individuals perceive what others think about them on the use of a system influences their adoption of the system. If the public employees think usage of the new system has social status gain, they are likely to adopt it. The following assumption is developed.

H3A: *Social influence positively impacts public employees’ intention to adopt big data analytics.*

Venkatesh et al. (2003) argued that gender and age moderates social influence. The authors posited that females are more sensitive to the opinions of others about them which ultimately impacts social influences. It is also reported that as employees grow older, their level of affiliation reduces and they are not easily influenced by social influence (Venkatesh et al. 2003). The following hypothesis is used to determine of social influence is moderated by age and gender of the public employees.

H3B: *The impact of social influence on the intention of public employees to adopt big data analytics will be influenced by gender of the public employees such that the effect will be stronger for females.*

H3C: *The impact of social influence on the intention of public employees to adopt big data analytics will be influenced by age of the public employees such that the effect will be stronger for younger employees.*

According to Venkatesh et al. (2003) social influence is contextual based, that is, its influence could vary based on if the new system is mandatory or voluntary. Venkatesh (2003) posited that social influence may have a compliance mechanism, whereby individuals are required to act in a certain way. That is, individuals must comply with the social influence. One thing to note about compliance is the existence of either a reward or compensation that can be used to reinforce the desired behaviour. The reinforcement of a behaviour can be seen as part of organizational culture of leadership. It is expected that leadership will moderate social influence especially in the compliance context. Also, if the innovation or new system is a response to crisis, emergency or overall government’s goals, public employees will be required to comply. This implies that innovation that are top-down, are likely to the adopted. Also Lai et. al. (2017) opined that top management support influences employees to adopt big data analytics. It can be theorized that:
H3D: The impact of social influence on the intention of public employees to adopt big data analytics will be moderated by leadership.

Facilitating Condition

Facilitating condition is the extent to which an individual believes that the available technical and organizational resources can support the use of a new system (Venkatesh et al. 2003). Existing adoption literatures argued that facilitating condition is positively related to adoption of new system (Dakduk, Banderalli & Woude 2018; Venkatesh et al. 2012). It can be theorized that a low facilitating condition will lead to low adoption rate, vice versa. The following hypothesis shows that facilitating condition influences the intention to adopt big data analytics.

H4A: Facilitating Conditions positively impacts public employees’ intention to adopt big data analytics.

The original UTAUT model postulates that facilitating condition is moderated by gender (Venkatesh et al. 2003). Also, Venkatesh et al. (2012) reported that gender moderates facilitating condition. The following is the hypothesis to determine if gender is a moderating factor for facilitating condition.

H4B: The impact of Facilitating Condition on the intention of public employees to adopt big data analytics will be influenced by gender of the public employees.

Facilitating condition is assumed to be moderated by the data expertise of the public employee. Dakduk, Banderalli and Woude (2018) argued that data experience influences facilitating condition. That is employees with data experience are less likely to worry about available technical and organizational resources than employees that do not have data knowledge. We can theorize that knowledge and expertise of the public employees will moderate Facilitating Condition.

H4D: The impact of Facilitating Conditions on the intention of public employees to adopt big data analytics will be influenced by data expertise of the public employees such that the effect is stronger for employees for employees with data experience.
3.0 METHODOLOGY

This section discusses the research methodology. The section starts with an explanation of the research worldview and research design, followed by the quantitative research method, the qualitative research method, and lastly the research quality and limitations.

3.1 Research Worldview

Worldviews are set of belief system that allow researchers to agree on the most important questions in a research field and the best methods of answering the questions (Morgan 2009). According to Creswell (2009 p. 6), there are four types of worldviews: post positivism, a deterministic philosophy that relates to studying cause and effect. It is suitable for experiments; social constructivism, that is, the researcher seeks to understand the research topic through research participants’ experiences, understandings and interactions with the subject matter. The researcher relies heavily on the research participants’ views of the subject matter studied. It is suitable for qualitative research; advocacy/participatory worldview, a research worldview where the research is connected with politics or a political agenda. This worldview leads to an action agenda that can change the lives of the research participants, their environment and the researcher’s life or view about the subject matter; pragmatic worldview, this is concerned with the applications of what works and the solutions to a problem (Creswell 2009, p. 6).

The pragmatic worldview aligns with the objectives of this thesis. The pragmatic worldview is concerned with applications of what works and the solutions to a problem (Creswell 2009, p. 10). Pragmatism enables the researcher to conduct a research using a mixed research approach of qualitative and quantitative methods. It allows a researcher to apply multiple methods, different assumptions, different worldviews and different forms of collecting and analysing data (Creswell 2009, p. 11). Using a mixed method enables the researcher to investigate the factors that influence the adoption of big data analytics by public sector by examining relationships between multiple variables and gathering qualitative data through interviews to understand the results better. The interviews conducted were used to gather information used to validate the survey and also provide reasonable explanations to the insights gathered from the quantitative analysis.

3.2 Research Design and Strategy: Mixed Method

The research design is informed by the nature of the research question, research strategies and the data collection methods (Creswell 2009 p. 3). The research methods used in previous UTAUT model are diverse. Majority of the existing studies used quantitative methods. Williams, Rana and Dwivedi (2015) reviewed 174 UTAUT studies, 102 of these studies used quantitative research methods.

A mixed method of both quantitative and qualitative methods is used for this thesis. The nature of the research question explored in this thesis fit both quantitative and qualitative research methods. To answer the research question, developing and testing the hypotheses statistically is required, this is quantitative. To get more understanding of the findings, a qualitative method
in form of interview was used. Using both methods enabled the researcher to use the data collected from both methods as complementary. The quantitative method enables the researcher to determine the user adoption of big data analytics by public employees statistically, and the interviews enable the researcher to gather qualitative information that provide insights and context to the quantitative data. It will be possible to understand some patterns or insights that cannot be explained with quantitative analyses. Also, data collected from the interviews are used to validate the quantitative data collected from the survey.

Mixed methods have multiple benefits. It allows the researcher to conduct in-depth research. This allows an exploratory agenda as unspecified theme can emerge from the qualitative study. This ensures completeness purpose of a research. It is complementary, the qualitative data and information can be used to provide meanings to the trends and patterns shown by the quantitative data. Mixed methods can also provide stronger evidences for drawing conclusions when findings from one approach converge or corroborate the findings from another method (Johnson & Onwuegbuzie 2004).

The research strategy is the sequential approach. Sequential approach allows the researcher to use the findings of one method to elaborate or expand on the other (Creswell 2009, p. 14). A survey was used to collect quantitative data and quantitative analysis was used to test the user adoption using an adapted UTAUT theory followed by a qualitative analysis that helped provide insights by analyzing data collected from the interviews. A survey was sent to employees that are identified in the quantitative data population section below. After the completion of the survey and initial data analyses, interviews were conducted with selected five respondents.

3.3 Quantitative Methods

This section discussed the quantitative method for the thesis: data population; data collection; survey procedure and data analysis.

3.3.1 Quantitative Data Population

Population implies all individuals or objects that meet certain membership requirements for a particular group. The individuals or objects that qualify are termed population elements (Tashakkori & Teddlie 2010). The population elements for the thesis is 85 public sector employees. The first criterion is that the respondent must be a public sector employee. Second, the employee’s primary responsibility should be in any of analysts or consultants in the areas of data, operation, evaluation, program, and policy. Lastly, the respondent must not be a member of the senior management. The survey was sent to 85 population elements. There were 78 completed surveys. The response rate is 92%.

3.3.2 Quantitative Data Collection

In broad categories, the two types of data that are collected are categorical and numerical data. Categorical data are qualitative data both can be codified to have values. The responses can be coded and grouped into different categories. Categorical data collected include gender and level of education. Numerical data are quantitative data that comes from measurement, counting or
mathematical operations (Doane et al. 2010, p. 21). The respondents are asked about their years of work experience, experience working in the policy shop or data analysis, age, and questions related to the adoption of big data analytics developed based on previous studies and the hypotheses.

Likert scale is used for the survey questionnaire. Likert scale is a survey instrument that allows respondents to indicate the agreement or disagreement to a statement on a five-point or seven-point scale (Doane et al. 2010, p. 25). Previous UTAUT studies such as Brunink (2016) used Likert Scale measured on a 5 – point scale, of which 5 is the most positive end and 1 is the most negative end (5 = Strongly Agree; 4 = Agree; 3 = Neither Agree nor Disagree; 2 = Disagree; 1 = Strongly Disagree).

3.3.2.1 Independent Variables

A total of 16 questions were used for the measurement of the four constructs of Performance Expectancy (4 questions), Effort Expectancy (4 questions), Social Influence (3 questions), and Facilitating Conditions (4 questions). See appendix A for the survey questionnaire questions, the constructs and sources of each question.

Performance Expectancy (PE) was measured based on anticipated benefits such as reductions in tasks/projects turnaround time, improvements to output quality, and improvement in job effectiveness.

One special objective of this thesis is determining if big data analytics is applicable to policy development. This is meant to determine if the current public employees in the ministry are willing to move away from the traditional analytic system to big data analytics. This can only be determined from the expected performance perspective, as this constructs determine if end user’s perceive usefulness of a system is likely to impact its adoption (Moore & Benbasat 1991). The survey consists of four questions that measure the Performance Expectancy in relation to policy development.

Effort Expectancy (EE) the questions for this construct was based on the assumed ease of use and complexity of using big data. The questions were termed around learning curve of big data analytics, difficulty in understanding the mechanism of big data analytics, and flexibility of big data analytics.

Social Influence (SI) was measured based on standards of interpersonal relationship, support of management and social status in the organization. Central to social influence is how public employees think they will be perceived by others in the organization.

