2020

User Perception of the U.S. Open Government Data Success Factors

Joy Alatta
Walden University

Walden University

College of Management and Technology

This is to certify that the doctoral study by

Joy Alatta

has been found to be complete and satisfactory in all respects,
and that any and all revisions required by
the review committee have been made.

Review Committee
Dr. Nicholas Harkiolakis, Committee Chairperson, Information Technology Faculty
Dr. Jodine Burchell, Committee Member, Information Technology Faculty
Dr. Steven Case, University Reviewer, Information Technology Faculty

Chief Academic Officer and Provost
Sue Subocz, Ph.D.

Walden University
2020

Abstract

User Perception of the U.S. Open Government Data Success Factors

by

Joy Alatta

MS Walden University, USA, 2018

MS, Middlesex University London, UK, 2001

MBA, Lagos State University, Nigeria, 1998

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Information Technology

Walden University

2020

Abstract

This quantitative correlational study used the information systems success model to examine the relationship between the U.S. federal departments' open data users' perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data from U.S. federal departments. A pre-existing information system success model survey instrument was used to collect data from 122 open data users. The result of the standard multiple linear regression was statistically significant to predict the intent to use the U.S. open government data $F(3,99) = 6479.916$, $p < 0.01$ and accounted for 99% of the variance in the intent to use the U.S. open government data ($R^2 = .995$), adjusted $R^2 = .995$. The interdependent nature of information quality, system quality, and service quality may have contributed to the value of the R^2. Cronbach's alpha for this study is $\alpha = .99$, and the value could be attributed to the fact that users of open data are not necessarily technical oriented, and were not able to distinguish the differences between the meanings of the variables. The result of this study confirmed that there is a relationship between the user's perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data from U.S. federal departments. The findings from this study might contribute to positive social change by enabling the solving of problems in the healthcare, education, energy sector, research community, digitization, and preservation of e-government activities. Using study, the results of this study, IT software engineers in the US federal departments, may be able to improve the gathering of user specifications and requirements in information system design.

User Perception of the U.S. Open Government Data Success Factors

by

Joy Alatta

MS Walden University, 2018

MS, Middlesex University London, 2001

MBA, Lagos State University, Nigeria 1998

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Information Technology

Walden University

2019

Dedication

I dedicate this study to the memory of my late mother, who advocated for equal educational opportunity for the girl child and imbibed in me the importance of getting a quality education.

Acknowledgments

I give glory to God for the grace to make the doctorate dream a reality. Despite all the distractions and drama of life, God strengthened me and gave me the wisdom to have a laser-sharp focus on HIM because His grace is sufficient for me. Glory be to God for having given a loving family, especially my sister Chidinma, who unknowingly laid the foundation for my career in information technology when she paid for my first training in the use of computers. Thank you all for all the support. I am very grateful to my dissertation committee chairperson Dr. Nicholas Harkiolakis, whose mentorship, timely provision of feedback, leadership, and advice enabled me to learn from him and keep focused on completing the study. I am grateful to Dr. Jodine Burchell as my dissertation committee member, whose thoroughness and inputs supported my progress. I am also thankful to Dr. Steven Case as the university research reviewer for his valuable contributions to my study and mentorship at the DIT residency sessions. All the participants that spared a portion of their time to complete the questionnaire for this study are the stars that helped the light of this study to shine, and I appreciate your support and inputs. The journey to concluding this study was difficult, but other DIT students helped to lighten the burden. I give you all a shout out appreciation and wish you successful completion of your research.

Table of Contents

List of Tables

List of Figures

Section 1: Foundation of the Study

The open government data project promotes the opportunity for citizens to exploit the data and have the ability to use the data for the development of civic and business applications including welfare, security, and healthcare (Cabitza, Locoro, & Batini, 2015). Though open data is expected to contribute and enhance the democratic processes, there is the need to collect specific user-centric requirements for designing open data platforms. Many researchers have conducted studies that indicate low usage of open data (e.g. Jurisch et al., 2015), provision of inaccessible, low quality, and unusable open data (e.g. Chu & Tseng, 2016; Dawes, Vidiasova, & Parkhimovich, 2016). The three tenets of quality identified by DeLone and McLean (2003), system quality, information quality, and service quality, were used in this study. The purpose is to examine the relationship between the U.S. federal departments' open data users' perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data. I reviewed works of literature that described the potentials and challenges of open data, important drivers of open government data, and the gaps in understanding how open data providers can make open data usable. I evaluated the foundation for providing an enabling environment for improving open data information systems through understanding the perception of open data users and intent to use open data. Based on the findings of this study, practitioners could make informed decisions to contribute to the long-term success of businesses and organizations through designing and implementing open data information systems that can improve and promote the usage of open data.

Background of the Problem

Open data refers to data that is freely available and accessible online for re-use, distribution, and universal participation by application developers, organizations, and citizens (Bannister & Connolly, 2014), without limitation for commercial or noncommercial purposes. In the government sector, open data enables ease of discovery of government information, generating contextually relevant information and improving efficiency. Open data can be used to determine the efficient allocation of resources, capacity boosting, improve efficiency, and effectiveness of decision making (Hellberg & Hedström, 2015) in business and organizations. The open data standards (Project Open Data, n.d.) defined a set of specifications for publishing data for every object, including the use of schematic, semantic, and atomic standards (Raggett, 2017). The success of open data depends on its ability to meet the variety of intended use and disparity in user's needs. Many open data portals publish low-quality data using diverse formats like lack of schema descriptions (Sadiq & Indulska, 2017) that make the data hard to find and almost impossible to use (Weerakkody, Irani, Kapoor, Sivarajah, & Dwivedi, 2017).

State governments and other organizations have set up open data platforms, data repositories, and catalogs to meet the objectives of open data (Hossain, Dwivedi, & Rana, 2016). The open data portal set up by governments is described as the open government data (OGD), and this study is focused on the OGD. Jurisch, Kautz, Wolf, and Krcmar (2015) noted that OGD is published without recourse to users, which results in frequently low usage. The low usage level of open data portals reported by many researchers (see Jurisch et al., 2015; Susha, Grönlund, & Janssen, 2015a; Viscusi, Castelli, & Batini,

2014) has necessitated the need to understand the relationship between user's perception of the quality of open data and the intent to use that data.

Problem Statement

Open data users face usage challenges due to the low quality of the datasets open data providers release (Vetrò et al., 2016). Danneels, Viaene, and Van den Bergh (2017) described some of the quality problems reported by practitioners as the absence or poor documentation of datasets and inconsistent technical formats. About 75% of the U.S. municipalities published open datasets without describing each available dataset on their portals (Thorsby, Stowers, Wolslegel, & Tumbuan, 2017). The general IT problem is the lack of practical knowledge of the open standards data quality by publishing data in various other standards. The specific IT problem is that some IT software engineers in the U.S. federal departments lack information about the relationship between the U.S. federal departments' open data users' perception of the systems quality, perception of information quality, perception of service quality, and the intent to use open data.

Purpose Statement

The purpose of this quantitative correlational study was to examine the relationship between the U.S. federal departments' open data users' perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data. Despite all the potentials of open data to spur open governance and enable the creation of social value and innovative services, open data providers are not yet clear on how to realize the potentials in practice. Many researchers (e.g. Kapoor, Weerakkody, & Sivarajah, 2015; Susha et al., 2015a; Zuiderwijk, Shinde, & Janssen,

2018) have identified the various challenges of using open data but did not fully address how to mitigate the challenges. The independent variables of my study are the perception of system quality, perception of information quality, perception of service quality, and the dependable variable is the intent to use open data. The population for this study is users of the open data. The anticipated positive social change is that an easily accessible and usable open data may result to citizens and organizations having access to data that can be used to study government transparency, plan smart cities, create product and services that increases the quality of life of the citizens and organizations.

Nature of the Study

I used a quantitative methodology approach to examine the relationship between the U.S. federal departments' open data users' perception of the systems quality, perception of information quality, perception of service quality, and the intent to use open data. Quantitative methods enable the use of statistical techniques that allow researchers to examine the relationships between variables with elements that can be reduced to numerical codes for accurate analysis and reproducibility (Basias & Pollalis, 2018). I chose the quantitative method for this study because the purpose of this study is to examine the relationship between variables using statistical methods that can allow for the testing of hypotheses rather than understanding human experiences. Qualitative research is used to study and understand human experiences as described by the group or the individual that had the experience and from the perspective of the researcher (Kaur, 2016). The qualitative method was not chosen as the research question does not seek to understand human experiences. Mixed methods research combines the qualitative and quantitative data in a single research project, to enable exploration of complex phenomena while giving equal attention to each of the methods (Halcomb & Hickman, 2015). Mixed methods research is not an appropriate choice because this study does not need a mix of quantitative and qualitative methods. Because this study examines the relationship between variables, which requires the use of statistical analysis, the quantitative method is the most appropriate.

A quantitative correlational design was chosen for this study because of the primary purpose, which is to examine the relationship between the identified independent variables and the use of open data. The quantitative correlational methodology is used to determine if there is a relationship between two or more variables within a population, and to what extent if there exists a relationship (Apuke, 2017). This study used a nonexperimental cross-sectional correlational analysis design because of the key objective of the study to examine the relationship between U.S. federal departments' open data users' perception of the system quality, perception of information quality, perception of service quality and the intent to use open data. The experimental design randomly assigns and manipulates variables to understand the causal relationship between the variables (Stichler, 2016). Experimental design was not considered an appropriate choice because the study does not require randomized manipulation of the variables. The quasi-experimental design uses a nonrandomized approach to assign and manipulate variables (Waddington et al., 2017). A nonrandomized approach to manipulation of variables was not considered for this study because the approach contradicts the objective of the study, which is to examine the relationship between the variables. Experimental and quasi-experimental designs were not appropriate for this study because this study examines the relationship between variables and not to manipulate or control the variables.

Research Question

DeLone and McLean (2003) proposed six core variables to study information system success as information quality, system quality, service quality, (intention to) use, user satisfaction, and net benefits. The variables deemed appropriate to meet the focus of this study are the system quality, service quality, information quality, and intent to use. In alignment with the purpose of this study, the central research question (CRQ) of this research was as follows:

RQ1: What is the relationship between the user's perception of the systems quality, perception of information quality, perception of service quality, and the intent to use open data from U.S. federal departments?

H_0: There is no relationship between the user's perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data from U.S. federal departments.

$H_{\square}$: There is a relationship between the user's perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data from U.S. federal departments.

Theoretical Framework

This quantitative correlational study used the information systems success model, as developed by DeLone and McLean (2003), to present a more integrated approach to measuring IS success. The expanded mathematical theory of communication (Shannon & Weaver, 1949) is the anchor of the information systems success model. The model defined six key dimensions of information systems: (a) information quality, (b) system quality, (c) service quality, (d) (intention to) use, (e) user satisfaction, and (f) net benefits. The 2003 model was an update of DeLone and McLean’s 1992 model which defined the six key dimensions of information success as system quality, information quality, use, user satisfaction, individual impact, and organizational impact. The constructs for this study were (a) information quality (b) system quality (c) service quality, that served as the independent variables, and (d) intent to use, which served as the dependent variable. The framework is useful for studying human-centered- technology and usability issues in information systems and eGovernment systems (Scott, DeLone, & Golden, 2016).

This study is focused on understanding the relationship between the U.S. federal departments’ open data users’ perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data. The information systems success model can be applied to this study using the systems quality, information quality and service quality as the independent variable, while the intent to use is the dependent variable. The model has six variables, but I only used four of the variables. The other two variables are outside the scope of this study because the target is at the individual user level and not at the system level that requires measuring user satisfaction and net benefits. The success model is chosen for its suitability towards understanding information systems' success by classifying the measures to determine information systems success. Figure 1 is developed based on the theory of the information system model of DeLone and McLean 2003.

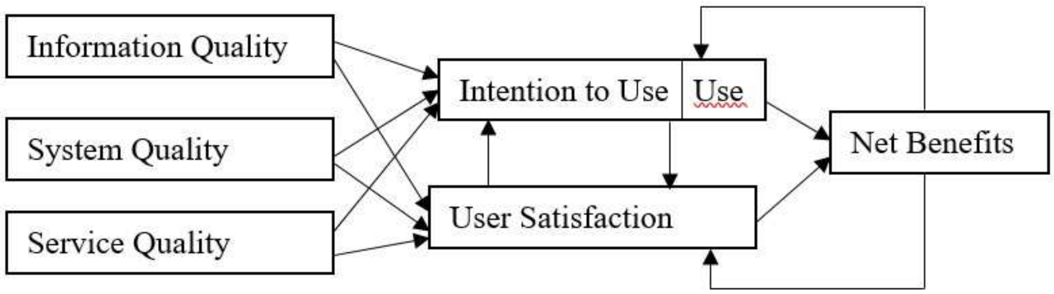


Figure 1. Information system success model.

From "The DeLone and McLean model of information systems success: a ten-year update" by DeLone, W. H., and McLean, E. R. (2003). Copyright 2003 by the *Journal of management information systems.*

Definition of Terms

The following are the definitions of the key terms used throughout this study.

5-Star model: A rating model proposed by Berners-Lee and adopted by the open definition as the standards for grading the conformance of web data portals to the principles of open access, open license, and open formats (Bello, Akinwande, Jolayemi, & Ibrahim, 2016).

Information quality: Information quality refers to the measure of the value of the content of information systems with regards to the fitness for use in a specific context (McNab & Ladd, 2014).

Metadata: The description of the data about data (Schauppenlehner & Muhar, 2018).

Open data: Data that is freely available for use and reuse by anyone and for any purpose (Sadiq & Indulska, 2017)

Open government data (OGD): The open data portal set up by governments state agencies (Jurisch et al., 2015)

Open standards: The open standards are format definitions for the publication of web data based on the three core principles of open license, open access, and an open format (Valdivia, & Navarrete, 2016).

Service quality: The service quality describes the system support available to the user from the service provider (Jing & Wenting, 2014).

Assumptions, Limitations, and Delimitations

Assumptions

Yang, Liang, and Avgeriou (2017) described an assumption as a fact or statement taken for granted and accepted as true or as certain to happen but without proof. Quantitative methods employ statistical quantities, theoretical entities, and empirical facts to study a phenomenon (Pang, 2016). I made certain assumptions, including that the measuring instrument was understandable and would not confuse the participants, and that the instrument reliably captured the intended variables and not something else. It was assumed that the quantitative methodology, correlational research design, and purposive sampling data collection chosen for this study were appropriate and suitable for answering the research question and hypothesis. The participants were assumed to be people who understand the importance of giving clear and accurate responses that can be quantified and compared. Other assumptions included that respondents are familiar with the open data concept, have used the U.S. open data portal, and were willing to participate in research.

Limitations

Farooq (2017) referred to the limitation of a study or research as the systematic bias that could affect the result of the study and yet was not controlled because the researcher could not control it. The perspectives of the users of the open data portal of the U.S. federal departments were collected using nonprobability purposive sampling. The use of a nonprobability sampling method for this study could limit the findings from being generalized to other open government data portals. The methodology and research design may impose limitations and the outcome of the research (Horga, Kaur, & Peterson, 2014). The use of quantitative methods for the collection and analysis of data in this study may pose some limitations on how the data is collected and analyzed, including how the outcomes of the study are interpreted. The data collected may not be appropriate for answering the research question. Though the participants may be familiar with the open data concept and have used the U.S. open data portal, they may not be available to give accurate information that reflects their perceptions.

Delimitations

Delimitations in research refer to the boundary imposed by its scope (Manescu, 2014). The scope defines the boundaries that the researcher placed on the study (Dean, 2014) by the choices made in the research design and methodology. In this study, the choice of the research question, variables, nature of the study, population, theoretical framework, and the data collection method posed a limitation to the study. There is a geographical perspective that delimits the research as the participants are the users of the U.S. federal departments' open data portal. The participants are delimited to individuals with specific characteristics. Using a quantitative method delimits the expression and full description of the phenomenon to only the variables under investigation in this research.

Significance of the Study

In this study I evaluated the foundation for providing an enabling environment for improving open data information systems. The low information quality and inability to meet the technical standard expected by users (Jurisch et al., 2015) can be improved upon by evaluation of the system to understand stakeholder needs. This study was focused on providing an analysis of the system to enable open data providers to present data in a usable format. The significance of this study to the IT profession is emphasizing the use of empirical research to determine ways of fulfilling the technical responsibility of presenting open data in a usable format (Charalabidis, Alexopoulos, & Loukis, 2016). Identifying the solution to surmounting the technical challenges of open data (Hossain et al., 2016) will enhance the IT profession in the development of best practices in the development of information systems that meet its stated objective.

The potential for positive social change in this study is that an easily accessible open dataset that is interoperable and reusable may help to solve problems in the healthcare, education, energy sector, and the research community (Sansone, Cruse, & Thorley, 2018). With data sharing, clinical science research is set to explode with the new world of open data and the potential to enrich healthcare research (Dey et al., 2017) because of its ability to improve the practice of medicine to save more human lives. Open government data project promises to allow citizens to exploit the data and perform a comparative analysis of the performance of publicly funded organizations, especially in the welfare, security, and healthcare (Cabitza, Locoro, & Batini, 2015).

A Review of the Professional and Academic Literature

This literature review provided four major sections, including the theoretical framework, open standard format, overview of open government data, supporting, and alternative theories. In order to fully examine the subject matter of this study, the major sections are further divided into subsections that provide a detailed description of the subjects. The overview of the open government data has subsections of open data metadata quality, the potential value of open data, stakeholders of open data, and the challenges of open data. The theoretical framework has subsections of information quality, system quality, service quality, intention to use/use, user satisfaction, and net benefits. The supporting and alternative theories have a subsection of technology acceptance model, unified theory of acceptance and use of technology, and the task-technology fit.

The sources that I have studied and cited for references in this study was a total number of 292, of which 264 (90%) were within 5 years, and 266 (91%) are peer-reviewed. The literature review includes 257 research publications of which 239 (93%) are within 5 years, and 234 (91%) are peer-reviewed. The primary libraries and databases that I used to conduct the study are ProQuest Central, ScienceDirect, Association for Computing Machinery (ACM), IEEE Xplore and Google Scholar. Some of the main keywords used included *benefits and barriers of open data, facilitating and motivating* *factors of open government data, open data adoption, open data models, open government data portals, metadata of open data, usability of open data, use of open data, Information system success, Information system success theory, citizen evaluation of Open data, multiple regression analysis, reliability analysis,* and *validity analysis.* Each of the search keywords or phrases returned several results and I screened the results for relevancy. The relevant articles are downloaded, and their abstracts are evaluated to search for a semblance of relevancy. If there was an indication that the contents may be relevant, then an in-depth study of the article was conducted. I also study the references to search for a potential article that that may provide a good lead for relevant articles.

Application to the Applied IT problem

The purpose of this study was to examine the relationship between the U.S. federal department open data users' perception of the system quality, perception of information quality, perception of service quality, and the intention to use open data. The null hypothesis states that there is no relationship between the user's perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data from U.S. federal departments. The alternate hypothesis states that there is a relationship between the user's perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data from U.S. federal departments. Analysis of the literature showed that open data may have the potential to impact the citizens and entire society of the human race in a positive way that includes improvement in healthcare management, efficient use of resources, and effective decision-making process for businesses and organizations. Some researchers have conducted many studies that indicate low usage of open data (e.g. Jurisch et al., 2015), provision of inaccessible, low quality, and unusable open data (e.g. Chu & Tseng, 2016; Dawes et al., 2016). Others include important drivers of OGD (e.g. Janssen, Konopnicki, Snowdon, & Ojo, 2017), and the importance of ex-post evaluation of information systems by the users (Roky & Al Meriouh, 2015). All the research conducted on open data so far revealed gaps in understanding how open data providers can make open data usable. An objective of this study is to provide critical insight to open government data providers to enable the provision of usable and high-quality open data using open standards format.

Theoretical Frameworks

Information Systems Success Theory

The DeLone and McLean (2003) model of information systems success was first proposed in 1992 as a framework for measuring the dependent variable of information systems success and was improved and updated in 2003. The original model is based on the information influence theory by Shannon and Weaver (1949). DeLone and McLean's (1992) theory is based on the importance of measuring the various and possible interactions of information systems variables to understand their dependencies. The variables are system quality, information quality, service quality, information use, user satisfaction, individual impact, and organizational impact. After various studies from other researchers and considerations of their inputs, the information systems success model was updated with the variables of system quality, service quality, information quality, intention to use/use, user satisfaction, and net benefits. DeLone and McLean (2003) described three major dimensions of quality, referred to as information quality, service quality, and systems quality, which must be measured separately. Use and user satisfaction are closely related because positive experience with use can lead to *user satisfaction*. The potential of information systems and their many associated benefits are evidenced in the accelerated growth of the use of information systems. The theoretical framework of this study is based on the model of DeLone and McLean (2003), which many authors referred to as still being very relevant and the best model for measurement of IS success (Zohreh et al., 2017). DeLone and McLean (2003) information system success model has been used extensively for the evaluation of several types of information systems using the six variables of information quality, system quality, service quality, intention to use/use, user satisfaction, and net benefits.

The three tenets of quality identified by DeLone and McLean (2003), which are system quality, information quality, and service quality, are used to measure the quality of the OGD portal of the U.S. federal departments. Rana, Dwivedi, Williams, and Weerakkody (2015) performed a study to validate the DeLone and McLean (2003) in the context of government to citizen (G2C). Rana et al. (2015) emphasized the need to highlight the ease of use and usefulness of the system and to ensure that the risks associated with using the system are minimal. Ojo (2017) maintained that system quality is an important measure of hospital information systems and validated the DeLone and McLean using the context of hospital information systems in five Nigerian teaching hospitals. Mudzana and Maharaj (2015) emphasized the need to evaluate the DeLone and McLean model of information quality.

Information Quality

Information quality refers to the measure of the value of the content of information systems with regards to the fitness for use in a specific context (McNab & Ladd, 2014). The different contexts of the use of information make it useful to consider different user perspectives in trying to improve the quality of information. The growing importance of IS is causing many of the stakeholders like scholars and practitioners to continue to seek a solution on how to improve its quality and functionality (Dwivedi et al., 2015). Information quality can be used to describe the content and characteristics of the output of a system. DeLone and McLean (2003) stated that information quality has been prominently used to measure information systems and can be described to include completeness, relevance, ease of understanding and security of information. The relevancy measure relates to the content and the context determines desirability. Evaluation of information quality using the nonspecific context criteria may lead to ambiguity in the definition of the quality criteria.

Vetrò et al. (2016) defined data quality using the ISO 25012 and standard fitness for use. Todoran, Lecornu, Khenchaf, and Caillec (2015) described the information quality as being equivalent to the degree of confidence that a user had on the IS and emphasized the need to optimize the quality of each part of an information systems. Evidence from practitioners indicates that OGD sprang up so fast that datasets were published without proper quality control. The lack of quality control mechanisms may have a negative impact on the use and reuse of open datasets (Vetrò et al., 2016). Wang and Strong (1996) described quality information as being fit for use and identified four categories of data quality named intrinsic, contextual, representational, and accessibility. The description of fit for use is viewed from the subjective perception of the user, who ultimately evaluates the usefulness regarding context. Information quality means different things to different people.

In a study by Roky and Al Meriouh (2015), it was determined that a high level of information quality has a positive impact on user satisfaction and that quality of information has a positive influence on the intention to use. Hjalmarsson, Johansson, and Rudmark (2015) identified that difficulty of finding and using the relevant data, inconsistencies in data quality, and formatting are hindering software developers in their bid to use open data. What constitutes a competitive advantage in the use of information systems is the data and the information that the system can output. Dedeke (2000) described a high information system quality as one that can be used with minimal effort and identified five information quality categories as representation, contextual, accessibility, ergonomic, and transactional quality. Pipino, Lee, and Wang (2002) described high-quality data as data that is fit for use by data consumers. Information systems professionals need to understand the broader concerns of data consumers. In a study to investigate the relationship between information quality dimension in the e-banking service in Palestine, Ayyash (2017) indicated that accuracy, completeness, timeliness, and relevancy of information has a positive effect on customer satisfaction.

The quality of an information system may have an impact on the wellness of the user. Gopinathan and Raman (2016) researched the role of information systems quality on work-life balance using Malaysian information and communication technology (ICT) employees. A sample population of 79 respondents was used to collect data, and it was concluded that the information quality, system quality, and service quality have a direct effect on employees' work-life balance. The participants in Gopinathan and Raman (2016) implied that the participants preferred clear, well-formatted, and easy access to information to prevent long operational hours that results in stress and the lack of quality family time.

The effectiveness of government service depends on information quality. Alenezi, Tarhini, and Sharma (2015) investigated the relationship between improvements in information quality, benefits, and performance of e-government. The findings indicate that usability and usefulness attributes of information quality have a key influence on both strategic benefits and institutional value. Russo, Ciancarini, Falasconi, and Tomasi (2018) described information quality as relating to its content, which can be measured with item completeness, ease of understanding, personalization, relevance, and security. Information systems quality (ISQ) is considered a critical source of competitive advantage for organizations, especially in an increasing era of competition with digital services. The main issues are affecting data accessibility include data availability, data performance, and data security policy. Several examples of quality problems with OGD, as reported by practitioners, include the absence of metadata, incomplete data, the use of different schemas and ID for different departments, inaccurate data, data inconsistency, and lack of timeliness (Danneels et al., 2017). Data quality has a very crucial role to play in decision making, planning, and enabling access to the data. Standardization of data quality is expected to improve the accessibility of data.

System Quality

Information systems have become more relevant to organizational performance than in the last decade. DeLone and McLean (2003) described system quality as the usability, availability, reliability, adaptability, and response time of a system. The need to understand the success of information systems is a concern for researchers and practitioners (Subiyakto, Ahlan, Kartiwi, & Sukmana, 2015). The opportunities that using information systems opens for business include the improvement of the capability for the collection, processing, distributing, and sharing data in the web 2.0 era (Campos, 2016). The ease and speed of processing information improve efficiency, minimalizes geographical borders, and may improve productivity and profitability. Evaluating information systems is usually not an easy task considering their diverse stakeholders and their perspectives (Mahmood & Miller, 2017).

The quality of an information system is made up of the characteristics that made it desirable for users to want to use it (DeLone & McLean, 2016). These are the usability aspects, which include ease of use, efficiency, navigation, and reliability. The system quality is often described from the perspective of convenience and hardware performance (Liu, Jin, & Nam, 2017). Information systems are expected to simplify and satisfy user needs. Budiardjo, Pamenan, Achmad, Meyliana, and Cofriyanti (2017) described system quality as being measured by several factors that include the user interface, ease of use, quality and maintenance of program code. A good quality program code is expected to contain no bugs, facilitates user productivity, and can increase users' perceptions of the usefulness of the system (Smith, Zeng & Carette, 2018). There have been notable changes in the use of information systems as it shifts from simple tasks, like classification problems, and processing homogeneous data to more complex usage (Todoran et al., 2015). The information system of today stores large amounts of heterogeneous data, unlike in the past (Campos, 2016). Changes in the volume of data stored and its quality of data is assumed to impact information system performance.

The characteristics of the information in a system are used to describe the system quality. Rosdini and Ritchi (2017) described users' confidence with the quality of a software system as affecting the use of such a system. In the context of an open data website, system quality relates to the degree to which a website possesses desired capabilities such as availability, reliability, and response time, network speed, and security of the system (Máchová, & Lnenicka, 2017). The measurement of the properties of efficiency, availability, reliability, and security sums up the system quality which should satisfy customers' needs. Lee and Kim (2017) stated that the inability of a system to satisfy users' requirements could influence continuance usage intention. Dependence on information systems continues to grow as organizations and institutions leverage the use of information technology for service delivery. Dos Santos, Santoso, and Setyohadi (2017) analyzed the impact of user intention on an academic information system using the DeLone and McLean (2003) information system success model. The result of the study shows that system quality influences information quality, and service quality influence the intention to use.

Accessibility to an information system can be described as the ease and quick retrieval of useful information (Theophil, Kalegele, & Chachage, 2017). System requirements are as diverse as users, and that results in the use of different technologies. In an interconnected world, an information system cannot be expected to function in isolation and causes a need to ensure that information systems can communicate with other systems to facilitate the exchange of data for transaction communications (Theophil et al., 2017). Efforts to promote access to information and communication technology solutions for all is creating the need to understand accessibility metadata. Beyene (2017) described metadata as the fabric that holds together components of the newer generation accessibility solutions. Metadata can assist in bridging the accessibility and usability of an information system. A personalized usability is a significant approach to enhancing accessibility. The metadata quality enriches the usability of a system. Digital resources producers such as digital libraries, eLearning centers, and digital publishers benefit immensely from incorporating accessibility in system design (Theophil et al., 2017). Despite the importance of metadata, there is no consensus on the classification of metadata by types or functions, as many organizations have different classification for metadata. Users of digital resources, including users with disabilities, can benefit from improved visibility and accessibility through the fast discovery of relevant materials from search engines and libraries (Beyene, 2017).

System integration is said to occur when two systems establish communication rules with which to establish a communication link and agreement on the communication protocols to use for information sharing. Information system integration enables consistent information support to enable organizations to respond to the dynamic challenges in business environments. Poor integration and interoperability may contribute to the failure of ICT in organizations. Dlodlo and Hamunyela (2017) described disparate information sources and repositories, including databases, object stores, knowledge bases, file systems, digital libraries, information retrieval systems, and electronic mail systems as a common challenge for many organizations.

Some of the challenges to the effective integration of information systems include poor data quality and fragmentation, budgetary constraints, irreconcilable systems architectures, a history of incompatible data standards, privacy jurisdictions, and a lack of access to proven evaluation results (Adenuga, Kekwaletswe, & Coleman, 2015). The need for empowering efficient and effective decision-making using an integration of information systems data, processes and infrastructure is driving the maintenance of system quality. Dlodlo and Hamunyela (2017) described types of system integration models as information-oriented, process-oriented, process-oriented, service-oriented and user-oriented integrations respectively. According to the authors, information system quality includes designing the system for ease of accessibility and adaptability, security, fast response and ability to integrate with other systems.

