FACTORS INFLUENCING POLICY RESEARCHERSBEHAVIORAL INTENTION TO USE OPEN DATA TECHNOLOGIES IN NAIROBI, KENYA

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A Research Project submitted to the School of Computing and Informatics-University of Nairobi, in partial fulfillment of the requirements for the award of Masters of Science in Information Technology Management

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DECLARATION

This research project is my original work and to the best of my knowledge, has not been presented to any other university for the award of a degree.

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This research project has been submitted for examination with my approval as University Supervisor.

Signature ……………………………..… Date ……………………………

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DEDICATION

This work is dedicated to my parents and siblings for their moral and financial support, and continuous belief in me. My dedication also goes to my adorable friends for inspiring and challenging me throughout this journey. In all your endeavors, remember that in life achievers rarely sit back and let things happen to them, they go out and make things happen. Thank you and God bless you all abundantly.

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Acronyms and Abbreviations

KODI	Kenya Open Data Initiative
OGD	Open Government Data
UTAUT	Unified Theory of Acceptance and Use of Technology
ICT	Information Communication Technology
CKAN	Comprehensive Knowledge Archive Network
API	Application Programming Interface

ABSTRACT

With the growing open government movement, governments have put effort to open their data, and provide it through open data technology. One important determinant of the success of open data initiatives is the extent to which the data and its related technologies are made use of. Kenya launched its open data initiative in July 2011 and previous research cited low usage of the open data platform. Methodical research that uses rigorous theoretical bases about use of technology is also deficient. It has not yet been clear which theories are most applicable. This study explored factors which influence behavioral intention of policy researchers to use open data technology, guided by UTAUT theory. The target population was 110 policy researchers drawn from ten research organizations and think tanks, in Nairobi County, Kenya. Out of the sample size of 52, 45 responded giving a response rate of 86.5%. Questionnaires were used as the data collection instrument, and a pilot test was undertaken to confirm their reliability, and validity. Regression analysis results indicated that performance expectancy, social influence, and effort expectancy were significant in determining policy researchers' intention to use open data technology. Facilitating conditions and the moderators; age, gender, and experience were found to be insignificant. The modified UTAUT model was found to account for a significant variance (86.6%) of the behavioral intention to make use of open data technology.

Keywords*: Open data, UTAUT, Open government, use, Open data technology*

CHAPTER ONE

INTRODUCTION

1.1. Background of the Study

1.1.1. History of Open Government

The widely used definition of open data is adapted from the Open Definition project of the Open Knowledge Network. Open data is referred to as raw data that can be used or reused freely, and can also be redistributed (Open Knowledge Foundation, 2007). In turn, Open Government Data(OGD) is such open data that is produced or commissioned by a government and any other public body. Open Government Data is a key enabler of the open government concept (Open Government Data, 2016).

According to Tauberer (2014), open government data began to really take off in 2009 when the first two transparency camp conferences were held. He further notes that the OGD movement was also stimulated by United States' (US) President Obama's Open Government Directive in December, 2009, to use open data for transparency, participation and collaboration. The same year, the US launched Data.gov portal.

In 2010, the United Kingdom (UK), followed suit by launching data.gov.uk. In the same year, the World Bank launched its own open data initiative. Then in 2011, the Open Government Partnership (OGP) was launched. Its intention was to ensure that governments are increasingly open and more accountable to their citizens. Today, the OGP consists of more than 69 member countries with Kenya being one of them (Tauberer, 2014).

In Africa, open data has rapidly been gaining momentum. The Africa Data Consensus by African Union was developed in March 2015. Later in September 2015, the Inaugural Africa Open Data Conference was held in Tanzania. Other noteworthy initiatives include Open Data for Africa initiative by African Development Bank (AfDB) and Open Africa by Code for Africa. Code for Africa is an umbrella body for a series of open data initiatives including Code for Kenya, Code for Ghana, Code for Nigeria, Code for South Africa, and incubated initiatives in Morocco, Rwanda, Senegal, Tanzania, Tunisia, and Uganda.

Kenya was the 22nd country worldwide, second in Africa after Morocco and first in Sub-Saharan Africa to join the open government movement. Kenya's initiative, named the Kenya Open Data Initiative (KODI), was launched in 2011(Majeed, 2012). Tunisia launched its initiative in 2012, Edo State in Nigeria in 2013 and Ghana in 2012. Other countries in Africa such as Ghana, Uganda, Rwanda and Tanzania followed suit, and they have made significant effort to open up their government data (Brown, 2013) The second version of Kenya's portal was launched in July 2015 (ICT Authority, 2016).

1.1.2. Open data technology

ICT has been pivotal in open government initiatives all over the world. Robinson and Yu (2012), note how the power of the Internet to avail government information in the last several years has become a vital topic for policy makers, researchers and citizens. Most open data implementations use an open data platform. A platform consists of an open data catalogue and a front end through which users access all resources. Other services may include a blog for communications, an online forum for questions, technical support and feedback, and a knowledge base of training materials. Commonly used open data platforms include CKAN which is open-source, DKAN, Junar, OpenDataSoft, Semantic Media Wiki, Socrata and Swirrl.

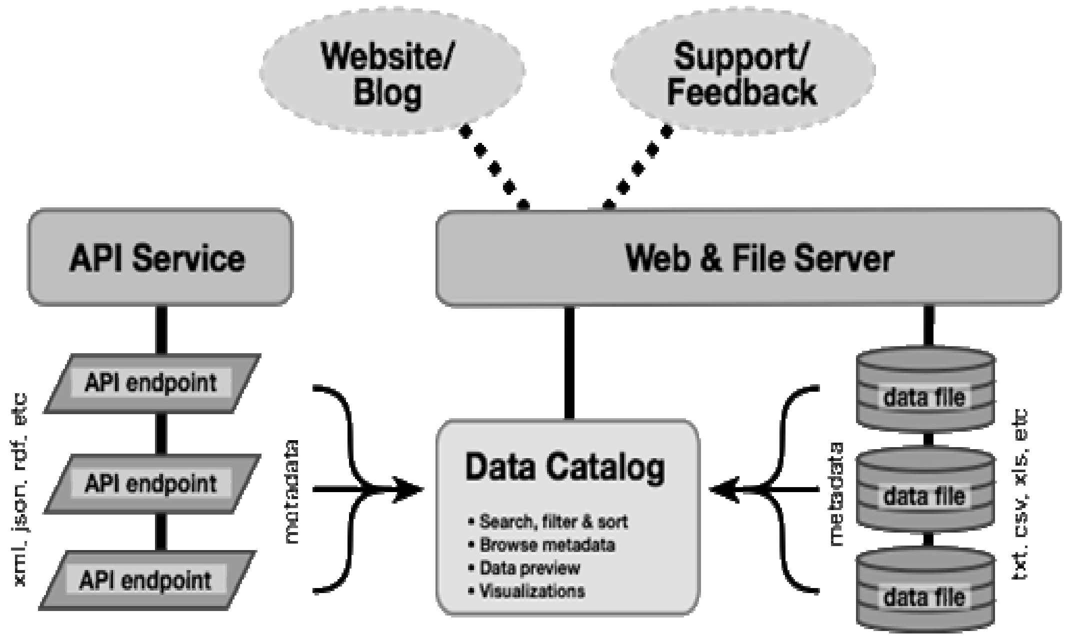

Figure 1.1 Open Data Platform Infrastructure (adapted from World Bank, 2013)

Data itself can also be viewed as a digital object (Lindman, Rossi and Tuunainen, 2013) Computer science conceptualizes a dichotomy of data and application, whereby data is used for storage, and applications are used for different operations based on data. Data can thus be presented for processing. The main difference between open data and open source concepts is that open data is about the openness of data, while open source is about the openness of applications and their source code (Lindman, Rossi and Tuunainen, 2013).

The Kenya Open Data Initiative (KODI) uses Socrata, which is a cloud-based Software-as-a-Service platform (World Bank, 2013) In this study, open data technology with regards to Kenya' open data platform will refer to; national government datasets, county datasets, files and documents, maps, visualizations (graphs/charts), filtered user views, Application Programming Interface, open budget, open data blog, embed code, forms, data request or suggestion function, filter function, discuss function, data export function and other basic website functions such as Sign Up and Login (KODI, 2014)

1.1.3. Use of Open data technology

Open data on its own has little intrinsic value if it's not used. Open data should not just be published, but rather it should be accompanied by an infrastructure that can handle it in a way that makes it easy for users to use it. Open data technology is essential for not only publishing, but also making use of open data. For instance, a usage process may consist of discovery of a dataset, then using visualization tools to process and evaluate the data (Janssen et al., 2012)

According to GovDelivery (2015), despite open data being a potentially powerful tool in the public sector, its power is unlocked when its audiences use it. Use of open data, for instance by analyzing a dataset, and then visualizing the results, may provide significant benefits. These benefits include increased transparency and accountability by a government to its citizens (Parsons et al., 2011; Bertot, Jaeger and Grimes, 2010). This in turn encourages more citizen participation in government issues. Open data technology can also be used by both businesses and individual citizens to create innovative products and services (Robinson et al., 2009; Janssen, 2011; Robinson and Yu, 2012; Palka et al., 2013;Veenstra and Broek, 2013).

Users of open data technology may be varied and with different needs. For example, an individual citizen might expect to find dataset on national budget spending, a business may want data about tenders, and a software developer may use the API, and require data to be available in machine-readable format. As a result, there may be huge differences with regard to contents and shape of use for different actors involved in open data (Hunnius, Krieger and Schuppan, 2014). Therefore, so as to meet the requirements of disparate users, portal architects and developers, data suppliers, and publishers need to understand factors that influence different users' intent to use open data technology.

1.1.4. Open data technology for Policy Research

Policy research is concerned with drawing alternative approaches and specifying potential differences in the intention, effect and cost of programs. It aids in the solution of fundamental problems, leading to provision of socially useful lives for all citizens. Policy researchers seek to address questions such as which are the best methods of reducing unemployment in a given society, in a given period (Etzioni, 1971).

The range of data sources used in policy making and research is increasing, and combining and linking data is becoming common. Two main sources of data that are being used are public datasets, and social media, sensors and mobile phones. Public datasets that are being used include (open) data and statistics about populations, economic indicators and education. Open data is widely promoted in the public sector and among NGOs. The most common uses of the datasets in policy are for agenda setting, problem analysis, the use of open data for transparency, accountability and enhancing participation and use of administrative and statistical data for policy implementation and monitoring (Martijn et al., 2015)

Simply presenting data in a more dynamic and interactive way can allow both analysts and policy makers to gain insight in data that they may not have seen in thousands or millions of rows on a spread sheet (Bateman, 2015). Data-driven policy however must be democratic and ethically sound; open process needs open data alongside. In turn, this would lead to agility in policy and implementation, resulting into corrective action and iterative interventions, informed by early monitoring of effects, better awareness of reality and continuous flow of evidence (Zacharzewski, Agarwal and Watson-Brown, 2015)

The availability of open data technology offers policy researchers a huge potential to perform more accurate and informed analysis, leading to more reliable data-driven and evidence-based policy making. However, according to (Martijn et al., 2015) previous analyses of the quality of freely available open government datasets has shown that heterogeneity of datasets is still an issue. Also, some datasets are semi-open, requiring some kind of pre-requisite registration. Open data technology support open policy making. Open policy making involves developing and delivering policy in a fast-paced and increasingly networked and digital world (Gov.uk, 2016)

1.2. Research Problem

Locally in Kenya, low usage of open data technology has been noted. For instance, a year after the launch of Kenya open data portal, it was noted that the portal was not being used as broadly as it had been anticipated (Majeed, 2012; Mutuku and Colaco,2012). Low usage of the Kenya open data technology had also been cited by Hammer (2013), Mutuku and Mahihu (2014), and Muigai (2014).