Facilitating Conditions (FC) was measured based on perceived behavioral control and objective environmental factors the public employees perceived will make it easy for them to use big data analytics. The environmental factors measured include technical support, resources, and compatibility with legacy tools and technology.
3.3.2.2 Dependent Variable

The dependent variable in this study is *Adoption Intention (AI)*. Venkatesh et al. (2003) used a five point Likert Scale to measure *Adoption Intention*. In this study a closed question with two options were used to measure the variable. The scope of this thesis is to measure the adoption intention of the public employees while Venkatesh et al. (2003) ultimate objective is to measure *Usage Behavior*. Previous UTAUT tests have also included time horizon, that is when the respondent intends to adopt big data analytics (Brunink 2016), since the adopting big data analytics in the ministry understudy is at the pre-implementation stage, the researcher finds it redundant to include time horizon of adopting big data analytics in the questions.

3.3.2.3 Moderating Variables

The moderating variables in this thesis are *Gender* (1 question), *Age* (1 question), *Data Expertise* (6 questions), and *Leadership* (2 questions).

*Gender* was measured with a nominal scale where 1 represents female, and 2 represents male. Though, there is a third option of undefined gender, however, all the respondents identified as either female or male.

*Age* was measured as a continuous numeric variable. The public employees were asked to enter their age as a number. The response box was validated to ensure only numeric variables are entered.

*Data Expertise* is measured in terms of experience and expertise in data analytics. The term was described in a caption statement and the response is either yes or no. Respondents were also asked to rate their knowledge, skills, and abilities in data based on the following: Expert level; Advanced Level; Intermediate; and Basic.

3.3.3 Quantitative Survey Procedure

The questionnaire was developed based on the constructs of the UTAUT model. To ensure data completeness, all questions are forced response questions. Majority of the questions are single choice questions. The questionnaire has four sections. The first part includes information about the purpose of the research, introduction to the research topic, statement of confidentiality, contact of the researcher and informed consent. Also included in the introduction is an introduction of big data analytics to ensure that all respondents have the same understanding of big data analytics which is the core theme of the study. The second section of the questionnaire was divided into four sub parts based on the four constructs of the UTAUT model: performance expectancy; effort expectancy; social influence; and facilitating condition. The questions for each constructs were presented in a block format such that similar questions related to each construct are together. The third section is focused on the intentions to use big data analytics. The fourth section of the questionnaire is used to collect data on moderating variables such as leadership, age, gender, and data expertise and the last section is the closing remarks and the contact of the researcher should the respondent decide to withdraw after completing the questionnaire.
The questionnaire was pilot tested with two public employees prior to sending it to all the respondents. The checks include critical evaluation of wording, measurement scales, contents, structure, completion time, and readability. The survey was sent to 85 respondents. The initial sample size was 60 respondents but this was increased after consultations with more departments and units.

The questionnaire and an accompanying cover letter were sent directly to all the respondents via the contact information provided to the researcher. The respondents were given one week to complete the survey. A reminder correspondence was sent to the respondents two days to the deadline.

3.3.4 Quantitative Data Analysis

The data is analyzed using STATA software. The following tests were conducted: reliability tests; correlation and relationship analyses; The following tests were conducted but are explained in the results and analysis section: multicollinearity test and an analyses of variance using the Kruskal-Wallis test method (KW).

3.3.4.1 Reliability Tests

Cronbach’s alpha test was conducted to measure the consistency and scale reliability of the model constructs. Cronbach’s alpha results are usually between 0 and 1. A general rule of thumb is that a Cronbach’s alpha above 0.70 shows the model constructs are consistent and reliable (Santos 1999). Multiple questions were used to measure a constructs in the questionnaire to ensure reliability of the survey.

3.3.4.2 Regression Analysis

Some of the previous UTAUT studies have used the structural equation modelling to determine relationship between user adoption and the constructs. However, structural equation model requires a large sample size (Khechine et al. 2014; Wang et al. 2017). The study of Dwivedi et al. (2015) employed a different approach by using the multivariate regression method to determine the user adoption of open data technologies. Due to the limitation of sample size, multivariate probit regression analysis was used in this thesis to determine the relationship between the independent variable, Adoption Intention and the independent variables identified in the conceptual framework.

The measure for the dependent variable, Adoption Intention is dichotomous, that is either yes or no. The response is constructed in binary number format and was converted to a dummy variable. According to Studenmund (1992), a dummy variable is a binary that is coded either 1 or 0 to quantify a response. For the dependent variable (YES = 1, that is big data analytics will be adopted, and NO = 0, that is big data analytics will not be adopted).

Since our independent variable Adoption Intention is dichotomous, only a logit or probit regression can be used. Both regression models will arrive at the same conclusion. The difference between the two models is the assumption of the errors, the errors in the probit model
are assumed to follow a normal distribution while the errors in the logit model are assumed to follow the standard logistic distribution. So a researcher may choose either models. Probit models is used in this thesis because the estimates can be interpreted as probability instead of odds ratio given by a logistic model. Probit model is a qualitative response regression models that are used to measure the probability of something happening. Since this thesis focus on the pre-implementation stage of big data analytics, it is logical to measure probability of adoption. For example, if performance expectancy increases by 1, the probability of adopting big data analytics increases by \( X\% \) (Gabler, Lasiney & Lechner 1993; Gujarati 2004 p. 581).

The following is the main multivariate model used to determine the probability of adopting big data analytics based on the four constructs of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI) and Facilitating Condition (FC).

\[
D_i = \theta + \beta_1 PE + \beta_2 EE + \beta_3 SI + \beta_4 FC + \varepsilon_i
\]

\( D \) is a dummy variable, \( \theta \) is a constant and \( \varepsilon \) is the disturbance.

The main model specified above was tested for the moderating variable Age, Gender, Data Expertise, and Leadership.

### 3.4 Qualitative Methods

This section discussed the qualitative methodology, including the data sampling, interview procedure, and data analysis.

#### 3.4.1 Qualitative Data Sampling

Purposive sampling was used for the interview. This is when individuals that are knowledgeable or have experience in the research topic are identified and selected for the interview (Palinkas et al. 2015). The public employees that were interviewed were selected based on their experience and knowledge with data analytics, policy analysis, gender and the department they work. The respondents are named A – E and described below.

- Respondent A has worked for the government for more than 5 years. Respondent A roles and responsibilities include policy and data analysis. Respondent A is a male;
- Respondent B has worked for the government for over 15 years. Respondent B develops dashboards, involved in cross government data initiatives. Respondent B is a female;
- Respondent C has worked for the government for 5 years. Respondent C leads data analytics initiatives. Respondent C has been involved with the development and evaluation of major policy changes. Respondent C is a female;
- Respondent D has worked for the government for more than 10 years. Respondent D has been involved with policy analysis, policy development, and policy implementation. Respondent D has used outputs of data analytics and reports. Respondent D is a male; and
• Respondent E has worked for the government for over 26 years. Respondent A performs data analytics and have led the development and implementation of many public policies and programs. Respondent E is a male.

3.4.2 Qualitative Data Collection and Interview Procedure

The interviews were conducted with five public employees to collect qualitative data. The respondents were contacted via email and follow-up calls. A reminder was sent to the respondents a week before the interview. The interview structure was semi-structured. Some of the benefits of semi-structured interviews include less intrusiveness by encouraging respondents the opportunity to express themselves (Thomas 2009). Also, the researcher is able the interview in focus. The choice of semi-structured interviews was decided based on two reasons. It will allow the researcher to understand the constructs of the user adoption deeper; respondents can add additional information. Semi-structured interview allows the respondents to express themselves openly, without any constraints (Newton 2010). This allowed the researcher to identify themes and trends that were not preconceived or hypothesized by the researcher.

The interview includes providing the purpose of the research to the respondents. The respondents were informed about the confidentiality, and how to get in touch with the researcher if they intend to contact the researcher later. Respondents consented to be interviewed and participated in the research. The researcher also verified responses with the respondents. There were 10 interview questions. Please see appendix C for the interview questions.

3.4.3 Qualitative Data Analysis

The qualitative data analysis used in this thesis followed the constant comparative analysis approach. This involved selecting a piece of data from the interviews and comparing it with others to identify similarities or differences (Thorne 2000). According to the similarity and contrast principles, the interpretation of a symbol can be determined by finding out its level of similarities to other symbols while the contrast principle implies that the meaning of a symbol can be determined by finding out the difference of a symbol from other symbols (Tashakkori & Teddlie 2010). The collected data was broken into units of information and then categorized. Comparing and analyzing the data helped to identify the relationships between the various variables that influence the adoption of big data analytics by public sector employees.

3.5 Validity and Reliability

Validity is the degree to which a research measurement measures what it was supposed to measure (Bolarinwa 2015). Validity can be categorized into internal and external. Internal validity is how the measures accurately quantify what it was supposed to measure while external validity is how the measures obtained from the research sample accurately describes the research population (Bolarinwa 2015). The interview questions were reviewed and the questionnaire was reviewed thoroughly. To ensure content and constructs validities, the content
of the questionnaire was developed based on the hypothesis, UTAUT theoretical constructs and previous studies on user acceptance of technology. This is to ensure that research instrument fully measures the parameters of interests of the research as well as capture the theoretical constructs. Furthermore, responses from the interview conducted were used to validate the data collected with the survey instrument.

Reliability is the degree to which a research instrument measures the same results consistently if it is used in the same situation repeatedly (Heale & Twycross 2015). A reliable instrument will produce the same results when used repeatedly (Bolarinwa 2015). The questionnaire was pilot tested with two research elements not included in the survey sample. This is done to ensure clarity, completeness, avoidance of ambiguity, and to determine if the time required to complete the survey is reasonable. Cronbach test which is explained in the following chapter was used to establish the reliability of the survey instrument. The interview questions were reviewed with two research elements before finalizing the questions used for the interviews.