Service Quality

The service quality describes the system support available to the user from the service provider (Jing & Wenting, 2014). Depending on the type of organization, it could be the IT department support or helpdesk. Service quality is an important aspect of business performance because of its strong impact on business profitability. Pather (2017) emphasized the need for information systems evaluation from a service perspective. Quality is always measured from the perspective of the customer, and competitive organizations try to understand customer perception of the quality of service. Though service quality outcomes and measurement depend on the type of service, measuring service can be a complex issue. As organizations continued to quest for superior service quality, the need to provide a model for evaluating service quality continues to grow. The SERVQUAL service quality model (Parasuraman, Zeithaml, & Berry, 1988) identified five dimensions of service quality named reliability, responsiveness, tangibles, assurance. Palese and Usai (2018) described the need to measure service quality adequately and used the SERVQUAL model to measure reviews from an online price comparison engine in Italy. The determinants of service quality, as described in Parasuraman et al., 1988), are access, communication, competence, courtesy, credibility, reliability, responsiveness, security, tangibles, and understanding/know your customer and used it to form the SERVQUAL model.

Service quality can be conceptualized as perceived quality versus objective quality and quality as an attitude. Silalahi, Handayani, and Munajat (2017) used the models developed by (Salameh & Hassan, 2015) and (Huang, Lin, & Fan, 2015) to measure online transportation service quality. The conclusion of Silalahi et al., (2017) is that the perceived cognitive has the highest weight under service quality, content usefulness is the highest weight under information quality, and ease of use has the highest weight under system quality. The issue of culture, attitudes, and behavior could be compounding the challenge for services delivered across cultural and geographical boundaries. Globalization and the rising interconnected economies make cross-cultural and cross-national services difficult to avoid. Zhu, Freeman, and Cavusgil (2018) studied the influential elements of cross-cultural service delivery using the service culture and service quality delivery in China, Japan, Australia, Turkey, and the USA. The results of the study recognized the effect of culture on service delivery and concluded that it is important to understand the impact of culture on service quality assessment. In a study to understand the perception and understanding of user behavior relative to service quality, Alonso, Barreda, Dell'Olio, and Ibeas (2018) identified that waiting time has the greatest impact on the perceived quality of service for online transportation. Janita and Miranda (2018) suggested that improvement in service quality depends on gathering information from users about their perception of service quality using the dimensions of reliability, security, quality of information, technical efficiency, communication, or user support.

Intention to Use/Use

The increase in the dependency of the web for almost everything ranging from seeking information, buying and selling, learning, and many other web-enabled activities have increased the need for web user interface studies because of its impact on the web usability (Islam & Islam, 2016). An open data website is a gateway to the resources and services available for the use of citizens and other stakeholders. The website plays an important role in disseminating open data information and resources to users. DeLone and McLean (2003) used web visit, navigation, information retrieval, and execution processes to describe the measurement of the intention to use/use.

Usability of a product or software refers to the efficiency of use, ease of learning, and the ability to recover from errors. Information systems are important in enabling organizations to meet their goals. This goal can only be achieved through the effective use of the information system. Suryanto et al. (2016) justified the need to measure the relationship between the desire to use, usage, user satisfaction, and benefit to the organization because of its importance to understanding and improving user expectations.

Mvungi and Tossy (2015) defined usability as the extent to which a product can be used by specified users to achieve specific goals with effectiveness, efficiency, and satisfaction in the specific context of use. Usability is an important factor in improving products and services (Khajouei, Gohari, & Mirzaee, 2018). Understanding the factors that affect usage intention of a computing resource is an important aspect of making improvement decisions. Using the methodology of dataset search and analysis, and information item definition, Cabitza et al., (2015) concluded that fitness for use and gender-related factors play a significant part in the continued use of open data. The process of evaluating the usability of a website includes verifying if the application design enables users to retrieve documents and access available services easily. Evaluations of the use of software provide an important basis for product quality improvement and monitoring of contracts. Acosta-Vargas, Luján-Mora, and Salvador-Ullauri (2017) described the success of e-government adoption as depending on design, security, and ease of navigation.

One of the ways to understand the usage of a website is to classify the data of success response and analyze user navigation (Prakash & Jaya, 2016). The traversal pattern can be discerned with the use of the users' navigation weblog. A weblog is recorded as users access the web server through web pages. Most web pages have categories and attributes that can be used to identify user behavior. Usability can be evaluated using interaction-based user evaluation, metric-based evaluation, and model-based evaluation, as is being used by search engines. Bakaev, Mamysheva, and Gaedke (2016) suggest that there are ambiguities in usability conceptualization for quantitative measurements and its dimension of efficiency and effectiveness. Effectiveness measures the ratio between successful users' action and erroneous ones, the share of utilized factors and commands, and the cognitive load on the user. Efficiency measures learnability, time to complete tasks, errors, and memorability. The difference between the two dimensions is that effectiveness relates to the completeness and accuracy, while efficiency relates to the minimization of resources for completeness' of a task in each context.

Okhovati, Karami, and Khajouei (2017) conducted a study using the Nielsen's 12 library heuristics to evaluate and identify problems with a university website and identified issues that include visibility of system status, flexibility, and efficiency of use, consistency, and use of web standards. Usability can be measured by adaptive user level, screen reading level, satisfaction, and learnability. Ain et al. (2016) explained that one of the main problems of usability is the communication gap between users' mental mode and designers' perception and conducted a study to develop an eLearning usability evaluation model that can reduce the identified gap between the mental mode of the user and the designers' perception of the user need. The findings of the study suggested that this problem can best be solved by conducting surveys, interviews, and using the feedback for website usability improvement but concluded that user surveys are best for evaluation of websites or learning management systems. The resultant effect of designing websites without understanding user needs is the design of web portals that suffer from low usage. Karaim and Inal (2017) stated that the usability of a website has a direct influence on user satisfaction. Poor usability features may result in low usage, while some users may never return to use the website again. The most violated heuristic rules, as identified by Karaim and Inal (2017), were visibility of system status, user control, freedom, helping users to recognize, diagnose and recover from errors.

Using an online evaluation tool to evaluate open data websites of 20 countries, Acosta-Vargas et al. (2017) concluded that countries like the USA, UK, China, Singapore, and Qatar, among others, did not reach the acceptable level of accessibility with evaluation criteria of priority AA. The seven commonly identified usability constructs are consistency, supportability, learnability, simplicity, interactivity, telepresence and readability. Lack of trust in e-government is noted as one of the major challenges of using e-government. Alzahrani, Al-Karaghouli, and Weerakkody (2017) evaluated several perspectives of trust using psychological, sociological, economic, computer science, organizational science, business, and marketing. Poor usability denies certain users an equal opportunity to access and use government resources.

User Satisfaction

User satisfaction is described as a positive or negative feeling with system implementation. An important success determinant of OGD is the usability of the open data websites and its ability to enable users to achieve their goals effectively and efficiently. The public sector is gaining and changing from the impact of information technology (IT) and the use of information systems, just as the citizens are gaining from them. Information system is of immense help in environments that use a massive amount of data such as the open data portals. Kasaj (2016) asserted that user satisfaction is one of the most widely used constructs in ensuring information system success. User satisfaction has been studied in many contexts. Evaluating user satisfaction in the use of information systems is key to system improvement (Saghaeiannejad-Isfahani et al., 2014).

Sebetci and Çetin (2016) studied e-prescription using the information system success model of DeLone and McLean (2003) in a correlation study and identified that use and user satisfaction were important predictors of net benefits. Chaveesuk and Hongsuwan (2017) conducted a study to identify factors that are critical to the success of ERP implementation in organizations and concluded that system quality and information quality have a direct effect on user satisfaction. Sultono, Seminar, and Erizal (2016) conducted a study to discover the relation, influences, and analysis of the quality of academic information systems towards user satisfaction in Indonesia University of Education. The result indicates that there is a strong relation between system quality, information quality, service quality, and user satisfaction. Information quality is the most important precedent for user satisfaction in the use of information systems because of the importance placed on the availability and accuracy of the information. Organization results stem from usage, and usage is preceded by user satisfaction (Almazán, Tovar, & Quintero, 2017). Website-related factors like page design and navigation impact user satisfaction, where ease of use is one of the most significant dimensions that influence user satisfaction and behavior (Zeglat, Shrafat, & Al-Smadi, 2016).

Information is now regarded as a new national resource, and a library is one of the places that can be characterized by the richness or availability of information. Library information systems provide automation and the ability to generate or develop a wide range of administrative, technical processes, databases, and other services to enhance user satisfaction (Atanda, 2017). Hong, Cao, and Wang (2017) described user satisfaction to be the overall effective evaluation of end-user experience with an information system, and the interface of a device or a website affects the ability for it to be used for specified tasks.

Many users of information systems tend to use workarounds to complete tasks that are supposed to be completed using an identified information system. The use of workarounds is often an indication that there are inherent challenges with using the information systems. In such situations, user satisfaction is likely to be lacking. Farzandipour, Meidani, Gilasi, and Dehghan (2017) evaluated information systems from the technical, functional usability, vendor capability, and care quality provided by health information systems (HIS) vendors. The study emphasized the quality of service provided, the quality of IT services including service by IT software vendors, affect user satisfaction with information systems. In a study to understand the determinants of user continuance intentions to use a mobile money service called the M-Pesa from users in Kenya, Osah and Kyobe (2017) concluded that user satisfaction is considered the most critical factor in continuance usage and utilization have direct significance effects on usage continuance with M-Pesa. As one of the most important determinants of information systems system success, user satisfaction inclusion in system development tends to help in system development.

Net Benefits

Net benefits of an information system refer to the extent to which the information system has contributed to the success of helping the stakeholder to achieve stated objectives. DeLone and McLean (2003) combined the individual impact and organizational impact from DeLone and McLean 1992 and societal impact to describe net benefits. The impact of an information system includes many stakeholders, such as the immediate user, industry, and society. Information system benefits are one of the least studied constructs because of the difficulty of generalizing across populations and contexts. All the other constructs in the DeLone and McLean (2003) information system success model is constantly being evaluated from the user perspective. Sun and Teng (2017) evaluated the net benefits from the context of information in the organization and concluded that net benefits have a strong significance for overall information system satisfaction. The net benefits of an information system include the individual, group, organizational, and even societal benefits from IT use. The concept of net benefits in the DeLone and McLean information system success model grouped all the impact measures into a single impact, or benefit category called net benefits.

An information system is assumed to be contributing to individual users for improvement in decision making, improved productivity, increased sales, market efficiency, customer welfare, creations of jobs, and economic development. Zohreh et al. (2017) evaluated a virtual education eLearning system based on the DeLone and McLean (2003) model, and the result indicated that the net benefits of the system had the highest correlation with user satisfaction. It was also identified that net benefits would be greater when the system is in a favorable condition, and that service quality has an indirect effect on net benefits.

Open Standard Format

The open standard format (Valdivia & Navarrete, 2016) is based on the three core principles upon which to describe openness named an open license, open access, and an open format. Openwork is work that is provided in a convenient and modifiable form with the data being machine-readable, provided in an open format, and can be processed with at least one free, open-source software tool (McKiernan, 2017). The convenient form could be image, text, tabular or geographic data, and its purpose is to make the work easy to be reused, shared and modified without the need for any proprietary software. Openwork as a data form must be machine-readable and in an open format without any technical obstacle like a license right (Irani & Kamal, 2016). All digital materials are not machine-readable. A PDF file with a table may not easily be parsed by a computer to access the data the way a spreadsheet can be accessed. Common open standard formats include comma-separated variables (CSV), Extensible Markup Language (XML), JavaScript Object Notation (JSON) and Resource Description Framework (RDF) (Bello et al., 2016). Other data formats that meet the open definition requirement for machine readability include application programming interface (API), Atom, five-star (linked open) data, hypertext markup language (HTML) (Krewinkel & Winkler, 2017).

Open standards are free to use and are available for anyone and for any project (Open definition (N.d), unlike proprietary standards that are not free and usually cannot use. Interoperability features of open standards enable the interconnection and integration of other software components for innovative automation of application development, growth of new businesses, and e-commerce (Lapôtre, 2017). Open standards are important in an interconnected world of web 2.0, where having a wide network of connections affect rating and performance. Technological products depend on the interoperability of other software components across the Internet (Chen, 2016). Open access to data provides opportunities for individuals and organizations to share the burden of application development in collaborative participation (Schauppenlehner & Muhar, 2018). A piece of work published in an open standard format should be published with the capacity to allow users to download the work in pieces or bulk through the internet. Open data formats by nature of being described as open must ensure usability, open access, and open formats. Open formats are required to facilitate use, reuse, and simplify data management for publishers and users (Rocca-Serra et al., 2016). Linked data provides an integrated source of a dataset that can be re-published as machine-readable linked data, to make application development an easier task (Bischof, Harth, Kämpgen, Polleres, & Schneider, 2018). Many datasets on the web are available in diverse formats, but the linked data concept is designed to enable the provision of standard structure to interlink them (Jovanovik & Trajanov, 2017). The linked data concept has introduced standards for representing, storing, retrieving data and enables the combination of data with modern semantic technologies. The production of platform-neutral data resources can aid collaboration and dissemination of information (Binding & Tudhope, 2016).

The rating of open data portals using the 5-Star model refers to the description of the data presentation and availability of data on the web. The 5-Star model rating presents the steps that can enable easy identification of the level of conformance of web data portals (Open Data Handbook, n.d.). 1-Star rating describes data that is made available on the web using an open license where the format can be in any form or standard. 2-Star is achieved if the data is presented as a structured data using proprietary software such as Excel. A 3-Star rating is achieved if the structured data is made available without a proprietary format such as CSV. Web data presented with universal resource identification (URI) to enable linking to the data achieves a 4-Star rating. The 5-Star rating is for web data that is linked to other data to enable full processing with flexibility in the choice of software using the resource definition framework (RDF). A combination of data from multiple sources is easily achieved by using RDF that identifies the data using its URLs (Bello et al., 2016). Many OGD portals published open datasets on the web without regard to the open format standards (Kucera, 2015). Open standards formats are crucial to the achievement of the objective of open government data. The level of openness of OGD (Vostrovský, Tyrychtr, & Ulman, 2015) has a direct influence on the intention to use OGD in a way to meet the objectives of OGD.

Overview of Open Government Data

Open government data (OGD) is data that is published, produced, or commissioned by a government, made freely available for use, reuse and redistributed by anyone (Jurisch et al., 2015). OGD has the objective of improving transparency in governance, encourage collaboration between the state and citizens (Saxena, 2017). The usage of OGD is expected to aid the development of smart cities (Siuryte & Davidaviciene, 2016), smart transportation, smart housing (Walravens, Breuer, & Ballon, 2014), and many other civic applications that can add tremendous value to civil societies, governments, and organization. Transparency may be achieved when the citizens have more control over how they gain access to raw data and influence the level of their aggregation. While the intermediary between the government and the public are the open data websites or portals, only a few of those intermediaries provide the processes and procedures to enable transparency (Janssen, Matheus, Longo, & Weerakkody, 2017). One of the objectives of open data is to allow citizens to participate in the governance process. The objective is when the governance-related data is made openly available and in real-time. Real-time availability of governance data enables citizens to provide inputs before a government decision is finalized.

OGD is widely accepted around the world for its potential benefits in improving the transparency of government departments, strengthen the public participation of and decrease the distance between government agencies and citizens (Lourenço, Piotrowski, & Ingrams, 2017). It is a widely held notion that government agencies facilitate data collection by utilizing tax money from citizens, therefore, the government should make the data to be easily available to the citizens. Saxena (2017) noted that though transparency is one of the core objectives of open government data, the logical target is supposed to be the extent to which data usage is facilitated. Meeting the objectives for setting up open data sites is proving difficult in practice because various open data portals were not designed from a user perspective. After studying open government data initiatives at different government levels in 61 countries, Zuiderwijk et al., (2018) concluded that there is a mismatch between the benefits delivered and the objectives of open data.

There is a big gap between the availability of open data and the use of open data due to the challenges in using open data portals in a way that enables the reaping of all the benefits of the open data initiative (Charalabidis et al., 2016). The availability of open data is not an indication of achieving the objectives of open data initiatives (Csáki & Prier, 2018). Universal participation and usage are the keys to unlocking the economic value of open data. The uptake and usage of open data have not been as envisaged, and this has been attributed to issues like inconsistencies in the data standards and accessibility protocols. The way open data is delivered determines and shapes the way it is used. Sieber and Johnson (2015) determined that the way open data is currently provided is at crossroads with the objectives of OGD and challenged the mission accomplished attitude of governments, urging them to acknowledge the challenges of users and developers.

Improving data accessibility, availability, reusability, re-distribution, and participation is core to the full maturity potential of OGD. Thorsby et al., (2017) used regression models on a descriptive study to categorize and describe 37 open data portals in US cities and emphasized that the actual value of OGD lies in the application and use of the datasets. Chu and Tseng (2016) stated that the success of OGD is determined by its accessibility, quality of data, security and platform functions. Cantor et al. (2018) described an exemplary process of using open data to shape government decisions through interaction and collaboration with the public. Re-using and sharing data between the public and the government is expected to reduce the cost making data available through the principle of collect once, reuse many times to improve open data quality by employing user feedback to correct errors of incomplete data and unusable data (Donker, VanLoenen, & Bregt, 2016). The publishing of OGD with accessibility issues has resulted in a frequently low usage threshold (Jurisch et al., 2015). Magalhaes and Roseira (2017) conducted empirical research on the issue of value creation in the commercial use of open government data and concluded that the use of open government data by the private sector could positively impact private sector innovation.

As more citizens move towards consuming government services through the internet, the need to identify the users and their perception about the open data system tends to increase. Scott and Golden (2009) identified the need to study the citizen's perspective and use it to understand the features of the system that influences user perception. Three key areas of research recommended for further inquiry into making open datasets usable are the shared understanding of data quality dimensions, support for quality awareness, and strengthening the quality to use nexus (Sadiq & Indulska, 2017). Ruijer et al., (2017) recommend further exploration to ascertain if there is a tension between using context-specific user requirement and the objective of generic user requirements. Roky and Al Meriouh (2015) proposed an ex-post evaluation by users of information systems. The observations above suggest that the importance of open data to society makes it imperative to evaluate its quality to have a clear understanding of the factors that influence the intention to use open data.

Open Data Metadata Quality

Metadata, which is described as the data about data, is the key to ensuring the long-term value of any piece of data (Schauppenlehner & Muhar, 2018). Metadata support interoperability and integration of different systems and can be necessary for the description of data, understandability, searchability, and preservation of dataset entries. Data accessibility for a larger audience is made possible by using standard metadata to improve linked data quality, readability, and completeness of data (Kubler, Robert, Neumaier, Umbrich, & Le Traon, 2018). The national information standards organization ("ISO/IEC 11179-4:2004", n.d.) defines metadata as structured information that describes, explains, locates, or otherwise makes it easier to retrieve, use, or manage an information resource.

There is a growing reliance on accessing data through websites and web applications. These applications tend to use different formats irrespective of the format used by other open data publishers, and that makes it impossible for users to connect and link data. Jiménez-Ramírez, Burke, and Rodríguez-Flores (2017) defined statistical metadata as any information needed by people or systems to make proper and correct use of the real statistical data, regarding capturing, reading, processing, interpreting, analyzing and presenting the information or any other use. Fan and Zhao (2017) constructed three quality indicators of OGD described as publishing all collected data except for data that is related to national security, patents, personal and private data, publishing data according to the eight OGD principle and finding out if the public uses the published data. Metadata is provided for interoperability between information systems, and provide the basis for data quality validation, data preparation, data comprehension, and dissemination.

Good quality metadata supports knowledge discovery, which enables better decision making to increase the efficiency and effectiveness of business processes (Ramesh, Vivekavardhan, & Bharathi, 2015). Metadata quality of open data portals can help to guarantee the reliability of information and enhance the motivation of users to use open data portals. Jiménez-Ramírez et al. (2017) stated that the metadata usually found in many OGD repositories are not enough to facilitate knowledge discovery processes and suggested the need for more comprehensive metadata. Kubler et al., (2018) developed an open data quality assessment framework that can be used for quality assessment of open data portals. The absence of metadata may have a negative impact on open data usage while publishing open data in a reusable format enables the motivation and engagement of users.

Though open data has the potentials to facilitate innovation, the uncertainty of datasets poses a quality challenge that can become a threat to their usage (Sadiq & Indulska, 2017). The absence of metadata in many open datasets poses usage challenges, including the very long time to value creation due to low-quality characteristics of the datasets, deficiency through missing data, duplicates, inconsistencies, and lack of schema descriptions (Corsar & Edwards, 2017). Timeliness and recency of data are required for timely decision making and the powering of civic applications. Many open data portals do not provide information about the datasets' update history. Outdated data can have a negative effect on all stakeholders including the open data provider. Applications that rely on current information will be compromised when data freshness cannot be determined. Neumaier and Umbrich (2016) noted that the prominent open data frameworks which are the CKAN, OpenDataSoft, and Socrata all have the option to set the metadata field of “last_modified,” but most of the providers do not use that field, thus making it impossible to determine the freshness of data.

The need to focus on inclusive data, openness, and quality is the foundation of open data usability. Corsar and Edwards (2017) recommend that open data providers need to consult with users to document user experience and the quality issues to improve the discoverability of the data. Tygel, Auer, Debattista, Orlandi, and Campos (2016) subdivided open data challenges into two categories, defined as structuring the datasets and provision of well-structured and organized metadata for datasets. OGD platforms use different tags for the same objects and calls for the need for a collaborative strategy approach for improving tag curation with open data portals. The use of a standard set of categories and data provision standards to enable consistency in the presentation of OGD is expected to improve open data usability. The inclusion of metadata is suggested to make OGD easier and faster to use, including enhancing user experience.

The efficient use of data from various sources will require the creation of good metadata to improve searchability and data consumption. Zeleti and Ojo (2017) identified eight new open data value capabilities described as knowledge of data standards and data on the web best practices, knowledge of data value, data strategy, aggregation process, database architecture, knowledge of graph data models, verifying data integrity, and web-based front-end for open data. The quality of an OGD may vary from country to country, and this calls for the need for standardized format and presentation, quality evaluation, and benchmarking framework that will aid in better understanding of the quality issues in open data portals and to study the impact of improvement methods over time.

The Potential Value of Open Data

In a bid to bridge the gap on the lack of research on how businesses are using open data, Susha et al., (2015a) investigated the driving factors of open data adoption by businesses. Their result indicates that the way open data is organized is affecting the usage of the datasets. The size of open data is growing and is expected to reach the size that it can be described as big data. Big data is any dataset that is very large and complex and requires advanced capture, storage, management, and analytical technologies (Ylijoki & Porras, 2016). The unique characteristics of big data are its volume, variety, and velocity but the unique characteristic of open data is that it is freely available without restrictions. Dwivedi et al. (2015) suggested that though open data is voluminous in size, the usefulness for decision making is limited unless it can be interlinked to provide more context. Linked open data have greater opportunities for stakeholders to exploit the data for innovative purposes, collaboration and co-creation of value (Karanth, & Mahesh, 2015). The term big open linked data (BOLD) is rapidly emerging in the technology-oriented business world for the integration of diverse data, without predefined restrictions or conditions of use, to create new insights. BOLD is expected to increase the reach of statistical and operational information and deepen the analysis of their outcome and impact (Janssen, Konopnicki, Snowdon, et al., 2017).

OGD is a potential motivator for strengthening democracy through increased transparency, participation, and collaboration of citizens (Pereira, Macadar, Luciano, & Testa, 2017). Open data is envisaged as a potential business enabler and a valuable business resource. It is discovered that many private organizations, especially software developers, are interested in using open data. Herala, Kasurinen, and Vanhala (2018) indicated that through professional software development companies perceived that there is added value from open data, they are not using it because they consider open data as a difficult asset to use for a business.

The adoption of open data by companies plays an important part in the value chain of open data. Zuiderwijk, Janssen, Poulis, and van de Kaa (2015b) examined open commercial data use for competitive advantage using the resource-based theory, and the findings indicate that achieving competitive advantage from open data requires an organization to have in-house capabilities and resources. Data sharing has been promoted as having the potential to enrich healthcare research because of its ability to improve the practice of medicine and be able to save more human lives. Sansone et al., 2018 emphasize that high quality of open data infrastructure has the potential to enable high-quality science.

Open research powered by the open data concept is having a positive effect on researcher communities by enabling research works to get more citations, attract media attention, funding opportunities, potential collaborators. Healthcare practitioners suggest that about 50% of clinical studies are never shared or published, thereby resulting in missed opportunities for learning and validation (Dey et al., 2017). An open access policy allows the researcher to open up access and yet retain ownership rights. McKiernan et al. (2016) suggested that because publishing under open access can be at little or no cost, researchers are highly motivated to increase their productivity. Open access enables resource management, sharing, reproducibility, and validation of research findings due to the effectiveness of sharing through open data access.

Open e-learning is not only creating self-taught experts, but it is also equipping organizations in public and private sectors with knowledge and learning (Gascó-Hernández, Martin, Reggi, Pyo, & Luna-Reyes, 2018). The need to understand and use the economic value of the n data asset is increasing, even as the open data volume is expanding. Though there is potential for using open data for business competitiveness, certain capabilities must be acquired and used before value can be derived from open data. Cabitza et al. (2015) relate the social value of open government data as depending on how potential consumers can access, understand and exploit the data for comparative analysis. Despite all the potential of open data to spur open governance and enable the creation of innovative value-added services, it is not yet clear how to realize the potential in practice.

Stakeholders of Open Data

Open government data has many stakeholders from a variety of origins that bring with them a variety of meanings of OGD. The primary stakeholders have a formal, direct, and necessary impact on OGD planning and implementation, while the secondary stakeholders had informal or non-essential planning and implementation roles in OGD (Gonzalez-Zapata & Heeks, 2015). The primary stakeholders include the politicians, public officials, public sector practitioners, and international agencies. The secondary stakeholders include civil societies, funding donors, ICT providers, and academics. Open data stakeholders can also be classified using perspective analysis (Gonzalez-Zapata & Heeks, 2015). In the prospective analysis, the stakeholders can be identified as having bureaucratic, political, technological and economic perspectives respectively. The bureaucratic and political perspectives have dominance, and the technological and economic perspectives are not incorporated into the mainstream of the OGD. The bureaucratic perspective defaults to the ideas of using OGD to support transparency of the public sector, and the technological perspective conceives OGD as a technical innovation for processing public sector data. The political perspective sees OGD as a fundamental right that can enable citizens to have access to the public-sector data they paid for while the economic perspective regards OGD as an economic enhancer. Differences in stakeholders and motivating factors are an indication that using a uniform strategy to manage the relationships with different stakeholders will not boost the usage of open data (Susha, Zuiderwijk, Charalabidis, Parycek, & Janssen, 2015b).

The understanding and clarification of various stakeholder's priorities are one of the success factors of open data. Lindman, Kinnari, and Rossi (2016) categorized the potential roles of businesses in enriching open data as the roles of open data publishers, data extractors and transformer, data analyzers, user experience providers and support service providers. Academic researchers are one of the stakeholders of open data who are facing the challenges of opening their data (Aadinarayana & Sharma, 2017). In the academic research ecosystem, some funders and researchers have different perspectives about joining the open data movement. Funders are mindful of their investment, while researchers want to have abundant data to use in their research. Irreproducibility is one of the challenges that open data is expected to resolve. The primary objectives of researchers supporting the open data movement are to enhance reproducibility and reusability of scientific research. Zuiderwijk et al., (2015b) suggests that open data benefits should be focused to specific stakeholder category and should not be generalized because what constitutes a benefit to citizens, researchers and non-profits may not be benefits to commercial companies.

Challenges of Open Data Usage

The barriers of OGD can be categorized as user-specific, provider-specific and both user and provider-specific (Beno, Figl, Umbrich, & Polleres, 2017). Identified user-specific issues are open data portals, data quality, user legal constraints, while the identified provider-specific issues are strategic and business, privacy, and security, provider legal constraints. Knowledge and experience are the issues in the category of both user and provider. The availability of massive amounts of data provides the opportunity for reuse of the data for civic applications, but OGD users identified technical, management, and cultural challenges as prohibiting the use (Alromaih, Albassam, & Al-Khalifa, 2016).

The value of open data can only be realized through their usage, but the implementation of most open government data is still supplier driven (Susha et al., 2015b). Kapoor et al., 2015 identified open data challenges as for how to increase public interest in the use and re-use of open data, cost of opening data, data ownership risks, legality concerns, and data quality concerns. Open data portals are designed from a technology-driven perspective and not from a social value perspective. Viscusi et al. (2014) identified the need to position open data portals from the perspective of the social value it can add to the stakeholders. The sociotechnical risks and barriers to open government data adoption include the complexity of activities needed to understand and use open data, lack of incentives, data provenance, management and quality, completeness, metadata, technical and semantic interoperability (Dawes et al., 2016).

The government has an important role in stimulating open data usage. Open government data (OGD) does not support the dynamic use of data (Buranarach, Krataithong, Hinsheranan, Ruengittinun, & Supnithi, 2017), and users are in some cases required to download the entire dataset, even when the user wants only some portion of the dataset. The barriers of the usage of OGD are the absence of metadata in the data sets, irregular updates of the data sets, limited and unusable formats of the data sets, lack of data visualization facility, and lack of collaborative approach for the OGD initiative (Saxena, 2017). Though open data is expected to contribute and enhance the democratic processes, there is the need to collect specific user-centric requirements for designing open data platforms. Collecting specific user requirements will enable the understanding of the context-based specific requirement to ensure the development of an open data portal that meets user needs and increases usage level.