In their research study, Mutuku and Mahihu (2014) noted that low usage may be attributed to low quality of the available data i.e. irrelevant data, out-dated data and poorly structured data, plus difficulty in navigating the open data platform. This is despite there being an active communications office on the Kenya open data initiative, and numerous awareness activities with different parts of the ecosystem (Muigai, 2014).

Policy research done using open data technology can subsequently be used in better policy-making, which is evidence-based and data-driven. This in-turn can lead to achievement of some of the initial goals of the Kenya open data initiative such as increased transparency and more citizen participation. This study then, aimed to assess factors that influence policy researchers' behavioral intention to use open data technology in Nairobi, Kenya.

Open data research is still in its early stages. As a result, existing literature uses limited application and development of theory and it is also not yet clear which theories are most relevant, nor whether a single theory or integrated theory is required (Zuiderwijk et al., 2014). By using UTAUT theory construct this research study would increase the amount of open data literature that uses theory.

1.3. Research Objectives

The overall objective of the study was to assess factors that influence policy researchers' intention to make use of Kenya open data technology in Nairobi, Kenya. The study was guided by the following specific objectives:

i. To establish what influence performance expectancy has on policy researchers' intention to make use of open data technology in Nairobi, Kenya.
ii. To establish what influence effort expectancy has on policy researchers' intention to make use of open data technology in Nairobi, Kenya.
iii. To examine what influence social influence has on policy researchers' intention to make use of open data technology in Nairobi County, Kenya.
iv. To examine what influence facilitating conditions has onpolicy researchers' intention to make use of open data technology in Nairobi, Kenya.
v. To explore the moderating effects of age, gender, and experience.
vi. To examine UTAUT model in the open data technology context.

1.4. Hypotheses

The hypotheses were;

1) H1: Performance expectancy positively influences policy researchers' intention to make use of open data technology.
2) H1a: Gender moderates the influence of performance expectancy on policy researchers' intention to make use of open data technology.
3) H1b: Age moderates the influence of performance expectancy on policy researchers' intention to make use of open data technology.
4) H1c: Experience moderates the influence of performance expectancy on policy researchers' intention to make use of use open data technology.
5) H2: Effort expectancy negatively influences policy researchers' intention to make use of open data technology.
6) H2a: Gender moderates the influence of effort expectancy on policy researchers' intention to make use of open data technology.
7) H2b: Age moderates the influence of effort expectancy on policy researchers' intention to make use of open data technology.
8) H2c: Experience moderates the influence of effort expectancy on policy researchers' intention to make use of use open data technology.

9) H3: Social influence positively influences policy researchers' intention to make use of open data technology.
10) H3a: Gender moderates the influence of social influence on policy researchers' intention to make use of open data technology.
11) H3b: Age moderates the influence of social influence on policy researchers' intention to make use of open data technology.
12) H3c: Experience moderates the influence of social influence on policy researchers' intention to make use of use open data technology.
13) H4: Facilitating conditions positively influence policy researchers' intention to make use of open data technology.
14) H4a: Gender moderates the influence of facilitating conditions on policy researchers' intention to make use of open data technology.
15) H4b: Age moderates the influence of facilitating conditions on policy researchers' intention to make use of open data technology.
16) H4c: Experience moderates the influence of facilitating conditions on policy researchers' intention to make use of open data technology.
17) H5: UTAUT accounts for a significant variance (R^2) of intention to make use of open data technology.

1.5. Significance of the Study

This study contributes to open government data literature and its findings may be used in future by other academic researchers in the open data space. By understanding factors that influence intention to make use of open data technology, then developers of such technologies can better understand user needs that can be used to develop better platforms, or enhance existing ones. Insights from this study can be used to understand usage of open data technology from the context of a developing country. Developing countries owned 12 out of the 41 national open government data portals launched by 2013 (Mutuku and Mahihu, 2014).

1.6. Scope

Respondents were selected from Nairobi County, Kenya. The target population was policy researchers based in ten think tanks in Nairobi, Kenya. Though there are other open data initiatives by the private sector and civil society organizations in Kenya, our research focused on the Kenya government's open data initiative.

1.7. Limitations and Assumptions

It was difficult to ascertain who actually uses the Kenya open data portal. Our experience is supported by the views of Johnson, Zheng, and Padman (2014). They posit that measuring real usage of technology is usually challenging, and such kind of information is usually inaccessible by researchers. Therefore, our study focused on behavioral intention, rather than actual usage. Also, our sample size was small and considered only policy researchers based in research institutes; there could be policy researchers in other types of organisations.

1.8. Definition of terms

Performance expectancy indicated the extent to which a policy researcher supposed that making use of open data technology would lead to improved performance in their work.

Effort expectancy was used to mean the perceived extent of ease of use of open data technology, by a policy researcher.

Social influence was used to mean the extent to which a policy researcher supposed that other people believed that the researcher should make use of open data technology.

Facilitating conditions meant the extent of a policy researcher's belief that organizational support, and technical infrastructure to enable them use open data technology, existed.

Behavioral intention was used to mean a policy researcher's future plan or intention of making use of open data technology.

Age referred to the number of years lived, gender as either male or female, and experience in using open data tools was categorized into either conversant or not conversant.

Open data technology was used to mean national datasets, county datasets, files and documents, maps, visualizations (graphs/charts), filtered user views, Application Programming Interface, open budget, open data blog, embed code, forms, data request or suggestion function, filter function, discuss function, data export function and general website functions such as About, Contact Us, Home, Partners, Terms of Use, Sign Up, Login.

CHAPTER TWO

LITERATURE REVIEW

2.1. Theoretical Review

A theoretical framework refers to how the researcher develops thoughts on what the possible answers could be to the research problem. These thoughts and theories are then clustered into themes that frame the subject (Kothari, 2008).Technology acceptance models explore factors which influence adoption of technologies, the aim usually being to promote technology use (Kripanont, 2007).Several of these models have been developed. They include; Theory of Reasoned Action, Technology Acceptance Model, Theory of Planned Behavior, Diffusion of Innovations theory, and Unified Theory of Acceptance and Use of Technology. We reviewed theories that explicitly have behavioral intention as a construct.

2.1.1. Theory of Reasoned Action

This theory was originally drawn from social psychology. It is one of the most prominent theories in behavioural and social sciences, and information systems (Sheppard, Hartwick, and Warshaw, 1988; Venkatesh, et al., 2003). TRA is concerned with predicting behaviour on the basis of the suggested associations between behaviour, behavioral intentions, and attitudes.

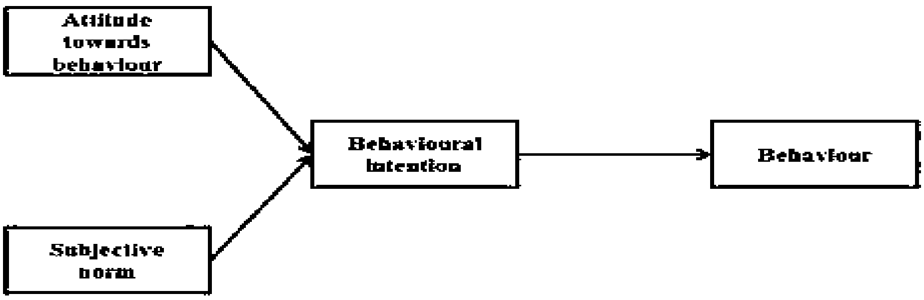

Fig.2.1 Theory of Reasoned Action (adapted from Fishbein and Ajzen, 1975).

Behavioural intention is defined as a “person’s subjective probability that he or she will perform some behaviour” (Fishbein and Ajzen, 1975, p. 288). It is determined by the attitude towards behaviour and subjective norm. Attitude is a positive or negative feeling about performing certain behaviour, while subjective norm is a person’s perception that most people who are important to them think they should or should not perform certain behaviour (Fishbein and Ajzen, 1975)

Attitudes arise as a result of beliefs about the perceived consequences of a given action. A subjective norm is more related to a person's motivation or normative beliefs about conforming to the perceived normative standards (Ajzen, 1991; Fishbein and Ajzen, 1975). In technology acceptance research, TRA has been used widely, both directly to explain acceptance, and to advance new models (Venkatesh, et al., 2003).

2.1.2. Theory of Planned Behaviour

TPB is a descendent of TRA where there is always a need to provide a more detailed explanation for the complex human behaviour (Ajzen, 1991). It has the additional construct of perceived behaviour control, and additional correlations between the antecedents of behavioural intention. Perceived behavioural control represents the extent to which the resources and opportunities available to a person dictate their likelihood of behavioral achievement. It also influences both behaviour and behavioural intention (Ajzen, 1991).

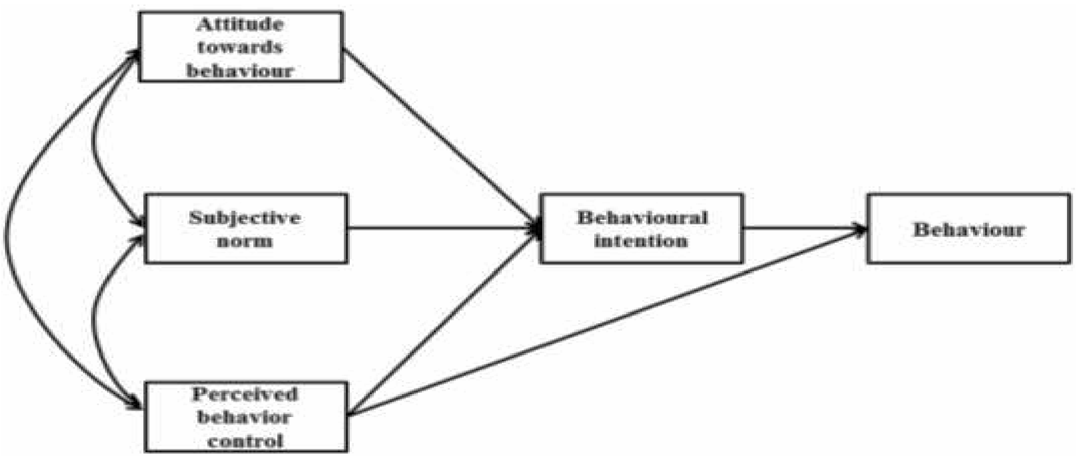

Fig. 2.2 Theory of Planned Behaviour (adapted from Ajzen, 1991, p. 182).

2.1.3. Technology Acceptance Model

TAM is an adaptation and technology-oriented contextualisation of the social psychological TRA (Davis, 1986; Fishbein and Ajzen, 1975). Original TAM was then extended by Venkatesh and Davis (2000) to contain social and organisational factors, resulting to TAM2.

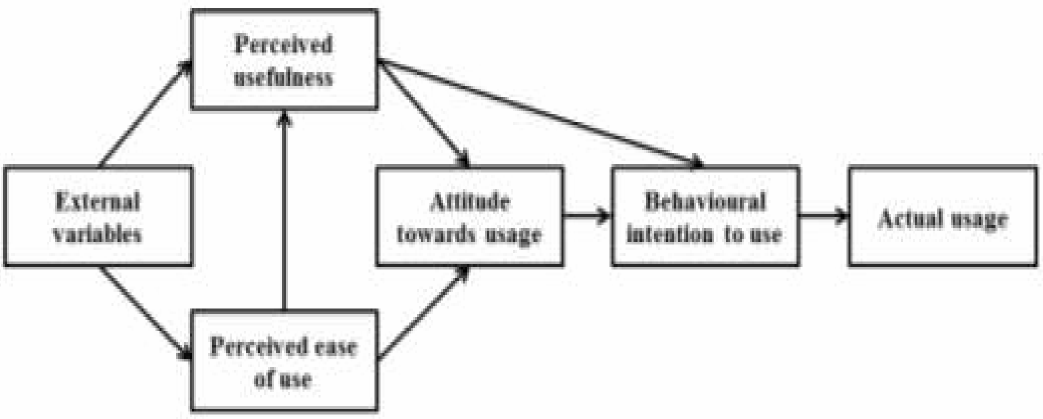

Fig. 2.3 TAM model (adapted from Davis, 1986, 1989).