3.6 Ethical Considerations

Ethical consideration is about making judgements according to a standard for what is right and what is wrong (Brevik 2013). According to Creswell (2013), ethical issues may arise prior to conducting a research, at the beginning of the research, during data collection, during data analysis and reporting. Prior to conducting the research, appropriate approvals were sought from the ministry to access the research settings and respondents.

Informed consent was collected from all respondents. Please see appendix D for the informed consent. Respondents that completed the survey are required to read the consent and voluntarily agree to participate in the survey before proceeding. For the interviews, respondents are required to read the consent and voluntarily agree to participate in the interview. All respondents were also informed that they are able to withdraw from the research at any time during the survey and interview and may withdraw from the research after the survey and interviews by contacting the researcher. Respondents were provided with information about the objectives and purpose of the research, how the data collected will be used, and how the data will be stored.

According to the UTAUT model, age is one of the moderating variables that influence the adoption of a new system. Instead of asking for respondents’ date of birth, the respondents were asked to provide their age as a number. Date of birth, names, mailing addresses, and phone numbers are considered personal information that can be used to identify an individual. These types of information were not collected during the interview and survey. The identities of the respondents and the ministry were not disclosed in the report. Responses collected during interview and data from questionnaires were kept safe.

Due to the researcher’s knowledge of the studied organization, potential researcher bias is acknowledged. For example, there is a possibility of confirmation biases, that is, the tendency for a researcher to accept the results that support preexisting beliefs and reject any evidence to
the contrary (Schwind & Buder 2012). To mitigate potential researcher bias, some controls were established by the researcher during the entire research process. The researcher avoided leading questions in the interview and avoided implying there is a right answer. This prevents the research participants from responding in favour of a particular preconceived assumption. The researcher also verified responses with the respondents. Furthermore, the hypotheses were developed based on the constructs of the UTAUT model and existing studies and the developed hypotheses were critically reviewed multiple times. This is an effort to ensure the researcher’s preexisting beliefs do not influence the research hypotheses. The survey and interview questions were pilot tested to determine flaws, weaknesses and limitations and the questions were revised according to the feedback received.

Furthermore, a mixed method of qualitative and quantitative analyses was used for the thesis. All data collected from the survey and interviews were considered in totality and analyzed accordingly. Responses from the interview participants were evaluated promptly and re-evaluated and responses were shared with the respondents for validation. Responses from the interview were analyzed objectively without preconceived beliefs of the researcher and interpretations were thoroughly reviewed. Quantitative data were analyzed using statistical analyses. This is objective as statistical analyses are what it is. Results from quantitative analyses are interpreted objectively based on statistical standards.
4.0 RESULTS AND FINDINGS

The findings and results of the quantitative analysis are presented first, followed by the findings from the interviews conducted with five respondents.

4.1 Quantitative Analysis

Table 4.1 below shows the characteristics of the survey respondents in terms of gender, age, work experience and education.

Table 4.1: Characteristics of Survey Respondents

<table>
<thead>
<tr>
<th>CATEGORY</th>
<th>Frequency</th>
<th>% of total</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>GENDER</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>38</td>
<td>49%</td>
</tr>
<tr>
<td>Male</td>
<td>40</td>
<td>51%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>78</td>
<td>100%</td>
</tr>
<tr>
<td><strong>AGE</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>20 to 29</td>
<td>12</td>
<td>15%</td>
</tr>
<tr>
<td>30 to 39</td>
<td>40</td>
<td>51%</td>
</tr>
<tr>
<td>40 to 49</td>
<td>18</td>
<td>23%</td>
</tr>
<tr>
<td>50 and More</td>
<td>9</td>
<td>10%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>78</td>
<td>100%</td>
</tr>
<tr>
<td><strong>WORK EXPERIENCE</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 to 1 Year</td>
<td>7</td>
<td>9%</td>
</tr>
<tr>
<td>2 to 3 Years</td>
<td>13</td>
<td>17%</td>
</tr>
<tr>
<td>&gt; 3 to 4 Years</td>
<td>17</td>
<td>22%</td>
</tr>
<tr>
<td>&gt; 4 to 5 Years</td>
<td>6</td>
<td>8%</td>
</tr>
<tr>
<td>More than 5 Years</td>
<td>35</td>
<td>45%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>78</td>
<td>100%</td>
</tr>
<tr>
<td><strong>EDUCATION</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Master Degree</td>
<td>27</td>
<td>35%</td>
</tr>
<tr>
<td>Bachelor Degree</td>
<td>45</td>
<td>58%</td>
</tr>
<tr>
<td>Post-Secondary Diploma</td>
<td>6</td>
<td>8%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>78</td>
<td>100%</td>
</tr>
</tbody>
</table>

As shown in table 4.1 above, all the respondents declared their gender, 49% identified as females and 51% identified as males. 66% of the respondents are below 40 years and only 1% is close to retirement. In terms of work experience, 53% of the respondents have been working for the government for more than 4 years and 7% have worked for the government for less than one year. In the area of education, almost 92% of the respondents have at least a University...
bachelor degree, while 35% have a master degree. This highlights the respondents level of knowledge and skills.

4.2 Reliability Test

It is important to determine the reliability of the survey questionnaire. Cronbach’s alpha, a measure of internal consistency is used to determine the reliability of the survey questionnaire. Internal consistency is the degree all the items in the survey questionnaire measure the same construct (Tavakol & Dennick 2011). A construct is the hypothetical variable the survey intends to measure (Santos 1999). Cronbach’s alpha is also used to determine the amount of measurement errors in a questionnaire (Tavakol & Dennick 2011). Cronbach’s alpha is between 0 and 1 and considered acceptable if it is 0.70 or higher (Santos 1999). The Cronbach’s alpha test was carried out on the four constructs. Table 4.2 below shows the Cronbach’s alpha for the test scale. All the constructs have a Cronbach’s alpha that is more than 0.70. This implies that the survey tool is reliable, that is, responses to the test items are consistent.

Table 4.2: Reliability Tests - Cronbach’s Alpha

<table>
<thead>
<tr>
<th>UTAUT Construct</th>
<th>Numbers of Items</th>
<th>Cronbach’s Alpha coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>Performance Expectancy (PE)</td>
<td>4</td>
<td>0.795</td>
</tr>
<tr>
<td>Effort Expectancy (EE)</td>
<td>4</td>
<td>0.740</td>
</tr>
<tr>
<td>Social Influence (SI)</td>
<td>3</td>
<td>0.775</td>
</tr>
<tr>
<td>Facilitating Condition (FC)</td>
<td>4</td>
<td>0.818</td>
</tr>
</tbody>
</table>

Note: 0.5 < $\alpha$: NOT ACCEPTABLE; 0.5 $\leq$ $\alpha$ $\leq$ 0.6: POOR; 0.6 $\leq$ $\alpha$ $\leq$ 0.7: ACCEPTABLE; $\alpha$ > 0.70: GOOD.

4.3 Multicollinearity

The VIF test for multicollinearity was used to determine if there is any association between the independent (explanatory) variables. The presence of multicollinearity of variables in a regression analysis leads to biased estimates. It is possible for estimated coefficient to be deemed significant when they are not (Yoo et al. 2014). Multicollinearity is determined by examining the variance inflator factors (VIF). A VIF that is less than 10 means there is no evidence of multicollinearity among the variables (Yoo et al. 2014). Table 4.3 on the next page shows the mean VIF for each constructs. The highest VIF is 6.54 and this is for Effort Expectancy. Since all the VIF values are less than 10, the results indicate there is no evidence of multicollinearity among the explanatory variables.
Table 4.3: VIF – Multicollinearity Test

<table>
<thead>
<tr>
<th>UTAUT Construct</th>
<th>Number of Items</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Performance Expectancy (PE)</td>
<td>4</td>
<td>1.90</td>
</tr>
<tr>
<td>Effort Expectancy (EE)</td>
<td>4</td>
<td>6.54</td>
</tr>
<tr>
<td>Social Influence (SI)</td>
<td>3</td>
<td>2.17</td>
</tr>
<tr>
<td>Facilitating Condition (FC)</td>
<td>4</td>
<td>1.93</td>
</tr>
</tbody>
</table>

Note: VIF < 10: NO MULTICOLLINEARITY; VIF > 10: MULTICOLLINEARITY

4.4 Regression Analysis

A probit regression analysis was ran. The independent variable is Adoption Intention and the explanatory variables are Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Condition. Table 4.4 below presents the marginal effects and the corresponding value. Marginal effect is between 0 and 1, it is the change in probability of the dependent variable occurring when the explanatory variable changes by one unit (Gabler, Lasiney & Lechner 1993). The p-values are reported to determine the significance of each construct. As a rule of thumb, a p-value that is less than or equals to 0.05 indicates the estimate is statistically significant, that is, the result did not occur by chance (Doane et al. 2010, p. 370). The result for each construct is explained below.

Table 4.4: Effects of Explanatory Variables on Adoption Intention

<table>
<thead>
<tr>
<th>CONSTRUCTS</th>
<th>MARGINAL EFFECTS</th>
<th>P-VALUE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Performance Expectancy (PE)</td>
<td>0.417</td>
<td>0.001*</td>
</tr>
<tr>
<td>Effort Expectancy (EE)</td>
<td>-0.491</td>
<td>0.015*</td>
</tr>
<tr>
<td>Social Influence (SI)</td>
<td>0.0334</td>
<td>0.067</td>
</tr>
<tr>
<td>Facilitating Condition (FC)</td>
<td>0.808</td>
<td>0.002*</td>
</tr>
</tbody>
</table>

Note: Dependent Variable is Adoption Intention.
Significance level is *p≤0.05

The marginal effect for Performance Expectancy is positive and the p-value is 0.001. This implies that an increase in Performance Expectancy by 1 unit will increase the probability of adoption of big data analytics by public sector employees by 41.7% and it is statistically significant. We accept the hypothesis that Performance Expectancy positively impacts the intention of public sector employees to adopt big data analytics.