Open data providers are still unwilling to publish their data, while some users find it difficult to use available open data (Beno et al., 2017). OGD has been severely criticized for being one dimensional, lack of usability, inadequate data, and weak application stewardship principles. It is believed that data presented in an easy to use way can lower user threshold (Jurisch et al., 2015). OGD platforms have different presentation formats, structures, different processes and features for data search. Beno et al., (2017) identified that heterogeneity of portals and formats of implementing the features of OGD are causing a limitation on the ability of users to reuse the datasets. On the side of the open data publishers, the most severe barriers are lack of resources and time, cost, and fear of users drawing the wrong conclusion from the data. Government data is heterogeneous and often interwoven with the implication of the limitation of the level of integration between systems (Janssen, Konopnicki, Snowdon et al., 2017). Hjalmarsson et al. (2015) identified that open data users have challenges ranging from localization issues, lack of quality in data, and technical format. Kool and Bekkers (2016) investigated the perceived value relevance of open data published by the Dutch Inspectorate of education in the parent's choice of Dutch primary schools and identified that there is a mismatch between the demand and supply of open data about primary schools.

A study by Toots, McBride, Kalvet, and Krimmer (2017) to gather information from 63 experts in six European countries of Belgium, Estonia, Greece, Ireland, Lithuania, and the United Kingdom identified many challenges and barriers. The challenges are data and technology, organizational, legislation, and policy barriers, respectively while enablers and drivers are data and technology, stakeholder, organizational, legislation, and policy drivers, respectively. Zeleti and Ojo (2017) identified the knowledge gap and conducted a design science research to construct a theoretically grounded open data value capability architecture that explains how open data-driven organizations can identify, map, develop and plan open data value capabilities. The study noted that open data providers are not paying enough attention to building capabilities required for data storage and computing facilities, data release, providing access to data and APIs', data retrieval, and data usage. Despite the availability of many datasets, the barrier of metadata quality has made it impossible to integrate multiple datasets, even within the same agency (Oliveira & Moreno, 2016). Low metadata quality poses a limitation to data discovery (Kubler et al., 2018) and the combination of dataset both within and across data portals because good quality metadata is as important as the quality of data themselves (Máchová & Lnenicka, 2017). The lack of incentives, data origin, management and quality, completeness, metadata, technical and semantic interoperability (Dawes et al., 2016) are part of the barriers.

Supporting Theories and Alternative Theories

Dependence on information systems continues to grow as academic institutions leverage the use of information technology for service delivery. Dos Santos et al., (2017) analyzed the impact of user intention on an academic information system using the DeLone and McLean (2003) information systems success model. Results of the study indicate that system quality influences information quality, information quality influences intention to use, and service quality influences intention to use. A study by Mudzana and Maharaj (2015) indicates that information quality is positively related to system use and user satisfaction. It was also concluded that the results agree with the previous studies that used the information systems success model.

The alternative theories that other researchers used to study information system utilization and usage include the technology acceptance model (TAM), the unified theory of acceptance and use of technology (UTAUT) model, and the task-technology fit (TTF) model among others.

Technology Acceptance Model (TAM)

The technology acceptance model (TAM) was developed with the key reasoning that increasing the usage of information systems starts with the acceptance of the system, and acceptance is preceded by the user's intention to continue using the system (Davis, 1989). Understanding the factors that affect intention to use can enable an organization to manipulate the factors towards acceptance and then increased the use of the system. The variables of TAM are perceived usefulness, perceived ease of use, intention to use and usage. The goal of any information system is to meet the need of its target audience and for it to be used for the intended purpose (Taherdoost, 2018). Al-Ghazali, Rasli, Yusoff, and Mutahar (2015) noted that there had been inconsistencies with previous findings that were trying to provide a one size fits all model of post-adoption usage behavior.

Kasaj (2016) studied the adoption of mandatory e-government service and identified gaps in many other studies on the adoption of technology by noting that the studies were based on systems that are not mandatory to use. System reuse is an important indicator of system success. Yang, Shao, Liu and Liu, C. (2017) identified the gap in research on how e-learning users' experience impacts their behavioral intentions to reuse the system and studied the quality factors that support the acceptance of massive open online courses (MOOC) to foster improved continuance intention using a combination of the information system success model and TAM. The study used a sample of 294 respondents to conclude that system quality, course quality, and service quality have positive effects on the continuance intention to use MOOCs. Mardiana, Tjakraatmadja, and Aprianingsih (2015) identified that the technology acceptance model (TAM) has a stronger and sound theoretical background for predicting behavioral intention and that TAM has a focus on the attitudes that precede using a technology. TAM could not be used for my study because the focus is not on adoption but is focused on understanding users' intention to use through examining the relationship between the US federal departments' open data users' perception of the systems quality, perception of information quality, perception of service quality and the intent to use open data.

Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT identified four key factors and four moderators that are related to predicting behavioral intention to use technology and actual technology use in organizational contexts (Venkatesh, Morris, Davis, & Davis, 2003). The key factors are performance expectancy, effort expectancy, social influence, and facilitating conditions while the moderators are age, gender, experience, and voluntariness. Venkatesh, Thong, and Xu (2016b) reviewed and synthesized the information systems literature on UTAUT and extensions from September 2003 until December 2014. The review identified the merits of the UTAUT and the reason why there is a hindrance to further theoretical development in research into technology acceptance and use. According to Venkatesh et al. (2016b), performance expectancy, effort expectancy, and social influence were theorized and found to influence behavioral intention to use technology, while behavioral intention and facilitating conditions determine technology use. Saxena and Janssen (2017) suggested that the UTAUT framework is the best framework for examining both social and non-social factors, which can impact IT linked with open data.

Maduku (2015) described technology acceptance as an individual's psychological state about his or her voluntary or intended use of technology and used the UTAUT model to understand the factors that influence behavioral intention towards e-book use among students in tertiary intuitions in South Africa. The UTAUT is not considered suitable for my study because the framework is focused on predicting the factors that influence behavioral intention to use technology, while my study is focused on examining the facilitating conditions that determine the intent to use OGD.

Task-Technology Fit

The task fit technology (TTF) refers to the extent to which technology fits the task requirement, individual ability, functionalities and interface of the technology (Mohd Daud & Zakaria, 2017). TTF is one of the constructs been used to measure the effectiveness of information systems in the way it impacts individual or organizational performance. The core objective of making a huge investment in an information system is to improve individual or organizational performance. Technology is viewed as a tool that individuals use to turn inputs into outputs, and if the tool did not fit the task, the tool is described as not being effective (Wipawayangkool & Teng, 2016). The TTF has been used by many researchers to evaluate system characteristics and task characteristics effectively. Irick (2008) asserted that the task-technology fit is more important than the user interface of an information system.

Two major research paths link technology to performance described as the utilization model and the task fit model. The utilization models are focused on understanding user attitude, beliefs and behavior while the task-technology fit model is focused on the features of a technology that is fit for a task. Irick (2008) asserts that strict reliance on either the utilization model or the adoption models may not give a good outcome and concluded that the information system must be utilized and be fit for the task before it can positively impact performance. The task-technology fit is not used for my study because it refers only to the individual ability, functionalities, and interface of the technology. The other aspects of the three tenets of quality like the service and information cannot be addressed with it.

Transition and Summary

This study introduced the problems and challenges associated with open government data quality. Section 1 started with an introduction to the background of the problem to provide an understanding of the issues with open data platforms as an information system. The problem statement is used to add structure to the issues that will be the focus of the study. The purpose statement re-iterated the purpose of the study and what it hopes to achieve, and the nature of the study explained how the study would be conducted and to justify the choice of methodology. The relevance of the study to the society and the IT profession is presented to support the need for the study. Every research has a lens through which it is structured, and this study is presented through the lens of the information system success model.

A literature review of the past and present studies relating to information systems, open data metadata, potentials of open data, stakeholders of open data, challenges of open data, and measurement of information systems success was conducted. The usage of OGD is expected to aid the development of smart cities (Siuryte & Davidaviciene, 2016), smart transportation, smart housing (Walravens et al., 2014), and many other civic applications that can add tremendous value to civil societies, governments, and organization. Standardization of data quality using the open standard quality can improve the accessibility of data. The open standard format (Valdivia & Navarrete, 2016) is based on the open license, open access, and an open format. Technological products depend on the interoperability of other software components across the Internet (Chen, 2016), and open formats are required to facilitate use, reuse and simplify data management for publishers and users (Rocca-serra et al., 2016).

Metadata, which is described as the data about data, is the key to ensuring the long-term value of any piece of data (Schauppenlehner & Muhar, 2018). Metadata quality of open data portals can ensure the reliability of information and enhance the motivation of users to use open data portals. Low metadata quality poses a limitation to data discovery and the integration of dataset both within and across data portals (Máchová & Lnenicka, 2017). Jiménez-Ramírez et al. (2017) stated that the metadata usually found in many OGD repositories are not enough to facilitate knowledge discovery processes and suggested the need for more comprehensive metadata. The issue of finding and using the relevant data, inconsistencies in data quality, and formatting of open data are hindering software developers and other users in their bid to use open data (Hjalmarsson et al., 2015).

OGD barriers include the absence of metadata, incomplete data, the use of different schemas and IDs for different departments, inaccurate data, data inconsistency, and lack of timeliness (Danneels et al., 2017; Oliveira & Moreno, 2016; Saxena, 2017). The sociotechnical risks and barriers to open government data adoption include the complexity of activities needed to understand and use open data, lack of incentives, data provenance, management and quality, completeness, metadata, technical and semantic interoperability (Dawes et al., 2016). Zeleti and Ojo (2017) noted that open data providers are not paying enough attention to building capabilities required for data storage and computing facilities, data release, providing access to data and APIs', data retrieval, and data usage. Corsar and Edwards (2017) recommend that open data providers need to consult with users to document user experience and the quality issues to improve the discoverability of the data. Roky and Al Meriouh (2015) proposed an ex-post evaluation by users of information systems to have a clear understanding of the factors that influence the intention to use open data.

The research question identified in this study is addressed through the examination of the variables of information system success model named the system quality, service quality, information quality, intention to use/use, nets benefits, and user satisfaction. Section 1 ends with a discussion of the alternative theories that could have been used for the study. Section 2 will provide a restatement of the purpose statement, the role of the researcher, description of the participants, the research method, population and sampling, data collection and data analysis techniques, and a transition into Section 3.

Section 2: The Project

This study used the information system success model (DeLone & McLean, 2003) to examine the relationship between the U.S. federal departments' open data users' perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data. The section begins with a restatement of my purpose statement and is followed by a discussion of my role as the researcher and an overview of the participants in the study. The research method and the description of the design, including supporting evidence from the literature review are presented next and then followed by the discussions about the population, sampling technique, ethical research concerns, instrumentation, data collection and analysis validity of the study and a conclusion. The section ended with a transition into Section 3.

Purpose Statement

The purpose of this quantitative correlational study is to examine the relationship between the U.S. federal departments' open data users' perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data. Despite all the potentials of open data to spur open governance and enable the creation of social value and innovative services, open data providers are not yet clear on how to realize the potentials in practice. Many researchers (see Kapoor et al., 2015; Susha et al., 2015a; Zuiderwijk et al., 2018) have identified the various challenges of using open data but did not fully address how to mitigate the challenges. The independent variables are the perception of system quality, perception of information quality, and perception of service quality, and the dependable variable is the intent to use open data.

The population for this study is users of the open data. The anticipated positive social change is that an easily accessible and usable open data may result in citizens and organizations having access to data that can be used to study government transparency, plan smart cities, create product and services that increases the quality of life of the citizens and organizations.

Role of the Researcher

The ethics of quantitative research requires that the researcher plays a neutral and unbiased role in the data collection process to provide an impartial view of the subject matter of the study (Elo et al., 2014). The researcher is never fully detached but may still have some influence on the way the research is conducted. This research was designed by drawing on my experience and interest. I chose the subject of this research based on my interest and passion for business and organizational efficiencies and the need for investigating business systems and performance to align processes and projects to business objectives strategically. As a person that has been working in the areas of redesigning business processes, specifying systems, optimizing business benefits, and aligning business processes with a business strategy for over 17 years, the skillset applied in this research design and method is based on prior interest and experience. That prior interest and experience influenced the choice of variables used in the research, the choice of the survey instrument and the technique to be employed in data analysis. I have used many open data portals, interacted with other users of open data portals, and can understand the challenges of trying to derive insight from data that was designed from a different perspective than the publisher cited.

Considering my relationship with the subject matter, this study mitigated subjective bias by using an Internet-based anonymous survey to ensure no direct contact with the participants. The use of formal statistical analysis methods to analyze and describe the collected data further mitigates researcher bias (Katz, 2015). Any other researcher that follows the same research process would be allowed to verify the results of the study. Such bias mitigation strategies are expected to fulfill the requirement for neutral and an unbiased role of a quantitative researcher (McCullagh, Sanon, & Cohen, 2014). Other aspects of ethical consideration include compliance with the guidelines for the respect of research participants, as described in the Belmont Report (Tavakol & Sandars, 2014). The Belmont Report (Bromley, Mikesell, Jones, & Khodyakov, 2015) prescribed allowing participants to have the free will to participate in the study, while the researcher aims to ensure the protection of identity, protection from harm and informing participants of the research findings. In preparation for this study, I took the National Institutes of Health (NIH) web-based training course on protecting human research participants, as can be evidenced in the certification number 2434587 issued on July 14, 2017, and attached as Appendix F to this document. This study did not directly involve humans nor any personally identifiable information (PII). The Belmont protocols for protecting vulnerable populations while conducting research involving humans did not apply to this doctoral study.

Participants

The participants for this study were users of open data from across many industries and may be resident in any part of the world. The specific requirement is that they must have used open data government portals like data.gov and census.gov. Purposive sampling is the preferred method for this study because of the ability to access hard to reach participants and tends to be inexpensive to conduct (Valerio et al., 2016). Social media platforms such as LinkedIn, Twitter, Facebook, Reddit is used as the main option for recruiting participants.

The strategy to use online communities is based on the flexibility, speed, timeliness, convenience, and ease of data entry and analysis they allow for research (Evans & Anil, 2018). As an active member of those online communities, participants trusted my inivitation to participate in the survey. The web page for the survey stated the objective and the conditions for participation because not all the interested participants have may be eligible to participate in the survey. The scope and the purpose of the study were made available to the participants to enable them to decide if they wish to participate. Specifying the eligibility criteria and the purpose enabled intending participants to make an informed decision about whether to participate or not to participate.

Anonymity and confidentiality are ensured for all participants in compliance with the Walden University Internal Review Board (IRB). There were no financial reward incentives to participants but sincere gratitude. I used the surveymonkey.com website for the survey because of the need to ensure the privacy of the data. The data collected from the survey was encrypted and stored in a thumb drive for 5 years according to the specification of the IRB safety guideline.

Research Method and Design

This study used a quantitative methodology to examine the relationship between the U.S. federal departments' open data users' perception of the systems quality, perception of information quality, perception of service quality, and the intent to use open data. An ontological assumption of the quantitative method is that universal laws are external to the individual, and the intangible structures of the laws exist irrespective of the perception of any individual (Palagolla, 2016). A positivism or realism belief is that the physical world functions according to general laws and tend to be objective, including an assumption that authentic knowledge must be verifiable (Ma, 2015). The positivism epistemological stance claims objectivity as a means of reaching the truth without allowing the researcher's opinions, perceptions, and experiences to interfere with the truth (Roy, 2014) and are adopted in support of the quantitative methodology of this research. The objectivity claims are evidenced on the confirmation of hypotheses, quantification of variation, or prediction of causal relationships by the use of numerical data and statistical analysis (Divan, Ludwig, Matthews, Motley, & Tomljenovic-Berube, 2017). Quantitative methods enable the use of statistical techniques that allow researchers to examine the relationships between variables with elements that can be reduced to numerical codes for formal analysis and verification (Basias & Pollalis, 2018). I chose the quantitative method for this study because the purpose of this study is to examine the relationship between variables using statistical methods that can allow for the testing of hypotheses rather than understanding human experiences.

A qualitative method that is based on a constructivist paradigm enables the understanding of the complex social phenomenon as it relates to human behavior or experiences (Stickler & Hampel, 2015). Using a qualitative approach enables the development of an in-depth understanding of social phenomena using a case study, focus group discussion, unstructured interviews and others (Imran & Yusoff, 2015). Qualitative research is used to study and understand human experiences as described by the group or the individual that had the experience and from the perspective of the researcher (Kaur, 2016). Understanding human experiences require the researcher to be in the same setting with the participant, and this could be a hindrance to the objectivity concept of the study (Venkatesh, Brown, & Sullivan, 2016). This study used participants who may choose to remain anonymous to collect survey responses that are systematically counted and recorded to produce a numerical description of the data. The interpretive paradigm for a qualitative study differs from the positivist paradigm from their epistemology and ontological assumptions. The quantitative method assumes objectivity and can be deductively used to prove a theory (Riazi & Candlin, 2014). The qualitative method assumes interpretivism and explores the phenomenon to develop theories (Petrescu & Lauer, 2017). The qualitative method was not chosen as the research question does not seek to understand human experiences.

Mixed methods research combines the qualitative and quantitative data in a single research project, to enable exploration of complex phenomena while giving equal attention to each of the methods (Halcomb & Hickman, 2015). The combination of the qualitative and quantitative methods enables expanding and strengthening the conclusion from research (Schoonenboom & Burke Johnson, 2017) thereby improving knowledge and validity. In mixed methods research, various elements of the qualitative and the quantitative research methods such as the data collection, analysis, and inference techniques are employed to achieve breadth and depth of the issue under investigation (Guetterman, 2017). Mixed methods research was not an appropriate choice because this study did not need a mix of quantitative and qualitative methods. I examined the relationship between variables, which required the use of statistical analysis; the quantitative method is the most appropriate.

Research Design

Quantitative research design may be described as experimental, quasi-experimental, or nonexperimental designs. An experimental design uses a controlled environment to isolate the identified phenomena where one group receives an intervention while the other group will not receive an invention (Ghosh & Jacobson, 2016). Quasi-experimental designs use intervention to measure outcomes pre and post-intervention implementation (Alami, 2015). The nonexperimental design observes a phenomenon without any control, intervention or manipulation to identify if and to what extent a relationship exists between variables (Kusumawardhani, Gundersen, & Tore, 2017).

A quantitative correlational design is chosen for this study because of the primary purpose, which is to examine the relationship between the identified independent variables and the use of open data. The quantitative correlational methodology is used to determine if there is a relationship between two or more variables within a population, and to what extent if there exists a relationship (Apuke, 2017). I used a nonexperimental cross-sectional correlational analysis design because of the key objective of the study to examine the relationship between U.S. federal departments' open data users' perception of the system quality, perception of information quality, perception of service quality and the intent to use open data. Correlational research is nonexperimental research where variables are measured and assessed to determine whether and to what extent a statistical relationship exists between them (Rutberg & Bouikidis, 2018).

This correlational research design did not involve the manipulation of any variable either due to ethical reasons or the inability to manipulate the variables. Correlational research could be conducted using naturalistic observation, survey method, or archival research. The naturalistic observation is carried out in the natural environment by observing the participants without interference or manipulation by the researcher (Sussman et al., 2016). In a survey method, selected participants may complete a test or questionnaire at their own time and in their environment (Szabó, 2015), while archival research involves using secondary data to perform the analysis (Rhee, 2015). An existing 5-point Likert scale survey (Awang, Afthanorhan, & Mamat, 2016) was used for collecting the data. The accuracy of measurement, testing of hypothesis, and establishment of correlations and associations are the strengths of quantitative research (Ngulube, 2015). I used the survey method because the naturalistic observation was not feasible or practical and archival was not appropriate because I was interested in what happens now and not what happened in the past.

An experimental design is used for predicting an outcome by introducing a change to preconditions to find the relationship among the variables, including the contribution of each variable to the outcome of the research (Wang, Sun, Liu, Fu, & Pan, 2017). Participants in experimental designs are assigned to different conditions, and the result is observed and examined for causal relationships (Phan & Ngu, 2017). The experimental design randomly assigns and manipulates variables to understand the causal relationship between the variables (Stichler, 2016). In an experimental design, a variable may be manipulated in different ways to determine the effect of each control on the variable. Experimental design is not considered an appropriate choice because the study does not require randomized manipulation of the variables.

The quasi-experimental design uses a nonrandomized approach to assign and manipulate variables (Waddington et al., 2017). Quasi-experimental research designs are applied to situations where a random assignment of conditions is impossible or unethical (Ewusie et al., 2017). The core basis of quasi-experimental design is in the use of one group with a pretest and posttest implementation (Krass, 2016). Quasi-experiments are not known to distort the natural context because it is typically observation (Bärnighausen, John-Arne Røttingen, Rockers, Shemilt, & Tugwell, 2017). Nonrandomized approach to manipulation of variables was not considered for this study because the approach contradicts the objective of the study, which was to examine the relationship between the variables. Experimental and quasi-experimental designs were not appropriate for this study because this study examined the relationship between variables.

Population and Sampling

Open data is accessible by a variety of stakeholders (Styrin, Luna-Reyes, & Harrison, 2017), including but not limited to policymakers, commercial users, civic advocacy groups, technology providers, journalists, and IT professionals (Gonzalez-Zapata & Heeks, 2015). Open data is still at a nascent stage and users are not yet easily identified. A nonprobability sampling method, known as purposive sampling, was used for this study. Nonprobability sampling technique is used to select participants based on a subjective judgment instead of a random selection (Valerio et al., 2016). In situations where the population size is not known, where it is not practical to draw random sampling, the population is not easy to reach, time and cost considerations are of paramount imperative, the nonprobability sampling technique is considered the most appropriate. There are different types of nonprobability sampling which include convenience, consecutive, quota, purposive and snowball sampling (Setia, 2016).

In the convenience sampling method, the samples are selected based on convenience, availability, and ease of access (Kaushik & Baliyan, 2017). Consecutive sampling uses the same concept as convenience sampling, but the difference is that all the samples are not selected at the same time. A group is selected and analyzed; then, another group is subsequently selected and analyzed. In quota sampling, the population is divided into strata or groups (Robinson, 2014). Purposive sampling involves selecting the sample based on the researcher's perception of best fit concerning known attributes of the population (Reis, Amorim, & Melão, 2018). The snowball sampling is used where the sample is hard to locate, and referrals from an existing participant are used to locate additional ones (Ngwakongnwi, 2017).

The purposive sampling was chosen for this study because it can enable the researcher to select the sample that possesses the traits or characteristics of the target population (see van Rijnsoever, 2017). Selecting a sample with the core characteristics of the population will help to ensure that only those that can contribute to the study are included (Hamid, 2016). Purposive sampling is cost effective and works well when there is a time and resources constraint. The disadvantage of purposive sampling is that it is vulnerable to a judgmental error by the researcher. Another aspect of the weakness of purposive sampling is that it has the potential to be biased and the sample may not represent the population. The identified weakness of purposive sampling has been mitigated by an in-depth review of the characteristics of the population and the continuous update of the knowledge held about the population.

Sample Size

The sample size has the potential to influence the precision of the estimate and the potential for generalization of the research outcome (Nelson, Wooditch, & Dario, 2015). The use of the appropriate sample size can influence the confidence level, the margin of error. This study used two approaches to estimate the sample size. The equation sample size (Green, 1991) which is 50 + 8 (m), where (m) is the number of independent variables. In this case it is 50 + 8(4) = 82 participants. The second estimation method is the G*Power to conduct F-test for linear multiple regression analysis. The calculation is the apriori estimation using the error probability, the power, and numbers of predictors.

Medium effect size: f=0.15

Error probability: α=0.05

Table 1

Sample Estimation with G*Power

	Power	Number of participants
1	0.85	87
2	0.95	119
3	0.99	161

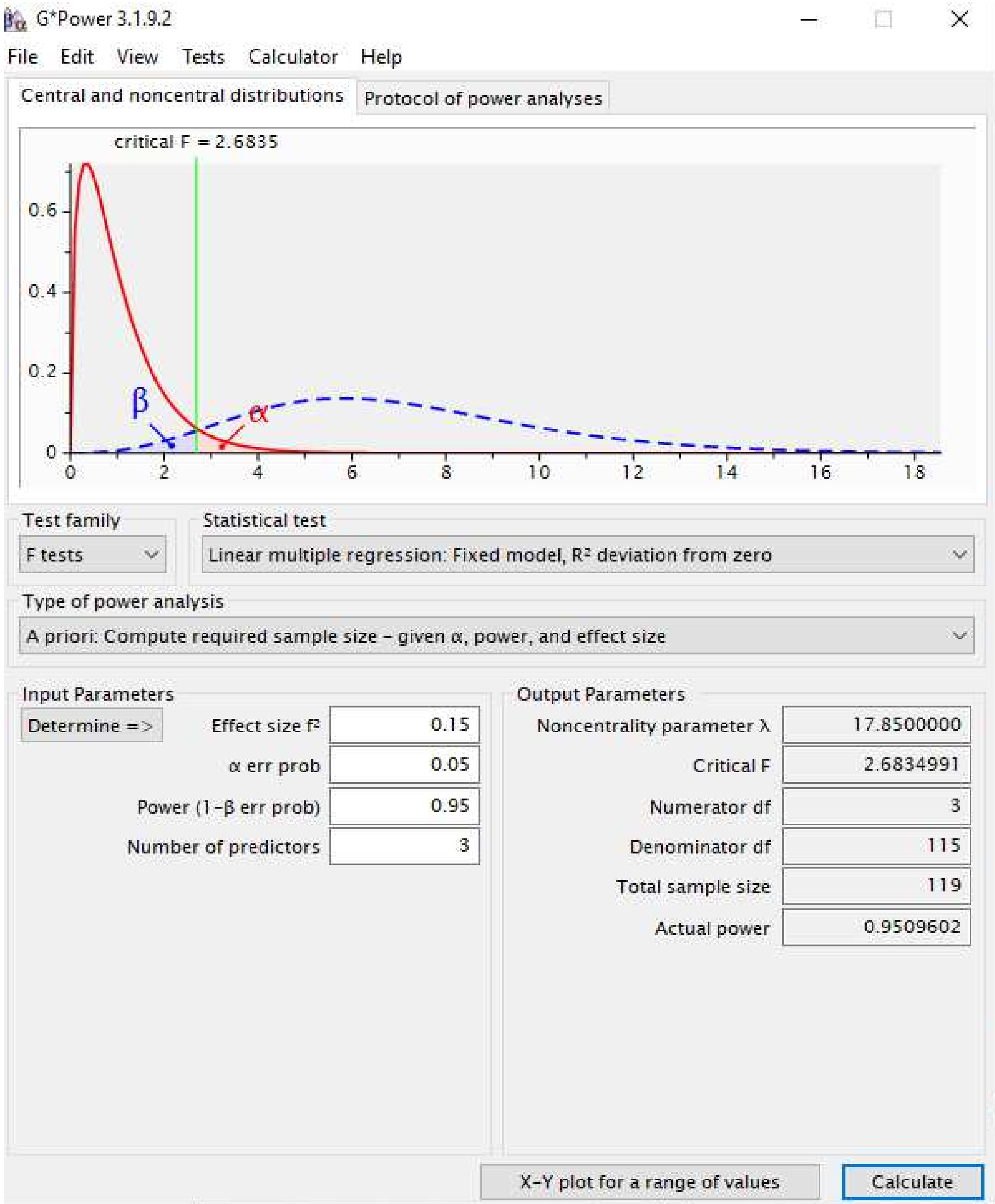


Figure 2. G*Power Analysis to Compute the Required Sample Size

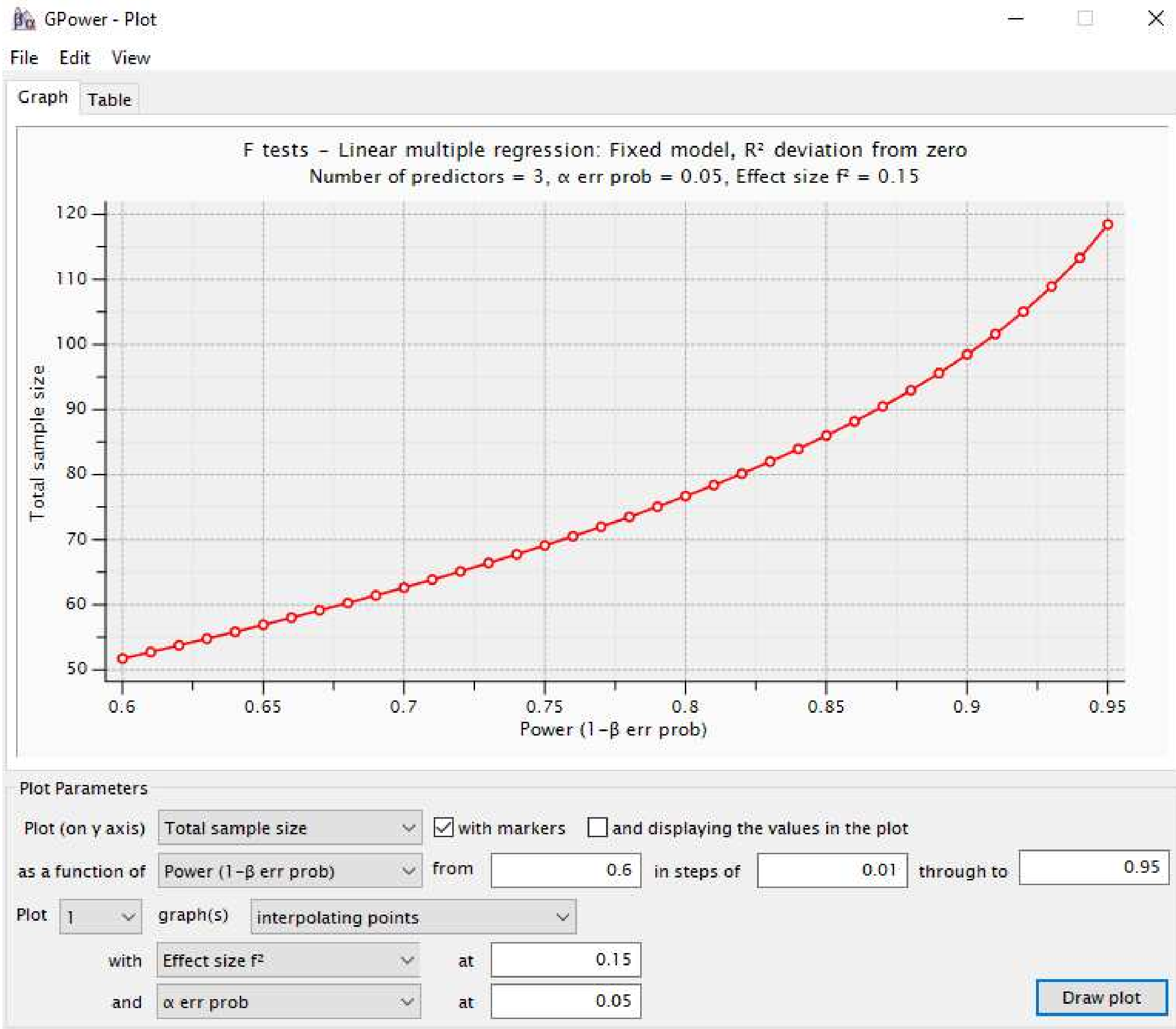


Figure 3. Power as a Function of Sample Size

The lower range of the apriori analysis is below the Walden University requirement of a minimum of 115 participants. The power of the analysis is increased to 0.95, which gave an estimated sample size of 119. Though using a sampling estimate may not always be accurate, it is assumed that a larger sample may minimize variation and increase accuracy (Dobson, Woller-Skar, & Green, 2017). The estimated sample of 119 will meet the minimum number of size of participants as required by Walden

University. It is good practice for researchers to do a priori estimate of sample size (Das, Mitra, & Mandal, 2016) to enable the use of an adequate sample size because a small sample size may not be suitable for answering the research question. The G* Power (Das et al., 2016) statistical analysis package with version number 3.1.9.2 is used to determine the appropriate sample size.