The TAM constructs of perceived ease of use and perceived usefulness were the basis of the model. However, TAM2 included social influence (subjective norm, voluntariness and image) and cognitive instrumental processes (job relevance, output quality and result demonstrability). Image, job relevance, output quality and result demonstrability were considered determinants of perceived usefulness. Perceived usefulness and usage intention were proposed to influence actual usage.

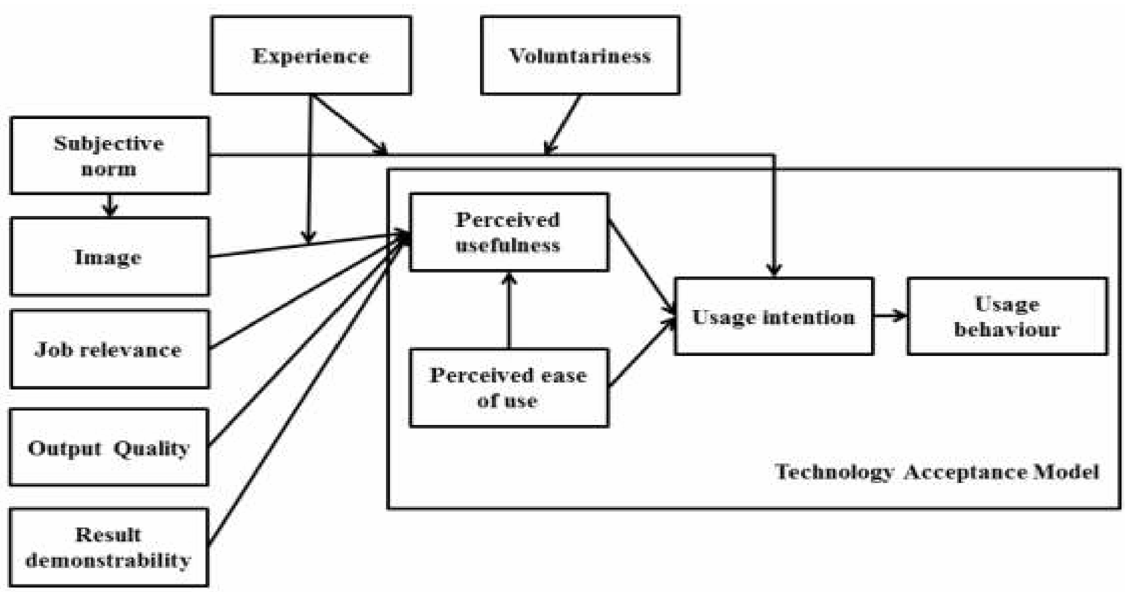

Figure 2.4 TAM2 model (adapted from Venkatesh and Davis, 2000).

Burton-Jones and Hubona (2005) posited that TAM constructs are insignificant in determining system usability. Lu et al., (2003) argued that TAM, as a result of its generality, is unable to give detailed information on users' opinions of a system. Another key criticism mentioned by Legris et al. (2003) is that TAM should have included social and organisational factors which are important factors for determining technology acceptance.

2.1.4. Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT was developed by Venkatesh et al. (2003), and it aims to explain behavioral intention to use a technology, plus its actual use. It combines elements from eight existing models. According to UTAUT, the primary constructs; performance expectancy, effort expectancy and social influence, have influence on intention to use a technology. Then the intention to use, coupled with facilitating conditions, influence the actual use of the technology. Gender, experience, age, and voluntariness of use of the technology by the user, in turn moderate the effects of the primary constructs (Sykes, Venkatesh and Gosain, 2009).

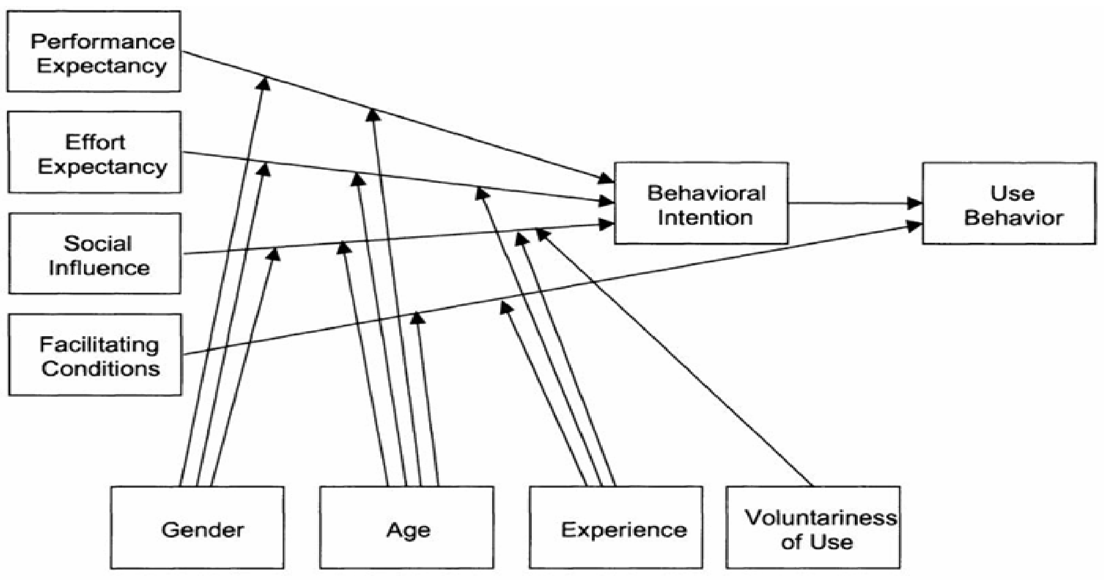

Figure 2.5.UTAUT (Adapted from Venkatesh et al., 2003)

This study used UTAUT because it is a sound technology adoption theory, and hence viable in exploring adoption and usage of open data technology. UTAUT also considers both information technology factors and social factors. Social factors are very important in technology adoption research (Gwebu and Wang, 2011). During its validation, UTAUT performed better than previous technology adoption models. It was able to explain up to 70% variance of intention to use technology, while previous models' variance ranged between 17 and 41 percent (Venkatesh et al., 2003).

2.2. Empirical Review

2.2.1. Influence of performance expectancy on intention to use open data technology

Performance expectancy indicated the extent to which a policy researcher supposed that making use of open data technology would lead to improved performance in their work. For instance, people may opt to use the normal sources of public sector data which they are used to, if they perceive that using open data technology will not lead to any better performance. Previous research shows that performance expectancy is one of the highest determinants of intention to use a technology (Duyck et al., 2008).

According to Carter and Bélanger (2005), most existing open government initiatives often lack adequate motivations to make users want to use them. This view is supported by Weinstein and Goldstein (2012), who note that the accomplishment of open government initiatives is contingent upon the public's willingness to use and further exploit these data sets. Ntale et al. (2014) carried out a study whose aim was to understand the specific efforts required to ensure effective use of open data, with Kenya and Uganda as case studies. One of their research findings was that lack of adequate quality data is a barrier to the demand for and use of open data. They posited that low quality data on the portals would discourage users from the portal again after first attempts.

Other significant factors that influence usage of e-government services are information quality, efficiency, relevancy, completeness, accuracy, precision and timeliness (Wangpipatwong, Chutimaskul and Papasratorn, 2005). Thus, if use of open data technology would lead to better efficiency, then users are more likely to use and accept these technologies. According to Dimitrova and Chen (2006), supposed usefulness, and previous interest in government influenced intention to use e-government services. Another significant factor is frequency and continuity of data delivery, which is a factor that has kept many businesses from depending merely on government data (Kaasenbroon, 2013). We anticipated that performance expectancy would have positive influence on behavioral intention.

H1: Performance expectancy positively influences policy researchers' intention to make use of open data technology.

H1a: Gender moderates the influence of performance expectancy on policy researchers' intention to make use of open data technology.

H1b: Age moderates the influence of performance expectancy on policy researchers' intention to make use of open data technology.
H1c: Experience moderates the influence of performance expectancy on policy researchers' intention to make use of use open data technology.

2.2.2. Influence of effort expectancy on intention to use open data technology

Effort expectancy was used to mean the perceived extent of ease of use of open data technology, by a policy researcher. If the effort required to use a technology is perceived as too high, then the user may not use it, despite perceiving the technology as useful. Zuiderwijk et al. (2012) posited that some relevant determinants of usage of open data technology include availability of data, ease of finding the data, ease of comprehending the data, ease of utilizing the data in ways such as linking datasets and comparing datasets.

Data should not only be published, its use should also be encouraged. The publicizing of data needs to be accompanied by an infrastructure which is able to handle the data in an easy-to-use way to lower the user threshold (Janssen et al., 2012).Open Data Barometer (2015) suggests that in order to increase the availability of open data and increase the power of citizens to use this data effectively, resources need to be dedicated to capacity-building. They opine that enhancing the capacity of data users both inside and outside the government is critical to maintaining a supply-demand data balance. This can be accomplished through trainings and adapting open data tools to local needs.

Mutuku and Mahihu (2014) also noted that despite their findings that well-designed and implemented technology intermediaries would enhance access and usability of open data, most open data applications had been abandoned by their developers. The developers cited low quality of open data and low demand and usage of the applications as the main reasons. Low quality data was defined as that which is irrelevant i.e. data supplied mismatching data in demand, irregularly updated data, poorly structured data that had to be refined before use in their applications.

H2: Effort expectancy negatively influences policy researchers' intention to make use of open data technology.
H2a: Gender moderates the influence of effort expectancy on policy researchers' intention to make use of open data technology.

H2b: Age moderates the influence of effort expectancy on policy researchers' intention to make use of open data technology.
H2c: Experience moderates the influence of effort expectancy on policy researchers' intention to make use of use open data technology.

2.2.3. Social influence' influence on usage of open data technology

Social influence was used to mean the extent to which a policy researcher supposed that other people believed that the researcher should make use of open data technology. Social influence may be from peers at work or other people such as friends and family. The important role of peers in organizations is highlighted by Talukder and Quazi (2010). For instance, peers can be involved in discussions about an individual's performance. Thus, one's peers' perceptions about the value of a certain technology are important. Talukder et al., (2008) posit that perception of value of a technology can be created through the messages and signals delivered by peers.

Most employees within organizations are interested in what their fellow colleagues are doing, and they then tend to replicate those same activities (Frambach and Schillewaert, 2002). Effective communication between colleagues of an organization that leads to powerful synergies can lead to better adoption of technologies. External pressure from colleagues can also be categorized as social influence and for technological innovations to be successful, there needs to be quality communication and interaction between employees and their peers (Sykes et al., 2009). Another factor is the importance attached to certain individuals within an organization. We posited that if a colleague is perceived as being a key person within the organization, and as having significant influence on other members within the organization, then their attitude towards a certain technology would likely influence others' attitude towards the same technology. Our view is corroborated by (Sarker et al., 2011).

Apart from fellow colleagues in an organizational setting, friends and family may also be significant influencers. These two groups are treated separately because voluntariness or lack thereof is an important factor. If open data technology use is urged by fellow work colleagues such as senior management, then use may not be voluntary. However, when use is as a result of recommendations by friends and family, then it is seen as more voluntary (Conradie and Choenni, 2012; Zuiderwijk et al., 2015).