The marginal effect for Effort Expectancy is negative and the p-value is 0.015. This implies that an increase in Effort Expectancy by 1 unit will decrease the probability of adoption of big data analytics by public sector employees by 49.1% and it is statistically significant. Therefore, we accept the hypothesis that Effort expectancy negatively impacts the intention of public employees to adopt big data analytics.
The marginal effect for *Social Influence* is positive and the associated *p-value* is 0.067. While this implies that an increase in *Social Influence* by 1 unit will increase the probability of adoption of big data analytics by public employees by 3.3%, but is not statistically significant at 95% confidence level. Therefore, we can reject the hypothesis that *Social influence* positively impacts public employees’ intention to adopt big data analytics.

The marginal effect for *Facilitating Condition* is positive and the associated *p-value* is 0.002. So, an increase in *Facilitating Condition* by 1 will increase the probability of adoption of big data analytics by public employees by 80.8%. We can accept the hypothesis that *Facilitating Condition* positively impacts public employees’ intention to adopt big data analytics.

### 4.5 Effect of Moderating Variables on Adoption Intention of Big Data Analytics

In the hypothesis section, it was hypothesized that: Age, Gender, Experience and Leadership moderate the *Performance Expectancy*; Age, Gender, and Experience moderate both *Effort Expectancy* and *Facilitating Condition*; and *Social Influence* is hypothesized to be moderated by Age, Gender and Leadership. Since the data collected from the survey are nonparametric, therefore the one-way ANOVA test for determining differences in means of a group is inappropriate because the one-way ANOVA assumes normal distribution of data. Using the one-way ANOVA test may lead to incorrect conclusions (Doane et al. 2010, p. 459). The Kruskal-Wallis (KW) test is more suitable because it assumed a non-normal distribution of the data. It is a rank-based non-parametric test used to determine if there are differences between two or more groups of a variable on another variable and if the differences are statistically significant (Leon 1998). The Kruskal-Wallis test was used to test the effect of the moderating variable groups on the influence of the four constructs on the *Adoption Intention*. Table 4.5 below shows the results of the Kruskal-Wallis test ran using the STATA software. The null hypothesis is that there is no difference between the groups in the moderating variable.

#### Table 4.5: Kruskal-Wallis (KW) Equality of Populations Rank Test

<table>
<thead>
<tr>
<th>CONSTRUCTS</th>
<th>MODERATING VARIABLES</th>
<th>CHI-SQUARED</th>
<th>P-VALUE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Performance Expectancy</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PE_GENDER</td>
<td>24.4</td>
<td>0.001*</td>
<td></td>
</tr>
<tr>
<td>PE_AGE</td>
<td>10.8</td>
<td>0.001*</td>
<td></td>
</tr>
<tr>
<td>PE_EXPERIENCE</td>
<td>5.1</td>
<td>0.025*</td>
<td></td>
</tr>
<tr>
<td>PE_LEADER</td>
<td>2.7</td>
<td>0.099</td>
<td></td>
</tr>
<tr>
<td><strong>Effort Expectancy</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EE_GENDER</td>
<td>4.0</td>
<td>0.045*</td>
<td></td>
</tr>
<tr>
<td>EE_AGE</td>
<td>6.1</td>
<td>0.106</td>
<td></td>
</tr>
<tr>
<td>EE_EXPERIENCE</td>
<td>3.6</td>
<td>0.058</td>
<td></td>
</tr>
<tr>
<td><strong>Social Influence</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI_GENDER</td>
<td>1.8</td>
<td>0.175</td>
<td></td>
</tr>
<tr>
<td>SI_AGE</td>
<td>4.0</td>
<td>0.261</td>
<td></td>
</tr>
<tr>
<td>SI_LEADER</td>
<td>6.2</td>
<td>0.014*</td>
<td></td>
</tr>
</tbody>
</table>
The KW test was used to determine if Performance Expectancy for the gender group, the $\chi^2$ is 24.4 and the $p$ value is 0.001, this showed there was a statistically significant difference in Performance Expectancy between males and females. For the four age groups (20 to 29; 30 to 39; 40 to 49; 50 and more), the $\chi^2$ is 10.8 and the $p$ value is 0.001, this showed there was a statistically significant difference in Performance Expectancy for the four age group category. For respondents with data experience and without data experience, the $\chi^2$ is 5.1 and the $p$ value is 0.025, this showed there was a statistically significant difference in Performance Expectancy between employees with data experience and employees without data experience. For the moderating variable leadership, $\chi^2$ is 2.7 and the $p$ value is 0.099, this showed there is no statistically significant difference in Performance Expectancy between employees that think there is leadership support and employees that think there is no leadership support.

For Effort Expectancy, the KW test for the gender group category, the $\chi^2$ is 4.0 and the $p$ value is 0.045, this showed there was a statistically significant difference in Effort Expectancy between males and females. For the age group categories (20 to 29; 30 to 39; 40 to 49; 50 and more) the Chi Squared $\chi^2$ is 6.1 and the $p$ value is 0.106, this showed there was no statistically significant difference in Effort Expectancy for the four age group category. For respondents with data experience and without data experience, the $\chi^2$ is 3.6 and the $p$ value is 0.058, this showed there was no statistically significant difference in Effort Expectancy between employees with data experience and employees without data experience.

For Social Influence, the KW test for the gender group category, the $\chi^2$ is 1.8 and the $p$ value is 0.175, this showed there was no statistically significant difference in Social Influence between males and females. For the four age groups (20 to 29; 30 to 39; 40 to 49; 50 and more) has a Chi Squared $\chi^2$ of 4.0 and $p$ value of 0.261, this implies that there was no statistically significant difference in Social Influence for the four age group category. For the moderating variable leadership, $\chi^2$ is 6.4 and the $p$ value is 0.014, this showed there is a statistically significant difference in Social Influence between employees that think there is leadership support and employees that think there is no leadership support.

For Facilitating Condition, the KW test for the gender moderating variable, the $\chi^2$ is 5.7 and the $p$ value is 0.017, this showed there was a statistically significant difference in Facilitating Condition between males and females. For the four age groups (20 to 29; 30 to 39; 40 to 49; 50 and more), the Chi Squared $\chi^2$ is 6.5 and the $p$ value is 0.090, this showed there was no statistically significant difference in Facilitating Condition for the four age group category. For respondents with data experience and without data experience, the $\chi^2$ is 21.8 and the $p$ value is 0.000, this showed there is a statistically significant difference in Facilitating Condition between employees with data experience and employees without data experience.
The Kruskal-Wallis test is only useful for determining if there is a statistically significant difference between the expression of two or more groups of a moderating variable on another variable, however, it can neither determine the specific groups of the variable that is statistically significant nor quantify how a particular group of a variable impact the relationship (Leon 1998). It cannot show the impact of the moderating variable on the explanatory variable. Using the probit model, the impacts of the moderating variables are shown in Table 4.6 below.

Table 4.6 below shows the results from the probit regression analysis of the moderating variables’ categories of Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Condition. The \( p \)-values are reported to show the significance of the estimates result for each variable. If \( p \)-value is less than or equals to 0.05, this indicates the estimate is statistically significant and the results did not occur by chance (Doane et al. 2010, p. 370).

Table 4.6: Effects of Moderating Variables on Adoption Intention

<table>
<thead>
<tr>
<th>CONSTRUCTS</th>
<th>MODERATING VARIABLES/ITEMS</th>
<th>MARGINAL EFFECTS</th>
<th>P-VALUE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Performance Expectancy (PE)</strong></td>
<td><strong>PE_GENDER</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>MALE</strong></td>
<td>0.164</td>
<td>0.150</td>
</tr>
<tr>
<td></td>
<td><strong>FEMALE</strong></td>
<td>-0.164</td>
<td>0.151</td>
</tr>
<tr>
<td><strong>PE_AGE</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>20 - 29</strong></td>
<td>0.011</td>
<td>0.230</td>
</tr>
<tr>
<td></td>
<td><strong>30 - 39</strong></td>
<td>0.014</td>
<td>0.093</td>
</tr>
<tr>
<td></td>
<td><strong>40 - 49</strong></td>
<td>0.333</td>
<td>0.009*</td>
</tr>
<tr>
<td></td>
<td><strong>50 and More</strong></td>
<td>0.354</td>
<td>0.002*</td>
</tr>
<tr>
<td><strong>PE_EXPERIENCE</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>NO</strong></td>
<td>-0.342</td>
<td>0.003*</td>
</tr>
<tr>
<td></td>
<td><strong>YES</strong></td>
<td>0.341</td>
<td>0.002*</td>
</tr>
<tr>
<td><strong>PE_LEADER</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>NO</strong></td>
<td>-0.266</td>
<td>0.076</td>
</tr>
<tr>
<td></td>
<td><strong>YES</strong></td>
<td>0.266</td>
<td>0.076</td>
</tr>
<tr>
<td><strong>Effort Expectancy (EE)</strong></td>
<td><strong>EE_GENDER</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>MALE</strong></td>
<td>0.402</td>
<td>0.001*</td>
</tr>
<tr>
<td></td>
<td><strong>FEMALE</strong></td>
<td>-0.402</td>
<td>0.001*</td>
</tr>
<tr>
<td><strong>EE_AGE</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>20 - 29</strong></td>
<td>0.192</td>
<td>0.242</td>
</tr>
<tr>
<td></td>
<td><strong>30 - 39</strong></td>
<td>-0.192</td>
<td>0.242</td>
</tr>
<tr>
<td></td>
<td><strong>40 - 49</strong></td>
<td>0.532</td>
<td>0.001*</td>
</tr>
<tr>
<td></td>
<td><strong>50 and More</strong></td>
<td>-0.327</td>
<td>0.123</td>
</tr>
<tr>
<td><strong>EE_EXPERIENCE</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>NO</strong></td>
<td>-0.502</td>
<td>0.002*</td>
</tr>
<tr>
<td></td>
<td><strong>YES</strong></td>
<td>0.502</td>
<td>0.002*</td>
</tr>
</tbody>
</table>


The marginal effect estimates and the associated *p*-value presented in table 4.6 above are explained below.