Ethical Research

Research ethics are the pillars that hold and protect standards for conducting research. Researchers are expected to adhere to stated principles for the conduct of research to protect the dignity, rights, and welfare of research participants (Gelling, 2016). Adhering to research ethics and standards enables public trust in a research outcome. The research ethics can be categorized as informed consent, beneficence – do not harm, respect for anonymity and confidentiality, and respect for privacy. Informed consent describes the documentation of what research participants should know about the research and how it may affect the participant (Roberts & Allen, 2015). Research participants have the right and freedom to decide what should be allowed and what should not be allowed during their involvement with the research. The researcher must get the participants to consent before enrolling the participant in the research (Kaye et al., 2015).

Beneficence refers to the duty of care to which the researcher owes the participant, and the researcher must ensure the welfare of the participants (Pandya-Wood, Barron, & Elliott, 2017). Confidentiality is required for protecting the research participant's personally identifying information (Resnik, Miller, Kwok, Engel, & Sandler, 2015). In maintaining the anonymity of the participant, certain strategies like the use of codes instead of names, encryption of the data and securing the data are required. Respect for privacy is a fundamental right of every individual. Research participants' identity and privacy need to be protected by the researcher. As part of my preparation to undertake this study, I completed a National Institutes of Health (NIH) web-based training course on Protecting Human Research Participants and was issued certificate number 2434587, which is included in Appendix F. I filled an application to the Walden University IRB and received an approval. Walden University's approval number for this study is 06-20-19-0658386.

This study aims to ensure that ethical standards are maintained. The participants are informed, and their consent obtained before enrollment to allow them to make an informed decision on participation. The online survey is used for data collection, and the form is designed in a way that the participant can be able to opt-out of completing the survey at any time. As part of ethical consideration, no monetary incentive will be offered to participants. All the necessary care is taken to ensure the safety, anonymity, and privacy of participants. Personally identifiable information is not be collected in the survey to protect participant privacy. Encryption of data using a secured server layer (SSL) protocol that can enable encryption for transmitting sensitive information through a web page (Breeding, 2016) is used to ensure the safety of the collected data. In compliance with the Walden University IRB, the data collected from the survey has been encrypted and will be stored for five years before destroying it.

Data Collection

Instruments

The source of data for the study comes from the survey instrument. A survey refers to the method of gathering data for use in analysis to be able to answer the research question (Corsi, Perkins, & Subramanian, 2017). Surveys have been extensively used in the investigation of relationships between variables. Survey research uses standardized information to collect data on the opinions of a group of people about the characteristics of the phenomena under study (Awang et al., 2016). The survey research is conducted using a sample of the identified population, but the outcome will be used to generalize the population. The sample is from present and past users of open data. Survey research is chosen for its usefulness in determining the values and relations of variables and constructs (Alam, Khusro, Rauf, & Zaman, 2014).

Description of the Instrument

The data for the survey is collected using a survey instrument designed to have close-ended questions based on the extant literature. The questions in the table in Appendix C were adapted from an instrument developed by Suryanto, Setyohadi, & Faroqi, 2016, in Appendix A, which was used to validate the information system success model (DeLone & McLean, 2003). The instrument is reworded slightly to suit the purpose of this study. Suryanto et al., 2016 adapted the instrument from the work of Li et al. (2012) in Appendix B. The permission to use the instrument of Li et al., 2012 is in Appendix D. The permission to use the instrument in Appendix A is in Appendix E.

The survey instrument in Appendix C is designed to measure four constructs within the information system success model, which are the system quality, information quality, service quality, and the intent to use. The survey questions used an ordinal scale of measurement with a five-point Likert scale (Awang et al., 2016) ranging from 1- strongly disagree to 5 – strongly agree. Participants were able to access the survey through an online web page. The survey period was slated for an initial period of 30 days to make room for maximum possible participation. After the initial 30 days, the minimum number of participants, which is 119 participants, was not attained and was extended for extended to another 30 days until the required numbers of responses are received. The Likert scale data is analyzed with SPSS using a mixture of descriptive and inferential statistics.

Data Collection Technique

Survey instruments have been used to collect data on almost any subject and have been known to facilitate surveys (Cardamone, Eboli, & Mazzulla, 2014). The use of questionnaires to collect survey information is affordable and can enable a wider reach to the target audience (Roberts & Allen, 2015). Online questionnaires come at a much lower cost because printing and postage cost is removed. The ease of using online questionnaires includes that the link can be emailed, placed on a website, or a link can be used to distribute it using short messaging service (SMS) to send it to smartphones (Lesser, Yang, Newton, & Sifneos, 2016). Online questionnaires are inexpensive, flexible, can transcend geographical boundaries, and enable research participants to maintain their anonymity (Mueller, Straatmann, Hattrup, & Jochum, 2014).

As part of researcher responsibility, the instrument for this study is designed to protect the privacy of the participants. Analysis of the results of online surveys tends to be easier because the data is already machine-readable. Closed-ended questions (Fernandez, Husser, & Macdonald, 2016) is used for the survey. The weakness of the use of a questionnaire as a survey instrument can be described as no response, partial response or false response (Wouters, Maesschalck, Peeters, & Roosen, 2014). In some cases, the participants may not understand the questions or may not be willing to provide an accurate response. Loomis and Paterson (2018) stated that declining response rates and survey fatigue might affect online survey outcomes. In other to mitigate the identified weakness of online surveys, the questions were designed to be easy and can be answered in a very short time. This study did not conduct a pilot test.

The data for this study is collected within six weeks of the approval of the Walden University IRB (approval number 06-20-19-0658386). The survey form was designed using one of the survey templates provided by Survey Monkey. I posted and shared the link in various online social communities and forums, including Facebook, Reddit, LinkedIn, and Twitter. The survey was designed for anonymity, and that made it impossible for me to know who participated. All I could do was to maintained presence according to the rules of the community, while monitoring responses from participants. The initial lifespan of the survey was one month, but it was expanded to six weeks to enable the acquisition of the minimum participants of 119. As soon as I received the minimum number of participants, I communicated my intention to end the data collection to the Walden University IRB. The response from the Walden University IRB came on the second day, and I ended the data collection with a response from 122 participants. The survey becomes officially closed after I received a response from the Walden University IRB.

Data Analysis Technique

The purpose of this research study is to answer a research question about the relationship between the US federal departments' open data users' perception of the systems quality, perception of information quality, perception of service quality, and the intent to use open data. The independent variables are the information quality, system quality, and service quality while the dependent variable is the intent to use. The hypotheses tested are:

H_0: There is no relationship between the user's perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data from US federal departments.

H_1: There is a relationship between the user's perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data from US federal departments.

The statistical analysis used for this study is the multiple regression analysis. Multiple regression analysis is used to examine the relationship between multiple independent variables, enables the correction of effects that predictor variables have on one another, and reduces the chance to erroneously find a significant result (De Groot, Sijens, Reijngoud, Paans, & Van Spronsen, 2015). Analysis of multiple regression assumes certain conditions that are necessary for making a good analysis. The assumptions of multiple regression include linearity, normality, homoscedasticity, and multicollinearity (Khundaqji et al., 2018). The linearity assumes a linear relationship between the dependent variable and each independent variable. In linearity assumption, a linear relationship is also expected to exist between each independent variable and other independent variables. The homoscedasticity assumption is that the variance around the regression line is the same as that of the independent variables. Multicollinearity is that no two or more independent variables are highly correlated with each other. The normality assumption is that residual errors are approximately normally distributed. All the assumptions may not always be met. It is good practice for the researcher to run statistical tests to check that the assumptions are met. Violating the assumptions may result in having biased, inconsistent estimators and inefficient ordinary least squares (Anja & Albers, 2017).

Other alternatives that could have been chosen for this study are hierarchical regression, stepwise regression, or logical regression. The hierarchical regression employs the process of adding or removing predictor variables from the regression model in steps or hierarchies (Winters & Rudolph, 2014). Hierarchical regression is best suited for nested data and enables the researcher to add or remove variables in multiple steps. This study is not designed to have nested data, and hierarchical regression is not considered suitable for this study because the objective of this study is not to evaluate the influence or control of each independent variable on the other independent variables.

The stepwise regression enables the identification of the most influential independent variable in the prediction of the outcome and then removing the weakest correlated variable at each step (Morozova, Levina, Uuskula, & Heimer, 2015; Rathod & Mishra, 2017). A known problem associated with the use of stepwise regression is that an independent variable with good potential may be rejected as not being statistically significant (Smith, 2018). The stepwise regression is not considered suitable to this study because the objective is to examine the relationship between the independent variables and the dependent variable, and not to find the most influential independent value in predicting the outcome of the study. The logistic regression is used for analyzing a dataset with one or more independent variables that determine an outcome and can predict the probability of an outcome that can only have two values (Budimir, Atkinson, & Lewis, 2015). Logistic regression is not considered suitable for this study because the objective of this study is not to find the best fitting outcome between dichotomous variables.

Testing for Normality

Analysis of the data is performed using the IBM SPSS Statistics software. Data quality may have a profound influence on the result of the analysis. SPSS has been considered useful for analysis in multiple regression studies (Fitriyah & Nagara, 2017; Kuntiyawichai, Dau, & Inthavong, 2017). The first action on the collected data is to screen the data to ensure that it is clean, usable, reliable, consistent, and meets the conditions for multiple regression analysis. Descriptive statistics are used to summarize, organize and describe the data to make it easy to understand the data. Measures of central tendency, measures of variability or measures of frequency are used to describe data (Mălinaș, Oroian, Odagiu, & Safirescu, 2017). This study used measures of variability to describe the data. Box plot and scatterplot is generated using the SPSS data description to provide a graphical presentation of the data and to provide the opportunity to screen the data for outliers.

The data is tested for normality to ensure that the normality assumption for multiple regression analysis is met. Testing for normality can be graphical or numerical. The graphical tests include Q-Q probability plots and Cumulative frequency (P-P) plots. The statistical test includes Kolmogorov-Smirnov (K-S) test, Lilliefors corrected K-S test, Shapiro-Wilk test, Anderson-Darling test, Cramer-von Mises test, D'Agostino skewness test, Anscombe-Glynn kurtosis test, D'Agostino-Pearson omnibus test, and the Jarque-Bera (Ahmad & Khan, 2015). Using the graphical test will require a good judgment by the researcher, which may leave room for different interpretations, but the numerical test may lead to more objective judgement and can be replicated (Mishra et al., 2019). This study used the Kolmogorov-Smirnov (K-S) test and the Shapiro-Wilk test to compare the best result for normality.

Pearson Correlation Test

The result of the test for normality indicates the progress of the analysis. If the assumptions of normality are met without any bias, Pearson's Product-Moment Correlation test will be used to analyze the data further. The Pearson product-moment correlation coefficient measures the strength and direction of association that exists between two continuous variables (Hazra & Gogtay, 2016). The variables must be measured on at least an interval scale. Where the assumptions of normality are not met, and there are outliers, Kendall's tau-b correlation coefficient test will be used for further analysis of the data (Unal, Temizel, & Eren, 2017). The Kendall's tau-b is a nonparametric measure that is used to test the strength and direction of association that exists between two variables. Variables in Kendall’s tau-b test must be measured on at least an ordinal scale. After conducting the various tests for the assumption of multiple regression analysis, it was confirmed that the data meets the requirement for Pearson's Product-Moment Correlation test.

Reliability and Validity

The factors of reliability and validity are two important factors for assessing research studies. The reliability refers to the accuracy of the measuring instrument, and validity refers to the extent to which a measure is accurately measured (Hagan, 2014). An instrument is said to meet the quality of reliability when it is reasonably expected to yield the same results if reproduced under a similar methodology and can maintain stability when measured over time. The validity of an instrument also tests if the instrument performs as it is designed to perform and may to increase transparency in research (Shekhar Singh, 2014) because of the ability to enable enhancing the accuracy of research instrument assessment and evaluation. The validity of the instrument is used to evaluate the tools used in the study and may form evidence of the rigor and quality of the research (Hayashi, Abib, & Hoppen, 2019).

Reliability

The reliability of a quantitative study can be measured using test-retest, internal consistency, and scorer reliability (Hagan, 2014). Researchers select instruments on the assumptions+ that the instrument score is dependable, consistent, and has the likelihood to be suitable for generalization. Cronbach's alpha can be used to measure internal consistency (Janzen, Nguyen, Stobbe, & Araujo, 2015). The use of Cronbach's alpha provides a way to measure if a score is reliable and can produce a number from 0 to 1, but the general rule of thumb is that alpha of 0.70 and above is good while alpha of 0.80 and above is better, but 0.90 and above is the best (Islam, Selim, & Dzuljastri, 2015). The survey instrument adapted for this study, originally developed by Suryanto et al. (2016), has component reliability between 0.89 ~ 0.90. This study used Cronbach's Alpha to test the reliability of the survey instrument.

Validity

Validity provides answers to questions like how the outcome measured the intended (Hayashi et al., 2019). The validity of a study can be assessed from the content, conclusion, constructs, criterion, internal and external validity, respectively (Bolarinwa, 2015). Content validity verifies if the instrument covers the relevant domain related to the variables. Construct validity is used to measure if the inferences drawn from the study relates to the concept under study. Construct validity can be measured by checking if the instrument is homogenous, capable of convergence, and has theoretical evidence. Construct validity can be assessed using composite scores and inter-correlations (Eiras, Escoval, Isabel, & Silva-Fortes, 2014). Criterion validity measures the extent to which the different instruments measure the same variable and can be measured by the convergence, divergent and predictive (Bolarinwa, 2015). Conclusion validity verifies if there is there a relationship between the objective of the study and the observed outcome. Internal validity verifies the relationship between the objective and the outcome. External validity refers to the ability to generalize the outcome of the study to other settings or populations (Wong & Cooper, 2016).

Threats to Internal Validity

The potential threats to the validity of a study can affect the outcome of the study. The threats to internal validity include the extent to which the effects of the study are related to the study (Whaley, 2018). The factors affecting internal validity are selection, maturation, instrumentation, statistical regression, and mortality. Internal validity threat can be mitigated by using appropriate design, sampling techniques, and knowledge about the population characteristics (Nascimento, 2018). This study chose the purposive sampling that will enable the selection of the sample based on the researcher's knowledge about the population (Reis et al., 2018).

To mitigate the threat of internal validity, the researcher will continue to monitor and upgrade knowledge about the characteristics of the population (van Rijnsoever, 2017) through the entire study. This study used two approaches, which are the equation sample size (Green, 1991) and the G*Power statistical analysis to estimate the sample size and to mitigate the threat of statistical regression. A validated survey instrument that has been used in previous research studies is- used in this study to mitigate the threat of instrumentation.

Threats to External Validity

External validity refers to the generalizability of the conclusions of a study to a wider population, across populations, treatments, contexts, and time (Nascimento, 2018). Considering that most quantitative research uses a sample from a wider population, it is imperative that the result of the study can be used to generalize to the population, including across the population for contexts and time (Belland, Walker, Megan, & Leary, 2015). The level of external validity in quantitative research design is affected by the research design and the potential threats to external validity. Drawing the population from an available population instead of drawing from the target population poses a risk of generalization (Hales, 2016). This study used purposive sampling to enable the selection of the sample from the target population. Accurate knowledge and description of the target population (Highsmith et al., 2016) and means of accessing the population enabled drawing from the target population.

The threat of ecological validity, which relates to the generalization of the results across contexts, settings, and conditions may pose a risk of replicability where the research is not adequately described. This study is designed to enable the generalization of the outcome to other contexts and time by using an easy to understand documentation that can facilitate replication and mitigate the threat of external validity. Steps to increase a high degree of internal validity may pose a restriction to the generalization of the study, and a trade-off between internal validity and external validity may be necessary for some situations (Stuart, Bradshaw, & Leaf, 2015).

Threat to Construct Validity

The relationship of the concept under study and inferences drawn from a study can be measured using construct validity. Construct validity can be measured by checking if the instrument is homogenous, capable of convergence, and has theoretical evidence. Construct validity can be assessed using composite scores and inter-correlations (Eiras et al., 2014). The representativeness of variables can be used to infer using construct validity. Construct validity has a convergent and a divergent component where the convergence measures the consistency in assessment, and the divergence distinguishes between related but conceptually different concepts. How the assessment is conducted will affect the accuracy of the result of the study. Construct validity enables the assessment to determine if a construct can assess what it claims to assess (Whelan & DuVernet, 2015). Other threats to construct validity may be described as an unclear construct and construct irrelevance where unclear construct refers to constructs that feature a question that may be subject to multiple interpretations and construct irrelevance when the construct measures what is not intended to measure (Ford & Scandura, 2018). This study will mitigate the risk of construct validity by ensuring that the wording of the survey instrument describes exactly what it tends to measure without introducing any form of ambiguity.

Threat to Statistical Conclusion Validity

Conclusion validity, which is also referred to as statistical conclusion validity is the degree to which conclusions about relationships in data are reasonable (Martins, Garcia, & Marçal, 2017). Conclusion validity verifies if there is a relationship between the objective of the study and the observed outcome. Common threats to conclusion validity can be caused by low reliability of measures, statistical power and violated assumptions of statistical tests. Low reliability of measure could mean that the instrument is weak and is not able to collect enough information that can be used to conclude relationships (Nascimento, 2018). Statistical power refers to a potential threat to conclusion validity where there is an error in the conclusion about a relationship. The errors are concluding that there is no relationship when there is a relationship or concluding that there is a relationship when no relationship exists (Malhotra & Khanna, 2016). A violation of the assumptions is a threat conclusion validity and may result in wrong conclusions about relationships. The analysis is usually based on some assumptions about the data, and the assumption guides the procedure and processes for analyzing the data.

This study used measures that will mitigate the risk of conclusion validity by selecting an instrument that has the power to enable the collection of data that can be used to make a valid conclusion about any relationship in the data. Multiple regression analysis is used to analyze the data, and the assumptions of multiple regression include linearity, normality, homoscedasticity, and multicollinearity. Relevant statistical test for each of the assumptions is carried out to ensure that the conditions for each assumption are met. Any deviation from the assumptions is tested with an alternative statistical test to ensure the mitigation of assumption violation threat to conclusion validity.

Transition and Summary

This section started with a reinstatement of the purpose statement, which is to examine the relationship between the U.S. federal departments' open data users' perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data. Other areas addressed in this section are the role of the researcher, description of the participants, the research method and research design, ethical research, instrumentation, population and sampling, data collection, and data analysis techniques. The research validity and reliability were also discussed, including the strategies that I used to mitigate the threats to internal and external validity. Some of the highlights of this section include a description of how my professional experience contributed to the choice of research design and method. The population and the sampling method justified how the sample size is selected to mitigate the threat to validity. The data analysis technique was identified as the multiple regression analysis and the justification for choosing it above the other forms of statistical analysis that are used to examine the relationship between multiple independent variables. The instrument used for collecting data is identified and discussed with a sample of the instrument included in the appendix section.

The next section will present the findings and the general overview of the data analysis and the collected surveys. Others are the potential application of the findings to professional practice, the way it may impact the society, and a recommendation for action and further study.

Section 3: Application to Professional Practice and Implications for Change

This section presents an overview of the study and a summary of the research findings. A quantitative method with the correlational design is used to examine the relationship between the U.S. federal departments' open data users' perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data. I used an online survey to collect data, and the results of the analysis are presented in this section. Other contents of this section include the impact of the research findings on the IT practice and the society, recommendation for action, recommendation for further study, reflections and summary. The section is concluded with the summary and conclusions of the study.

Overview of Study

The purpose of this quantitative correlational study is to examine if there is a relationship between the U.S. federal departments' open data users' perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data.

The G*Power apriori estimation method for conducting *F* test for linear multiple regression analysis is used with medium effect size: f=0.15 and power of α=0.05, which gave an estimated minimum sample size of 119 with error probability: α=0.05. I collected a total of 122 responses from individuals that have used the U.S. open government data at data.gov or census.gov, out of which 103 were fully completed. The survey was designed to be anonymous and did not collect demographic and personally identifiable information. The survey was designed with 17 questions and are answered on a 5-point

Likert scale, where 1 means strongly disagree and 5 signifies strongly agree. As soon as I received the minimum number of responses from 119 participants, I contacted the Walden University IRB to signify my intention to end the data collection. By the time the IRB responded, 122 responses were recorded.

The sample size of the standard multiple linear regression was statistically significant to predict the intent to use the U.S. open government data $F(3,99) = 6479.916$, $p < 0.01$ and accounted for 99% of the variance in the intent to use the U.S. open government data ($R^2 = .995$), adjusted $R^2 = .995$. The interdependent nature of information quality, system quality, and service quality may have contributed to the value of the R^2. The overall Cronbach's alpha for this study is $\alpha = .99$. The value of the Cronbach's alpha could be attributed to the fact that users of open data are not necessarily technical oriented, and were not able to distinguish the differences between the meanings of the variables. Hence, I rejected the null hypothesis that there is no relationship between the user's perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data from U.S. federal departments. The result of this study confirmed that there is a relationship between the user's perception of the system quality, perception of information quality, perception of service quality and the intent to use open data from U.S. federal departments.

Presentation of the Findings

This part of the study will examine the reliability of the constructs and test the various assumptions for multiple regression analysis. The statistical results emerging from the data analysis will be presented and analyzed. This section will close with the analysis and summary of the findings.

Reliability Analysis

Reliability analysis is used to ensure that a scale can produce results that can perform consistently over time (Hayashi et al., 2019) and study the properties of measurement scales, including the items that constitute the scales. Using a reliability analysis, the items and properties of the measurement scale are estimated, and the result provides information about the relationships between items in the scale. Cronbach's alpha, which measures internal consistency, is a measure of scale reliability. As one of the most commonly used measure of reliability (Cho, & Kim, 2015), Cronbach's Alpha is most commonly used with Likert questions in a survey to determine the reliability of the survey scale. The formula for Cronbach's alpha is:

$$\alpha = \frac{N\bar{c}}{\bar{v} + (N-1)\bar{c}}$$

Where

N - equal to the number of items,

C - the average inter-item covariance among the items and

υ - equals the average variance.

A reliability coefficient of α=.70 or higher is considered acceptable (Ravan, Ahmad, Chabria, Gadhari, & Sankhla, 2015). The overall Cronbach's alpha for this study is α=.99 (Table 2). The high value of Cronbach's alpha could be attributed to the fact that users of open data are not necessarily technical oriented, and were not able to distinguish the differences between the questions of the variables.

The mean in the item statistics can be seen to follow the same pattern. The interitem correlation matrix depicts how each item correlates with each other. The total correlation is an indication of how well the questions in the survey are correlated with the overall survey score (Yildirim & Correia, 2015). Item-total correlation with a score that is less than 0.30 indicates that an item may not belong to the group (Zencir, Zencir, & Khorshid, 2019). In this study, the values of information quality (.98), system quality (.98), service quality (.97), and intent to use (.96) is an indication that all the items correlated well together. The survey consists of 17 items answered on a 5-point Likert scale with four items in the information quality dimension, four items in system quality dimension, five items in service quality dimension, and four items in intent to use dimension. In this study, Cronbach's alpha for each dimension was the following: Information Quality (α=.99), System Quality (α=.99), Service Quality (α=.99), and Intent to Use (α=.99) as evidenced in Table 2.

Table 2

Reliability Analysis

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.999	.999	17

Factor Analysis

Factor analysis evaluates the construct validity of a scale and is useful for examining the structure or relationship between variables (Besnoy, Dantzler, Besnoy, & Byrne, 2016). Factor analysis assumes that there are sets of underlying variables called factors, which are usually smaller than the observed variables and cannot be observed directly except by exploring the interrelationship among variables (Nadine et al., 2015). Factor analysis is a combination of statistical techniques aiming at reducing or simplifying the data, using a correlation or covariance matrix (Koyuncu & Kılıç, 2019). Factor analysis can be performed using the concept of factor extraction or factor rotation where factor extraction is used to decide the type of model and the number of factors to extract while the factor rotation is used to achieve a simple structure for improving interpretability. This study used factor extraction with KMO and Bartlett’s test to understand the underlying structure in the data. Table 3 indicates the proportion of variance in the variables, which may likely be caused by underlying factors. KMO and Bartlett's test value, as indicated in Table 3, where the KMO=0.82 and (sig) or p=0.000, is an indication that factor analysis is suitable for analyzing the data.

Table 3

KMO and Bartlett's Test

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.824
Bartlett's Test of Sphericity	Approx. Chi-Square	1589.035
	df	6
	Sig.	.000

The total variance is an indication of the number of factors based on the eigenvalues. In Table 4, the number of factors describes the variability of all the variables with an eigenvalue of less than 1. Eigen values less than 1 is not used for calculating the numbers of factors formed. Only one factor component at 3.989 is formed.

Table 4

Total Variance Explained

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.989	99.720	99.720	3.989	99.720	99.720
2	.007	.171	99.892			
3	.003	.066	99.958			
4	.002	.042	100.000			

Extraction Method: Principal Component Analysis.

A correlation coefficient is statistically significant, with a $p < 0.05$. The correlation matrix in table Appendix G displays the relationship between all the variables.

Relationships between the predictor variables and the outcome variable were all positives correlated, and all the relationships were significantly correlated ($p < 0.01$).

Assumptions of Multiple Regression Analysis

Methodologies have a profound influence on the quality of the results from data analysis. The data collected for this study were inspected, cleaned, and prepared for reliability, consistency, and tested for conditions of the assumptions of multiple regression analysis. The assumptions, as indicated in section two, are the assumptions of normality, linearity, multicollinearity, and homoscedasticity.

Testing for Normality

Assessment of normality of data is required for statistical tests in parametric testing. Descriptive statistics are employed for the organization, description, and summarization of data. Testing for normality could be graphical or numerical (Badara & Saidin, 2014). The statistical test helps to make an easier objective judgment, but it may not be sensitive enough to lower sample size and large sample size. I used both the statistical and graphical approaches to test the data for normality. The test of normality Table 5 is shown using the Kolmogorov-Smirnov test and the Shapiro–Wilk test.

Table 5

Test of Normality

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	*df*	Sig.	Statistic	*df*	Sig.
InformationQuality	.246	5	.200*	.916	5	.507
SystemQuality	.323	5	.096	.809	5	.096
ServiceQuality	.229	5	.200*	.914	5	.492
IntentToUse	.209	5	.200*	.932	5	.611

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Data is said to be normally distributed if the sig value of the Shapiro-Wilk test is greater than 0.05 and said to significantly deviate from normal distribution if the value is below 0.05 (Mishra et al., 2019). In this study, the Shapiro-Wilk test is above 0.05 for each of the variables at information quality=0.507, system quality=0.096, service quality=0.492, and intent to use=0.611.

A logarithmic transformation (log10) that is commonly used to convert skewed data to a normal distribution (Changyong et al., 2014) is applied to the system quality variable that has the sig=.096 using. The transformation resulted in a better normalization of the system quality variable with sig=.121, as displayed in Table 6. The sig value of the Kilmorov-Smirnov test for this study is greater than 0.05, indicating that the data is normally distributed.

Table 6

Test of Normality with Transformation

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	*df*	Sig.	Statistic	*df*	Sig.
IntentToUse	.209		.200*	.932	5	.611
Log10	.313	5	.122	.822	5	.121
InformationQuality	.246	5	.200*	.916	5	.507
ServiceQuality	.229	5	.200*	.914	5	.492

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

The Normal Q-Q Plots (Appendix H) of information quality, service quality, system quality, and the intent to use are not strictly on the straight line, but they are not significantly far from the straight line and are therefore accepted as indicators of normality (Mishra et al., 2019).