H3: Social influence positively influences policy researchers' intention to make use of open data technology.

H3a: Gender moderates the influence of social influence on policy researchers' intention to make use of open data technology.

H3b: Age moderates the influence of social influence on policy researchers' intention to make use of open data technology.

H3c: Experience moderates the influence of social influence on policy researchers' intention to make use of use open data technology.

2.2.4. Influence of facilitating condition on intention to make use open data technology

Facilitating conditions meant the extent of a policy researcher's belief that organizational support, and technical infrastructure to enable them use open data technology, existed. Several previous studies had shown facilitating conditions to be an insignificant determinant of intention to use technology (Zuiderwijk et al., 2015; Rana et al., 2011).However, other studies such as one by Choudrie and Dwivedi, (2005), showed facilitating condition to be a significant factor, despite the fact that their study was carried out in a developed country. We can argue then that there is contention as to the significance of facilitating conditions.

Kenya is a developing country and thus has limited resources. We anticipated facilitating conditions would be a very significant determinant of policy researchers' intention to make use of open data technology. Such kinds of resources include internet access and availability of support. Ahmad et al. (2012), opined that unawareness, lack of helpand guidelines, influenced adoption of e-government services in Pakistan, which is also a developing country. Similar findings have been conveyed by other studies carried out in developing countries such as AlAwadhi, (2008) in Kuwait and Colesca and Dobrica (2008) in Romania.

Awareness about open data is a key factor that would lead to higher intention to make use of open data technology in Kenya. Ideally, awareness about existence of a technology precedes usage of the technology. Ntale et al. (2014) carried out a study whose aim was to understand the specific efforts required to ensure effective use of Kenya open data. One of their findings was that most Kenyans in the grassroots do not know of Kenya Open Data Initiative, and hence have not used it.

Mutuku and Mahihu (2014) from iHub Research carried out an early-impact analysis of Kenya open data applications and services. Key findings of their research were that there is demand for government data, and citizens obtained it mostly from media followed by online resources but very few knew about KODI. Following these claims, we posited that facilitating conditions in terms of awareness and provision of support by government would be significant factors.

To make use of open data, the availability of technical infrastructure in form of devices such as computers and internet-enabled phones, and access to internet are very important factors. According to the Kenya National Bureau of Statistics economic survey 2015, Kenya's internet penetration stood at 54.8% (KNBS, 2015). These numbers place Kenya in a comparatively good position to avail open data via online means. We posited that people with internet access are more likely to have higher intention to make use of open data technology.

H4: Facilitating conditions positively influence policy researchers' intention to make use of open data technology.
H4a: Gender moderates the influence of facilitating conditions on policy researchers' intention to make use of open data technology.
H4b: Age moderates the influence of facilitating conditions on policy researchers' intention to make use of open data technology.
H4c: Experience moderates the influence of facilitating conditions on policy researchers' intention to make use of open data technology.

2.2.5. Moderator Effects

It is vital to explore potential moderating variables in studies on technology acceptance (Sun and Zhang, 2006). In this study, we designed hypotheses for three moderating variables; gender of respondent, age of respondent and technical experience of respondent. We sought to understand the moderating effects of the three variables, on the direct effects of performance expectancy, social influence, facilitating conditions, and effort expectancy, on the behavioral intention of policy researcher to use open data technology.

2.2.6. Critique of Existing Literature

Some previous research studies (Zuiderwijk et al., 2015; Rana et al., 2011) indicated that facilitating conditions was an insignificant determinant of intention to make use of an open technology while others (Choudrie and Dwivedi, 2005) indicated that it was significant. There was thus need to investigate this variable further. This study was also carried out in Kenya, which is a developing country and thus has limited resources; meaning facilitating conditions may be a highly significant factor.

Two of the major open data studies carried out in Kenya; Mutuku and Mahihu (2014) and Ntale et al. (2014), were donor-funded. Though we did not seek evidence of existence of bias, we posited that there is a risk of these studies having had funding or sponsorship bias, intentional or unintentional. Bias is any deviation from the reality in research that can lead to incorrect conclusions, and can occur either intentionally or unintentionally (Gardenier and Resnik, 2002).

2.3. Research Gap

Open data research is still in its infancy stages, and theoretical contributions in particular, are limited (Magalhaes, Roseira, and Manley, 2014). Theories that can be appropriately applied to open data are yet to be identified or developed. It is also not clearly known whether single or unified theories should be applied (Zuiderwijk et al., 2014). Our study helped in gathering insight as to the appropriateness of UTAUT as a theory.

2.4. Conceptual Framework

According to Mugenda (2008), a conceptual framework is the brief description of the concept under study, along with a graphical structure. It illustrates the researcher’s view of the relationships between the variables being studied, based on guiding theories and existing literature. Kothari (2008) explains that independent variables, also called predictor variables, are factors that may cause, influence, or affect another variable, while the dependent variable is influenced or changed by independent variable.

Our study was based on the UTAUT model. Voluntariness of use moderator was not considered in our study. This is because currently, there is no Freedom of Information law in Kenya. With the lack of a legislative framework and policies, use is only voluntary, thus policy researchers are not obliged to use them. It is worth noting however, that the Access to

Information Bill was passed by Kenya parliament on 28th April 2016, and as of the writing of this work, it is awaiting approval. It was difficult to get information on who actually uses the KODI portal; thus influence of behavioral intention on actual usage, which is present in the original UTAUT model, was also not considered in our study.

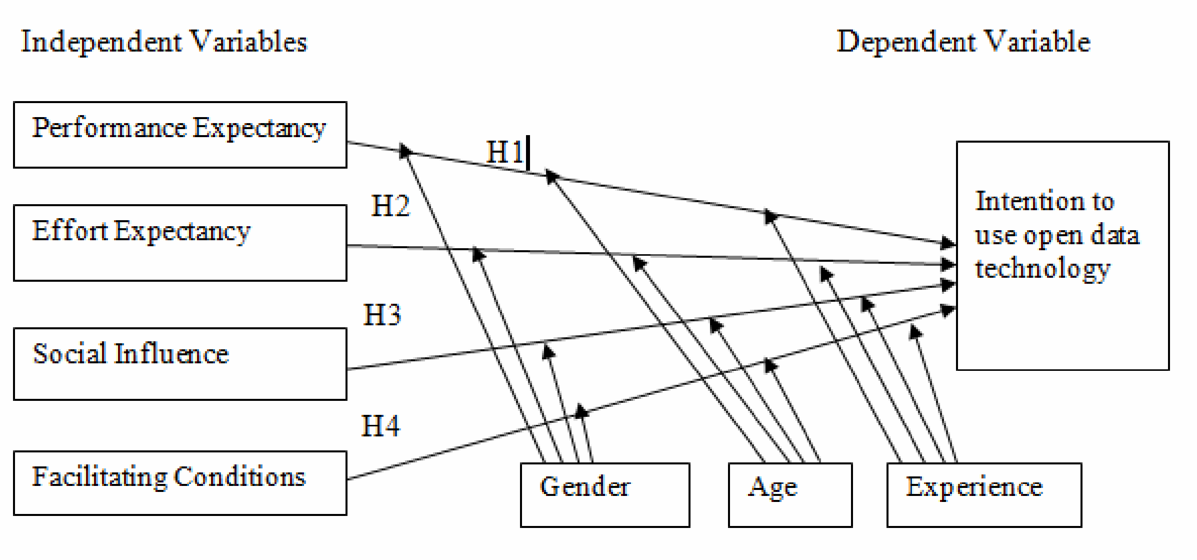

Figure 2.2 Conceptual Framework

CHAPTER THREE

RESEARCH METHODOLOGY

In this chapter, methods and processes which were employed to execute the study to achieve its objectives are outlined. Mugenda (2008) observes that social science researchers routinely collect data for both quantitative and qualitative analysis to establish the 'cause and effect' relationships between variables in an attempt to analyze and understand human beings' social life. They use various research designs, tools and procedures to achieve this objective.

3.1. Research Design

Descriptive and correlational research designs were used. Mugenda and Mugenda (2003) argue that descriptive designs provide important clues regarding the issues that the investigator should focus on. Kothari (2008) observes that a descriptive research design is used to get information on the current status of people and their attitude, opinions and habits. On the other hand, correlational research focuses on the relationships among variables. If a statistically significant relationship exists between two variables, then it is possible to predict one variable using the information available on the other variable (Mugenda, 2008).

3.1.1. Research Philosophy

Research philosophy refers to a researchers' view of the relationship between knowledge and the process by which it is developed (Saunders, Lewis and Thornhill, 2009). In this study we used positivist philosophy, because the study is mainly quantitative. According to Mugenda (2008), the positivist's paradigm assumption is that there is a single tangible reality that can be studied independent of human actors, and variables can be studied independent of each other, and also related to each other using expressions. Interpretivist philosophy is based upon the ontological assumption that reality and our knowledge thereof are social constructions, incapable of being studied independent of the social actors that construct and make sense of this reality. Pragmatist philosophy argues that the most important thing is the research question, and that it is perfectly possible to work with variations in one's views (Saunders, Lewis and Thornhill, 2009). The research approach was deductive, and the research strategy was a survey, with questionnaires used for data acquisition.

3.2. Target Population

Mugenda (2008) explains that population is the whole group of individuals, having mutual observable characteristics, from where a sample is drawn for the study. On the other hand, a target population refers to the specific population about which information is desired and results generalized (Kothari, 2008). Ideal respondents for this study would be actual users of the KODI portal. Previous research on open data in Kenya has cited not only low usage of data on the portal, but also low awareness about existence of the initiative.

We found it difficult to determine who exactly uses the portal. However, according to the results of a Kenya open data user survey carried out by ICT Authority in 2014, primary uses of Kenya's portal are for academic research and policy research (KODI, 2014). Our study target population was policy researchers. These policy researchers were randomly selected from ten research organizations or think tanks in Nairobi, Kenya. These organizations were ranked top in Kenya in the "2015 Global Go to Think Tank Index". This ranking index is produced by the Think Tanks and Civil Societies Program.

Table 3.1 Target Population

No	Organization	No. of researchers
1	Kenya Institute for Public Policy Research and Analysis (KIPPRA)	28
2	Institute for Development Studies (IDS-UoN)	20
3	African Center for Technology Studies (ACTS)	12
4	African Economic Research Consortium (AERC)	10
5	Institute of Economic Affairs (IEA)	10
6	African Technology Policy Studies Network-Kenya (ATPS)	10
7	Institute of Policy Analysis and Research (IPAR)	5
8	Inter-Region Economic Network (IREN)	5
9	Rift valley Institute (RVI)	5
10	Eastern Africa Policy Centre (EAPC)	5
	Total	**110**

Source: 2015 Global Go-To Think Tank Index Report

3.3. Sampling

3.3.1. Sample Size

According to Mugenda and Mugenda (2003), a sample is a portion of the population of researcher's interest. The purpose of sampling is to gain an understanding about some attributes of the whole population centred on characteristics of sample. According to Mugenda (2008), sample size of at least 30 % is a good representation of the target population since it allows for reliable levels of accuracy for testing significance. Slovin's sample size determination formula was used (Altares et al., 2003).

Slovin's formula:

$$n = \frac{\mathrm{N}}{(1 + Ne^2)}$$

Whereby; N = population, e = error tolerance, n = sample size

The confidence level of this study is 90%, which gives a margin of error of 0.1

Therefore, using e=0.1 and N= 110, we calculated the sample size n as follows;

n =110 / (1+110*0.1^2) =110/ 2.1= 52.38= 52 researchers.