### 4.5.1 Performance Expectancy

The marginal effects for male is positive while it is negative for females, however, the *p*-value is 0.150, this means the estimates are not statistically significant. The hypothesis that the impact of *Performance Expectancy* on the adoption of big data analytics by public employees is moderated by gender is not accepted.

For the age group category, the marginal effect estimates are all positive for all age group but only the estimates for respondents in the 40 to 49 and 50 and more category are statistically significant. The hypothesis that the impact of *Performance Expectancy* on the adoption of big data analytics by public employees is accepted for two groups (40 to 49 and 50 years and more) but the hypothesis is rejected for two groups (20 to 29 and 30 to 39).

In terms of the impact on the moderating variable, experience on *Performance Expectancy*, the probability adoption by respondents with data experience increases by 0.341 compared to respondents without data experience. These estimates are statistically significant and we accept the hypothesis that impact of *Performance Expectancy* on the adoption of big data analytics by public sector employees is moderated by data expertise and the effect is stronger for employees with data expertise.

The impact of leadership on *Performance Expectancy* is not statistically significant, although the marginal effect estimate is positive for respondents that perceive a positive leadership
support. So the hypothesis that leadership support moderates the impact of *Performance Expectancy* on adoption of big data analytics by public sector employees is rejected.

### 4.5.2 Effort Expectancy

The marginal effects for male is positive while it is negative for females, the *p-value* is 0.001, this means the estimates are statistically significant. The hypothesis that the impact of *Effort Expectancy* on the adoption of big data analytics by public employees is moderated by gender is accepted.

The marginal effect estimates for the age group is positive for 20 to 29 years old and 40 to 49 years old while it is negative for 30 to 39 years old and 50 years and more. Only the estimate for 40 to 49 years old is statistically significant. The hypothesis that the impact of *Effort Expectancy* on the intention of public employees to adopt big data analytics is influenced by the age of the public employees is accepted for only the 40 to 49 age group and rejected for all other age groups.

The impact of experience on *Effort Expectancy* is positive for respondents with data experience and negative for respondents without data experience. The *p-value* is 0.002 which is statistically significant. We accept the hypothesis that impact of *Effort Expectancy* on the adoption of big data analytics by public sector employees is moderated by data expertise.

### 4.5.3 Social Influence

The marginal effect estimate for male is positive while it is negative for females, the *p-value* is 0.050, this means the estimates are statistically significant. The hypothesis that the impact of *Social Influence* on the adoption of big data analytics by public employees is moderated by gender is accepted.

The marginal effect estimates for the age group is positive for all groups but negative for 20 to 29 age group. The marginal effect estimates for 40 to 49 and 50 and more age groups are statistically significant. The hypothesis that the impact of *Social Influence* on the intention of public employees to adopt big data analytics is influenced by the age of the public employees is accepted for groups 40 to 49 and 50 and more age groups and rejected for age groups 20 to 29 and 30 to 39.

The impact of leadership on *Social Influence* is statistically significant, the marginal effect for respondents that perceive positive leadership support is 0.395 and the *p-value* is 0.017. So the hypothesis that leadership support moderates the impact of *Social Influence* on adoption of big data analytics by public sector employees is accepted.

### 4.5.4 Facilitating Condition

The marginal effect estimate for male is positive while it is negative for females, the *p-value* is 0.003, this means the estimates are statistically significant. The hypothesis that the impact of
Facilitating Condition on the adoption of big data analytics by public employees is moderated by gender is accepted.

The impact of experience on Facilitating Condition is positive for respondents with data experience and negative for respondents without data experience. The estimate is statistically significant. We accept the hypothesis that impact of Facilitating Condition on the adoption of big data analytics by public sector employees is moderated by data expertise.

4.6 Qualitative Findings

The responses from all the interview respondents are grouped under each question accordingly. The first four questions are based on the four constructs of Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Condition. The remaining questions include responses to factors that positively influence adoption of big data analytics and factors that can reduce the adoption of big data analytics.

The first question asked was “Do you perform data analytics or use analytics deliverables/reports performed by others?” Four respondents answered yes and one respondent performs data analytics and also use the output of analytics performed by others.

When asked if big data analytics will improve the quality of policy?

Respondent A said big data analytics help policy to better target and segment the need. Big data analytics will show new needs or changes of needs for policy more timely than the traditionally methods (surveys, focus groups, etc.). Respondent A also mentioned that big data will also show the effectiveness of the policy much faster when the policy or program are reviewed or evaluated. According to Respondent B, evidence based analysis has become a gold standard for policy analysis. Having data to reinforce your ideas is becoming the standard in public policy creation. For that to happen, large data sets from many program areas need to be used to provide more information than previously possible. Respondent C opined that the potential benefits of big data analytics is of wide scope. Further, Respondent C mentioned that from a policy perspective, government will be able to make more informed decisions and have more confidence in its decision making when big data analytics are used. As well, if you have the right data sets you should be able to undertake more efficient and quick program policy evaluations to determine if new policy or policy changes are seeing the desired outcomes that were proposed.

In the words of Respondent D, big data analytics will contribute insights into issues in society and inform decisions about what interventions are needed; it can help measure whether an intervention was effective or not and it can do this in a much faster way. Respondent D mentioned that big data analytics will improve all aspect of the tasks they perform: the policies developed; the recommendations; and it will improve decisions by providing relevant evidences and insights to the decision makers.

According to Respondent E, using big data from different data sets and many sources and seeing correlations can be invaluable in determining where or how to use limited resources to achieve
maximum impacts. For example, some early research linking various data sets (i.e. housing and education outcomes) has shown that affordable housing is not linked to better educational outcomes for teens. However, the location (i.e. those in better neighborhoods) of affordable housing is strongly linked to better educational outcomes. In other words, peer pressure (i.e. the values of one’s peers) seems to be a stronger determinant. With this knowledge, if Government wants to improve the educational outcomes for children of low income family, government can achieve a better result if buildings are built in more affluent neighborhoods, particularly given the marginal cost of land vis-à-vis the total capital life cost of a building. Respondent E also mentioned that big data analytics will determine the type of impacts and also inform the government of limitations of the impacts.

**When asked if big data analytics will be easy to use?**

*Respondent A* thinks big data analytics is complicated and needs expertise to use. It is an advanced tool with many value, but it “requires both techniques and experience to show its value” said by *Respondent A*. It is not just a tool to analyze data, but a way of thinking for the team. *Respondent B* commented that “will it be easy for everyone in government? No, it is a tool for experts and slowly trickle down to staff with less expertise as the ministry build capacity”.

*Respondent B* mentioned that it will be easy to use big data analytics. However, the ease of use will depend on the data sources. More importantly, if the right algorithm must be developed or purchased from a third party. The algorithm should be able to get the information required to make good policy decisions for government as a whole or for individual Ministries. The sources and variety of data is unlimited, so developing the right model that meets a particular policy question is important. *Respondent C* stated that big data analytics will be flexible to use. *Respondent D* also agreed that big data analytics will be easy to use depending on how it is implemented. *Respondent E* mentioned that big data analytics will easy to use by the employees with the right level of skills, education, and training. Respondent E also mentioned that linking big data with one’s career is likely the best way to have it adopted. Employees needs to know that it is related to their career advancement as well and this could start from the senior management.

**When asked if their managers’ support may make employees to adopt big data analytics?**

*Respondent A* mentioned that it will be very good if there is managers’ support for big data analytics and the respondent perceives limited support. However, *respondents B, C, D and E* stated they perceive good manager’s support. According to *Respondent B*, it will be easier for employees to request for what they need when using big data analytics when they know they have the support of their managers. *Respondent C* mentioned that manager’s support influences attitudes and behaviours of employees in a positive manner. *Respondent C* stated that “changing behaviours and attitudes is easy when managers create a positive work environment and showing their staff that they have their back and encourage open discussions”. *Respondent D* mentioned that their current manager is very supportive and this goes a long way in motivating them to do more. *Respondent E* stated that manager’s support is required because managers act
as change agents and their support will likely make it easier for the employees to use big data analytics.

When asked if their ministry’s current technology and infrastructure will support big data analytics?

Respondent A said the ministry’s data technologies will support big data analytics but will need to add more recent analytical tools like Hadoop or IBM tools. Respondent B said they have the computer power and the expertise for big data analytics. Respondent C do not think the current technology will be able to support big data analytics but they believe the ministry has the human resources with the right skills to use big data analytics. Respondent D mentioned that they currently use some advanced data analytics tool and they recently got the license for other tools like Tableau and R. Respondent D thinks the current technology support big data analytics. According to Respondent E, the current computers and analytical tools support big data analytics. However, they think more resources is needed for data cleaning instead of the actual analysis.

When asked if public sector employees will adopt big data analytics if it is a corporate initiative?