Linearity Assumption for Multiple Regression Analysis

Linearity assumption relates to the relationships between predictor variables and dependent variables (Boldina & Beninger, 2016). The relationship is considered linear if most of the residuals should are scattered around zero points, including having a straight-line relationship between the predictor and the dependent variable scores. Linearity assumption for multiple regression can be determined using a scatterplot. A scatterplot is useful for determining whether a relationship is linear and to detect outliers using a graphical representation of the items and their relationship with others (Al Anazi, Shamsudin, & Johari, 2016). Appendix H has scatterplots for each of the predictor variables and the dependent variable implying linear relationships between the predictor variables and the dependent variable. The linearity assumption is met.

Multicollinearity Assumption for Multiple Regression Analysis

Multicollinearity assumes that the independent variables are not highly correlated with each other. Multicollinearity assumption can be checked using the correlation coefficients and variance inflation factor (VIF) values (Rahman & Siswowiyanto, 2018). VIF values greater than 10 are an indication of multicollinearity. In this study, the VIF values range from 18 to 37, which indicates a multicollinearity symptom (Table 7). Tolerance measures the influence of one predictor over the other predictors. Tolerance value less than .01 is considered a concerning issue. I dropped up to two variables, to improve the result, but the attempt did not yield a better result. A further drop of a variable may degrade the quality of data. The high VIFs do suggest the variables are correlated, which suggests that in the eyes of the participants, the independent variables seem to be the same variable. Therefore, the multicollinearity assumption is considered to have not been met.

Table 7

Multicollinearity Analysis

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	-.909	1.737		-.524	.693		
	InformationQuality	.911	.361	1.065	2.520	.241	.028	35.509
	SystemQuality	-.922	.347	-1.160	-2.655	.229	.026	37.962
	ServiceQuality	1.051	.295	1.072	3.561	.174	.055	18.027

a. Dependent Variable: IntentToUse

Testing for the Assumption of Homoscedasticity

The assumption of homoscedasticity is that the variance around the regression line is the same for all values of the predictor variables (Ernst & Albers, 2017). One of the assumptions of regression is that the observations are independent. Homoscedasticity assumption assumes equal levels of variability between quantitative dependent variables across a range of independent variables (Parra-frutos, 2016). A scatter plot is a good option to check for homoscedasticity. If the homoscedasticity assumption is met, the pattern should have no clear pattern in the distribution (Belás & Gabcová, 2016). An absence of a regular pattern in the scatterplot of the standardized residuals (Figure 4) indicates that the assumptions are met.

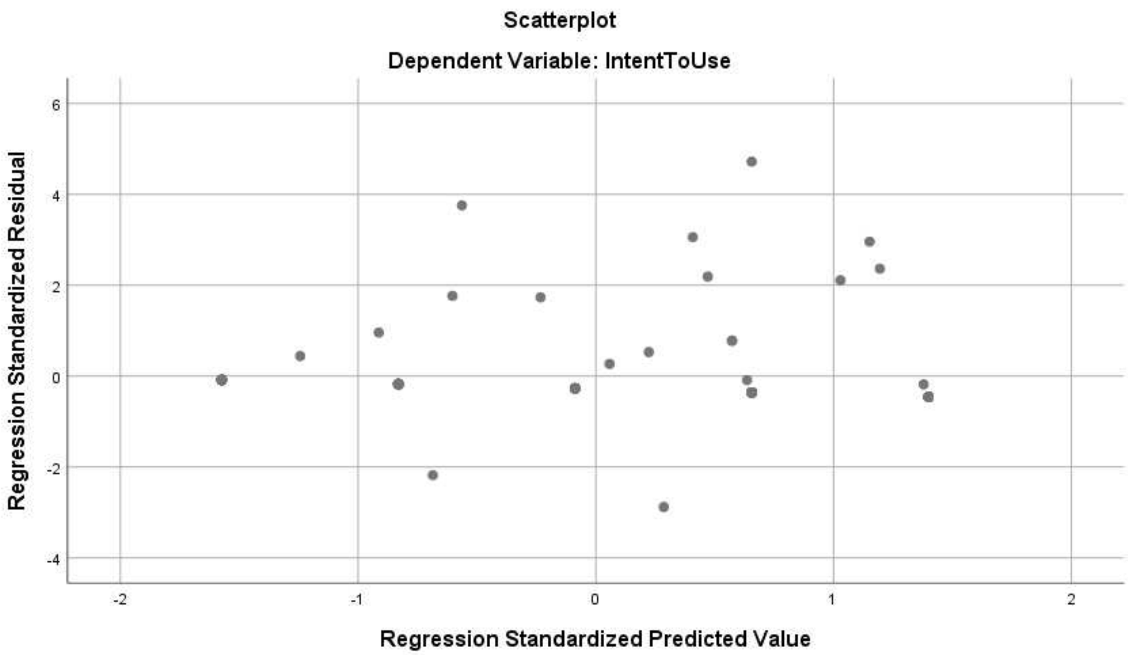


Figure 4. Scatterplots

Multiple Linear Regression Data Analysis

The multiple linear regression analysis is conducted with the data "as is" with no transformations or corrective actions. The data collected for this study are assessed to be normal though there was an insignificant violation that has no consequence on the accuracy of the analysis. Barker and Shaw (2015) stated that an insignificant violation may be permitted with a participant that is greater than 100. This study has a participant size of 122, out of which the 103 completed responses were used for the analysis.

Inferential Results. This study used a standard multiple linear regression, α = .05 (two-tailed), to examine the relationship between the U.S. federal departments' open data users' perception of the system quality, perception of information quality, perception of service quality and the intent to use open data. The independent variables were system quality, information quality, and service quality. The dependent variable is intent to use. The null hypothesis and alternative hypothesis were:

H_0: There is no relationship between the user's perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data from U.S. federal departments.

H_1: There is a relationship between the user's perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data from U.S. federal departments.

This study used the standard multiple linear regression to test the data, and the model was statistically significant to predict the intent to use the U.S. open government data $F(3,99) = 6479.916$, $p <0.01$ and accounted for 99% of the variance in the intent to use the U.S. open government data ($R^2 = .995$), adjusted $R^2 = .995$ (Table 8). The interdependent nature of information quality, system quality, and service quality (DeLone & McLean, 2003) may have contributed to the high value of the R^2. Considering that there is no single definition of information system success (Alter, 2008; Petter, DeLone, & McLean, 2008); Urbach, Smolnik, & Riempp, 2009), respondents may have different interpretations of the definition of the variables. I rejected the null hypothesis that there is no relationship between the user's perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data from U.S. federal departments. Each of the independent variables with information quality=IQ ($p <0.01$), system quality=SE ($p <0.01$), service quality=SEQ ($p <0.01$) were statistically significant predictors of the intent to use the US open government data. The positive slope for each of the predictor value (Appendix H) indicates that an increase in each predictor variable will lead to an increase in the intent to use the U.S. open government data. There is a statistically significant relationship between the U.S. federal departments' open data users' perception of the service quality and the intent to use open data.

Table 8

Multiple Linear Regression

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.997[a]	.995	.995	.39348	1.149

a. Predictors: (Constant), InformationQuality, SystemQuality, ServiceQuality

b. Dependent Variable: IntentToUse

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3009.721	3	1003.240	6479.916	.000[b]
	Residual	15.327	99	.155		
	Total	3025.049	102			

a. Dependent Variable: IntentToUse

b. Predictors: (Constant), InformationQuality, SystemQuality, ServiceQuality

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t
1	(Constant)	-.004	.099		-.038
	SystemQuality	-.342	.112	-.334	-3.040
	ServiceQuality	.450	.097	.553	4.643
	InformationQuality	.789	.104	.778	7.615

a. Dependent Variable: IntentToUse

Analysis summary. The study examined if there is a relationship between the U.S. federal departments' open data users' perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data. Multiple linear regression was used for further analysis after testing the data to confirm suitability for the assumptions of multiple regression. The linear regression model was statistically significant to predict the intent to use the U.S. open government data, $F(3,99) = 6479.916$, $p < 0.01$. Each of the predictor variables had a statistically significant correlation with intent to use where information quality ($r=.99$, $p < 0.01$), system quality ($r=.99$, $p < 0.01$) and service quality ($r=.99$, $p < 0.01$). The linear regression model output has intent to use the U.S. open government data ($p < 0.01$) = perception of information quality ($p < 0.01$), perception of system quality ($p < 0.01$) and perception of service quality. The findings in this study rejected the null hypothesis showing that there is a relationship between the U.S. federal departments' open data users' perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data.

Theoretical Conversation on Findings

This study makes some significant theoretical contributions to the literature on intent to use information system using the updated information system success model (DeLone & McLean, 2003) in the context of the U.S. open government data. The key constructs of the study are the information quality, system quality, service quality, and the intent to use. Findings from this study indicate that each of the predictor variables had a statistically significant correlation with intent to use, where information quality ($r=.99$, $p < 0.01$), system quality ($r=.99$, $p < 0.01$) and service quality ($r=.99$, $p < 0.01$), and lends support to the information system success model constructs on the intent to use an information system. There is a statistically significant correlation between the U.S. federal departments' open data users' perception of the system quality and the intent to use open data. There is a statistically significant correlation between the U.S. federal departments' open data users' perception of the information quality and the intent to use open data, and there is a statistically significant correlation between the U.S. federal departments' open data users' perception of the perception of service quality and the intent to use open data. The results for the validity using factor analysis KMO and Bartlett's Test ($p<0.01$) and reliability (Cronbach alpha value = 0.99) tests indicated that the information system success model was relevant to examine if there is a relationship between the U.S. federal departments' open data users' perception of the system quality, perception of information quality, perception of service quality and the intent to use open data. The validity and reliability results supported the arguments in Chen & Cheng, (2009); Ojo, 2017; Suryanto et al., (2016); Veeramootoo, Nunkoo, and Dwivedi (2018) that the information system success model is appropriate to measure the intent to use.

Information Quality The relationship between information quality and intent to use has been validated in other studies (DeLone & McLean, 2003; Suryanto et al., 2016; Yang, Shao, Liu, et al., 2017). This finding in this study supports the previous studies on statistically significant correlation between information quality and intent to use ($r=.99$, p

< 0.01). Some other studies (Veeramootoo et al., 2018; Wei, Tang, Kao, Tseng, & Wu, 2017) did not find a significant relationship between the two constructs.

System Quality Findings provided the support that system quality has a statistically significant correlation to intent to use ($r=.99$, $p < 0.01$). The result corroborates the classification of the relationship between system quality and higher usage continuance intention of online technologies (Petter & McLean, 2009). In the case of open data users, the technical capabilities and ease of use of the system are considered important because the primary motivation is to locate and download data successfully. This implies that, for open data publishers to encourage the intent to use the open data, the ease of use, availability of metadata, resources, and user guide must be given consideration. This finding is in line with the results of previous studies (Veeramootoo et al., 2018).

Service Quality The service quality and intent to use indicated a statistically significant correlation ($r=.99$, $p < 0.01$), and is in line with the results in other studies (Petter & McLean, 2009; Wei et al., 2017). Open data users reside in different parts of the world with differences in languages, social values, and regulations. It is not surprising that the responsiveness of the system, easy to learn, assurance, and security are considered essential.

Applications to Professional Practice

The increase in the generation of data from every human activity has led to the emergence of new economic activities in data-related businesses and governance (Zeleti & Ojo, 2017). Success in a data dominated world will depend on understanding user perception and intention to use data from a data provider. The findings in this study confirmed that there is a relationship between information quality, system quality, service quality, and intent to use where information quality ($r=.99$, $p < 0.01$), system quality ($r=.99$, $p < 0.01$) and service quality ($r=.99$, $p < 0.01$). The results indicated individually statistically strong correlations between the system quality, service quality, information quality, and intent to use. Information systems usage relies on efficiency and effectiveness for purpose and can only be useful for purpose if there is an intent to use and reuse.

The intent to use open data is expected to contribute to the long-term success of organizations. This study has provided an understanding of the perception of open data users on information quality, system quality, service quality, and intent to use open data. Results from the research can be useful for current and potential open data providers who can use the findings to improve and promote the usage of open data. The knowledge that there is a strong correlation between information quality, system quality, service quality, and intent to use will motivate emphasis on those factors during system analysis and design. The need to analyze user specifications to improve the technical infrastructure and service capacity of the open data information systems is recommended.

The basic assumption of the provision of open data is that of a strong association with the societal transformation (Baack, 2015). The transformational impact is expected from the effective exploration of open data. Robust information system infrastructures need to be provided to support open data usage (Zuiderwijk, Janssen, & Dwivedi, 2015a) with processes such as the discovery, processing, and visualization of data (Zuiderwijk, Janssen, & Susha, 2016). The diverse nature of open data requires implementing diversity in the design of information systems.

The open data standards, as defined in the principles of open license, open access, and an open format (Valdivia & Navarrete, 2016) is crucial to the objective of open data and can make

application development an easier task (Bischof et al., 2018). The design of open data information systems with open data standards has a direct influence on the intention to use OGD (Vostrovský et al., 2015). The era of social data sharing necessitates interactions among open data stakeholders (Styrin et al., 2017) and IT professionals, which can support the gathering of requirements in systems design.

Implications for Social Change

Open government data enable governments and other open data providers to provide better quality services that intelligently reflect the diversity of open data stakeholders. Access to actionable data has the potential to provide economic benefits if governments, enable policy innovation that promotes transparency and accountability (Adu, Dube, & Adjei, 2016; Lourenço et al., 2017). Open government data allows citizens to participate in governance and then be able to contribute to policy innovation. The ability to analyze societal issues by integrating formal government data with formal non-government data and social data (Gerunov, 2017) has the potential to create higher economic value. Domains such as traffic, weather, geographical, tourist information, public sector budgeting, health, and city planning have successfully used open data to create societal values. One of the challenges of the knowledge economy is effective data acquisition and knowledge management (Corrêa, Paula, Correa, & Silva, 2017), and open data is expected to be the platform to bridge the gap.

Civil society groups and journalists expect that open data will support and empower distributed publics (Baack, 2015) by breaking the interpretative monopoly of governments. With open data, citizens can acquire and interpret data from the perspective of their understanding. The emergence of open data has resulted in the emergence of new business models to support available economic opportunities (Zeleti & Ojo, 2017). Traditionally, many state governments have not been committed to the digital preservation of records, but open data concept has triggered the need for digitization and preservation of e-government activities.

Recommendations for Action

The open data ecosystem has been reported to suffer from poor usability (Beno et al., 2017). Consequent upon this study's findings analysis that indicates a relationship between each of the three constructs of information quality, system quality, service quality and the intent to use the U.S. open government data, open data providers should emphasize information quality, system quality and service quality in designing open data information systems. Knowledge from this study can be used to refine the predictive model for further evaluation of the intent to use open data. The diverse nature of open data stakeholders calls for optimization and documenting of user requirements and analysis.

As open data has great potential for economic value, open data providers need to identify the relevant economic model that can enable the development and management of information systems for open data. The development of information systems for open data cannot be a one size fits all, and each open data provider will need to segment and profile stakeholders for effective representation in system design. The economic and societal importance of open data requires the deployment of robust technology infrastructures. Open standards formats that support the interoperability of other software components across the internet (Chen, 2016) can support and enable usability and collaboration to provide opportunities for users to collaborate on application development for open data (Schauppenlehner & Muhar, 2018). Open data providers can improve the use of open data technologies by integrating open e-learning focused models to equip stakeholders with skills to maximize open data usage.

Empirical studies on the intent to use open government data are still few, and this study is one of the few attempts to understand the relationship between user perception on information quality, system quality, service quality, and the intent to use open data. It is highly recommended that further research is conducted in this area. This study was limited to users of the U.S. open government data, and further research is recommended for other open data providers in other countries. Open data technologies may differ in country, culture, and societal value future research is recommended to recognize the diversity in open data stakeholders.

Recommendations for Further Study

This study had a few limitations. The study was targeted at anyone who has ever used the U.S. open data portal at census.gov or data.gov. There were high correlations in the predictor variables, and a possible explanation could be that the respondents were not able to distinguish between the questions of the variables. Considering that there is no single definition of information system success (Alter, 2008; Petter et al., 2008; Urbach, Smolnik, & Riempp), respondents may have different interpretations of defining the variables. The high VIF values and low tolerance values for the predictors may indicate that respondents considered some of the questions in the measure to be redundant. That is not unlikely considering that open data users are not necessarily IT professionals or technical oriented people. I recommend that further study should segment users to understand how different categories of users perceive open data. Theoretical contributions in the field of open government data (Magalhaes & Roseira, 2017) and the U.S. federal open data are scarce are still few.

There are few insights on the appropriateness of using specific theories for open data and the most promising theories for understanding open data (Zuiderwijk, Helbig, Gil-García, & Janssen, 2014). Likewise, best predictors on the relationship between user perception of the information quality, system quality, service quality, and intent to use open data are still unknown currently. This study is a contribution towards understanding which predictor of information system success model best describes the relationship between information quality, system quality, service quality, and the intent to use open data. The findings in this study confirmed that there is a relationship between information quality, system quality, service quality, and intent to use where information quality ($r=.99$, $p < 0.01$), system quality ($r=.99$, $p <0.01$) and service quality ($r=.99$, $p < 0.01$). The results indicated an individually statistically strong relationship between the system quality, service quality, information quality and intent to use.

This empirical quantitative correlational study tested the information system success model in the field of open data using a Likert scale questionnaire. I recommend further research using a mixed-method or case study approach to increase the explained variability in the intent to use open data technology. Other recommended areas of further research are to focus on specific uses of open data to understand the diversity of open data perspectives. This study did not collect information such as sex, age, country of residence, and the purpose of using open data. Future research using a qualitative method may reveal the human side of open data users to use it for improving the human-computer interaction on open data information systems. The number of participants used for this study was 122 participants. Considering that potential open data users are many, further study using a larger number of participants could help with the predictive ability of the information system success model. The information system success model has six constructs, but this study used only four of the constructs. I recommend that further research is conducted using other constructs of the same model in the field of open data research to identify salient variables in the context of open data information systems. Finally, causality cannot be inferred from the data. Further research could investigate causality in the same context.

Reflections

Towards the end of the DIT program, the ideas, hopes, and dreams that motivated me to begin a doctoral journey began turning to anxiety and sometimes worry about the reality that awaits me after the completion of DIT program. Despite the occasional concern, I have noticed the changes in my thinking and my perceptions as I found myself thinking more like a researcher. Remembering that I have learned exciting things that have positive possibilities of turning my dreams to reality always redeem my hope and the passion for completing the study despite all odds. I also know that completing DIT courses does not signify the end of learning. The truth is that the real learning begins after the doctorate, and I understand that completing the DIT program learning is just the beginning of learning.

This study was borne on my interest in business and organizational efficiencies, the need for investigating business systems and performance, to align processes and projects to business objectives strategically. The information technology (IT) arena is still evolving, and there are constant changes in the knowledge area. I support the need for defining and maintaining ethical standards in the provision and use of IT. I believe that both the provider and user of information systems have the ethical responsibility for ensuring security and confidentiality of information. Therefore, I am committed to educating society on the responsible use of IT.

I had some understanding of research approaches based on my working experience, but the DIT program enabled me to expand my knowledge of research processes and designs. Though I have been using open data portals, I did not have any preconceived biases as I began this research to examine the relationship between the U.S. federal departments' open data users' perception of the system quality, perception of information quality, perception of service quality and the intent to use open data. The findings in this study made theoretical contributions to the literature on intent to use an information system, and the updated information system success model. The results indicated a relationship between the system quality, service quality, information quality, and intent to use. These can be useful to current and potential open data providers who could use the findings to improve and promote the usage of open data. As open data is still at an emerging stage, IT practitioners need to continue to analyze user specifications to improve the technical infrastructure, open data quality, and service capacity of the open data information systems.

Summary and Study Conclusions

Information system success model (DeLone & McLean, 2003) has been extensively used for investigating information system evaluation from a general user's perspective (Charalabidis, Loukis, & Alexopoulos, 2014; Hossain et al., 2016; Susha et al., 2015a; Zuiderwijk, Susha, Charalabidis, Parycek, & Janssen, 2015). Accordingly, following a review of existing literature, it was concluded that the information system success model was relevant to the study's intent to use the U.S. open government data. This study validated the information system success model to understand the relationship between information quality, system quality, service quality, and intent to use. In response to the recommendation by DeLone and McLean (2003) to continuously test and adapt the model in different contexts, this study applied the model to the context of the U.S. open government data. This study rejected the null hypothesis that there is no relationship between the user's perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data from U.S. federal departments.

The aim of the study to examine if there is a relationship between the U.S. federal departments' open data users' perception of the system quality, perception of information quality, perception of service quality, and the intent to use open data. Different stakeholders of an information system may have different expectations resulting in different interpretations (Zuiderwijk et al., 2015b). There is still not much known about the factors which influence the success or failure of open data initiatives, but it is known that quality data and information system may stimulate use and facilitate value generation. Various researchers have described factors that are essential to open data usage intention (Fan & Zhao, 2017), but actual usage intentions may depend on the context of the initiative. There is a need for open data providers to identify context-dependent open data success factors to foster improvement in the publication and usage of open data. The successful use of published open data is expected to stimulate economic and societal gains.

References

Aadinarayana, V. D., & Sharma, S. (2017). Transitioning "Open data" from a NOUN to a VERB. *PeerJ PrePrints,* doi:10.7287/peerj.preprints.3015v1.

Acosta-Vargas, P., Luján-Mora, S., & Salvador-Ullauri, L. (2017). Quality evaluation of government websites. In *eDemocracy & eGovernment (ICEDEG), 2017 Fourth International Conference on* (pp. 8-14). IEEE. doi:10.1109/icedeg.2017.7962507.

Adenuga, O. A., Kekwaletswe, R. M., & Coleman, A. (2015). eHealth integration and interoperability issues: towards a solution through enterprise architecture. *Health information science and systems*, *3*(1), 1. doi:10.1186/s13755-015-0009-7.

Adu, K. K., Dube, L., & Adjei, E. (2016). Digital preservation: the conduit through which open data, electronic government and the right to information are implemented. *Library Hi Tech*, *34*(4), 733-747. doi:10.1108/lht-07-2016-0078.

Ahmad, F., & Khan, R. A. (2015). A power comparison of various normality tests. *Pakistan Journal of Statistics and Operation Research, 11*(3). doi:10.18187/pjsor.v11i3.845.

Ain, Q., Aslam, M., Muhammad, S., Awan, S., Pervez, M. T., Naveed, N., . . . Qadri, S. (2016). A technique to increase the usability of e-learning websites. *Pakistan Journal of Science, 68*(2), 164-169. Retrieved from https://www.researchgate.net/profile/Abdul_Dogar4/publication/305479002_A_TECHNIQUE_TO_INCREASE_THE_USABILITY_OF_E-LEARNING_WEBSITES/links/5790c67608ae0831552f8ca8.pdf.

Alam, I., Khusro, S., Rauf, A., & Zaman, Q. (2014). Conducting surveys and data collection: From traditional to mobile and SMS-based surveys. *Pakistan Journal of Statistics and Operation Research, 10*(2). doi:10.18187/pjsor.v10i2.758.

Alami, S. A. (2015). Research within the field of applied linguistics: Points to consider. *Theory and Practice in Language Studies, 5*(7), 1330-1337. doi:10.17507/tpls.0507.03.

Al Anazi, A. A., Shamsudin, F. M., & Johari, J. (2016). Linking organisational culture, leadership styles, human resource management practices and organisational performance: Data screening and preliminary analysis. *American Journal of Management, 16*(1), 70-79.

Alenezi, H., Tarhini, A., & Sharma, S. K. (2015). Development of quantitative model to investigate the strategic relationship between information quality and e-government benefits. *Transforming Government: People, Process and Policy, 9*(3), 324-351. doi:10.1108/tg-01-2015-0004.

Al-Ghazali, B. M., Rasli, A. M., Yusoff, R. M., & Mutahar, A. Y. (2015). Antecedents of Continuous Usage Intention of Mobile Banking Services from the Perspective of DeLone and McLean Model of IS Success. *International Journal of Economics and Financial Issues*, *5*(1S), 13-21. doi:10.11113/jt.v72.3934.

Almazán, D. A., Tovar, Y. S., & Quintero, J. M. M. (2017). Influence of information systems on organizational results. *Contaduríay Administración*, *62*(2), 321-338. doi:10.1016/j.cya.2017.03.001.

Alonso, B., Barreda, R., Dell'Olio, L., & Ibeas, A. (2018). Modelling user perception of taxi service quality. *Transport Policy*, *63*, 157-164. doi:10.1016/j.tranpol.2017.12.011.

Alromaih, N., Albassam, H., & Al-Khalifa, H. (2016). A proposed checklist for the technical maturity of open government data: an application on GCC countries. In *Proceedings of the 18th International Conference on Information Integration and Web-based Applications and Services* (pp. 494-499). ACM. doi:10.1145/3011141.3011211.

Alter, S. (2008). Defining information systems as work systems: implications for the IS field. *European Journal of Information Systems, 17*(5), 448-469. doi:10.1057/ejis.2008.37.

Alzahrani, L., Al-Karaghouli, W., & Weerakkody, V. (2017). Analysing the critical factors influencing trust in e-government adoption from citizens' perspective: A systematic review and a conceptual framework. *International Business Review*, *26*(1), 164-175. doi:10.1016/j.ibusrev.2016.06.004.

Anja, F. E., & Albers, C. J. (2017). Regression assumptions in clinical psychology research practice - A systematic review of common misconceptions. *PeerJ PrePrints,* doi:10.7287/peerj.preprints.2602v1.

Apuke, O. D. (2017). Quantitative research methods a synopsis approach. *Kuwait Chapter of the Arabian Journal of Business and Management Review, 6*(11), 40-47. doi:10.12816/0040336.

Atanda, L. A. (2017). Internet usage and user satisfaction with library services in federal university Otuoke main library. *International Research: Journal of Library and Information Science, 7*(3). Retrieved from http://irjlis.com/internet-usage-and-user-satisfaction-with-library-services-in-federal-university-otuoke-main-library/.

Awang, Z., Afthanorhan, A., & Mamat, M. (2016). The Likert scale analysis using parametric based structural equation modeling (SEM). *Computational Methods in Social Sciences, 4*(1), 13-21. doi:10.5539/mas.v9n9p58.

Ayyash, M. M. (2017). Scrutiny of Relationship between E-Banking Information Quality Dimensions and Customer Satisfaction. doi:10.3844/jcssp.2017.78.90.

Baack, S. (2015). Datafication and empowerment: How the open data movement re-articulates notions of democracy, participation, and journalism. *Big Data & Society*, *2*(2), 2053951715594634. doi:10.1177/2053951715594634.

Badara, M. A. S., & Saidin, S. Z. (2014). Internal audit effectiveness: Data screening and preliminary analysis. *Asian Social Science*, *10*(10), 76-85. doi:10.5539/ass.v10n10p76.

Bakaev, M., Mamysheva, T., & Gaedke, M. (2016). Current trends in automating usability evaluation of websites: Can you manage what you can't measure? In *Strategic Technology (IFOST), 2016 11th International Forum on* (pp. 510-514). IEEE. doi:10.1109/ifost.2016.7884307.

Bannister, F., & Connolly, R. (2014). ICT, public values and transformative government: A framework and programme for research. *Government Information Quarterly*, *31*(1), 119-128. doi:10.1016/j.giq.2013.06.002.

Barker, L. E., & Shaw, K. M. (2015). Best (but oft-forgotten) practices: checking assumptions concerning regression residuals. *American Journal of Clinical Nutrition*, *102*(3), 533-539. doi:10.3945/ajcn.115.113498.

Bärnighausen, T., Røttingen, J. A., Rockers, P., Shemilt, I., & Tugwell, P. (2017). Quasi-experimental study designs series-paper 1: Introduction: Two historical lineages. *Journal of Clinical Epidemiology, 89*, 4-11. doi:10.1016/j.jclinepi.2017.02.020.

Basias, N., & Pollalis, Y. (2018). Quantitative and qualitative research in business & technology: Justifying a suitable research methodology. *Review of Integrative Business and Economics Research, 7*, 91-105. Retrieved from http://sibresearch.org/uploads/3/4/0/9/34097180/riber_7-s1_sp_h17-083_91-105.pdf.

Belás, J., & Gabcová, L. (2016). The relationship among customer satisfaction, loyalty and financial performance of commercial banks. *E+M Ekonomie a Management, 19*(1), 132-147. doi:10.15240/tul/001/2016-1-010.

Belland, B. R., Walker, A. E., Megan, W. O., & Leary, H. (2015). A pilot meta-analysis of computer-based scaffolding in STEM education. *Journal of Educational Technology & Society, 18*(1), 183-197. doi:10.1007/978-3-319-02565-0_5.

Bello, O., Akinwande, V., Jolayemi, O., & Ibrahim, A. (2016). Open data portals in Africa: An analysis of open government data initiatives. *African Journal of Library, Archives & Information Science, 26*(2), 97-106. Retrieved from https://www.researchgate.net/publication/312057417_Open_Data_Portals_in_Africa_An_Analysis_ofOpen_Government_Data_Initiatives.

Beno, M., Figl, K., Umbrich, J., & Polleres, A. (2017). Open data hopes and fears: Determining the barriers of open data. In *E-Democracy and Open Government (CeDEM), 2017 Conference for* (pp. 69-81). IEEE. doi:10.1109/cedem.2017.22.

Besnoy, K. D., Dantzler, J., Besnoy, L. R., & Byrne, C. (2016). Using exploratory and confirmatory factor analysis to measure construct validity of the traits, aptitudes, and behaviors scale (TABS). *Journal for the Education of the Gifted, 39*(1), 3-22. doi:10.1177/0162353215624160.

Beyene, W. M. (2017). Metadata and universal access in digital library environments. *Library Hi Tech, 35*(2), 210-221. doi:10.1108/LHT-06-2016-0074.

Binding, C., & Tudhope, D. (2016). Improving interoperability using vocabulary linked data. *International Journal on Digital Libraries, 17*(1), 5-21. doi:10.1007/s00799-015-0166-y.