Our sample size of 52 researchers represented 47% of our target population.

3.3.2. Sampling Technique

A sampling technique is a technique of selecting subjects that will be part of the sample size of 52 with the aim of making sure the sample is representative. These subjects are selected from the sampling frame (Mugenda and Mugenda, 2003). To determine the sample size, stratified random sampling was used. This form of sampling ensures that existing sub-groups in the target population are fairly and randomly represented in the sample (Mugenda, 2008). The following formula was used; $n_i = n/N) N_i$,Where; n_i= sample size of the strata, n=total sample size, N= total population size, N_i=number of individuals in every strata i.e. each organization. The stratified sample size per organization is shown in the table below.

Table 3.2 Sample Size

No	Organization	Target population (N)	Sample size (n)
1	KIPPRA	28	14
2	IDS	20	9
3	ACTS	12	6
4	AERC	10	5
5	IEA	10	5
6	ATPS	10	5
7	IPAR	5	2
8	IREN	5	2
9	RVI	5	2
10	EAPC	5	2
	Total	**110**	**52**

3.4.Data Collection

3.4.1.Instruments

Primary and secondary data provide a comprehensive picture of the variables under study. Primary data is the first hand information gained from the field when conducting research, while secondary data is collected through comprehensive literature review study. The researcher collected primary data using structured questionnaires (Appendix II) to record respondents' responses. In the questionnaire, each item of the conceptual framework had corresponding questions, and Five-point Likert scales were used. These questions were adopted from questions that were originally tested by Venkatesh et al., (2003).

Other questions on background information of respondents, such as age and gender, were also included.For purposes of making questions short and easy to understand by respondents, some questions did not explicitly use the term open data technology. However, introduction information emphasized that the focus of the study was open data technology, and relevant definitions were given. Kothari (2008) observes that collecting data through questionnaires saves time and enables collection of a huge amount of data.

3.4.2. Procedure

An introduction letter was presented to each organization and individual respondents, and the researcher explained the purpose of the study and confirmed respondents' willingness to participate. The respondents were then given two weeks to fill. The researcher clarified any questions or issues raised by a respondent. After the two weeks were over, the researcher collected the filled questionnaires for data analysis. Where it was difficult to physically reach a respondent, the questionnaire was disseminated online through email.

3.5. Pilot Test

A pilot study was first carried out. This was done to ensure that items in the questionnaire were as understandable as possible, not ambiguous or insufficient. It also provided data to check for reliability of the questionnaires.

3.5.1. Validity

Validity is the ability of a questionnaire to accurately measure that which it claims to measure. Validity of the draft questionnaire was established by getting opinion from research experts and a field test. Based on experts' input, the draft questionnaire was reworded, resulting to a final questionnaire whose reliability was later tested through a pilot test. Mugenda (2008) define validity as the accuracy, significance and representativeness of content based on the research objectives.

3.5.2. Reliability

Mugenda and Mugenda (2003) indicate that prior to the main study, a pilot study consisting of at least 10% of the target population should be carried out to ascertain the reliability of instruments. Reliability measures internal consistency of the measuring instrument. To measure reliability of the final questionnaire, data collected through the pilot test was analysed using SPSS to obtain the Cronbach's Alpha values. Cronbach's Alpha values are used to measure internal consistency. According to Kothari (2008) an alpha coefficient of 0.70 or higher indicates a relatively high internal consistency and is generally acceptable. The closer the coefficient is to1, the greater the consistency of the items in a scale. All the study variables were found to have coefficients greater than 0.70, as shown in table 3.4 below.

Table 3.3: Reliability Coefficients

Variable	Cronbach's Alpha	Number of Items
Performance Expectancy (PE)	0.80	2
Effort Expectancy (EE)	0.82	2
Social Influence (SI)	0.87	2
Facilitating Conditions (FC)	0.83	3
Behavioral Intention (BI)	0.75	2

Social Influence had the highest reliability at 0.87 among the independent variables of the study, closely followed by facilitating conditions at 0.83, effort expectancy at 0.82 and performance expectancy at 0.80. Behavioral intention, which is the dependent variable of the study, had a reliability of 0.75.

3.6. Data Analysis and Presentation

After data collection, the questionnaires were coded, and then edited to detect errors and omission to enhance accuracy and precision. Using SPSS v20, correlation and multiple regression analysis were used to analyse data. Correlation analysis was used to establish the nature of the existing relationships, while multiple regression analysis was used to determine statistical significance and influence or effect of the independent variables. After data analysis, we derived the research findings from the evidence obtained. Then, guided by the objectives of the study, we made conclusions and gave recommendations. Mugenda and Mugenda (2003) explain that recommendations must be consistent with the purpose of the study and its objectives.

CHAPTER FOUR

RESEARCH FINDINGS AND DISCUSSION

Response rate, demographic data of respondents, distribution of data for the variables, and hypotheses testing are discussed in this chapter. The study was based on variables from the UTAUT model, and descriptive and inferential statistics were used for data analysis.

4.1. Response Rate

Out of the 52 questionnaires which were distributed to respondents, a total of 45 were returned, which represents a response rate of 86.5%. This response rate was satisfactory to draw conclusions from the study. According to Mugenda and Mugenda (2003)a response rate of 60% is good while that of above 70% is most desirable. This level of response may be attributed to the fact that the researcher personally issued the questionnaires to the respondents, and did follow-up. The respondents, being researchers themselves, were more willing to co-operate.

Table 4.1: Response Rate

No. of questionnaires Issued	No. of questionnaires Returned	Response Rate (%)
52	45	86.5%

4.2. Demographic Characteristics

4.2.1. Gender

Both gender participated in the study. Out of 45 participants who responded, 35 were male representing 78% while 10 were female representing 22%. Kothari (2008) asserts that a ratio of at least 1:2 in either gender representation in the study is representative enough. This is a big difference in the male and female respondents, indicating gender parity in the policy research field in Kenya. The results of this information are presented in the table below.

Table 4.2: Gender of Respondents

Gender	Frequency	Percentage
Male	35	78%
Female	10	22%

4.2.2. Age

The researchers' age was also a factor considered in this study. The distribution of age of respondents was as shown in the table below. Most of the respondents were aged between 36 to 45 years, followed closely by 46 to 55 years. Only two were below 25 years and two above 55 years.

Table 4.3: Age of Respondents

Age bracket	Frequency	Percentage
Less than 25 years	2	4%
26 - 35 years	8	18%
36 - 45 years	19	43%
46 - 55 years	14	31%
56 and above years	2	4%
Total	45	100%

4.2.3. Experience

In our study, we also sought to establish whether the policy researchers had any previous experience in using technical tools (e.g. visualization software, online data catalogues) to carry out policy research. 76% of the respondents rated themselves as conversant with the use of technical tools in conducting research. This may be due to the common use of tools such as SPSS and Excel. We also established that some of them did not necessarily deal with the data itself. They just did the field work, and had assistants carry out the data analysis. This may explain the 24% who rated themselves as not being conversant with the use of technical tools in policy research.

Table 4.4: Experience in using technical tools

Category	Frequency	Percentage
Conversant	34	76%
Not Conversant	11	24%
Total	45	100%

4.2.4. Level of Education

Most of the respondents had Master's degree, at 58 %. 24% had PhD and 18% had degree. The high number of post-graduate degree could be attributed to the nature of the field, and the fact that their work was mostly research-oriented, thus a research degree being preferable.

Table 4.5: Highest academic qualification

Academic Qualification	Frequency	Percentage
Degree	8	18%
Masters	26	58%
PhD	11	24%
Total	45	100%

4.2.5. Nature of Organization

In our study, we also sought to establish the nature of the organization in which the respondents' worked in. As shown in table 4.6 below, most (56%) were working in civil society organizations or non-governmental organizations, followed by public sector (33%), and then the private sector (11%). This may be attributed to the fact that there is a lot of policy research done by civil society organizations and NGOs. Policy work is also very prevalent and vital in the public sector.

Table 4.6: Nature of organization

Sector	Frequency	Percentage
Public	15	33%
Private	4	11%
CSO/NGO	26	56%
Total	45	100%

4.2.6. Sources of Kenya Open Data

In our study, we also sought to understand ways which policy researchers had used before to get access to Kenya public sector open data.

Table 4.7: Source of Kenya public sector open data

Source	Frequency	Percentage
Websites of individual government agencies	43	95.5%
Government agencies' offices (soft copy)	29	64.4%
Kenya open data website	41	91.1%
Government agencies' offices (hard copy)	37	82.2%

From the results, 82.2 % of respondents had obtained public sector open data from government offices in non-electronic format and 64.4% in electronic format. This indicated that there may still be a lot of data in government offices that is not yet in electronic format. There is need therefore to encourage digitization of government records to ease their access, and to make them available through open data technology.

As the results indicate, respondents had accessed data mostly through websites. 95.5% had accessed open public sector data from individual government agencies websites (95.5%) and from the Kenya open data website (91.1%) Having data publicly available through a website may have been interpreted by the researchers as an indicator of its openness, versus the traditional means of accessing it from the agencies' offices.

4.2.7. Use of Kenya Open Data Platform

Previous research study (Mutuku and Mahihu, 2014), had associated low usage of the Kenya open data platform to lack of awareness. However, from our study, 41 out of 45 respondents (91.1%) of the respondents had used the Kenya open data platform at least once, meaning they were aware of its existence. Therefore, other factors other than awareness may have led to low usage of the platform. We went further and investigated on how often policy researchers used the Kenya open data platform in comparison with other sources of Kenya public sector data. The results were as shown in table 4.8 below.

Table 4.8: Use of Kenya open data platform

Source	Monthly (%)	Yearly (%)	Weekly (%)	Only once (%)	<Once/year (%)	Total (%)
Websites of individual agencies	56.2	36.9	6.8	0.0	0.0	100
Government agencies' offices (soft copy)	26.8	68.3	0.0	0.0	4.8	100
Government agencies' offices (hard copy)	30.6	66.2	0.0	0.0	3.1	100
Kenya open data website/platform	14.5	60.9	4.8	2.4	17.3	100

Key: Only once=Used only once; <Once/year= Several times in many years

As the results in Table 4.8 indicate, most policy researchers accessed Kenya public sector data yearly. However, compared with other sources of Kenya public sector data, usage of the platform monthly was low. Also, there were researchers who had only used the platform only once. Open data platform also had the highest number of respondents who used it less than once in a year. This observation was in line with previous studies (Majeed, 2012; Mutuku and Colaco, 2012; Hammer, 2013; Mutuku and Mahihu, 2014), who also cited low usage of the Kenya open data platform.

4.2.8. Kenya Open Data Platform Tools

In our study, open data technology was used to mean open data tools such as national datasets, county datasets, files and documents, maps, visualizations (graphs/charts), filtered user views, Application Programming Interface, open data blog, embed code, forms, data request or suggestion function, filter function, discuss function, data export function and other general website functions.

Table 4.9: Respondents' opinion on usefulness of open data tools

Tool	SD (%)	D (%)	N (%)	A (%)	SA (%)	Total (%)
Open data catalogue	0.0	0.0	4.9	87.8	7.2	100
Metadata	0.0	0.0	4.9	73.2	21.9	100
Visualization tools	0.0	4.9	14.6	53.7	26.8	100
Search and filter tools	0.0	0.0	9.6	87.8	2.4	100
API	12.2	73.2	9.6	4.9	0.0	100
Filtered user views	7.3	27.8	28.3	24.4	12.2	100
Discussion feed	4.9	14.6	34.1	36.7	9.6	100
Embed code	4.9	27.8	28.3	21.9	17.1	100
Export function	0.0	0.0	9.6	73.2	17.1	100
Blog	17.1	31.7	24.3	21.9	4.9	100
Data suggestion	0.0	0.0	29.3	63.4	7.3	100

Key: SA = Strongly Agree; A = Agree; N = Neutral; D = Disagree; SD = Strongly Disagree.
%=Percentage frequency that gave the opinion

The results in Table 4.9 indicate that policy researchers found data catalogues, metadata, visualization tools, search and filter, export and data suggestion as the most useful open data tools for their kind of work. To encourage policy researchers to make use of open data platforms, then emphasis should be on the usefulness and capabilities of the former open data tools. Application Programming Interface (API), blog, embed code, filtered user views and discussion feed were the least useful tools for policy researchers in our study. These latter tools though not as useful to policy researchers, they may be useful to other kinds of users such as developers and data journalists.