Respondent A mentioned that employees will adopt it if there is strong and open leadership. Respondent A stated that “there is a current corporate push for data analytics across the government”. In the opinion of Respondent B, “employees may feel compelled to use big data analytics but there may not be less value because analytics require personal interests in the subject matter”. According to Respondent B, if the senior management enforce it instead of promoting the use of big data analytics, employees may just be using it for the bare minimum required. According to Respondent C, if it is a corporate initiative, employees will have to adopt big data analytics as part of policy development and implementation. However, there is a need for corporate champions, that is, individuals that will promote big data analytics within the government. Respondent C mentioned that employees may have to be convinced of how big data analytics can achieve better decision making and better outcomes. According to Respondent D, employees will adopt it but it depends on the leader. If the leader promoting big data analytics is perceived to be an innovator and a motivator by the employees, the adoption rate will be faster than if the champion is perceived otherwise. Respondent E explained that it is a leadership question. If leaders use outputs of big data analytics and demand for more of it, it will be adopted. But, if leaders do not use it or rely on anecdotal then it will not be adopted” as stated by Respondent E.

When asked the possible factors that may positively influence public sector employees to use big data analytics?

Respondent A mentioned solid business cases and examples from other jurisdictions may help to show the value of this tool. Respondent A also mentioned executive support and sufficient trainings that will enable the employee. According to Respondent B access to the data, establishing support groups as committee of practices, trainings and provision of the software
tools are factors that can positively influence public sector employees to use big data analytics. Respondent C mentioned resources, education and training as the main factors. While Respondent D mentioned communication and informing the potential users of the benefits of looking for insights; themes; correlations across big data sets, rather than in siloed information. And the potential users knowing that they may be able to make better evidence-informed decisions with a big influence. Respondent E stated that “the norm in government is that change is inevitable as the public issues we deal with is changing, we need big data analytics to improve what we do and as an employee with long public service, I want to leave a legacy of a high performing public service”. Respondent E mentioned five factors that can positively influence the adoption of big data analytics: better understanding of the data with respect to its sources and meanings is important; understanding the value of big data analytics; linking big data analytics to improvement in work performed by the employees; and senior leadership support.

**When asked what factors may prevent you from using big data analytics?**

Respondent A mentioned lack of resources with respect to software and computers, and access to the data and lack of support. Respondent B mentioned lack of support from direct supervisors and senior leadership. Respondent B added stated that “what is the essence of spending time on analytics that will not be recognized by the senior management or we not be used by anybody?”. Respondent C mentioned training and knowledge to use big data analytics. Respondent C also mentioned ability to develop the right model and algorithm, access to the right data and information that can be used to validate why or why not a policy option is the best instead of the other. Respondent D mentioned the time it takes to use big data analytics. If it takes too much time, then Respondent D will not use it. Respondent D stated that when supervisors and managers do not motivate their employees to learn or acquire new knowledge, adopting big data analytics will be slow.

According to Respondent E, factors that may make employees not to use big data analytics include: lack of knowledge about how to complete the analysis; lack of access to applicable data; reliability of the information; time to complete the analysis; and opportunity cost of time, this is when they consider the value of something else they should have done. In the opinion of Respondent E, government should provide training. Respondent E stated that “in many cases, the assumption of leadership is that employees should come with the skills but, skills change and evolve over time”. Respondent E suggested that government should ensure life-long learning for the employees as the software and tools used for big data analytics changes over time.
Table 4.7 shows the summary of the hypotheses, the interpretation and decisions whether the hypothesis are accepted or rejected.

Table 4.7 Summary of Hypotheses, Interpretations and Decisions

<table>
<thead>
<tr>
<th>CONSTRUCTS</th>
<th>HYPOTHESIS</th>
<th>INTERPRETATION</th>
<th>DECISION</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Performance Expectancy (PE)</strong></td>
<td>H1A</td>
<td>PE positively impacts the intention of public employees to adopt big data analytics.</td>
<td>Accepted</td>
</tr>
<tr>
<td></td>
<td>H1B</td>
<td>Impact of PE on the adoption of big data analytics by public employees is moderated by age of the public employees such that the effect will be stronger for younger employees than older employees.</td>
<td>Rejected</td>
</tr>
<tr>
<td></td>
<td>H1C</td>
<td>Impact of PE on the adoption of big data analytics by public employees is moderated by age of the public employees such that the effect will be stronger for younger employees than older employees.</td>
<td>Accepted for age groups 40 – 49 and 50 and More</td>
</tr>
<tr>
<td></td>
<td>H1D</td>
<td>Impact of PE on the adoption of big data analytics will be moderated by data expertise, such that the effect will be stronger for public employees with data expertise than public employees without data expertise.</td>
<td>Accepted</td>
</tr>
<tr>
<td></td>
<td>H1E</td>
<td>Impact of PE on the adoption of big data analytics by public employees will be moderated by leadership support, such that the effect will be stronger for public employees that perceive positive leadership support for innovation than employees that do not perceive positive leadership support.</td>
<td>Rejected</td>
</tr>
<tr>
<td><strong>Effort Expectancy (EE)</strong></td>
<td>H2A</td>
<td>EE negatively impacts the intention of public employees to adopt big data analytics.</td>
<td>Accepted</td>
</tr>
<tr>
<td></td>
<td>H2B</td>
<td>Impact of EE on the intention of public employees to adopt big data will be influenced by gender of the public employees such that the effect will be stronger for females.</td>
<td>Accepted</td>
</tr>
<tr>
<td></td>
<td>H2C</td>
<td>Impact of EE on the intention of public employees to adopt big data will be influenced by age of the public employees such that the effect will be stronger for older employees.</td>
<td>Accepted for age group 40 – 49</td>
</tr>
<tr>
<td></td>
<td>H2D</td>
<td>Impact of EE on adoption of big data analytics by public employees will be moderated by data expertise.</td>
<td>Accepted</td>
</tr>
</tbody>
</table>
Table 4.7: Summary of Hypotheses, Interpretation and Decisions (Continued)

<table>
<thead>
<tr>
<th>CONSTRUCTS</th>
<th>HYPOTHESIS</th>
<th>INTERPRETATION</th>
<th>DECISION</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Social Influence (SI)</strong></td>
<td>H3A</td>
<td>SI positively impacts public employees’ intention to adopt big data analytics.</td>
<td>Rejected</td>
</tr>
<tr>
<td></td>
<td>H3B</td>
<td>Impact of SI on the intention of public employees to adopt big data analytics will be influenced by gender of the public employees such that the effect will be stronger for females.</td>
<td>Accepted</td>
</tr>
<tr>
<td></td>
<td>H3C</td>
<td>Impact of SI on the intention of public employees to adopt big data analytics will be influenced by age of the public employees such that the effect will be stronger for younger employees.</td>
<td>Accepted for age groups 40 – 49 and 50 and More</td>
</tr>
<tr>
<td></td>
<td>H3D</td>
<td>Impact of SI on the intention of public employees to adopt big data analytics will be moderated by leadership.</td>
<td>Accepted</td>
</tr>
<tr>
<td><strong>Facilitating Condition (FC)</strong></td>
<td>H4A</td>
<td>FC positively impacts public employees’ intention to adopt big data analytics.</td>
<td>Accepted</td>
</tr>
<tr>
<td></td>
<td>H4B</td>
<td>Impact of FC on the intention of public employees to adopt big data analytics will be influenced by gender of the public employees.</td>
<td>Accepted</td>
</tr>
<tr>
<td></td>
<td>H4C</td>
<td>Impact of FC on the intention of public employees to adopt big data analytics will be influenced by data expertise of the public employees such that the effect is stronger for employees for employees with data experience.</td>
<td>Accepted</td>
</tr>
</tbody>
</table>
5.0 DISCUSSION

The results and findings from the analyses section are discussed in this section. This section started with performance expectancy, followed by effort expectancy, social influence and facilitating condition.

5.1 Performance Expectancy

Performance expectancy is the degree to which an individual think big data analytics will enable him or her to improve their job performances (Venkatesh et al. 2003). We expect performance expectancy to have a positive impact on the intention of public sector employees to adopt big data analytics. From our quantitative analysis, the coefficient is positive and it is statistically significant. This implies that an increase in performance expectancy will increase the probability of the employees to adopt big data analytics. This finding is similar to the findings of Brunink (2016) who reported that performance expectancy positively impacts the adoption of big data analytics in a Franco-Dutch company, and Dwivedi et al. (2015) who reported that performance expectancy positively influences the adoption of open data technologies. Data from the interviews show that all respondents were well aware of the benefits of big data analytics. Respondent A mentioned that big data analytics will improve public policy because it can show policy effectiveness faster than the traditional methods of analyzing data collected from surveys or focus groups. Respondent C mentioned that big data analytics will enable the government to make informed decisions and have more confidence in the decision made. According to Respondent E, linking big data analytics to the work performed by the employees is a factor that will positively influence the adoption of big data analytics. This excerpts from Respondent E makes the connection between perceived job performance improvement by the employees and big data analytics adoption.

Performance expectancy is expected to be moderated by gender and age of the respondents, however, our quantitative result did not support this statement. Although the impact of gender on performance expectancy is positive for males and negative for females, the results are not statistically significant. This results are similar to the conclusions of Brunink (2016) who reported that gender did not moderate performance expectancy, but in contrast to Ghalandari (2012) and Venkatesh et al. (2003), both studies reported that gender moderates the influence of performance Expectancy on user adoption. Age is expected to moderate the influence of performance expectancy on adoption of big data analytics. Our quantitative analysis shows that probability of adoption increases according to age, but it is only significant for respondents that are 40 years and more. This is contrary to previous UTAUT studies Venkatesh et al. (2003) that posited that the effect of age on performance expectancy will be larger in younger employees than older employees. Our results are interesting, 33% of the total respondents are 40 years and more, and 89% of them have worked for the government for more than five years, an average of 16 years in public service. Also, 85% of the respondents have at least a bachelor degree. Their long service in government and education may explain why the estimates for these age groups are higher than the other groups and statistically significant.
Data experience is expected to moderate performance expectancy such that the effect will be stronger for employees with data experience than employees without data experience. Results of the quantitative analysis support this hypothesis. The impact of the experience on performance expectancy is positive for employees with data experience and negative for employees without data experience and these estimates are statistically significant. Our findings are similar to Kwon et al. (2014) who reported that employees with data experience are likely to adopt big data analytics, but our findings are opposite of Brunink (2016) results, who reported a significant negative effect of data experience on the adoption of big data analytics.