Bischof, S., Harth, A., Kämpgen, B., Polleres, A., & Schneider, P. (2018). Enriching integrated statistical open city data by combining equational knowledge and missing value imputation. *Journal of Web Semantics*, *48*, 22-47. doi:10.1016/j.websem.2017.09.003.

Bolarinwa, O. A. (2015). Principles and methods of validity and reliability testing of questionnaires used in social and health science researches. *Nigerian Postgraduate Medical Journal*, *22*(4), 195. doi:10.4103/1117-1936.173959.

Boldina, I., & Beninger, P. G. (2016). Strengthening statistical usage in marine ecology: Linear regression. *Journal of Experimental Marine Biology and Ecology*, *474*, 81-91. doi:10.1016/j.jembe.2015.09.010.

Breeding, M. (2016). The current state of privacy and security of automation and discovery products. *Library Technology Reports, 52*(4), 13-28,3. doi:10.5860/ltr.52n4.

Bromley, E., Mikesell, L., Jones, F., & Khodyakov, D. (2015). From subject to participant: Ethics and the evolving role of community in health research. *American Journal of Public Health*, *105*(5), 900-908. doi:10.2105/AJPH.2014.302403.

Budiardjo, E. K., Pamenan, G., Achmad, N. H., Meyliana, D., & Cofriyanti, E. (2017). The impact of knowledge management system quality on the usage continuity and recommendation intention. *Knowledge Management & E-Learning, 9*(2), 200. doi:10.1145/3167020.3167021.

Budimir, M. E. A., Atkinson, P. M., & Lewis, H. G. (2015). A systematic review of landslide probability mapping using logistic regression. *Landslides, 12*(3), 419-436. doi:10.1007/s10346-014-0550-5.

Buranarach, M., Krataithong, P., Hinsheranan, S., Ruengittinun, S., & Supnithi, T. (2017). A Scalable Framework for Creating Open Government Data Services from Open Government Data Catalog. In *Proceedings of the 9th International Conference on Management of Digital EcoSystems* (pp. 1-5). ACM. doi:10.1145/3167020.3167021.

Cabitza, F., Locoro, A., & Batini, C. (2015). A user study to assess the situated social value of open data in healthcare. *Procedia Computer Science*, *64*, 306-313. F SciKA - Association for Promotion and Dissemination of Scientific Knowledge. doi:10.1016/j.procs.2015.08.494.

Campos, J. (2016). Managing the information systems in the industrial domain. *Cogent Business & Management, 3*(1) doi:10.1080/23311975.2016.1180967.

Cantor, A., Kiparsky, M., Kennedy, R., Hubbard, S., Bales, R., Pecharroman, L. C., ... & Darling, G. (2018). Data for Water Decision Making: Informing the Implementation of California's Open and Transparent Water Data Act through Research and Engagement. Retrieved from https://scholarship.law.berkeley.edu/cleepubs/56

Cardamone, A., Eboli, L., & Mazzulla, G. (2014). Drivers' road accident risk perception. A comparison between face-to-face interview and web-based survey. Advances in Transportation in Studies, 33, 59-72. doi:10.4399/97888548728995.

Changyong, F. E. N. G., Hongyue, W. A. N. G., Naiji, L. U., Tian, C. H. E. N., Hua, H. E., & Ying, L. U. (2014). Log-transformation and its implications for data analysis. *Shanghai archives of psychiatry*, *26*(2), 105. doi: 10.3969/j.issn.1002-0829.2014.02.009.

Charalabidis, Y., Alexopoulos, C., & Loukis, E. (2016). A taxonomy of open government data research areas and topics. *Journal of Organizational Computing and Electronic Commerce*, *26*(1-2), 41-63. doi:10.1080/10919392.2015.1124720.

Charalabidis, Y., Loukis, E., & Alexopoulos, C. (2014). Evaluating Second Generation Open Government Data Infrastructures Using Value Models. 2014 47th Hawaii International Conference on System Sciences (Hicss), pp. 2114-2126. http://10.1109/Hicss.2014.267.

Chaveesuk, S., & Hongsuwan, S. (2017). A structural equation model of ERP implementation success in Thailand. *Review of Integrative Business and Economics Research, 6*(3), 194-204. Retrieved from http://buscompress.com/uploads/3/4/9/8/34980536/riber_6-3_a17-176_194-204.pdf.

Chen, C. W. D., & Cheng, C. Y. J. (2009). Understanding consumer intention in online shopping: a respecification and validation of the DeLone and McLean model. *Behaviour & Information Technology*, *28*(4), 335-345. doi:10.1080/01449290701850111.

Chen, S. (2016). Open standards and license choice in open source software. *Journal of Economics and Economic Education Research, 17*(2), 97-104. Retrieved from https://www.alliedacademies.org/articles/jeeervol-17issue-3.pdf.

Cho, E., & Kim, S. (2015). Cronbach's coefficient alpha: Well known but poorly understood. *Organizational Research Methods*, *18*(2), 207-230. doi:10.1177/1094428114555994.

Chu, P. Y., & Tseng, H. L. (2016). A theoretical framework for evaluating government open data platform. In *Proceedings of the International Conference on Electronic Governance and Open Society: Challenges in Eurasia* (pp. 135-142). ACM. doi:10.1145/3014087.3014099.

Corrêa, A. S., Paula, E. C. D., Correa, P. L. P., & Silva, F. S. C. D. (2017). Transparency and open government data: a wide national assessment of data openness in Brazilian local governments. *Transforming Government: People, Process and Policy*, *11*(1), 58-78. doi:10.1108/tg-12-2015-0052.

Corsar, D., & Edwards, P. (2017). Challenges of Open Data Quality: More Than Just License, Format, and Customer Support. *Journal of Data and Information Quality (JDIQ)*, *9*(1), 3. doi:10.1145/3110291.

Corsi, D. J., Perkins, J. M., & Subramanian, S. V. (2017). Child anthropometry data quality from demographic and health surveys, multiple indicator cluster surveys, and national nutrition surveys in the west-central Africa region: Are we comparing apples and oranges? *Global Health Action, 10*(1), 1-10. doi:10.1080/16549716.2017.1328185.

Csáki, C., & Prier, E. (2018). Quality Issues of Public Procurement Open Data. In *International Conference on Electronic Government and the Information Systems Perspective* (pp. 177-191). Springer, Cham. doi:10.1007/978-3-319-98349-3_14.

Danneels, L., Viaene, S., & Van den Bergh, J. (2017). Open data platforms: Discussing alternative knowledge epistemologies. *Government Information Quarterly*, *34*(3), 365-378. doi:10.1016/j.giq.2017.08.007.

Das, S., Mitra, K., & Mandal, M. (2016). Sample size calculation: Basic principles. *Indian Journal of Anesthesia, 60*(9) doi:10.4103/0019-5049.190621.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 319-340. doi:10.2307/249008.

Dawes, S. S., Vidiasova, L., & Parkhimovich, O. (2016). Planning and designing open government data programs: An ecosystem approach. *Government Information Quarterly*, *33*(1), 15-27. doi:10.1016/j.giq.2016.01.003.

Dean, J. (2014). Personal Protective Equipment: An Antecedent to Safe Behavior? *Professional Safety*, *59*(02), 41-46. Retrieved from http://www.asse.org/professional-safety/.

Dedeke, A. (2000). A Conceptual Framework for Developing Quality Measures for Information Systems. In *IQ* (pp. 126-128). Retrieved from http://mitiq.mit.edu/ICIQ/Documents/IQ%20Conference%202000/Papers/AConceptualFramework4DevelopQualityMeasure.pdf.

De Groot, M. J., Sijens, P. E., Reijngoud, D., Paans, A. M., & Van Spronsen, F. J. (2015). Phenylketonuria: Brain phenylalanine concentrations relate inversely to cerebral protein synthesis. *Journal of Cerebral Blood Flow and Metabolism, 35*(2), 200-205. doi:10.1038/jcbfm.2014.183.

DeLone, W. H., & McLean, E. R. (1992). Information Systems Success: The Quest for the Dependent Variable. Information Systems Research, 3(1), 60-95. doi:10.1287/isre.3.1.60

DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: a ten-year update. *Journal of management information systems*, *19*(4), 9-30. doi:10.1080/07421222.2003.11045748.

DeLone, W. H., & McLean, E. R. (2016). Information systems success measurement. *Foundations and Trends® in Information Systems*, *2*(1), 1-116. doi:10.1561/2900000005.

Dey, P., Ross, J. S., Ritchie, J. D., Desai, N. R., Bhavnani, S. P., & Krumholz, H. M. (2017). Data sharing and cardiology. *Journal of the American College of Cardiology, 70*(24), 3018-3025. doi:10.1016/j.jacc.2017.10.037.

Divan, A., Ludwig, L. O., Matthews, K. E., Motley, P. M., & Tomljenovic-Berube, A. (2017). Survey of research approaches utilized in the scholarship of teaching and learning publications. *Teaching & Learning Inquiry, 5*(2), 16-29. doi:10.20343/teachlearninqu.5.2.3.

Dlodlo, N., & Hamunyela, S. (2017). The status of integration of health information systems in Namibia. *Electronic Journal of Information Systems Evaluation, 20*(2), 61-75. doi:10.1051/matecconf/20165803001.

Dobson, C., Woller-Skar, M., & Green, J. (2017). An inquiry-based activity to show the importance of sample size and random sampling. *Science Scope, 40*(8), 76-81. doi:10.2505/4/ss17_040_08_76.

Donker, F. W., VanLoenen, B., & Bregt, A. K. (2016). Open data and beyond. *ISPRS International Journal of Geo-Information, 5*(4), 48. doi:10.3390/ijgi5040048.

Dos Santos, A., Santoso, A. J., & Setyohadi, D. B. (2017). The Analysis of Academic Information System Success: A Case Study at Instituto Profissional De Canossa (IPDC) Dili Timor-Leste. In *Soft Computing, Intelligent System and Information Technology (ICSIIT), 2017 International Conference on* (pp. 196-201). IEEE. doi: 10.1109/ICSIIT.2017.14.

Dwivedi, Y. K., Wastell, D., Laumer, S., Henriksen, H. Z., Myers, M. D., Bunker, D., . . . Srivastava, S. C. (2015). Research on information systems failures and successes: Status update and future directions. *Information Systems Frontiers, 17*(1), 143-157. doi:10.1007/s10796-014-9500-y.

Eiras, M., Escoval, A., Isabel, M. G., & Silva-Fortes, C. (2014). The hospital survey on patient safety culture in Portuguese hospitals. *International Journal of Health Care Quality Assurance, 27*(2), 111-22. doi:10.1108/IJHCQA-07-2012-0072.

Elo, S., Kaariainen, M., Kanste, O., Polkki, T., Utriainen, K., & Kyngas, H. (2014). Qualitative content analysis: A focus on trustworthiness. SAGE Open, 4(1), 1-10. doi:10.1177/2158244014522633.

Ernst, A. F., & Albers, C. J. (2017). Regression assumptions in clinical psychology research practice—a systematic review of common misconceptions. *PeerJ,* doi:10.7717/peerj.3323.

Evans, J. R., & Anil, M. (2018). The value of online surveys: A look back and a look ahead. *Internet Research, 28*(4), 854-887. doi:10.1108/IntR-03-2018-0089.

Ewusie, J. E., Blondal, E., Soobiah, C., Beyene, J., Thabane, L., Straus, S. E., & Hamid, J. S. (2017). Methods, applications, interpretations, and challenges of interrupted time series (ITS) data: Protocol for a scoping review. *BMJ Open, 7*(6) doi:10.1136/bmjopen-2017-016018.

Fan, B., & Zhao, Y. (2017). The moderating effect of external pressure on the relationship between internal organizational factors and the quality of open government data. *Government Information Quarterly*, *34*(3), 396-405. doi:10.1016/j.giq.2017.08.006.

Farooq, R. (2017). A framework for identifying research gap in social sciences: Evidence from the past. *IUP Journal of Management Research, 16*(4), 66-75. Retrieved from https://www.questia.com/library/journal/1P4-1979951115/a-framework-for-identifying-research-gap-in-social.

Farzandipour, M., Meidani, Z., Gilasi, H., & Dehghan, R. (2017). Evaluation of key capabilities for hospital information system: A milestone for meaningful use of information technology. *Annals of Tropical Medicine and Public Health, 10*(6) doi:10.4103/ATMPH.ATMPH_531_17.

Fernandez, K. E., Husser, J. A., & Macdonald, M. G. (2016). Polling the pollsters: A survey of academic survey organizations. *PS, Political Science & Politics, 49*(4), 859-866. doi:10.1017/S104909651600144X.

Fitriyah, F. K., & Nagara, T. K. (2017). The effect of professionalism, violation severity levels, and internal locus of control on whistleblowing intention. *Review of*

Integrative Business and Economics Research, 6(4), 133-154. Retrieved from http://buscompress.com/journal-home.html

Ford, L. R., & Scandura, T. A. (2018). A typology of threats to construct validity in item generation. *American Journal of Management, 18*(2), 132-142. doi:10.33423/ajm.v18i2.298.

Gascó-Hernández, M., Martin, E. G., Reggi, L., Pyo, S., & Luna-Reyes, L. F. (2018). Promoting the use of open government data: Cases of training and engagement. *Government Information Quarterly*, *35*(2), 233-242. doi:10.1016/j.giq.2018.01.003.

Gelling, L. (2016). Applying for ethical approval for research: The main issues. *Nursing Standard (2014+), 30*(20), 40. doi:10.7748/ns.30.20.40.s46.

Gerunov, A. (2017). Understanding open data policy: evidence from Bulgaria. *International Journal of Public Administration*, *40*(8), 649-657. doi:10.1080/01900692.2016.1186178.

Ghosh, R., & Jacobson, S. (2016). Contending claims to causality: A critical review of mediation research in HRD. *European Journal of Training and Development, 40*(8), 595-614. doi: 10.1108/EJTD-07-2015-0056.

Gonzalez-Zapata, F., & Heeks, R. (2015). The multiple meanings of open government data: Understanding different stakeholders and their perspectives. *Government Information Quarterly*, *32*(4), 441-452. doi:10.1016/j.giq.2015.09.001.

Gopinathan, S., & Raman, M. (2016). Information system quality in work-life balance. *Knowledge Management & E-Learning, 8*(2), 216. doi:10.1016/j.sbspro.2015.11.161.

Green, S. B. (1991). How many subjects does it take to do a regression analysis? *Multivariate behavioral research*, *26*(3), 499-510. doi:10.1207/s15327906mbr2603_7.

Guetterman, T. C. (2017). What distinguishes a novice from an expert mixed methods researcher? *Quality and Quantity, 51*(1), 377-398. doi:10.1007/s11135-016-0310-9.

Hagan, T. L. (2014). Measurements in quantitative research: How to select and report on research instruments. *Oncology Nursing Forum, 41*(4), 431-3. doi:10.1188/14.onf.431-433.

Halcomb, E., & Hickman, L. (2015). Mixed methods research. Nursing Standard), 29(32), 41. doi:10.7748/ns.29.32.41.e8858.

Hales, A. H. (2016). Does the conclusion follow from the evidence? Recommendations for improving research. *Journal of Experimental Social Psychology*, *66*, 39-46. doi:10.1016/j.jesp.2015.09.011.

Hamid, S. S. (2016). Transforming teacher education for the globalization of education. *NUML Journal of Critical Inquiry, 14*(2), 70-IX. doi:10.5040/9781474219020.ch-001.

Hayashi, P., Jr., Abib, G., & Hoppen, N. (2019). Validity in qualitative research: A processual approach. *The Qualitative Report, 24*(1), 98-112. Retrieved from https://nsuworks.nova.edu/tqr/vol24/iss1/8/.

Hazra, A., & Gogtay, N. (2016). Biostatistics series module 6: correlation and linear regression. *Indian journal of dermatology*, *61*(6), 593. doi:10.4103/0019-5154.193662.

Hellberg, A., & Hedström, K. (2015). The story of the sixth myth of open data and open government. *Transforming Government: People, Process and Policy, 9*(1), 35-51. doi: 10.1108/tg-04-2014-0013.

Herala, A., Kasurinen, J., & Vanhala, E. (2018). Views on open data business from software development companies. *Journal of Theoretical and Applied Electronic Commerce Research, 13*(1), 91-105. doi:10.4067/S0718-18762018000100106.

Highsmith, M. J., Nelson, L. M., Carbone, N. T., Klenow, T. D., Kahle, J. T., Hill, O. T., ... & Randolph, B. J. (2016). Outcomes associated with the Intrepid Dynamic Exoskeletal Orthosis (IDEO): a systematic review of the literature. *Military medicine*, *181*(suppl_4), 69-76. doi:10.7205/MILMED-D-16-00280.

Hjalmarsson, A., Johansson, N., & Rudmark, D. (2015). Mind the gap: exploring stakeholders' value with open data assessment. In *System Sciences (HICSS), 2015 48th Hawaii International Conference on* (pp. 1314-1323). IEEE. doi:10.1109/hicss.2015.160.

Hong, H., Cao, M., & Wang, G. A. (2017). The effects of network externalities and herding on user satisfaction with mobile social apps. *Journal of Electronic Commerce Research, 18*(1), 18-31. Retrieved from http://www.jecr.org/node/515.

Horga, G., Kaur, T., & Peterson, B. S. (2014). Annual Research Review: Current limitations and future directions in MRI studies of child-and adult-onset developmental psychopathologies. *Journal of Child Psychology and Psychiatry*, *55*(6), 659-680. Retrieved from https://europepmc.org/abstract/med/24438507.

Hossain, M. A., Dwivedi, Y. K., & Rana, N. P. (2016). State-of-the-art in open data research: Insights from existing literature and a research agenda. *Journal of organizational computing and electronic commerce*, *26*(1-2), 14-40. doi:10.1080/10919392.2015.1124007.

Huang, E. Y., Lin, S. W., & Fan, Y. C. (2015). MS-QUAL: Mobile service quality measurement. *Electronic Commerce Research and Applications*, *14*(2), 126-142. doi:10.1016/j.elerap.2015.01.003.

Imran, A., & Yusoff, R. M. (2015). Empirical validation of qualitative data: A mixed method approach. International Journal of Economics and Financial Issues, 5(1). Retrieved from https://www.econjournals.com/index.php/ijefi/article/viewFile/1511/pdf.

Irani, Z., & Kamal, M. (2016). Transforming government: people, process, and policy. *Transforming Government: People, Process and Policy*, *10*(2), 190-195. doi:10.1108/tg-03-2016-0016.

Irick, M. L. (2008). Task-technology fit and information systems effectiveness. *Journal of Knowledge Management Practice*, *9*(3), 1-5. Retrieved from http://www.tlainc.com/articl165.htm.

Islam, M. N., & Islam, A. N. (2016). Ontology mapping and semantics of web interface signs. *Human-Centric Computing and Information Sciences, 6*(1), 1-13. doi:10.1186/s13673-016-0077-y.

Islam, R., Selim, A., & Dzuljastri, A. R. (2015). Identifying the gaps between customer expectations and perceptions on service quality dimensions of Islamic banks in Mmalaysia. *International Journal of Quality and Service Sciences, 7*(4), 424-441. doi:10.1108/IJQSS-12-2014-0053

ISO/IEC 11179-4:2004 (n.d). Information technology -- Metadata registries (MDR) -- Part 4: Formulation of data definitions. Retrieved October 28, 2018, from http://standards.iso.org/ittf/PubliclyAvailableStandards/c035346_ISO_IEC_11179-4_2004(E).zip.

Janita, M. S., & Miranda, F. J. (2018). Quality in e-government services: A proposal of dimensions from the perspective of public sector employees. *Telematics and Informatics*. doi:10.1016/j.tele.2018.01.004.

Janssen, M., Konopnicki, D., Snowdon, J. L., & Ojo, A. (2017). Driving public sector innovation using big and open linked data (BOLD). *Information Systems Frontiers, 19*(2), 189-195. doi:10.1007/s10796-017-9746-2.

Janssen, M., Matheus, R., Longo, J., & Weerakkody, V. (2017). Transparency-by-design as a foundation for open government. *Transforming Government: People, Process and Policy*, *11*(1), 2-8. doi:10.1108/TG-02-2017-0015.

Janzen, R., Nguyen, N., Stobbe, A., & Araujo, L. (2015). Assessing the value of inductive and deductive outcome measures in community-based programs: Lessons from the city kidz evaluation. *The Canadian Journal of Program Evaluation, 30*(1), 41-63. doi:10.3138/cjpe.30.1.41.

Jiménez-Ramírez, C., Burke, M. E., & Rodríguez-Flores, I. (2017). Statistical metadata in knowledge discovery. *Dyna*, *84*(202), 270-277. doi:10.15446/dyna.v84n202.61417.

Jing, F., & Wenting, Y. (2014). A study of G2C e-government citizen's satisfaction: Perspectives of online service quality and offline service quality. In *Service Systems and Service Management (ICSSSM), 2014 11th International Conference on* (pp. 1-5). IEEE. doi:10.1109/icsssm.2014.6943345.

Jovanovik, M., & Trajanov, D. (2017). Consolidating drug data on a global scale using linked data. *Journal of Biomedical Semantics, 8.* doi:10.1186/s13326-016-0111-z.

Jurisch, M. C., Kautz, M., Wolf, P., & Krcmar, H. (2015). An international survey of the factors influencing the intention to use open government. In System Sciences (HICSS), 2015 48th Hawaii International Conference on (pp. 2188-2198). IEEE. doi:10.1109/HICSS.2015.262.

Kapoor, K., Weerakkody, V., & Sivarajah, U. (2015). Open data platforms and their usability: Proposing a framework for evaluating citizen intentions. In *Conference* *on e-Business, e-Services and e-Society* (pp. 261-271). Springer, Cham. doi:10.1007/978-3-319-25013-7_21.

Karaim, N. A., & Inal, Y. (2017). Usability and accessibility evaluation of Libyan government websites. *Universal Access in the Information Society*, 1-10. doi:10.1007/s10209-017-0575-3.

Karanth, P., & Mahesh, K. (2015). From data to knowledge analytics: capabilities and limitations. *Information Studies, 21*(4), 261-274. doi:10.5958/0976-1934.2015.00019.1.

Kasaj, A. (2016). User adoption of mandatory e-government systems: Notarial system in Albania, an empirical analysis. In *CBU International Conference Proceedings...* (Vol. 4, p. 531). Central Bohemia University. doi:10.12955/cbup.v4.810.

Katz, J. (2015). A theory of qualitative methodology: The social system of analytic fieldwork. Méthod (e) s: African Review of Social Sciences Methodology, 1(1-2), 131-146. doi:10.1080/23754745.2015.1017282.

Kaur, M. (2016). Application of mixed method approach in public health research.*Indian Journal of Community Medicine, 41*(2) doi:10.4103/0970-0218.173495.

Kaushik, t., & Baliyan, r. (2017). A study on impact of celebrity and non-celebrity endorsed FMCG advertisement through online advertising on the consumer purchase behaviour. *Global Management Review*, *11*(1). Retrieved from https://www.numl.edu.pk/jci/docs/NUML%20JCI%20ISSN%202222-5706%20Vol%2014(lI),%20Dec_2016.pdf.

Kaye, J., Whitley, E. A., Lund, D., Morrison, M., Teare, H., & Melham, K. (2015). Dynamic consent: a patient interface for twenty-first-century research networks. *European Journal of Human Genetics*, *23*(2), 141. doi:10.1038/ejhg.2014.71.

Khajouei, R., Gohari, S. H., & Mirzaee, M. (2018). Comparison of two heuristic evaluation methods for evaluating the usability of health information systems. *Journal of biomedical informatics*, *80*, 37-42. doi:10.1016/j.jbi.2018.02.016.

Khundaqji, H., Samain, E., Climstein, M., Schram, B., Hing, W., & Furness, J. (2018). A comparison of aerobic fitness testing on a swim bench and treadmill in a recreational surfing cohort: A pilot study. *Sports, 6*(2) doi:10.3390/sports6020054.

Kool, D. D., & Bekkers, V. (2016). The perceived value-relevance of open data in the parents' choice of Dutch primary schools. *International Journal of Public Sector Management*, *29*(3), 271-287. doi:10.1108/ijpsm-02-2016-0022.

Koyuncu, İ., & Kılıç, A. F. (2019). The use of exploratory and confirmatory factor analyses: A document analysis. *Egitim Ve Bilim, 44*(198). doi:10.15390/eb.2019.7665.

Krass, I. (2016). Quasi experimental designs in pharmacist intervention research.*International Journal of Clinical Pharmacy, 38*(3), 647-654. doi:10.1007/s11096-016-0256-y.

Krewinkel, A., & Winkler, R. (2017). Formatting open science: Agilely creating multiple document formats for academic manuscripts with pandoc scholar. *PeerJ Computer Science,* doi:10.7717/peerj-cs.112.

Kubler, S., Robert, J., Neumaier, S., Umbrich, J., & Le Traon, Y. (2018). Comparison of metadata quality in open data portals using the Analytic Hierarchy Process. *Government Information Quarterly*, *35*(1), 13-29. doi:10.1016/j.giq.2017.11.003.

Kucera, J. (2015). Open government data publication methodology. *Journal of Systems Integration, 6*(2), 52-61. doi:10.20470/jsi.v6i2.231.

Kuntiyawichai, K., Dau, Q. V., & Inthavong, S. (2017). Community engagement for irrigation water management in Lao PDR. *Journal of Water and Land Development, 35*(1), 121-128. doi:10.1515/jwld-2017-0075.

Kusumawardhani, M., Gundersen, S., & Tore, M. (2017). Mapping the research approach of asset management studies in the petroleum industry. *Journal of Quality in Maintenance Engineering, 23*(1), 57-70. doi:10.1108/jqme-07-2015-0031.

Lapôtre, R. (2017). Library metadata on the web: The example of data.bnf.fr. *JLIS.it, 8*(3), 58-70. doi:10.4403/jlis.it-12402.

Lee, S., & Kim, B. G. (2017). The impact of qualities of social network service on the continuance usage intention. *Management Decision, 55*(4), 701-729. doi:10.1108/md-10-2016-0731.

Lesser, V. M., Yang, D. K., Newton, L. D., & Sifneos, J. C. (2016). Mixed-mode surveys compared with single-mode surveys: trends in responses and methods to improve completion. *Journal of Rural Social Sciences, 31*(3), 7-34. Retrieved from http://journalofruralsocialsciences.org/pages/Articles/JRSS%202016%2031/3/JRSS%202016%2031%203%207-34.pdf.

Li, Y., Duan, Y., Fu, Z., & Alford, P. (2012). An empirical study on behavioural intention to reuse e-learning systems in rural China. *British Journal of Educational Technology*, *43*(6), 933-948. doi:10.1111/j.1467-8535.2011.01261.x.

Lindman, J., Kinnari, T., & Rossi, M. (2016). Business roles in the emerging open-data ecosystem. *IEEE Software*, *33*(5), 54-59. doi:10.1109/ms.2015.25.

Liu, X. W., Jin, C. Y., & Nam, S. T. (2017). A Meta-Analysis of the Success Factors Based on the Information Systems Success Model Utilizing Big Data. *International Information Institute (Tokyo). Information*, *20*(1B), 603. doi:10.6109/jkiice.2016.20.11.2033.

Loomis, D. K., & Paterson, S. (2018). A comparison of data collection methods: Mail versus online surveys. *Journal of Leisure Research, 49*(2), 133-149. doi:10.1080/00222216.2018.1494418.

Lourenço, R. P., Piotrowski, S., & Ingrams, A. (2017). Open data-driven public accountability. *Transforming Government: People, Process and Policy, 11*(1), 42-57. doi: 10.1108/TG-12-2015-0050.

Ma, F. (2015). A review of research methods in EFL education. *Theory and Practice in Language Studies, 5*(3), 566-571. doi:10.17507/tpls.0503.16.

Máchová, R., & Lnenicka, M. (2017). Evaluating the quality of open data portals on the national level. *Journal of Theoretical and Applied Electronic Commerce Research, 12*(1), 21-41. doi:10.4067/S0718-18762017000100003.

Maduku, D. K. (2015). An empirical investigation of students' behavioural intention to use e-books. *Management Dynamics, 24*(3), 2-20. Retrieved from https://www.questia.com/library/journal/1P3-3968466261/an-empirical-investigation-of-students-behavioural.

Magalhaes, G., & Roseira, C. (2017). Open government data and the private sector: An empirical view on business models and value creation. *Government Information Quarterly*. doi:10.1016/j.giq.2017.08.004.

Mahmood, A., & Miller, L. (2017). ERP system implementation in large enterprises – a systematic literature review. *Journal of Enterprise Information Management, 30*(4), 666-692. doi:10.1108/JEIM-07-2014-0071.

Malhotra, R., & Khanna, M. (2016). Common threats to software quality predictive modeling studies using search-based techniques. In *2016 International Conference on Advances in Computing, Communications and Informatics (ICACCI)* (pp. 554-560). IEEE. doi:10.1109/icacci.2016.7732104.

Mălinaș, C., Oroian, I., Odagiu, A., & Safirescu, C. (2017). Application of descriptive statistics in monitoring climatic factors. *ProEnvironment Promediu, 10*(29). Retrieved from http://journals.usamvcluj.ro/index.php/promediu.

Manescu, N. (2014). The sociological research methodology in approaching of the theme: "the social impact of domination and voluntary servitude. "the research project

(II). *Research and Science Today,* 89-96. Retrieved from https://heinonline.org/HOL/LandingPage?handle=hein.journals/rescito8&div=26&id=&page=.

Mardiana, S., Tjakraatmadja, J. H., & Aprianingsih, A. (2015). DeLone-McLean information system success model revisited: The separation of intention to use-use and the integration of technology acceptance models. *International Journal of Economics and Financial Issues*, *5*(1S). doi:10.1016/j.procs.2015.12.150.