4.2.9.Open Data Challenges

Previous research studies (Mutuku and Mahihu, 2014; Majeed, 2012; Mutuku and Colaco, 2012) had cited low quality of open data available as one of the factors that led to low usage of the Kenya open data platform. We investigated this further by trying to identify which challenges policy researchers encountered when trying to access or use Kenya open data.

Table 4.10: Kenya public sector open data challenges

Challenge	SD (%)	D (%)	N (%)	A (%)	SA (%)	Total (%)
Irregularly updated datasets	2.4	12.2	14.6	63.4	7.3	100
Inadequate datasets	4.9	7.3	19.5	56.1	12.2	100
Irrelevant datasets	7.3	21.9	26.8	36.6	7.3	100
Difficult procedures of accessing data	2.4	14.6	7.3	68.3	7.3	100

Key: SA = Strongly Agree; A = Agree; N = Neutral; D = Disagree; SD = Strongly Disagree.
%=Percentage frequency that gave the opinion

As the results indicate in Table 4.10,policy researchers found available datasets tobe inadequate. Therefore both quality and quantity of open data were challenges. This may be attributed to the current low digitization of government records in Kenya, holding of data by agencies due to the Secrecy Act and lack of any laws mandating them to give the data in open formats. Difficult procedures in accessing government data was also a big challenge. However, there were mixed views on irrelevancy of datasets.

4.3. Behavioral Intention

From 45 respondents of our study, 41 had used the Kenya open data platform before. From these 41, we sought to know factors that influence their intention to use Kenya open data technology. The results in the table below indicate respondents' opinions on whether they intended to continue using Kenya open data technology in the future.

Table 4.11: Respondents' Opinion on Behavioral Intention

Statements	SD (%)	D (%)	N (%)	A (%)	SA (%)	Total (%)
I intend to use open data technologies in the future	7.3	26.8	29.3	24.4	12.2	100
I plan to use open data technologies in the future	7.3	27.8	28.3	24.4	12.2	100

Key: SA = Strongly Agree; A = Agree; N = Neutral; D = Disagree; SD = Strongly Disagree.
%=Percentage frequency that gave the opinion

Most respondents 29.3% were neutral to the statements that they intended to make use of Kenya open data technology in future, while 6.8% disagreed, 24.4% agreed, 12.2% strongly agreed, and 7.3% strongly disagreed. This meant that most were not yet sure whether they would use open data technology in the future. For variables to undergo further statistical analysis such as regression analysis, some assumptions must be met first.To conclude that a significant relationship existed between the variables and to test for multi-collinearity, Pearson Product Moment Correlation was used.

The probability (p-value) should be less than the value of the level of significance (α), which is often set at 0.05 or 0.01 (Mugenda and Mugenda, 2003).The computation yields a correlation coefficient (r) that ranges from -1 to +1. The score 1 indicates perfect correlation, which is found only when a variable is correlated with itself while 0 indicates no correlation at all hence no need for further analysis on such variables with no relationship. The higher the coefficient the greater the correlation between the variables that are being compared. The direction of the relationship is also important; it is either positive or negative.

Table 4.12: Summary of Correlations

		Performance Expectancy	Effort Expectancy	Social Influence	Facilitating Conditions	Behavioral Intention
Performance Expectancy	Pearson's Correlation	1				
	Sig. (2-tailed)					
Effort Expectancy	Pearson's Correlation	.609**	1			
	Sig. (2-tailed)	.000				
Social Influence	Pearson's Correlation	.612**	.694**	1		
	Sig. (2-tailed)	.000	.000			
Facilitating Conditions	Pearson's Correlation	.656**	.587**	.591**	1	
	Sig. (2-tailed)	.000	.000	.000		
Behavioral Intention	Pearson's Correlation	.893**	.837**	.796**	.662*	1
	Sig. (2-tailed)	.000	.000	.000	.000	

**. Correlation is significant at the 0.01 level (2-tailed).

The correlation coefficient results above show there was a highly significant linear correlation between independent variables, and the dependent variable. For all the variables, it was above the recommended .3 by Mugenda and Mugenda (2003). The variables were also not multi-collinear as shown by the correlation coefficients between each other, which Tabachnick and Fidell (2001, p. 84) suggest that they should be below .7.As the correlation coefficients in Table 4.12 show, behavioral intention had a positive correlation with all the four independent variables. This meant that unit decrease or increase in any independent variable would lead to unit increase or decrease in behavioral intention. Effort expectancy in the questionnaire was coded to mean the perceived ease of use of open data technology.

Table 4.13: Regression analysis results

Model Summary [b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.938[a]	.879	.866	.84188

a. Predictors (Constants), Performance Expectation, Effort Expectancy, Social Influence, Facilitating Conditions

b. Dependent Variable: Behavioral Intention

ANOVA [a]

Model	Sum of Squares	Df	Mean Square	F	Sig.
Regression	185.607	4	46.402	65.469	.000[b]
Residual	25.515	36	.709		
Total	211.122	40			

a. Predictors (Constants), Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions

b. Dependent Variable: Behavioral Intention

Results in table 4.13 indicated that our model explained 86.6% of the variation on behavioral intention by policy researchers to use open data technology in Nairobi, Kenya, as shown by the adjusted R^2 value. Therefore, other factors not covered in this study contributed to the other 13.4%. We considered the adjusted R^2 value instead of R Square because our sample was small; n=41.

The independent variables statistically significantly predicted the dependent variable (p<.005). The unstandardized coefficients as shown in Table 4.14 indicated how much the dependent variable varied with an independent variable, when all other independent variables were held constant. As seen in the "Sig." column, the coefficients of all independent variables except facilitating conditions were statistically significant (p<0.05).

Table 4.14: Regression Coefficients of all variables

	Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	T	Sig.
Performance Expectancy	0.172	0.712	0.521	4.702	0.000
Effort Expectancy	0.227	0.108	0.216	2.097	0.043
Social Influence	0.257	0.092	0.247	2.803	0.000
Facilitating Conditions	0.052	0.087	0.048	0.602	0.551

4.4. Performance Expectancy

The study sought to find out the influence of performance expectancy on policy researchers' intention to make use of Kenya open data technology.

Table 4.15: Respondents' opinion on Performance Expectancy

Statements	SD (%)	D (%)	N (%)	A (%)	SA (%)	Total (%)
Using open data technology will help me to accomplish research more quickly	9.8	31.7	14.6	29.3	14.6	100
Using open data technology will lead to better quality of my research output	12.2	29.3	17.1	31.7	9.8	100

Key: SA = Strongly Agree; A = Agree; N = Neutral; D = Disagree; SD = Strongly Disagree.
%=Percentage frequency that gave the opinion

As shown in table 4.15, 43.9% of respondents agreed or strongly agreed that using open data technology would help them accomplish research more quickly, 14.5% disagreed or strongly disagreed, while 14.6% were neutral. Generally, most strongly disagreed that it would lead to quicker research; 31.7%. 31.7% of respondents agreed that using open data technology would lead to better quality of research output. Generally, 41.5% agreed, 41.5% disagreed and 17.1% were neutral. Therefore, emphasizing how using open data technology would lead to better quality of research may be more effective than emphasizing on speed of carrying out research. However, previous research noted poor quality of open data technology as a problem (Martijn et al., 2015). There is need thus to improve quality so as to increase policy researchers' intention to use Kenya open data technology.

From regression analysis results, performance expectancy was highly significant in predicting behavioral intention of policy researchers to make use of open data technology ($p< .005$). It was also the highest contributor (52.1%) of the variance of behavioral intention. Hypothesis 1 was thus accepted. This corroborated prior research findings (Duyck et al., 2008; Zuiderwijk et al., 2015,VanDijk et al., 2008). Therefore if a policy researcher perceived that using open data technology would lead to better performance in their work, then they would be more willing to use that technology.

4.5. Effort Expectancy

Table 4.16: Respondents opinion on Effort Expectancy

Statements	SD (%)	D (%)	N (%)	A (%)	SA (%)	Total (%)
Learning to use open data technologies will be easy for me	4.9	53.7	7.3	26.8	7.3	100
It will be easy for me to become skillful at using open data technology	4.9	51.2	9.8	26.8	7.3	100

Key: SA = Strongly Agree; A = Agree; N = Neutral; D = Disagree; SD = Strongly Disagree.
%=Percentage frequency that gave the opinion

As shown in the results table above, if users deem a technology difficult to learn to use, their intention to use it then would be low. This may be caused by factors such as interfaces that are not user-friendly. Our findings were different from those of Zuiderwijk et al., (2015), whereby in their study most respondents perceived learning to use open data technology as easy. However, our findings were similar to those of Colesca and Dobrica (2008) who found out that the higher a citizen perceived an online service to be easy to use, the higher was their willingness to adopt it.

Effort expectancy was highly significant in predicting policy researchers' intention to use Kenya open data technology ($p< .005$) as shown by the regression analysis results. It was the third largest contributor at 21.6%., and hypothesis 2 was accepted. This meant that the easier it is to use open data technology, the higher the intention to use it. This finding was similar to that of research by Zuiderwijk et al., (2015).

4.6. Social Influence

Table 4.17: Respondents opinion on Social Influence

Statements	SD (%)	D (%)	N (%)	A (%)	SA (%)	Total (%)
People who influence my behavior think I should use open data technology	7.3	29.3	19.5	36.6	7.3	100
People who are important to Me (e.g. friends, colleagues) think that I should use open data technology	9.8	24.4	24.4	34.1	7.3	100

Key: SA = Strongly Agree; A = Agree; N = Neutral; D = Disagree; SD = Strongly Disagree.
%=Percentage frequency that gave the opinion

Most respondents at 36.6% consented that people who influenced their behavior expected that they should use open data technology, 7.3% strongly agreed and 29.3% disagreed. Most also agreed that colleagues and friends expected them to use open data technology; 34.1%. Therefore generally, social influence was high among policy researchers. Our findings corroborate those of Talukder and Quazi (2010), who highlighted that in organizations, peer influence is very high. Also, the opinions of influential people in organizations about a certain technology strongly influenced the opinions of other members in the same organization (Sarker et al., 2011).

Social influence was statistically significant($p<.005$), as shown by the regression analysis results, and thus hypothesis 3 was accepted. It was the second largest contributor at 24.7 %. This meant that the higher the social influence is to use open data technology, the higher the behavioral intention to use them. This finding was in line with previous research by Zuiderwijk et al., (2015) which had shown social influence as an important factor in determining the behavioral intention to use open data.