It was hypothesized that leadership moderates the influence of performance expectancy on big data adoption such that public sector employees that perceive positive leadership support are likely to adopt big data analytics more than employees that did not perceive positive leadership support. Although, the quantitative analysis shows that the effect is positive for employees that perceived positive leadership support and negative for employees that did not perceive it, however, the estimates are not statistically significant. This is in contrast to Hochtel et al. (2016) who argued that leadership qualities such as openness and innovation encouragement will promote big data in the public sector. It should be noted that the arguments of Hochtel et al. (2016) has not been empirically proven. Furthermore, one of the interview respondents mentioned that leadership qualities can influence adoption of big data analytics such that leaders perceived to be an innovator and encourages innovation among the employees will positively influence employees to adopt big data analytics, the significance of this statement cannot be proven statistically.

5.2 Effort Expectancy

Effort expectancy is the extent to which big data analytics is perceived to be easy or complicated to use (Venkatesh et al. 2003). We expect that effort expectancy will have a negative impact on the adoption of big data analytics. Estimates from the quantitative analysis shows that an increase in effort expectancy by one unit reduces the probability of adopting big data by 49% and the estimate is statistically significant. This concurs to the findings from the interview as well as all respondents mentioned that big data analytics will be easy and flexible to use. This is in contrast to the findings of Brunink (2016) that effort expectancy does not impact the adoption of big data analytics. It could be that employees sampled by Brunink et al. (2016) are more confident in analytics or might have used it before, so they did not see incremental efforts in using big data analytics. This assumption is tested in hypothesis H2A.

It was hypothesized that the influence of effort expectancy on the adoption of big data analytics will be influenced by the gender and age of the public sector employees. In terms of gender, the negative effect of effort expectancy is stronger for females than for males and is statistically significant. Females that perceives big data analytics to be complex to use, are more likely not to adopt it when compared to males. Our finding is similar to Venkatesh et al. (2003), who posited that a stronger negative effect of effort expectancy for females.

With respect to age, the negative effect of effort expectancy is stronger for employees that are 30 to 39 and employees that are 50 years and more. Age group 20 to 29 are not influenced by
effort expectancy at all. It should be noted that all of the estimates for the groups mentioned earlier are not statistically significant. The estimate for age group 40 to 49 is positive and statistically significant. This means that effort expectancy increases the probability of adoption for age group 40 to 49. This is in contrast to UTAUT model postulations that effort expectancy has a negative effect on adoption intention (Venkatesh et al. 2003). This can be due to the characteristics of this group. For example, out of the 18 respondents in this age category, 33% have a master’s degree, and roughly 45% have had data analysis training at the advanced or expert level. According to one of the interview respondents, big data analytics will be easy to use for employees with the right level of skills, education and training. Respondent E also mentioned that for employees that are able to link big data analytics to career advancement, adopting big data analytics will be effortless. Employees in the age group 40 – 49 are in their mid-career as the average work experience with the government is 13 years. They may perceive adopting big data analytics as a means to advance their career and as a result be influenced positively.

In terms of the impact of the moderating variable, experience on effort expectancy, the negative effect of effort expectancy on adoption of big data analytics is stronger for employees without data experience, and this effect is statistically significant. Big data is complex due to its characteristics such as variety, veracity, and the speed the data is being gathered (Lycett 2013). As a result, employees with the right set of skills, knowledge and experience will require less efforts to work with big data and their adoption of big data analytics will be different from employees without big data experience. This previous statement is corroborated by responses from the interviews. Respondent A mentioned that big data analytics is “a tool for experts and slowly trickle down to staff with less expertise as the ministry build capacity”. This means that employees with data expertise will adopt it at a faster pace than others with less data experience.

5.3 Social Influence

The construct of social influence is the extent to which individuals believe people that are important think they should use a new system (Venkatesh et al. 2003). We hypothesized that social influence will have a positive impact on the adoption of big data analytics by the public sector employees. Estimate of the impact of social influence on Adoption Intention is positive but not statistically significant. This implies that there is less confidence in the statement that social influence positively influences the adoption of big data analytics. Venkatesh et al. (2012) argued that social influence is subjective. Employees that perceive extrinsic values such as social status or recognition from using a new system are likely to adopt it.

We expect the influence of social influence on adoption of big data analytics to be moderated by the gender of the public sector employees such that the effect is stronger for females. Although the marginal effects for both female and male groups is not significant, it is different if the groups are treated separately as the marginal effects estimates for females is positive and is statistically significant. This finding is similar to that of Venkatesh et al. (2003).

In terms of age, Venkatesh (2003) posits that younger employees are influenced more by social influence than older employees because as employees grow older, their level of affiliations
reduces and as a result are not easily influence by social factors. Our results are opposite of the theoretical postulation of Venkatesh et al. (2003). Based on the quantitative analysis estimates, the effect of social effect is stronger in older employees than younger employees. One interesting note is that older public sector employees want to be perceived as promoter of change even if they do not have the official responsibility. As respondent E stated: “the norm in government is that change is inevitable as the public issues we deal is dynamic, we need big data analytics to improve what we do and as an employee with long public service, I want to leave a legacy of a high performing public service”.

It was hypothesized that the impact of social influence on the adoption of big data analytics by public sector employees will be moderated by leadership. This hypothesis is supported by the estimates from the quantitative analysis, the effect on employees that perceive a supportive leadership is positive and it is negative for employees that did not perceive a supportive leadership, these estimates are statistically significant. Therefore, we can say that leadership style moderates the influence of social influence on adoption of big data analytics. This finding concurs with the findings of Lai et al. (2017) that top management influences employees to adopt big data analytics. Also, Dwivedi et al. (2015) reported that leadership with open communication reinforces the adoption of a new technology. Some excerpts from the interview support our findings, respondent D mentioned that motivation from managers may influence the adoption of big data analytics. Respondent C mentioned that for big data analytics to be implemented corporately, there is a need for champions who are influencing leaders. This statement is corroborated by respondent E who mentioned that employees’ perception of their leaders may impact the adoption of big data analytics, with employees that perceive their leader to be supportive and motivating will adopt big data analytics faster than those that perceive their leaders not to be supportive or motivating.

5.4 Facilitating Condition

Facilitating condition is the degree to which individuals believe the technical and organizational resources available to them can support the use of a new system (Venkatesh et al. 2003). We hypothesized that employees that believe the available technical and organizational resources can support big data analytics are likely to adopt it, that is, facilitating condition has a positive influence on the adoption of big data analytics. The estimates from the quantitative analysis is positive and significant. This implies that an increase in facilitating condition will increase the probability of adopting big data analytics by public sector employees. Our results conform with the postulations of UTAUT model that facilitating condition and adoption are positively related (Venkatesh et al. 2003). Four out of five respondents confirm that the current technology and resources in their ministry support big data analytics.

The moderating effects of gender on the influence of facilitating condition on adoption of big data analytics was tested statistically. We hypothesized that the effect will be different for males and females. Our estimates show that the effect of facilitating condition is positive for males and negative for females and these estimates are statistically significant. This implies that lack of facilitating condition reduces adoption of big data analytics among female public employees.
These findings concur to the reports of Venkatesh et al. (2012) that facilitating condition is moderated by gender.

The moderating effects of data experience on the influence of facilitating condition was tested. It was hypothesized that the impact of facilitating condition on adoption of big data analytics is moderated such as the effect is different for employees with data experience and employees without data experience. The quantitative analysis estimates are positive for employees with data experience and negative for employees without data experience and these estimates are statistically significant. This is similar to the finding of Venkatesh et al. (2012) that when an individual is familiar with a system, the adoption of the system is faster.
6.0 CONCLUSIONS AND FUTURE RESEARCH

This section starts with the conclusion of the thesis, followed by contribution of the thesis and suggestions for future research.

6.1 CONCLUSION

The purpose of this thesis is to investigate the important factors that influence the adoption of big data analytics by public sector employees and to identify the factors that should be mitigated when implementing big data analytics in the public sector. This thesis has accomplished this purpose.

This thesis used the mixed research methods of quantitative and qualitative methods by sending a survey questionnaire to 85 employees and conducting interviews with five employees. The respondents are employees of Canadian provincial government ministry. The constructs of the Unified Theory of Acceptance and Use of Technology Model (UTAUT) were used to develop 16 hypotheses based on the four constructs of Performance Expectancy (5 hypotheses); Effort Expectancy (4 hypotheses); Social Influence (4 hypotheses); and Facilitating Conditions (3 hypotheses).

The quantitative results on the influence of performance expectancy, effort expectancy, and facilitating condition on the adoption of big data analytics by public employees are all statistically significant. So we can conclude that performance expectancy, effort expectancy and facilitating conditions are important factors that can impact the probability of adoption of big data analytics by public sector employees. The estimate of the impact of social influence on adoption of big data analytics by public sector employees is positive but not statistically significant. It is concluded that overall, social influence does not influence the probability of adopting big data analytics by all public sector employees.

For the impact of gender as a moderating variable is mixed. The gender of employees moderates the influence of effort expectancy, social influence, and facilitating condition with the effect stronger for females than males. However, gender was not found to moderate performance expectancy.