Martins, L. C. G., Garcia, R. E., & Marçal, I. (2017). Using Information Visualization to comprehend user interface layer. *Proceedings of the XVI Brazilian Symposium on Human Factors in Computing Systems - IHC 2017*. doi:10.1145/3160504.3160558.

McCullagh, M. C., Sanon, M. A., & Cohen, M. A. (2014). Strategies to enhance participant recruitment and retention in research involving a community-based population. Applied Nursing Research, 27, 249–253. doi:10.1016/j.apnr.2014.02.007.

McKiernan, E. C. (2017). Imagining the “open” university: Sharing scholarship to improve research and education. *PLoS Biology, 15*(10). doi:10.1371/journal.pbio.1002614.

McKiernan, E. C., Bourne, P. E., Titus, B. C., Buck, S., Amye, K., Lin, J., . . . Tal, Y. (2016). How open science helps researchers succeed. *ELife, 5.* doi:10.7554/eLife.16800.

McNab, A. L., & Ladd, D. A. (2014). Information quality: the importance of context and trade-offs. In *System Sciences (HICSS), 2014 47th Hawaii International Conference on* (pp. 3525-3532). IEEE. doi:10.1109/HICSS.2014.439.

Mishra, P., Pandey, C., Singh, U., Gupta, A., Sahu, C., & Keshri, A. (2019). Descriptive statistics and normality tests for statistical data. *Annals of Cardiac Anaesthesia, 22*(1), 67-72. doi:10.4103/aca.ACA_157_18.

Mohd Daud, N., & Zakaria, H. (2017). Impact of antecedent factors on collaborative technologies usage among academic researchers in Malaysian research universities. *The International Journal of Information and Learning Technology, 34*(3), 189-209. doi:10.1108/ijilt-09-2016-0046.

Morozova, O., Levina, O., Uuskula, A., & Heimer, R. (2015). Comparison of subset selection methods in linear regression in the context of health-related quality of life and substance abuse in Russia. *BMC Medical Research Methodology, 15.* doi:10.1186/s12874-015-0066-2.

Mudzana, T., & Maharaj, M. (2015). Measuring the success of business-intelligence systems in South Africa: An empirical investigation applying the DeLone and McLean Model. South African Journal of Information Management, 17(1), 1-7. doi:10.4102/sajim.v17i1.646.

Mueller, K., Straatmann, T., Hattrup, K., & Jochum, M. (2014). Effects of personalized versus generic implementation of an intra-organizational online survey on psychological anonymity and response behavior: A field experiment. *Journal of Business and Psychology, 29*(2), 169-181. doi:10.1007/s10869-012-9262-9.

Mvungi, J., & Tossy, T. (2015). Usability evaluation methods and principles for the web. *International Journal of Computer Science and Information Security*, *13*(7), 86. Retrieved from http://ijcsse.org/published/volume4/issue7/p1-V4I7.pdf.

Nadine, C. S., Patrício, S. C., Amorim, L., Pedro, S. M., Cunha, P., Cotter, J., & Sousa, N. (2015). Exploring the factor structure of neurocognitive measures in older individuals. *PLoS One, 10*(4) doi:10.1371/journal.pone.0124229.

Nascimento, A. G. S. (2018). A mapping study of scientific merit of papers, which subject are web applications test techniques, considering their validity threats. *Journal of Information Systems and Technology Management: JISTEM, 15*, 1-20. doi:10.4301/S1807-1775201815006.

Nelson, M. S., Wooditch, A., & Dario, L. M. (2015). Sample size, effect size, and statistical power: A replication study of Weisbrod's paradox. *Journal of Experimental Criminology, 11*(1), 141-163. doi:10.1007/s11292-014-9212-9.

Neumaier, S., & Umbrich, J. (2016). Measures for assessing the data freshness in Open Data portals. In *Open and Big Data (OBD), International Conference on* (pp. 17-24). IEEE. doi:10.1109/OBD.2016.10.

Ngulube, P. (2015). Trends in research methodological procedures used in knowledge management studies. *African Journal of Library, Archives & Information Science, 25*(2), 125-143. Retrieved from https://www.academia.edu/25052285/Trends_in_Research_Methodological_Procedures_Used_in_Knowledge_Management_Studies.

Ngwakongnwi, E. (2017). Methodological Challenges to Collecting Valid Research Data: Researching English Language Barrier Populations in Canada. *Health Science Journal*, *11*(3). doi:10.21767/1791-809x.1000510.

Ojo, A. I. (2017). Validation of the DeLone and McLean Information Systems Success Model. *Healthcare informatics research*, *23*(1), 60-66. doi:10.4258/hir.2017.23.1.60.

Okhovati, M., Karami, F., & Khajouei, R. (2017). Exploring the usability of the central library websites of medical sciences universities. *Journal of Librarianship and Information Science*, *49*(3), 246-255. doi:10.1177/0961000616650932.

Oliveira, R., & Moreno, R. (2016). Harvesting, integrating and distributing large open geospatial datasets using free and open-source software. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences-ISPRS Archives*, *41*, 939-940. doi:10.5194/isprs-archives-xli-b7-939-2016.

Open Data Handbook (N.d.). Five stars of open data. Retrieved November 1, 2018, from http://opendatahandbook.org/glossary/en/terms/five-stars-of-open-data/.

Open definition (N.d). Open Format Definition. Retrieved on October 31, 2018, from http://opendefinition.org/ofd/

Osah, O., & Kyobe, M. (2017). Predicting user continuance intention towards M-pesa in Kenya. *African Journal of Economic and Management Studies, 8*(1), 36-50. doi:10.1108/AJEMS-03-2017-148.

Palagolla, N. (2016). Exploring the Linkage between Philosophical Assumptions and Methodological Adaptations in HRM Research. *Journal of Strategic Human Resource Management*, *5*(1). Doi:10.21863/jshrm/2016.5.1.020.

Palese, B., & Usai, A. (2018). The relative importance of service quality dimensions in E-commerce experiences. *International Journal of Information Management*, *40*, 132-140. doi:10.1016/j.ijinfomgt.2018.02.001.

Pandya-Wood, R., Barron, D. S., & Elliott, J. (2017). A framework for public involvement at the design stage of NHS health and social care research: Time to develop ethically conscious standards. *Research Involvement and Engagement, 3* doi:10.1186/s40900-017-0058-y.

Pang, X. (2016). Shared challenges and solutions: The common future of comparative politics and quantitative methodology. *Chinese Political Science Review, 1*(3), 472-488. doi:10.1007/s41111-016-0033-z.

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). Servqual: A multiple-item scale for measuring consumer perc. *Journal of Retailing, 64*(1), 12. doi:10.1037/t09264-000.

Parra-frutos, I. (2016). Preliminary tests when comparing means. *Computational Statistics, 31*(4), 1607-1631. doi:10.1007/s00180-016-0656-4.

Pather, S. (2017, September). Contextualising Information Systems Evaluation Research: Towards a Classification of Approaches. In *the European Conference on Information Systems Management* (pp. 252-261). Academic Conferences International Limited. Retrieved from https://www.researchgate.net/profile/Shaun_Pather/publication/320099491_Contextualising_Information_Systems_Evaluation_Research_Towards_a_Classification_of_Approaches/links/59cdc9ab458515cc6aa4c35c/Contextualising-Information-Systems-Evaluation-Research-Towards-a-Classification-of-Approaches.pdf.

Pereira, G. V., Macadar, M. A., Luciano, E. M., & Testa, M. G. (2017). Delivering public value through open government data initiatives in a smart city context. *Information Systems Frontiers, 19*(2), 213-229. doi:10.1007/s10796-016-9673-7.

Petrescu, M., & Lauer, B. (2017). Qualitative marketing research: The state of journal publications. The Qualitative Report, 22(9), 2248-2287. Retrieved from https://nsuworks.nova.edu/tqr/vol22/iss9/1/.

Petter, S., & McLean, E. R. (2009). A meta-analytic assessment of the DeLone and McLean IS success model: An examination of IS success at the individual level. *Information and Management*, *46*(3), 159-166. https://doi.org/10.1016/j.im.2008.12.006.

Petter, S., DeLone, W., & McLean, E. (2008). Measuring information systems success: models, dimensions, measures, and interrelationships. *European journal of information systems, 17*(3), 236-263. doi:10.1057/ejis.2008.15.

Phan, H. P., & Ngu, B. H. (2017). Undertaking experiments in social sciences: Sequential, multiple time series designs for consideration. *Educational Psychology Review, 29*(4), 847-867. doi:10.1007/s10648-016-9368-0.

Pipino, L. L., Lee, Y. W., & Wang, R. Y. (2002). Data quality assessment. *Communications of the ACM*, *45*(4), 211-218. doi:10.1145/505248.506010.

Prakash, P. O., & Jaya, A. (2016). Analyzing and predicting user behavior pattern from weblogs. *International Journal of Applied Engineering Research*, *11*(9), 6278-6283. Retrieved from http://www.iaescore.com/journals/index.php/IJEECS/article/viewFile/8828/8789.

Project Open Data. (n.d.) Retrieved May 24, 2018, from https://project-open-data.cio.gov/

Raggett, D. (2017). W3C study of practices and tooling for Web data standardization. Retrieved from https://www.w3.org/2017/12/odi-study/

Rahman, H., & Siswowiyanto, H. P. (2018). Knowledge inertia in the innovation of coffee production. *The South East Asian Journal of Management, 12*(2), 144-163. Retrieved from https://doi/org/10.21002/seam.v12i2.9721.

Ramesh, P., Vivekavardhan, J., & Bharathi, K. (2015). Metadata diversity, interoperability, and resource discovery issues and challenges. *DESIDOC Journal of Library & Information Technology, 35*(3) doi:10.14429/djlit.35.3.8074.

Rana, N. P., Dwivedi, Y. K., Williams, M. D., & Weerakkody, V. (2015). Investigating success of an e-government initiative: Validation of an integrated IS success model. *Information Systems Frontiers*, *17*(1), 127-142. doi:10.1007/s10796-014-9504-7.

Rathod, S., & Mishra, G. C. (2017). Weather-based modeling for forecasting area and production of mango in Karnataka. *International Journal of Agriculture, Environment and Biotechnology, 10*(1), 149-162. doi:10.5958/2230-732X.2017.00015.8.

Ravan, A., Ahmad, F., Chabria, S., Gadhari, M., & Sankhla, C. (2015). Non-motor symptoms in an indian cohort of parkinson's disease patients and correlation of progression of non-motor symptoms with motor worsening. *Neurology India, 63*(2), 166-174. doi:10.4103/0028-3886.156276.

Reis, J., Amorim, M., & Melão, N. (2018). Guidelines for Qualitative Case Research in Operations Management: A Banking Service Industry Perspective. In *17th European Conference on Research Methodology for Business and Management Studies* (pp. 319-327). Academic Conferences and Publishing International Limited. Retrieved from https://www.researchgate.net/publication/326060211_Guidelines_for_Qualitative_Case_Research_in_Operations_Management_A_Banking_Service_Industry_Perspective.

Resnik, D. B., Miller, A. K., Kwok, R. K., Engel, L. S., & Sandler, D. P. (2015). Ethical issues in environmental health research related to public health emergencies: Reflections on the GuLF study. *Environmental health perspectives*, *123*(9), A227. doi:10.1289/ehp.1509889.

Rhee, H. L. (2015). Reflections on archival user studies. *Reference & User Services Quarterly, 54*(4), 29-42. doi:10.5860/rusq.54n4.29.

Riazi, A. M., & Candlin, C. N. (2014). Mixed-methods research in language teaching and learning: Opportunities, issues, and challenges. *Language Teaching, 47*(2), 135-173. doi:10.1017/S0261444813000505.

Roberts, L. D., & Allen, P. J. (2015). Exploring ethical issues associated with using online surveys in educational research. *Educational Research and Evaluation*, *21*(2), 95-108. doi:10.1080/13803611.2015.1024421.

Robinson, O. C. (2014). Sampling in interview-based qualitative research: A theoretical and practical guide. *Qualitative Research in Psychology, 11*(1), 25-41. doi:10.1080/14780887.2013.801543.

Rocca-Serra, P., Salek, R. M., Arita, M., Correa, E., Dayalan, S., Gonzalez-Beltran, A., . . . Neumann, S. (2016). Data standards can boost metabolomics research, and if there is a will, there is a way. *Metabolomics, 12*(1), 1-13. doi:10.1007/s11306-015-0879-3.

Roky, H., & Al Meriouh, Y. (2015). Evaluation by Users of an Industrial Information System (XPPS) Based on the DeLone and McLean Model for IS Success. *Procedia Economics and Finance*, *26*, 903-913. doi:10.1016/s2212-5671(15)00903-x.

Rosdini, D., & Ritchi, H. (2017). Examining accounting information system in a shared environment: The measure of system adoption efficacy – Indonesia case. *Review of Integrative Business and Economics Research, 6*(2), 326-342. Retrieved from http://buscompress.com/uploads/3/4/9/8/34980536/riber6-2_24k17-111_326-342.pdf.

Roy, A. (2014). Aboriginal worldviews and epidemiological survey methodology: Overcoming incongruence. *International Journal of Multiple Research Approaches, 8*(1), 117-128. doi:10.5172/mra.2014.8.1.117.

Ruijer, E., Grimmelikhuijsen, S., Hogan, M., Enzerink, S., Ojo, A., & Meijer, A. (2017). Connecting societal issues, users and data. Scenario-based design of open data platforms. *Government Information Quarterly*, *34*(3), 470-480. doi:10.1016/j.giq.2017.06.003.

Russo, D., Ciancarini, P., Falasconi, T., & Tomasi, M. (2018). A Meta-Model for Information Systems Quality: A Mixed Study of the Financial Sector. *ACM Transactions on Management Information Systems (TMIS)*, *9*(3), 11. doi:10.1145/3230713.

Rutberg, S., & Bouikidis, C. D. (2018). Focusing on the fundamentals: A simplistic differentiation between qualitative and quantitative research. *Nephrology Nursing Journal, 45*(2), 209-213. Retrieved from https://www.ncbi.nlm.nih.gov/pubmed/30303640?dopt=Abstract.

Sadiq, S., & Indulska, M. (2017). Open data: quality over quantity. *International Journal of Information Management*, *37*(3), 150-154. doi:10.1016/j.ijinfomgt.2017.01.003.

Saghaeiannejad-Isfahani, S., Jahanbakhsh, M., Habibi, M., Mirzaeian, R., Nasirian, M., & Rad, J. S. (2014). A Survey on the Users' Satisfaction with the Hospital Information Systems (HISs) based on DeLone and McLean's Model in the

Medical-Teaching Hospitals in Isfahan City. Acta Informatica Medica, 22(3), 179. doi:10.5455/aim.2014.22.179-182.

Salameh, A. A., & Hassan, S. B. (2015). Measuring Service Quality in M-commerce Context: A Conceptual Model. *International Journal of Scientific and Research Publications*, *5*(3), 1-9. Retrieved from http://www.ijsrp.org/research-paper-0315/ijsrp-p3954.pdf.

Sansone, S., Cruse, P., & Thorley, M. (2018). High-quality science requires high-quality open data infrastructure. *Scientific Data, 5*, 180027. doi:10.1038/sdata.2018.27.

Saxena, S. (2017). "Usage by stakeholders" as the objective of "transparency-by-design" in open government data. *Information and Learning Science, 118*(7), doi:10.1108/ILS-05-2017-0034.

Saxena, S., & Janssen, M. (2017). Examining open government data (OGD) usage in India through UTAUT framework. Foresight: The Journal of Futures Studies, Strategic Thinking, and Policy, 19(4), 421-436. doi:10.1108/FS-02-2017-0003.

Schauppenlehner, T., & Muhar, A. (2018). Theoretical availability versus practical accessibility: The critical role of metadata management in open data portals. *Sustainability, 10*(2), 545. doi:10.3390/su10020545.

Schoonenboom, J., & Burke Johnson, R. (2017). How to construct a Mixed methods research design. *Kölner Zeitschrift Für Soziologie Und Sozialpsychologie, 69*(2), 107-131. doi:10.1007/s11577-017-0454-1.

Scott, M., DeLone, W., & Golden, W. (2016). Measuring eGovernment success: a public value approach. *European Journal of Information Systems*, *25*(3), 187-208. doi:10.1057/ejis.2015.11.

Scott, M., & Golden, W. (2009). Understanding net benefits: A citizen-based perspective on e-government success. Retrieved from https://pdfs.semanticscholar.org/acc9/c43620d9e794d9b81bfcd6aa3fc39ddf0426.pdf.

Sebetci, Ö., & Çetin, M. (2016). Developing, applying and measuring an e-Prescription Information Systems Success Model from the perspectives of physicians and pharmacists. *Health Policy and Technology*, *5*(1), 84-93. doi:10.1016/j.hlpt.2015.10.008.

Setia, M. S. (2016). Methodology series module 5: Sampling strategies. *Indian journal of dermatology*, *61*(5), 505. doi:10.4103/0019-5154.190118.

Shannon, C. E., & Weaver, W. (1949). The mathematical theory of communication. (University of Illinois Press: Urbana, IL, USA). Retrieved from https://www.scirp.org/(S(vtj3fa45qm1ean45vvffcz55))/reference/ReferencesPapers.aspx?ReferenceID=1311827.

Shekhar Singh, A. (2014). Conducting case study research in non-profit organisations. *Qualitative Market Research: An International Journal*, *17*(1), 77-84. doi:10.1108/QMR-04-2013-0024.

Sieber, R. E., & Johnson, P. A. (2015). Civic open data at a crossroads: Dominant models and current challenges. *Government Information Quarterly*, *32*(3), 308-315. doi:10.1016/j.giq.2015.05.003.

Silalahi, S. L. B., Handayani, P. W., & Munajat, Q. (2017). Service Quality Analysis for Online Transportation Services: Case Study of GO-JEK. *Procedia Computer Science, 124*, 487–495. doi:10.1016/j.procs.2017.12.181.

Siuryte, A., & Davidaviciene, V. (2016). An Analysis of Key Factors in Developing a Smart City. *Mokslas, Lietuvos Ateitis, 8*(2), 254-262. doi:10.3846/mla.2016.900.

Smith, G. (2018). Step away from stepwise. *Journal of Big Data, 5*(1), 1-12. doi:10.1186/s40537-018-0143-6.

Smith, W. S., Zeng, Z., & Carette, J. (2018). Seismology software: state of the practice. *Journal of Seismology, 22*(3), 755–788. doi:10.1007/s10950-018-9731-3.

Stichler, J. F. (2016). Research, research-informed design, evidence-based design. *HERD* design. *HERD: Health Environments Research & Design Journal, 10*(1), 7-12. doi:10.1177/1937586716665031.

Stickler, U., & Hampel, R. (2015). Qualitative research in CALL. *calico journal*, *32*(3), 380-395. doi:10.1558/cj.v32i3.27737.

Stuart, E. A., Bradshaw, C. P., & Leaf, P. J. (2015). Assessing the generalizability of randomized trial results to target populations. *Prevention Science, 16*(3), 475-485. doi:10.1007/s11121-014-0513-z.

Styrin, E., Luna-Reyes, L., & Harrison, T. M. (2017). Open data ecosystems: An international comparison. *Transforming Government: People, Process and Policy, 11*(1), 132-156. doi:10.1108/TG-01-2017-0006.

Subiyakto, A., Ahlan, A. R., Kartiwi, M., & Sukmana, H. T. (2015). Measurement of information system project success based on perceptions of the internal stakeholders. *International Journal of Electrical and Computer Engineering, 5*(2), 271-279. Retrieved from https://www.researchgate.net/publication/272294813_Measurement_of_Information_System_Project_Success_Based_on_Perceptions_of_the_Internal_Stakeholders.

Sultono, S., Seminar, K. B., & Erizal, E. (2016). Analysis on Academic Information System Quality Toward User Satisfaction. *Bisnis & Birokrasi Journal*, *22*(2), 122-129. doi:10.20476/jbb.v22i2.5701.

Sun, J., & Teng, J. T. (2017). The construct of information systems use benefits: Theoretical explication of its underlying dimensions and the development of a measurement scale. *International Journal of Information Management*, *37*(5), 400-416. doi:10.1016/j.ijinfomgt.2017.04.010.

Suryanto, T. L. M., Setyohadi, D. B., & Faroqi, A. (2016). Analysis of the Effect of Information System Quality to Intention to Reuse of Employee Management Information System (Simpeg) Based on Information Systems Success Model. MATEC Web of Conferences, 58, 03001. doi:10.1051/matecconf/20165803001.

Susha, I., Grönlund, Å., & Janssen, M. (2015a). Organizational measures to stimulate user engagement with open data. *Transforming Government: People, Process and Policy, 9*(2), 181-206. doi:10.1108/Tg-05-2014-0016.

Susha, I., Zuiderwijk, A., Charalabidis, Y., Parycek, P., & Janssen, M. (2015b). Critical Factors for Open Data Publication and Use: A Comparison of City-level, Regional, and Transnational Cases. JeDEM-eJournal of eDemocracy and Open Government, 7(2), pp. 94-115. doi:10.29379/jedem.v7i2.397.

Sussman, S., Jon-Patrick, A., Garcia, J., Unger, J. B., Tess, B. C., Garcia, R., & Baezconde-Garbanati, L. (2016). Who walks into vape shops in southern California? A naturalistic observation of customers. *Tobacco Induced Diseases, 14.* doi:10.1186/s12971-016-0082-y.

Szabó, N. (2015). Methods for regionalizing input-output tables. *Regional Statistics, 5*(1), 44-65. doi:10.15196/RS05103.

Taherdoost, H. (2018). A review of technology acceptance and adoption models and theories. *Procedia Manufacturing*, *22*, 960-967. doi:10.1016/j.promfg.2018.03.137.

Tavakol, M., & Sandars, J. (2014). Quantitative and qualitative methods in medical education research: AMEE Guide No 90: Part II. Medical Teacher, 36(90), 838–848. doi:10.3109/0142159X.2014.915297.

Theophil, B. A., Kalegele, K., & Chachage, B. (2017). Evaluating information system integration approaches for fixed asset management framework in Tanzania.*Journal of Systems Integration, 8*(4), 3-11. doi:10.20470/jsi.v8i4.324.

Thorsby, J., Stowers, G. N., Wolslegel, K., & Tumbuan, E. (2017). Understanding the content and features of open data portals in American cities. *Government Information Quarterly*, *34*(1), 53-61 doi:10.1016/j.giq.2016.07.001.

Todoran, I. G., Lecornu, L., Khenchaf, A., & Caillec, J. M. L. (2015). A methodology to evaluate important dimensions of information quality in systems. *Journal of Data and Information Quality (JDIQ)*, *6*(2-3), 11. doi:doi.org/10.1145/2744205.

Toots, M., McBride, K., Kalvet, T., & Krimmer, R. (2017). Open data as enabler of public service co-creation: exploring the drivers and barriers. In *E-Democracy and Open Government (CeDEM), 2017 Conference for* (pp. 102-112). IEEE. doi:10.1109/cedem.2017.12.

Tygel, A., Auer, S., Debattista, J., Orlandi, F., & Campos, M. L. M. (2016). Towards cleaning-up open data portals: A metadata reconciliation approach. In *Semantic Computing (ICSC), 2016 IEEE Tenth International Conference on* (pp. 71-78). IEEE. doi:10.1109/ICSC.2016.54.

Unal, P., Temizel, T. T., & Eren, P. E. (2017). What installed mobile applications tell about their owners and how they affect users' download behavior. *Telematics and Informatics*, *34*(7), 1153-1165. doi:10.1016/j.tele.2017.05.005.

Urbach, N., Smolnik, S., & Riempp, G. (2009). The state of research on information systems success. *Business & Information Systems Engineering, 1*(4), 315-325. doi:10.1007/s12599-009-0059-y.

Valdivia, R., & Navarrete, M. (2016). Open standards and interoperability: GTFS case. *Ingeniare: Revista Chilena De Ingenieria, 24*(2), 184-187. doi:10.4067/s0718-33052016000200001.

Valerio, M. A., Rodriguez, N., Winkler, P., Lopez, J., Dennison, M., & Yuanyuan Liangrbara, J. T. (2016). Comparing two sampling methods to engage hard-to-reach communities in research priority setting. *BMC Medical Research Methodology, 16.* doi:10.1186/s12874-016-0242-z.

van Rijnsoever, F. J. (2017). (I Can't get no) saturation: A simulation and guidelines for sample sizes in qualitative research. *PLoS One, 12*(7) doi:10.1371/journal.pone.0181689.

Veeramootoo, N., Nunkoo, R., & Dwivedi, Y. K. (2018). What determines success of an e-government service? Validation of an integrative model of e-filing continuance usage. *Government Information Quarterly*, *35*(2), 161-174. doi:10.1016/j.giq.2018.03.004.

Venkatesh, V., Brown, S. A., & Sullivan, Y. W. (2016). Guidelines for conducting mixed-methods research: An extension and illustration. *Journal of the Association for Information Systems, 17*(7), 435-494. doi:10.17705/1jais.00433.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425-478. doi:10.2307/30036540.

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016b). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems, 17*(5), 328-376. doi:10.17705/1jais.00428.

Vetrò, A., Canova, L., Torchiano, M., Minotas, C. O., Iemma, R., & Morando, F. (2016). Open data quality measurement framework: Definition and application to Open Government Data. *Government Information Quarterly*, *33*(2), 325-337. doi:10.1016/j.giq.2016.02.001.

Viscusi, G., Castelli, M., & Batini, C. (2014). Assessing social value in open data initiatives: A framework. *Future Internet, 6*(3), 498-517. doi:10.3390/fi6030498.

Vostrovský, V., Tyrychtr, J., & Ulman, M. (2015). Potential of open data in the agricultural eGovernment. AGRIS on-Line Papers in Economics and Informatics, 7(2), 103-113. Retrieved from http://online.agris.cz/archive/2015/2/10.

Waddington, H., Aloe, A. M., Becker, B. J., Djimeu, E. W., Jorge, G. H., Tugwell, P., . . . Reeves, B. (2017). Quasi-experimental study designs series-paper 6: Risk of bias assessment. *Journal of Clinical Epidemiology, 89*, 43-52. doi:10.1016/j.jclinepi.2017.02.015.

Walravens, N., Breuer, J., & Ballon, P. (2014). Open Data as a Catalyst for the Smart City as a Local Innovation Platform (*). *Communications & Strategies,* (96), 15-33,165,167. Retrieved from https://ssrn.com/abstract=2636315.

Wang, R. Y., & Strong, D. M. (1996). Beyond accuracy: What data quality means to data consumers. *Journal of management information systems*, *12*(4), 5-33. doi:10.1080/07421222.1996.11518099.

Wang, X., Sun, B., Liu, B., Fu, Y., & Pan, Z. (2017). A novel method for multifactorial bio-chemical experiments design based on combinational design theory. *PLoS One, 12*(11). doi:10.1371/journal.pone.0186853.

Weerakkody, V., Irani, Z., Kapoor, K., Sivarajah, U., & Dwivedi, Y. K. (2017). Open data and its usability: An empirical view from the citizen's perspective. *Information Systems Frontiers, 19*(2), 285-300. doi:10.1007/s10796-016-9679-1.

Wei, K. M., Tang, Y. T., Kao, Y. C., Tseng, L. C., & Wu, H. H. (2017). Using an updated DeLone and McLean model to assess the success of implementing the ward cleaning logistics system in a medical center. *Journal of Statistics and Management Systems*, *20*(5), 965-976. doi:10.1080/09720510.2017.1338609.

Whaley, A. L. (2018). Advances in stereotype threat research on African Americans: Continuing challenges to the validity of its role in the achievement gap. *Social Psychology of Education: An International Journal, 21*(1), 111-137. doi:10.1007/s11218-017-9415-9.

Whelan, T. J., & DuVernet, A. M. (2015). The big duplicity of big data. *Industrial and Organizational Psychology, 8*(4), 509-515. doi:10.1017/iop.2015.75.

Winters, J. D., & Rudolph, K. S. (2014). Quadriceps rate of force development affects gait and function in people with knee osteoarthritis. *European Journal of Applied Physiology, 114*(2), 273-84. doi:10.1007/s00421-013-2759-8.

Wipawayangkool, K., & Teng, J. T. C. (2016). Paths to tacit knowledge sharing: Knowledge internalization and individual-task-technology fit. *Knowledge Management Research & Practice, 14*(3), 309-318. doi:10.1057/kmrp.2014.33.

Wong, S., & Cooper, P. (2016). Reliability and validity of the explanatory sequential design of mixed methods adopted to explore the influences on online learning in Hong Kong bilingual cyber higher education. *International Journal of Cyber Society and Education, 9*(2), 45-66. doi:10.7903/ijcse.1475.

Wouters, K., Maesschalck, J., Peeters, C. F. W., & Roosen, M. (2014). Methodological issues in the design of online surveys for measuring unethical work behavior: Recommendations on the basis of a split-ballot experiment. *Journal of Business Ethics, 120*(2), 275-289. doi:10.1007/s10551-013-1659-5.

Yang, C., Liang, P., & Avgeriou, P. (2017). Assumptions and their management in software development: A systematic mapping study. *Information and Software Technology*. doi:10.1016/j.infsof.2017.10.003.

Yang, M., Shao, Z., Liu, Q., & Liu, C. (2017). Understanding the quality factors that influence the continuance intention of students toward participation in MOOCs. *Educational Technology, Research, and Development, 65*(5), 1195-1214. doi:10.1007/s11423-017-9513-6.

Yildirim, C., & Correia, A. P. (2015). Exploring the dimensions of nomophobia: Development and validation of a self-reported questionnaire. *Computers in Human Behavior*, *49*, 130-137. doi:10.1016/j.chb.2015.02.059.

Ylijoki, O., & Porras, J. (2016). Perspectives to definition of big data: A mapping study and discussion. *Journal of Innovation Management, 4*(1), 69-91. Retrieved from https://journals.fe.up.pt/index.php/IJMAI/article/view/198.