4.7. Facilitating Conditions

Table 4.18: Respondents Opinion on Facilitating Conditions

Statements	SD (%)	D (%)	N (%)	A (%)	SA (%)	Total (%)
My organization supports the use of open data technology	0	7.3	9.8	65.9	17.1	100
I have technical resources to enable me use open data technologies	0	4.9	4.9	65.9	24.4	100
A specific person or group is available for assistance with difficulties concerning the use of open data technology	12.2	39.0	17.1	31.7	0	100

Key: SA = Strongly Agree; A = Agree; N = Neutral; D = Disagree; SD = Strongly Disagree.
%=Percentage frequency that gave the opinion

According to the results above, facilitating conditions in terms of organisational support and availability of technical resources was very high. 83% of the respondents agreed that they have organisational support. Only 7.3% disagreed, and none strongly disagreed. 90.3% of respondents agreed that they have technical resources to use open data. This may be due to high levels of computer use and internet access in Kenya.

However, only 31.7% of the respondents agreed about availability of support and assistance in case of difficulties when using open data technology. We also noted that the Kenya open data platform had no information under the user guides tab. There is need to provide support in order to encourage use of open data technology. Our results were similar to those of Ahmad et al. (2012) who found out that lack of appropriate help and adequate guidelines influenced adoption of online government service in Pakistan, which is also a developing country. Similar findings were conveyed by other studies carried out in developing countries such as AlAwadhi, (2008) in Kuwait and Colesca and Dobrica (2008) in Romania. Facilitating conditions was found to be insignificant and thus hypothesis 4, was not accepted. Our finding was similar to that of Rana et al., (2011).

4.8. Moderating Effects of Gender Age and Experience

Moderated multiple regression (MMR) was used to explore whether there existed moderating effects. Because hypothesis 4 was not accepted, we did not explore the effects of moderating variables on facilitating conditions. All our moderating variables were categorical. Hence, in order to use them in the moderated regression analysis, they were first dummy coded. Dummy coding refers to the construction of dichotomous dummy variables to make a categorical variable numerical. The number of dummy variables required for a given categorical variable is equal to the number of categories minus one (Penn State, n.d.).

Table 4.19: Moderating Effects of Gender

Model Summary [c]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of Estimate	R Square Change	F Change	df1	df2	Sig.F Change
1	.909[a]	.827	.818	.98129	.827	90.624	2	38	.000
2	.910[b]	.828	.814	.99151	.001	.221	1	37	.641

a. Predictors (Constants), Gender, Performance Expectancy

b. Predictors (Constants), Gender, Performance Expectancy, Gender X Performance Expectancy

c. Dependent Variable: Behavioral Intention

Model Summary [c]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of Estimate	R Square Change	F Change	df1	df2	Sig.F Change
1	.838[a]	.701	.686	1.28795	.701	44.636	2	38	.000
2	.841[b]	.707	.684	1.29193	.006	.776	1	37	.387

a. Predictors (Constants), Gender, Effort Expectancy

b. Predictors (Constants), Gender, Effort Expectancy, Gender X Effort Expectancy

c. Dependent Variable: Behavioral Intention

Model Summary [c]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of Estimate	R Square Change	F Change	df1	df2	Sig.F Change
1	.801[a]	.642	.623	1.41040	.642	34.066	2	38	.000
2	.802[b]	.643	.614	1.42803	.001	.067	1	37	.797

a. Predictors (Constants), Gender, Social Influence

b. Predictors (Constants), Gender, Social Influence, Gender X Social Influence

c. Dependent Variable: Behavioral Intention

As shown in Table 4.19, for performance expectancy, the change in R^2 due to gender was .001. Thus the percentage increase in variation explained by the addition of gender as a moderator was less that 1% (i.e. 0.001*100=0.1%). This change was highly insignificant as shown in the Sig. F Change column (p>.0005). Therefore, Hypothesis H1awas not accepted. For effort expectancy, the change in R^2 due to gender was 0.6% and it was highly insignificant (p>.0005). Therefore, Hypothesis H2awas not accepted. The change in R^2 for social influence due to gender was 0.1% and it was also insignificant. Therefore, Hypothesis H3a was also not accepted. Overall, gender was found to not have any moderating effect. As shown in Table 4.20, for all the independent variables, change in R^2 was insignificant and therefore, Hypotheses H1b, H2b, and H3b were not accepted.

Table 4.20: Moderating Effects of Age

Model Summary [c]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of Estimate	R Square Change	F Change	df1	df2	Sig.F Change
1	.909[a]	.826	.801	1.02510	.826	33.182	5	35	.000
2	.926[b]	.857	.821	.97197	.031	2.310	3	32	.095

a. Predictors (Constants), Age, Performance Expectancy

b. Predictors (Constants), Age, Performance Expectancy, Age X Performance Expectancy

c. Dependent Variable: Behavioral Intention

Model Summary [c]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of Estimate	R Square Change	F Change	df1	df2	Sig.F Change
1	.849[a]	.720	.680	1.29883	.720	18.030	5	35	.000
2	.874[b]	.765	.706	1.24638	.044	2.003	3	32	.133

a. Predictors (Constants), Age, Effort Expectancy

b. Predictors (Constants), Age, Effort Expectancy, Age X Effort Expectancy

c. Dependent Variable: Behavioral Intention

Model Summary [c]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of Estimate	R Square Change	F Change	df1	df2	Sig.F Change
1	.885[a]	.784	.753	1.14223	.784	25.364	5	35	.000
2	.900[b]	.809	.754	1.13968	.026	1.039	4	31	.403

a. Predictors (Constants), Age, Social Influence

b. Predictors (Constants), Age, Social Influence, Age X Social Influence

c. Dependent Variable: Behavioral Intention

Table 4.21: Moderating Effects of Experience

Model Summary [c]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of Estimate	R Square Change	F Change	df1	df2	Sig.F Change
1	.905[a]	.819	.809	1.00332	.819	85.863	2	38	.000
2	.906[b]	.821	.804	1.01676	.001	.002	1	37	.963

a. Predictors (Constants), Experience, Performance Expectancy

b. Predictors (Constants), Experience, PE, Experience X Performance Expectancy

c. Dependent Variable: Behavioral Intention

Model Summary [c]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of Estimate	R Square Change	F Change	df1	df2	Sig.F Change
1	.846[a]	.717	.702	1.25500	.717	48.022	2	38	.000
2	.847[b]	.718	.695	1.26941	.001	.142	1	37	.708

a. Predictors (Constants), Experience, Effort Expectancy

b. Predictors (Constants), Experience, Effort Expectancy, Experience X Effort Expectancy

c. Dependent Variable: Behavioral Intention

Model Summary [c]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of Estimate	R Square Change	F Change	df1	df2	Sig.F Change
1	.796[a]	.634	.614	1.42652	.634	32.873	2	38	.000
2	.797[b]	.635	.606	1.44243	.002	.167	1	37	.685

a. Predictors (Constants), Experience, Social Influence

b. Predictors (Constants), Experience, Social Influence, Experience X Social Influence

c. Dependent Variable: Behavioral Intention

Overall, experience in using technical tools was found to not have any moderating effect on relationship between independent and dependent variables, for all the variables. This was in line with our previous finding that facilitating conditions in terms of availability of technical resources did not influence intention to make use of Kenya open data technology. Our findings corroborate those of Alshehri, Drew and AlGhamdi (2012) who had also applied UTAUT model. They found out that age and gender were insignificant moderators.

4.9. UTAUT model applicability in open data technology context

To explore how much variance in intention the modified UTAUT model could explain, multiple regression analysis was applied, after dropping facilitating conditions, which was found to be insignificant. The results were as shown in below.

Table 4.22: Regression analysis for the modified UTAUT model

Model Summary [b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.937[a]	.878	.868	.83460

a. Predictors (Constants), Performance Expectancy, Effort Expectancy, Social Influence

b. Dependent Variable: Behavioral Intention

ANOVA [a]

Model	Sum of Squares	Df	Mean Square	F	Sig.
Regression	185.349	3	61.783	88.698	.000[b]
Residual	25.773	37	.697		
Total	211.122	40			

a. Predictors (Constants), Performance Expectancy, Effort Expectancy, Social Influence

b. Dependent Variable: Behavioral Intention

The results in table 4.22 indicated that the modified UTAUT model explained 86.8 % of the variation on behavioral intention by policy researchers to use open data technology in Nairobi, Kenya, as shown by the adjusted R^2 value. This was statistically significant (Sig=.000, i.e. $p<.0005$). Hypothesis 5: Modified UTAUT model accounts for significant percentage variance (R^2) of intention to make use of open data technology, was accepted.

4.10. Hypothesis Testing Summary

Table 4.23: Hypothesis Testing Results

No.	**Hypothesis**	**Accepted/ Not Accepted**
H1	Performance expectancy positively influences the behavioral intention to use open data technologies	Accepted
H1a	Gender moderates the influence of performance expectancy on behavioral intention to use open data technologies.	Not accepted
H1b	Age moderates the influence of performance expectancy on behavioral intention to use open data technologies.	Not accepted
H1c	Experience moderates the influence of performance expectancy on behavioral intention to use open data technologies.	Not accepted
H2	Effort expectancy negatively influences the behavioral intention to use open data technologies	Accepted
H2a	Gender moderates the influence of effort expectancy on behavioral intention to use open data technologies.	Not accepted
H2b	Age moderates the influence of effort expectancy on behavioral intention to use open data technologies.	Not accepted
H2c	Experience moderates the influence of effort expectancy on behavioral intention to use open data technologies.	Not accepted
H3	Social influence positively influences the behavioral intention to use open data technologies.	Accepted
H3a	Gender moderates the influence of social influence on behavioral intention to use open data technologies.	Not accepted
H3b	Age moderates the influence of social influence on behavioral intention to use open data technologies.	Not accepted
H3c	Experience moderates the influence of social influence on behavioral intention to use open data technologies.	Not accepted
H4	Facilitating conditions positively influence the behavioral intention to use open data technologies.	Not accepted
H4a	Gender positively moderates the influence of facilitating conditions on behavioral intention to use open data technologies.	Not accepted

H4b	Age moderates the influence of facilitating conditions on behavioral intention to use open data technologies.	Not accepted
H4c	Experience moderates the influence of facilitating conditions on behavioral intention to use open data technologies.	Not accepted
H5	Modified UTAUT model accounts for a significant percent of the variance (R^2) in behavioral intention to use open data technologies	Accepted

4.11. Optimal Model

Facilitating conditions was established to be an insignificant determinant. All the moderating variables also did not have any effect on the relationship between the independent and dependent variables. Therefore, facilitating conditions, gender, age, and experience were dropped from the final modified UTAUT model. Fig. 4.1 shows the final model.

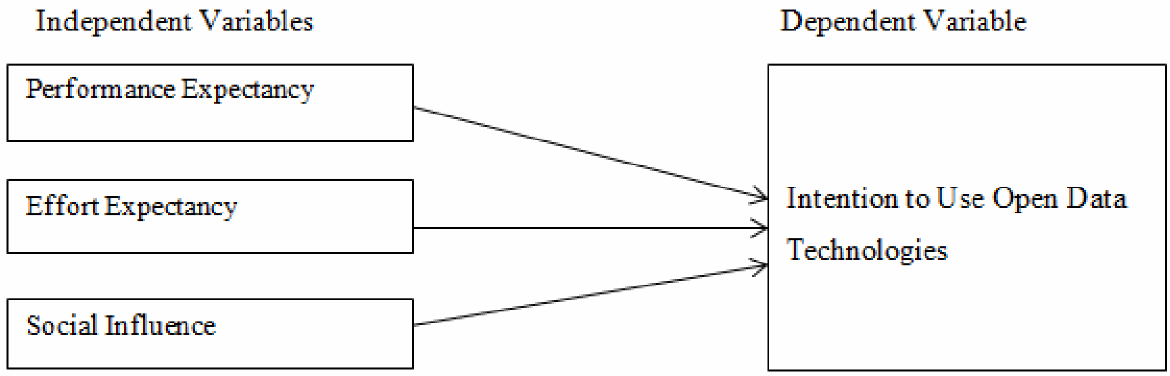

Fig.4.1. Optimal model

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1. Summary Findings

The main objective was to determine factors that influence intention of policy researchers in Nairobi, Kenya, to use the Kenya government open data platform. The study used variables from the UTAUT model. The findings indicated that up to 86.6% variance of intention to make use of open data technology by policy researchers in Nairobi, Kenya, could be attributed to the combined effects of all the variables in the modified UTAUT. Performance expectancy was the highest predictor. The second highest predictor was social influence, and then effort expectancy, while facilitating conditions was found to be insignificant.