Age of the public employees rarely moderates the influencing factors of big data analytics adoption. Age is found to be significant for employees in the 40 – 49 group for effort expectancy, while the effects of age on performance expectation and social influence is found to be significant for employees in the 40 – 49 and 50 years and more groups. It is concluded that age does not moderate all age groups.

Data expertise and experience as a moderating variable of the factors that influence the adoption of big data analytics is found to be significant for performance expectancy, effort expectancy, and facilitating condition. It is concluded that data experience is a significant moderating variable.
In the conceptual framework, leadership was added as a new moderating variable and was tested on performance expectancy and social influence. Our results show that leadership does not moderate performance expectancy but it is significant for social influence. This shows that leadership support can change the effects of social influence on adoption intention.

6.2 Contribution of Thesis and Further Research

This thesis has determined the important factors that impact the adoption of big data analytics by public sector employees. Government ministries or public organizations that want to implement big data analytics should focus on the important factors discussed below.

The following variables positively influence adoption of big data analytics:

- **Performance expectancy**: that is ensuring that employees understand how big data analytics can improve the work they perform and the value big data analytics can bring to their work.
- **Facilitating condition**: ensuring that existing technology and resources can support big data analytics or update existing technology and resources to be able to support big data analytics.
- **Leadership**: implementing big data analytics require a champion, that is someone that can lead the process in the organization. Leadership is needed to promote the adoption of big data analytics. Leadership can influence employees to adopt big data analytics by encouraging innovation and motivating employees.
- **Data expertise and experience**: the ministry should provide adequate training on big data analytics to their employees and encourage continuous learning.

The following variable negatively influence the adoption of big data analytics:

- **Effort expectancy**: when employees perceive big data analytics to be complicated or complex to use, the adoption is low. The ministry can provide training of big data analytics, provide adequate materials and resources that can enable the employee understand big data analytics, and organize hands-on experience whereby employees work with mock big data to understand big data and also experience how it works. This can change their perception about the complexity of big data analytics. Lastly, the ministry can provide mentorship where employees who are expert in data analytics mentor employees with limited knowledge.

This thesis has contributed to the existing research on big data in the public sector being the first to empirically determine the factors that positively influence the adoption of big data analytics and factors that should be mitigated when implementing big data analytics in the public sector. While the findings of the thesis are interesting, the researcher believes there are opportunities for further research.

This thesis focused on users’ perspectives, future research may investigate the perspective of public sector senior management towards big data analytics. Furthermore, the focus of this
thesis is on the pre-implementation of big data analytics, actual use of big data analytics was not investigated. Therefore, future studies can investigate the factors that influence the adoption of big data analytics by the end users based on post implementation perspectives.
REFERENCES


Gandomi, A., & Haider, M. 2015. Beyond the hype: Big data concepts, methods, and analytics. International Journal of Information Management, 35(2), 137-144


Appendix A: UTAUT Constructs, Questions and Source

<table>
<thead>
<tr>
<th>CONSTRUCT</th>
<th>QUESTION</th>
<th>ITEMS</th>
<th>SOURCE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Performance Expectancy (PE)</td>
<td>Big data analytics will enable me to accomplish tasks quickly.</td>
<td>PE1</td>
<td>(Davis 1989; Davis et al. 1989; Thompson et al. 1991)</td>
</tr>
<tr>
<td></td>
<td>Big data analytics will improve the quality of work I perform.</td>
<td>PE2</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Big data analytics will enhance my effectiveness on the job.</td>
<td>PE3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Big data analytics will improve the quality of program and policy developed.</td>
<td>PE4</td>
<td></td>
</tr>
<tr>
<td>Effort Expectancy (EE)</td>
<td>Learning how to use big data analytics will be time consuming.</td>
<td>EE1</td>
<td>(Moore and Benbasat 1991; Thompson et al. 1991)</td>
</tr>
<tr>
<td></td>
<td>Big data analytics is flexible to use and do what I want it to do.</td>
<td>EE2</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Big data analytics is complicated and difficult to understand what is going on.</td>
<td>EE3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>I believe big data analytics is easy to use.</td>
<td>EE4</td>
<td></td>
</tr>
<tr>
<td>Social Influence (SI)</td>
<td>I will use big data analytics if my co-workers are using it.</td>
<td>SI1</td>
<td>(Moore and Benbasat 1991; Thompson et al. 1991)</td>
</tr>
<tr>
<td></td>
<td>My manager will support the use of big data analytics.</td>
<td>SI2</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Ability to use big data analytics is recognized in my organization.</td>
<td>SI3</td>
<td></td>
</tr>
<tr>
<td>Facilitating Condition (FC)</td>
<td>I have the skills and competencies to use big data analytics.</td>
<td>FC1</td>
<td>(Ajzen 1991; Taylor and Todd 1995; Venkatesh et al. 2003)</td>
</tr>
<tr>
<td></td>
<td>There is no one available for technical support if I use big data analytics.</td>
<td>FC2</td>
<td></td>
</tr>
<tr>
<td></td>
<td>I have the resources available to use big data analytics.</td>
<td>FC3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Big data analytics is consistent with other tools I use.</td>
<td>FC4</td>
<td></td>
</tr>
</tbody>
</table>
### Appendix B: Moderating Variables and Other Variables

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>QUESTION</th>
<th>ITEMS</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Experience</strong></td>
<td>I am familiar with large data sets.</td>
<td>MODEX1</td>
</tr>
<tr>
<td></td>
<td>I perform data/information analytics.</td>
<td>MODEX2</td>
</tr>
<tr>
<td></td>
<td>I have experience using the output of data analysis.</td>
<td>MODEX3</td>
</tr>
<tr>
<td></td>
<td>I have experience using big data analytics</td>
<td>MODEX4</td>
</tr>
<tr>
<td><strong>Leadership</strong></td>
<td>There is senior leadership support for big data initiative.</td>
<td>MODLE1</td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td>My age is:</td>
<td>AGE</td>
</tr>
<tr>
<td><strong>Gender</strong></td>
<td>My gender is:</td>
<td>GENDER</td>
</tr>
<tr>
<td><strong>User Adoption</strong></td>
<td>I will use big data analytics if it is available</td>
<td>AI</td>
</tr>
<tr>
<td><strong>Work Experience</strong></td>
<td>Years of work experience in government is:</td>
<td>WORKEXP</td>
</tr>
<tr>
<td><strong>Education</strong></td>
<td>Highest level of education achieved:</td>
<td>EDUCATION</td>
</tr>
<tr>
<td></td>
<td>▪ High School</td>
<td></td>
</tr>
<tr>
<td></td>
<td>▪ Post-Secondary Diploma;</td>
<td></td>
</tr>
<tr>
<td></td>
<td>▪ University Degree;</td>
<td></td>
</tr>
<tr>
<td></td>
<td>▪ Master Degree;</td>
<td></td>
</tr>
<tr>
<td></td>
<td>▪ PhD. degree</td>
<td></td>
</tr>
<tr>
<td><strong>Data analytics skill</strong></td>
<td>My data analysis skills are at:</td>
<td>DATASKILLS</td>
</tr>
<tr>
<td></td>
<td>1. Expert Level</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2. Advanced Level</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3. Intermediate Level</td>
<td></td>
</tr>
<tr>
<td></td>
<td>4. Basic Level</td>
<td></td>
</tr>
<tr>
<td></td>
<td>5. Not at all</td>
<td></td>
</tr>
<tr>
<td><strong>Data analytics training</strong></td>
<td>I have had data analysis training at:</td>
<td>DATATRAINING</td>
</tr>
<tr>
<td></td>
<td>1. Expert Level</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2. Advanced Level</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3. Intermediate Level</td>
<td></td>
</tr>
<tr>
<td></td>
<td>4. Basic Level</td>
<td></td>
</tr>
<tr>
<td></td>
<td>5. Not at all</td>
<td></td>
</tr>
</tbody>
</table>
Appendix C: Interview questions

1. What is your general opinion about big data analytics?
2. Do you perform data analytics or use analytics deliverables/reports performed by others?
3. Do you think big data analytics will improve the quality of policy?
4. In your opinion do you think big data analytics will be easy to use?
5. Do you think you have adequate managers’ support that can influence you to adopt big data analytics?
6. Do you think the current technology, tools and infrastructure of your ministry will support big data analytics?
7. Do you think public sector employees will adopt big data analytics if it is a corporate initiative? Follow up: will you adopt big data analytics?
8. What do you think are the possible factors that may positively influence public sector employees to use big data analytics? Follow up – which of the factors do you think is important?
9. What do you think are the factors that may prevent you from using big data analytics?
Appendix D: Informed Consent

INFORMED CONSENT

Introduction of Research
You are invited to participate in a survey/research on user adoption of big data analytics by public sector employees. The research project is conducted as a fulfillment of the Master of Science in Information System program at Linnaeus University, Sweden.

Participation
Your participation in this research is voluntary. You may refuse to participate in the research, or discontinue at any time, and without any prejudice. You are free to decline to answer any question you do not wish to answer for any reason. You may withdraw your participation in the research at any time. If you wish to withdraw after participating in the research, please contact the researcher at Abayomi Akintola at ra222fk@student.lnu.se.

Confidentiality
Your responses will be kept confidential, stored in a safe place and will not be shared with parties that are not responsible for carrying out the research.

Anonymity
Your responses will remain anonymous. The respondents are not required to provide personal information. No one will be able to identify the respondent or the respondent’s answers.

Contact
If you have any question at any time about the study or the procedures, you may contact Abayomi Akintola at ra222fk@student.lnu.se.

Consent
Please select your choice below. By selecting the “Agree to participate”, this indicates that you:

- Have read and understood the above information thoroughly;
- Voluntarily agree to participate in the research; and
- Are 18 years of age or older.

☐ Agree to participate ☐ Disagree (Do not want to participate)