5.2. Recommendations for practice

5.2.1. Performance expectancy strategies

Performance expectancy was found to be the best motivator for use. Efforts to encourage use of open data technology should therefore focus most on their usefulness and the value they would bring. Governments can increase performance by having initiatives such as training and awareness programs that can illustrate case studies and success stories of how use of open data platforms have been used, and other potential ways of using these technologies.

In our research, policy researchers consented that making use of open data technology may lead to quicker achievement of their research goals, but not necessarily better quality of research. There were concerns that most data availed by government was just basic statistical data. As much as this data was useful as demographic data for their studies, they were more interested in detailed data that could help them answer their research questions, and they obtained this data by carrying out field research themselves. There is thus need to consider use scenarios of different kinds of users during development of open data initiatives.

Different users may require different kinds of data, in different formats, and presented in different ways through open data platforms. For instance, policy researchers may be interested in detailed data while software developers may be interested in machine-readable data. Considering then that different users have different needs, there is need to explore ways in which all these requirements can be integrated in a single technical platform. This may be achieved by incorporating these requirements into the design stage of these technologies, and also during their use when the data is being published.

5.2.2. Effort expectancy strategies

Open data platforms need to be user-friendly for instance, by having robust search capability and easy navigation. Other strategies may include providing online guides and helpdesk. Effort expectancy of open data users might also be influenced by availability or lack thereof of facilitating conditions. This includes technical devices, internet speeds, and availability of organizational technical support.

Another way of increasing ease of use is through establishment of effective open data ecosystems and governance. From the results of our study, most policy researchers indicated that they accessed this basic statistical data mostly from government agencies' websites and specific government departments, followed by obtaining it from government offices in hard copy. There is need therefore to encourage digitization of government records to ease their access, and to make them available through open data technology.

Government agencies can collaborate in their open data efforts to create an effective and efficient eco-system. There is need to build capacity to enable each government agency have its own open data initiative and platform, and then the national government can have an overall platform where data from the agencies' platforms is aggregated to provide overall insights. This may achieved by having open data policies and standards, and an open data governance structure that is effective even in the grassroots.

5.2.3. Social strategies

Social influence was the second strongest predictor after performance expectancy. This finding shows that there is need to focus not only on the technology aspect, but also on social factors. This can be achieved by building open data user communities. Other social strategies may include use of success stories and case studies. These may then be shared via social media such as Twitter, Facebook, and on blogs that are regularly accessed by a certain group of potential open data users.

5.2.4. Support as a facilitating condition

Facilitating conditions in terms of availability of organisational support and technical resources was found to be very high. This may be due to high levels of digital literacy among policy researchers, availability of computing devices, and adequate internet access. However, respondents cited low availability of support and assistance in case of difficulties when using open data technology. We also noted that the Kenya open data platform had no information under the user guides tab. Therefore, there is need to train technical staff who can provide support to open data users. Other strategies may be availability of open data e-learning platforms, online guides and helpdesk.

5.2.5. Considering developing country context

For our study, the research organizations were located in urban settings. However, there is a lot of work done in the field, where there is limited internet access. Open data technology that requires internet access may be not effective or they may be too expensive to use in such contexts. There is need then to consider developing open-source open data technology that can be accessed offline. In a context like Kenya's where most people access internet via mobile phones, design of open data portals should lay emphasis on mobility. There is generally need to develop open data platforms that are customized to a developing country context, taking into consideration issues such as mode of access, capacity of users and affordability.

5.3. Recommendations for research

5.3.1. Actual use and voluntariness of use

In this study, we did explore how intention to use open data technology influences actual use. We also did not explore the influence of voluntariness of use as a moderator as there was no yet any open data law or policies in Kenya. If mandatory use of open data technology in Kenya emerges, voluntariness of use can be explored in future open data research in Kenya. Future research can also explore applicability of UTAUT model in the context of actual use.

5.3.2. Facilitating conditions in developing countries

Our study was carried out in Kenya, which is a developing country. Contrary to our hypothesis, facilitating conditions was established to be highly insignificant. This may be attributed to the fact that most policy researchers may be tech-savvy. Majority of the respondents were able to access and use computers, mobile phones and tablets. This may be attributed to increasing availability of affordable gadgets and cheaper internet access in Kenya, plus that their organisations freely availed these resources. However, this may not be the case for all citizens or potential users of open data platforms especially those in rural areas and low-income earners. There is thus need to explore further whether facilitating conditions may be a significant factor when other kinds of users are considered.

5.3.3. Theories specific to the open data context

It is important to consider the context of a system and conditions specific to it (Orlikowski, 2000). Therefore, there is need of research that addresses the distinctive and diverse characteristics of open data such as legal and economic aspects, institutional complexity and heterogeneity of users. Thus, there is need to develop adoption theories specific to the open data context. Open data is an ecosystem incorporating diverse fields and thus multi-disciplinary research would be very useful.

5.4. Conclusion

Many governments around the world have made significant progress in ensuring that government datasets are availed through technologies such as open data platforms. However, these platforms and the open data in it have little intrinsic value if they are not used. There needs to be more focus not only on provision, but also on usage of these technologies. By using the UTAUT model this study assessed factors that influence policy researchers' intention to use open data technology in Nairobi, Kenya. Benefits gained from using open data platforms, such as improved performance at work, were found to be the best motivator to use these technologies. Other highly significant factors were social and peer influence, and ease of use. Overall, it was established that open data technology are useful, but more effort is needed to encourage their use.

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APPENDICES

APPENDIX I: Introduction Letter

UNIVERSITY OF NAIROBI
COLLEGE OF BIOLOGICAL AND PHYSICAL SCIENCES
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P.O. Box 30197
Nairobi
Kenya

Our Ref: UON/CBPS/SCI/MSC/ITM/2014

23 June 2016

TO WHOM IT MAY CONCERN

Dear Sir/Madam

RE: CECILIA WANGECI MUIGA: REG. NO. P54/72777/2014

This is to confirm that the above named is a bona fide student of the University of Nairobi, School of Computing and Informatics.

She is pursuing a MSc. course in Information Technology Management. She would like to collect data for her project entitled: ***"Factors Influencing Policy Researchers Intention to use Kenya Open Data in Nairobi, Kenya"*** Under the supervision of Dr. Robert. O. Oboko.

Any assistance accorded to her will be highly appreciated.

Yours faithfully

School of Computing & Informatics
University of NAIROBI
P. O. Box 30197
NAIROBI

CHRISTOPHER A MORUTI
DEPUTY DIRECTOR
SCHOOL OF COMPUTING & INFORMATICS

APPENDIX II: Questionnaire

QUESTIONNAIRE

The aim of this questionnaire is to collect information on the use of open data tools for policy research in Kenya. Data is open if anyone is free to use, re-use or redistribute it.

Section A: Background Information

1. Gender: (Tick where applicable)

   Male [ ] Female [ ]

2. Age in years: (Tick where applicable)

   20-25 [ ] 26-35 [ ] 36-45[ ] 46-55[ ] 56 and above [ ]

3. Highest level of education: (Tick where applicable)

   PhD [ ] Masters [ ] Degree [ ] Diploma [ ] other (specify)…………………..

4. Nature of organization: (Tick where applicable)

   Public Sector [ ] Private Sector [ ] Civil Society Organization or NGO [ ]

5. Experience in using open data tools (e.g. visualization software, online data catalogues) (Tick where applicable)

   Experienced (I am conversant with open data tools) [ ]
   Beginner (I recently started using open data tools) [ ]
   No experience (I have never used open data tools) [ ]

6. Which of the following sources of Kenya public sector open data have you obtained data from before? (Tick where applicable)

   i. Websites of individual government agencies [ ]
   ii. Government agencies' offices in soft copy [ ]
   iii. Kenya open data website/platform (opendata.go.ke) [ ]
   iv. Government agencies' offices in hard copy [ ]
   v. Other (specify)..

   If you selected (iii) in Question 6 above, kindly fill Section B and Section C, else fill Section C only.

SECTION B: Use of Kenya Open Data Platform

7. How often do you use the following sources to obtain Kenya public sector open data? (Tick where applicable)

	Frequency				
Source	Monthly or a few times per month	Yearly or a few times per year	Weekly or a few times per week	Only used once	Less than once per year
Websites of individual government agencies					
Government agencies' offices in soft copy					
Kenya open data website/platform (opendata.go.ke)					
Government agencies' offices in hard copy					

8. The following open data tools found on the Kenya open data platform (opendata.go.ke), are useful in policy research (Tick where applicable)

		Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Tool	**Definition**	1	2	3	4	5
Open data catalogue	A list of datasets. Open data catalogue has built-in support for various data formats (e.g., CSV, XML, JSON, etc.) Typically, each dataset is available as a unique and permanent URL, which makes it possible					

	to cite and link to the data directly.					
Metadata	This is "data about data." Metadata provides information about a dataset e.g. source of data, its structure, underlying methodology, topic, geographic and/or chronological coverage, license, when it was last updated, publication date, attribution etc.					
Visualization tools	Enable one to preview data prior to download e.g. in form of pie chart, line graph, bars, etc.					
Search and filter tools	Enable one to search for a certain dataset, and/or filter a dataset based on contents, by setting certain conditions.					
Application Programming Interface	APIs allow access to the open data catalogue through software. They facilitate data discovery, analysis, catalogue integration, harvesting of metadata from external sites and a host of applications.					
Filtered user views	Data views and visualizations that have been created by fellow users of an open data platform					
Discussion feed	Shows the conversation and activity around a dataset.					
Embed code	Enables one to publish a dataset on the Internet at large.					
Export function	Enables one to download a dataset in a static format e.g. txt					

Blog	Gives stories from data that might not be immediately obvious.					
Data suggestion	Enables one to request for certain data or certain filtered views.					
Support/feed back	Enables one to request for technical assistance and to give feedback.					

9. Performance Expectancy-Usefulness of open data tools (Tick where applicable)

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
	1	2	3	4	5
Using open data tools helps one to accomplish research more quickly					
Using open data tools leads to better quality of research output					

10. Effort Expectancy – Ease of use of open data tools (Tick where applicable)

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Learning to use open data tools is easy	1	2	3	4	5
Open data tools are easy to use					

11. Social influence- Others (friends, colleagues, etc.) use open data tools (Tick where applicable)

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
	1	2	3	4	5
People who influence my behaviour use open data tools					
People who are important to me (e.g. family, friends, colleagues) encourage me to use open data tools					

12. Facilitating conditions- Availability of technical resources and organisational support (Tick where applicable)

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
	1	2	3	4	5
My organisation supports the use of open data tools (e.g. through provision of internet access)					
I have technical resources for using open data tools (e.g. computer)					
I can easily get assistance in case of difficulties in using open data tools					

13. Behavioral Intention (Tick where applicable)

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
	1	2	3	4	5
I intend to use open data tools in the future					
I plan to use open data tools in the future					

SECTION C

14. Please select the challenges experienced when accessing and using Kenya public sector open data: (Tick where applicable)

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
	1	2	3	4	5
Irregularly updated datasets					
Inadequate datasets					
Irrelevant datasets					
Difficult procedures of accessing data					

Thank you!