Zeglat, D., Shrafat, F., & Al-Smadi, Z. (2016). The impact of the E-Service Quality of online databases on users' behavioral intentions: a perspective of postgraduate students. International Review of Management and Marketing, 6(1), 1-10. Retrieved from https://www.econjournals.com/index.php/irmm/article/view/1431.

Zeleti, F. A., & Ojo, A. (2017). Open data value capability architecture. *Information Systems Frontiers, 19*(2), 337-360. doi:10.1007/s10796-016-9711-5.

Zencir, G., Zencir, M., & Khorshid, L. (2019). Adaptation of the Turkish version of Nurses' Self Concept Questionnaire. *International journal of nursing sciences*, *6*(1), 43-49. doi:10.1016/j.ijnss.2018.12.004

Zhu, Y., Freeman, S., & Cavusgil, S. T. (2018). Service quality delivery in a cross-national context. *International Business Review*. doi:10.1016/j.ibusrev.2018.03.002.

Zohreh, M., Esmaelzadeh-, S. S., Razieh, L., Baradaran, E. M., Akbari, K. M., Mehdizadeh, T. Z., & Katayoun, S. (2017). The evaluation of a virtual education system based on the DeLone and McLean model: A Path Analysis. *F1000 Research.* doi:10.12688/f1000research.12278.1.

Zuiderwijk, A., Helbig, N., Gil-García, J. R., & Janssen, M. (2014). Special issue on innovation through open data: Guest editors' introduction. *Journal of theoretical and applied electronic commerce research*, *9*(2), i-xiii.doi:10.4067/S0718-18762014000200001.

Zuiderwijk, A., Janssen, M., & Dwivedi, Y. K. (2015a). Acceptance and use predictors of open data technologies: Drawing upon the unified theory of acceptance and use of technology. *Government information quarterly*, *32*(4), 429-440. doi:10.1016/j.giq.2015.09.005.

Zuiderwijk, A., Janssen, M., Poulis, K., & van de Kaa, G. (2015b). Open data for competitive advantage: insights from open data use by companies. In *Proceedings of the 16th Annual International Conference on Digital Government Research* (pp. 79-88). ACM. doi:10.1145/2757401.2757411.

Zuiderwijk, A., Janssen, M., & Susha, I. (2016). Improving the speed and ease of open data use through metadata, interaction mechanisms, and quality indicators. *Journal of Organizational Computing and Electronic Commerce*, *26*(1-2), 116-146. doi:10.1080/10919392.2015.1125180.

Zuiderwijk, A., Shinde, R., & Janssen, M. (2018). Investigating the attainment of open government data objectives: Is there a mismatch between objectives and results? *International Review of Administrative Sciences*, 0020852317739115. doi:10.1177/0020852317739115.

Zuiderwijk, A., Susha, I., Charalabidis, Y., Parycek, P., & Janssen, M. (2015). Open data disclosure and use: Critical factors from a case study. In *CeDEM15: Conference for E-Democracy and Open Government* (Vol. 197). MV-Verlag. doi:10.29379/jedem.v7i2.397.

Appendix A: Original Instrument

Suryanto et al, 2016

Suryanto, Setyohadi, and Faroqi (2016)	Question	Standardized Regression Coefficient	Error Variance
X1	SIMPEG provide actual information to the users	79	30
X2	SIMPEG has a data records to give user an easy way to look for some information	76	31
X3	SIMPEG provide a correct information which fits the needs of users and institution	79	27
X4	SIMPEG provide a concise information which help your work	73	37
X5	SIMPEG provide a Help Menu with which users can easily operate it without the assistance from colleagues	64	48
X6	SIMPEG has a direct benefit, hence users is not need to contact the person in charge to SIMPEG	70	43
X7	SIMPEG has a user guide with which help the users to operate it	69	43
X8	SIMPEG is easy to use and helpful both for users and institution	75	48
X9	SIMPEG provide a valid and complete data which suitable with user's needs according to his job/responsibility	60	56
X10	SIMPEG can be accessed by multiple users, which can gives a sense of security for users	68	48
X11	SIMPEG can be used and understood easily so that it can make the user's jobs done easier	78	40
X12	SIMPEG can be customized by the user to fits their needs and based on the level of their work	76	40
X13	SIMPEG can give a fast response of user input, so that users doesn't need help	69	41
X14	I intend to spend more time to use SIMPEG in order to share knowledge with colleagues	62	31
X15	I intend to use SIMPEG consistently in order to support my work	57	27
X16	I intend to learn the SIMPEG thoroughly in order to help the success of the institution work program	53	30
X17	I intend to use SIMPEG regularly to help institution to develop its assets	53	25

Composite reliability >90

Appendix B: Li, Duan, Fu, and Alford (2012)

Instrument used by Suryanto et al. (2016)

Table 2: Research constructs and related survey items

Construct	Items	Statement	References
System functionality	SF1	The system can clearly present the course information in a readable format.	Pituch & Lee (2006); self-developed
	SF2	The system provides multimedia types of course content.	
	SF3	The system can provide the function use accurately.	
	SF4	The system interface and design are complete and consistent.	
	SF5	The linking among all the system Webs is efficient.	
System response	SR1	The system response is fast.	Pituch & Lee (2006); self-developed
	SR2	The speed of download and upload is consistent.	
	SR3	In general, the system operation is stable.	
System interactivity	SI1	The e-learning system enables communication among students.	Pituch & Lee (2006); self-developed
	SI2	The e-learning system enables communication between students and teachers.	
	SI3	The communication tools in the e-learning system are effective.	
System service quality	SS1	The instruction and manuals have enhanced the learning efficiency.	DeLone & McLean (2003), Webster & Hackley (2003), Thurmond *et al* (2002)
	SS2	I believe the staff in charge of e-learning are aware of my concerns.	
	SS3	I find the communication and tutorials good between tutors and students.	
	SS4	Tutors show a sincere interest in solving my problems.	
E-learning course quality	EC1	e-Learning content provides abundant information and problem-solving techniques.	Saarinen (1996), Arbaugh (2000), DeLone & McLean (2003)
	EC2	The lecture content is communicated with few errors.	
	EC3	The methods of evaluation and assessment of the course are appropriate.	
Self-efficacy	SE1	I could complete the learning if the computer and Internet facilities are provided.	Joo *et al* (2000), Liaw *et al* (2007)
	SE2	I would feel confident to use the e-learning system even if I had never used it before.	
	SE3	I feel confident to complete my learning activities using the e-learning system with the instruction and manuals for reference.	
Perceived ease of use	PEOU1	I find it is easy to get the e-learning system to do what I want it to do.	Davis & Venkatesh (1996), Ngai *et al* (2007)
	PEOU2	Learning to operate the e-learning system is easy for me.	
	PEOU3	I believe the e-learning system is easy to use.	
Perceived usefulness	PU1	Using the e-learning system allows me to accomplish learning tasks more quickly.	Davis & Venkatesh (1996), Ngai *et al* (2007)
	PU2	Using the e-learning system enhances my effectiveness in learning.	
	PU3	Using the e-learning system makes it easier to learn course content.	
	PU4	Using the e-learning system increases my learning productivity.	
	PU5	I believe the e-learning system to be useful in my learning.	
Behavioural intention to use	BI1	Assuming that I had access to the e-learning system, I intend to reuse it.	Davis & Venkatesh (1996), Ngai *et al* (2007)
	BI2	Given that I had access to the e-learning system, I predict that I would reuse it.	
	BI3	I would reuse the e-learning system to assist my self-study.	

Appendix C: Survey Instrument

User perception of the US open government data success factors

Open data refers to data that is freely available and accessible online for re-use, distribution and universal participation by application developers, organizations, and citizens (Bannister & Connolly, 2014), without limitation for commercial or non-commercial purposes. In the government sector, open data enables ease of discovery of government information, generating contextually relevant information and improving efficiency. Open data can be used to determine the efficient allocation of resources, capacity boosting, improve efficiency and effectiveness of decision making (Hellberg & Hedström, 2015) in business and organizations. The open data standards (Project Open Data, n.d.) defined a set of specification for publishing data for every object, including the use of schematic, semantic and atomic standards (Raggett, 2017). The success of open data depends on its ability to meet the variety of intended use and disparity in user's needs. Many open data portals publish low-quality data using diverse formats like lack of schema descriptions (Sadiq & Indulska, 2017) that make the data hard to find and almost impossible to use (Weerakkody et al., 2017).

The open data portal set up by governments are referred to as the open government data (OGD), and this study is focused on the OGD. The potential for positive social change in this study is that an easily accessible open dataset that is interoperable and reusable may help to solve problems in the healthcare, education, energy sector, and the research community (Sansone et al., 2018). Jurisch, Kautz, Wolf & Kramar, 2015) noted that OGD is published without recourse to users, which results in frequently low usage. The low usage level of open data portals reported by many researchers (Susha, Grönlund & Janssen, 2015; Viscusi et al., 2014; Jurisch et. al, 2015) has necessitated the need to understand the relationship between user's perception of the quality of open data and the intent to use that data.

Note:

- **Please select only one answer for each question.**
- **Mark X on the selected Box**

1. The system provides actual information to the users.

1	2	3	4	5
Strongly disagree	Disagree	Neutral	Agree	Strongly agree

2. The system has a data record to give users an easy way to look for some information.

1	2	3	4	5
Strongly disagree	Disagree	Neutral	Agree	Strongly agree

3. The system provides correct information which fits the needs of users and institution.

1	2	3	4	5
Strongly disagree	Disagree	Neutral	Agree	Strongly agree

4. The system provides concise information which helps your work.

1	2	3	4	5
Strongly disagree	Disagree	Neutral	Agree	Strongly agree

5. The information about the creation and modification dates of metadata and resources is provided.

1	2	3	4	5
Strongly disagree	Disagree	Neutral	Agree	Strongly agree

6. The system has a direct benefit hence users do not need to contact the system provider.

1	2	3	4	5
Strongly disagree	Disagree	Neutral	Agree	Strongly agree

7. The system has a user guide which help users to operate it.

1	2	3	4	5
Strongly disagree	Disagree	Neutral	Agree	Strongly agree

8. The system is easy to use and helpful to both users and institution.

1	2	3	4	5
Strongly disagree	Disagree	Neutral	Agree	Strongly agree

9. The system provides a valid and complete data which is suitable with users' needs according to jo responsibility.

1	2	3	4	5
Strongly disagree	Disagree	Neutral	Agree	Strongly agree

10. The system can be accessed by multiple users which gives a sense of security for users.

1	2	3	4	5
Strongly disagree	Disagree	Neutral	Agree	Strongly agree

11. The system can be used and understood easily so that it can make users' job easier.

1	2	3	4	5
Strongly disagree	Disagree	Neutral	Agree	Strongly agree

12. The system can be customized by users to fit user need based on the level of work.

1	2	3	4	5
Strongly disagree	Disagree	Neutral	Agree	Strongly agree

13. The system can give a fast response to user input, so that user does not need help.

1	2	3		4	5
Strongly disagree	Disagree	Neutral		Agree	Strongly agree

14. I intend to spend more time to use the system in order to share knowledge with colleagues.

1	2	3	4	5
Strongly disagree	Disagree	Neutral	Agree	Strongly agree

15. I intend to use the system consistently in order to support my work.

1	2	3	4	5
Strongly disagree	Disagree	Neutral	Agree	Strongly agree

16. I intend to learn to use the system thoroughly in order to help the success of the provider program.

1	2	3	4	5
Strongly disagree	Disagree	Neutral	Agree	Strongly agree

17. I intend to use the system regularly to help the provider to develop its assets.

1	2	3	4	5
Strongly disagree	Disagree	Neutral	Agree	Strongly agree

Response for completed forms

Thank you for your time and participating in this survey. Your responses have been documented

and your privacy and confidentiality are ensured. Your participation will help to evaluate the foundation for providing the enabling environment for improving open data information systems and enable open data providers to realize the objectives of open data.

Please note that the information you provided cannot be removed from the system due to the anonymity of the survey as it will be practically impossible to identify it.

Best Regards

Joy Alatta

Appendix D: Permission to Use Instrument – Li et al. (2012)

JOHN WILEY AND SONS LICENSE TERMS AND CONDITIONS
This Agreement between Joy Alatta ("You") and John Wiley and Sons ("John Wiley and Sons") consists of your license details and the terms and conditions provided by John Wiley and Sons and Copyright Clearance Center.

License Number	4553230225454
License date	Mar 20, 2019
Licensed Content Publisher	John Wiley and Sons
Licensed Content Publication	British Journal of Educational Technology
Licensed Content Title	An empirical study on behavioural intention to reuse e□learning systems in rural China
Licensed Content Author	Yan Li, Yanqing Duan, Zetian Fu, et al
Licensed Content Date	Dec 7, 2011
Licensed Content Volume	43
Licensed Content Issue	6
Licensed Content Pages	16
Type of Use	Dissertation/Thesis
Requestor type	Author of this Wiley article
Format	Print and electronic
Portion	Figure/table
Number of figures/tables	2
Original Wiley figure/table number(s)	Table 2: Research constructs and related survey items Table 5: Results of estimations of construct measurements
Will you be translating?	No

Title of your thesis / dissertation	User perception of the US open government data success factors
Expected completion date	Aug 2019
Expected size (number of pages)	160
Requestor Location	Joy Alatta United States Attn: Joy Alatta
Publisher Tax ID	EU826007151
Total	**0.00 USD**
Terms and Conditions	**TERMS AND CONDITIONS**

This copyrighted material is owned by or exclusively licensed to John Wiley & Sons, Inc. or one of its group companies (each a"Wiley Company") or handled on behalf of a society with which a Wiley Company has exclusive publishing rights in relation to a particular work (collectively "WILEY"). By clicking "accept" in connection with completing this licensing transaction, you agree that the following terms and conditions apply to this transaction (along with the billing and payment terms and conditions established by the Copyright Clearance Center Inc., ("CCC's Billing and Payment terms and conditions"), at the time that you opened your RightsLink account (these are available at any time at http://myaccount.copyright.com).

Terms and Conditions

- The materials you have requested permission to reproduce or reuse (the "Wiley Materials") are protected by copyright.

- You are hereby granted a personal, non-exclusive, non-sub licensable (on a stand-alone basis), non-transferable, worldwide, limited license to reproduce the Wiley Materials for the purpose specified in the licensing process. This license, **and any CONTENT (PDF or image file) purchased as part of your order,** is for a one-time use only and limited to any maximum distribution number specified in the license. The first instance of republication or reuse granted by this license must be completed within two years of the date of the grant of this license (although copies prepared before the end date may be distributed thereafter). The Wiley Materials shall not be used in any other manner or for any other purpose, beyond what is granted in the license. Permission is granted subject to an appropriate acknowledgement given to the author, title of the material/book/journal and the publisher. You shall also duplicate the copyright notice that appears in the Wiley publication in your use of the Wiley Material. Permission is also granted on the understanding that nowhere in the text is a previously published source acknowledged for all or part of this Wiley Material. Any third-party content is expressly excluded from this permission.

- With respect to the Wiley Materials, all rights are reserved. Except as expressly granted by the terms of the license, no part of the Wiley Materials may be copied, modified, adapted (except for minor reformatting required by the new Publication), translated, reproduced, transferred or distributed, in any form or by any means, and no derivative works may be made based on the Wiley Materials without the prior permission of the respective copyright owner.**For STM Signatory Publishers clearing permission under the terms of the STM Permissions Guidelines only, the terms of the license are extended to include subsequent editions and for editions in other languages, provided such editions are for the work as a whole in situ and does not involve the separate exploitation of the permitted figures or extracts,** You may not alter, remove or suppress in any manner any copyright, trademark or other notices displayed by the Wiley Materials. You may not license, rent, sell, loan, lease, pledge, offer as security, transfer or assign the Wiley Materials on a stand-alone basis, or any of the rights granted to you hereunder to any other person.

- The Wiley Materials and all of the intellectual property rights therein shall at all times remain the exclusive property of John Wiley & Sons Inc, the Wiley Companies, or their respective licensors, and your interest therein is only that of having possession of and the right to reproduce the Wiley Materials pursuant to Section 2 herein during the continuance of this Agreement. You agree that you own no right, title or interest in or to the Wiley Materials or any of the intellectual property rights therein. You shall have no rights hereunder other than the license as provided for above in Section 2. No right, license or interest to any trademark, trade name, service mark or other branding ("Marks") of WILEY or its licensors is granted hereunder, and you agree that you shall not assert any such right, license or interest with respect thereto

- NEITHER WILEY NOR ITS LICENSORS MAKES ANY WARRANTY OR REPRESENTATION OF ANY KIND TO YOU OR ANY THIRD PARTY, EXPRESS, IMPLIED OR STATUTORY, WITH RESPECT TO THE MATERIALS OR THE ACCURACY OF ANY INFORMATION CONTAINED IN THE MATERIALS, INCLUDING, WITHOUT LIMITATION, ANY IMPLIED WARRANTY OF MERCHANTABILITY, ACCURACY, SATISFACTORY QUALITY, FITNESS FOR A PARTICULAR PURPOSE, USABILITY, INTEGRATION OR NON-INFRINGEMENT AND ALL SUCH

WARRANTIES ARE HEREBY EXCLUDED BY WILEY AND ITS LICENSORS AND WAIVED BY YOU.

- WILEY shall have the right to terminate this Agreement immediately upon breach of this Agreement by you.

- You shall indemnify, defend and hold harmless WILEY, its Licensors and their respective directors, officers, agents and employees, from and against any actual or threatened claims, demands, causes of action or proceedings arising from any breach of this Agreement by you.

- IN NO EVENT SHALL WILEY OR ITS LICENSORS BE LIABLE TO YOU OR ANY OTHER PARTY OR ANY OTHER PERSON OR ENTITY FOR ANY SPECIAL, CONSEQUENTIAL, INCIDENTAL, INDIRECT, EXEMPLARY OR PUNITIVE DAMAGES, HOWEVER CAUSED, ARISING OUT OF OR IN CONNECTION WITH THE DOWNLOADING, PROVISIONING, VIEWING OR USE OF THE MATERIALS REGARDLESS OF THE FORM OF ACTION, WHETHER FOR BREACH OF CONTRACT, BREACH OF WARRANTY, TORT, NEGLIGENCE, INFRINGEMENT OR OTHERWISE (INCLUDING, WITHOUT LIMITATION, DAMAGES BASED ON LOSS OF PROFITS, DATA, FILES, USE, BUSINESS OPPORTUNITY OR CLAIMS OF THIRD PARTIES), AND WHETHER OR NOT THE PARTY HAS BEEN ADVISED OF THE POSSIBILITY OF SUCH DAMAGES. THIS LIMITATION SHALL APPLY NOTWITHSTANDING ANY FAILURE OF ESSENTIAL PURPOSE OF ANY LIMITED REMEDY PROVIDED HEREIN.

- Should any provision of this Agreement be held by a court of competent jurisdiction to be illegal, invalid, or unenforceable, that provision shall be deemed amended to achieve as nearly as possible the same economic effect as the original provision, and the legality, validity and enforceability of the remaining provisions of this Agreement shall not be affected or impaired thereby.

- The failure of either party to enforce any term or condition of this Agreement shall not constitute a waiver of either party's right to enforce each and every term and condition of this Agreement. No breach under this agreement shall be deemed waived or excused by either party unless such waiver or consent is in writing signed by the party granting such waiver or consent. The waiver by or consent of a party to a breach of any provision of this Agreement shall not operate or be construed as a waiver of or consent to any other or subsequent breach by such other party.

- This Agreement may not be assigned (including by operation of law or otherwise) by you without WILEY's prior written consent.

- Any fee required for this permission shall be non-refundable after thirty (30) days from receipt by the CCC.

- These terms and conditions together with CCC's Billing and Payment terms and conditions (which are incorporated herein) form the entire agreement between you and WILEY concerning this licensing transaction and (in the absence of fraud) supersedes all prior agreements and representations of the parties, oral or written. This Agreement may not be amended except in writing signed by both parties. This Agreement shall be binding upon and inure to the benefit of the parties' successors, legal representatives, and authorized assigns.

- In the event of any conflict between your obligations established by these terms and conditions and those established by CCC's Billing and Payment terms and conditions, these terms and conditions shall prevail.

- WILEY expressly reserves all rights not specifically granted in the combination of (i) the license details provided by you and accepted in the course of this licensing transaction, (ii) these terms and conditions and (iii) CCC's Billing and Payment terms and conditions.

- This Agreement will be void if the Type of Use, Format, Circulation, or Requestor Type was misrepresented during the licensing process.

- This Agreement shall be governed by and construed in accordance with the laws of the State of New York, USA, without regards to such state's conflict of law rules. Any legal action, suit or proceeding arising out of or relating to these Terms and Conditions or the breach thereof shall be instituted in a court of competent jurisdiction in New York County in the State of New York in the United States of America and each party hereby consents and submits to the personal jurisdiction of such court, waives any objection to venue in such court and consents to service of process by registered or certified mail, return receipt requested, at the last known address of such party.

WILEY OPEN ACCESS TERMS AND CONDITIONS

Wiley Publishes Open Access Articles in fully Open Access Journals and in Subscription journals offering Online Open. Although most of the fully Open Access journals publish open access articles under the terms of the Creative Commons Attribution (CC BY) License only, the subscription journals and a few of the Open Access Journals offer a choice of Creative Commons Licenses. The license type is clearly identified on the article.

The Creative Commons Attribution License

Appendix E: Permission to Use Original Instrument

creative commons | Share your work | Use & remix | What we do

Attribution 4.0 International (CC BY 4.0)

This is a human-readable summary of (and not a substitute for) the license. Disclaimer.

You are free to:

Share — copy and redistribute the material in any medium or format

Adapt — remix, transform, and build upon the material for any purpose, even commercially.

Free Cultural Works APPROVED FOR

The licensor cannot revoke these freedoms as long as you follow the license terms.

Under the following terms:

Attribution — You must give appropriate credit, provide a link to the license, and indicate if changes were made. You may do so in any reasonable manner, but not in any way that suggests the licensor endorses you or your use.

No additional restrictions — You may not apply legal terms or technological measures that legally restrict others from doing anything the license permits.

Notices:

You do not have to comply with the license for elements of the material in the public domain or where your use is permitted by an applicable exception or limitation.

No warranties are given. The license may not give you all of the permissions necessary for your intended use. For example, other rights such as publicity, privacy, or moral rights may limit how you use the material.

Retrieved on May 17, 2019 from from https://creativecommons.org/licenses/by/4.0/

Appendix F: NIH Certificate

Certificate of Completion

The National Institutes of Health (NIH) Office of Extramural Research certifies that **Joy Alatta** successfully completed the NIH Web-based training course "Protecting Human Research Participants".

Date of completion: 07/14/2017.

Certification Number: 2434587.

Appendix G: Interitem Correlation Matrix

	IQ1-Information Quality	IQ2-Information Quality	IQ3-Information Quality	IQ4-Information Quality
IQ1-Information Quality	1.000	.990	.968	.972
IQ2-Information Quality	.990	1.000	.976	.980
IQ3-Information Quality	.968	.976	1.000	.995
IQ4-Information Quality	.972	.980	.995	1.000
SYQ5-System Quality	.985	.989	.980	.985
SYQ6-System Quality	.992	.987	.965	.969
SYQ7-System Quality	.983	.992	.983	.987
SYQ8-System Quality	.982	.992	.982	.987
SE9-Service Quality	.982	.992	.982	.987
SE10-Service Quality	.983	.992	.983	.987
SE11-Service Quality	.976	.985	.990	.995
SE12-Service Quality	.984	.985	.963	.967
SE13-Service Quality	.990	.989	.976	.980
ITU14-Intent To Use	.983	.992	.983	.987
ITU15-Intent To Use	.968	.976	.995	.995
ITU16-Intent To Use	.974	.983	.987	.992
ITU17-Intent To Use	.981	.990	.985	.990

Inter-Item Correlation Matrix

	SYQ5-System Quality	SYQ6-System Quality	SYQ7-System Quality	SYQ8-System Quality
IQ1-Information Quality	.985	.992	.983	.982
IQ2-Information Quality	.989	.987	.992	.992
IQ3-Information Quality	.980	.965	.983	.982
IQ4-Information Quality	.985	.969	.987	.987
SYQ5-System Quality	1.000	.982	.992	.992
SYQ6-System Quality	.982	1.000	.980	.980
SYQ7-System Quality	.992	.980	1.000	.989
SYQ8-System Quality	.992	.980	.989	1.000
SE9-Service Quality	.997	.980	.995	.995
SE10-Service Quality	.992	.980	.989	.989

SE11-Service Quality	.985	.974	.992	.982
SE12-Service Quality	.980	.992	.978	.977
SE13-Service Quality	.989	.987	.987	.981
ITU14-Intent To Use	.987	.980	.995	.984
ITU15-Intent To Use	.981	.966	.983	.983
ITU16-Intent To Use	.987	.972	.984	.990
ITU17-Intent To Use	.990	.978	.992	.987

Inter-Item Correlation Matrix

	SE9-Service Quality	SE10-Service Quality	SE11-Service Quality	SE12-Service Quality
IQ1-Information Quality	.982	.983	.976	.984
IQ2-Information Quality	.992	.992	.985	.985
IQ3-Information Quality	.982	.983	.990	.963
IQ4-Information Quality	.987	.987	.995	.967
SYQ5-System Quality	.997	.992	.985	.980
SYQ6-System Quality	.980	.980	.974	.992
SYQ7-System Quality	.995	.989	.992	.978
SYQ8-System Quality	.995	.989	.982	.977
SE9-Service Quality	1.000	.995	.987	.977
SE10-Service Quality	.995	1.000	.987	.978
SE11-Service Quality	.987	.987	1.000	.972
SE12-Service Quality	.977	.978	.972	1.000
SE13-Service Quality	.987	.992	.985	.985
ITU14-Intent To Use	.990	.995	.992	.978
ITU15-Intent To Use	.983	.983	.990	.964
ITU16-Intent To Use	.990	.990	.987	.970
ITU17-Intent To Use	.992	.992	.995	.976

Inter-Item Correlation Matrix

	SE13-Service Quality	ITU14-Intent To Use	ITU15-Intent To Use	ITU16-Intent To Use

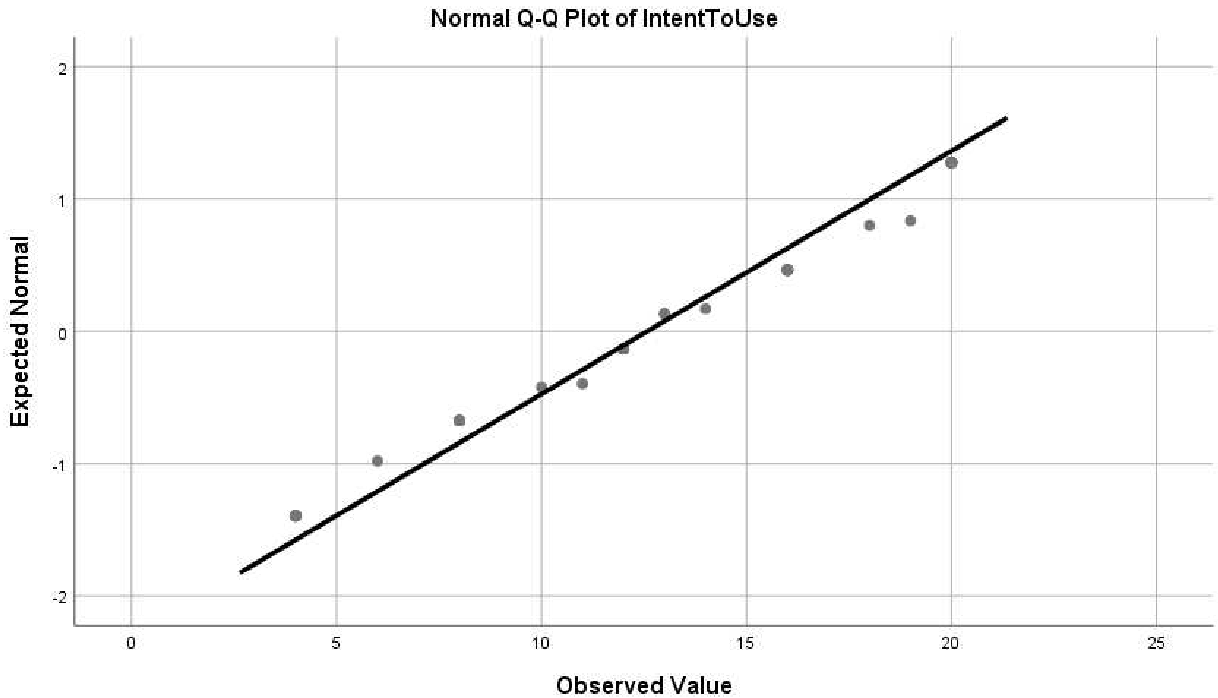
IQ1-Information Quality	.990	.983	.968	.974
IQ2-Information Quality	.989	.992	.976	.983
IQ3-Information Quality	.976	.983	.995	.987
IQ4-Information Quality	.980	.987	.995	.992
SYQ5-System Quality	.989	.987	.981	.987
SYQ6-System Quality	.987	.980	.966	.972
SYQ7-System Quality	.987	.995	.983	.984
SYQ8-System Quality	.981	.984	.983	.990
SE9-Service Quality	.987	.990	.983	.990
SE10-Service Quality	.992	.995	.983	.990
SE11-Service Quality	.985	.992	.990	.987
SE12-Service Quality	.985	.978	.964	.970
SE13-Service Quality	1.000	.992	.976	.983
ITU14-Intent To Use	.992	1.000	.983	.985
ITU15-Intent To Use	.976	.983	1.000	.992
ITU16-Intent To Use	.983	.985	.992	1.000
ITU17-Intent To Use	.990	.992	.985	.992

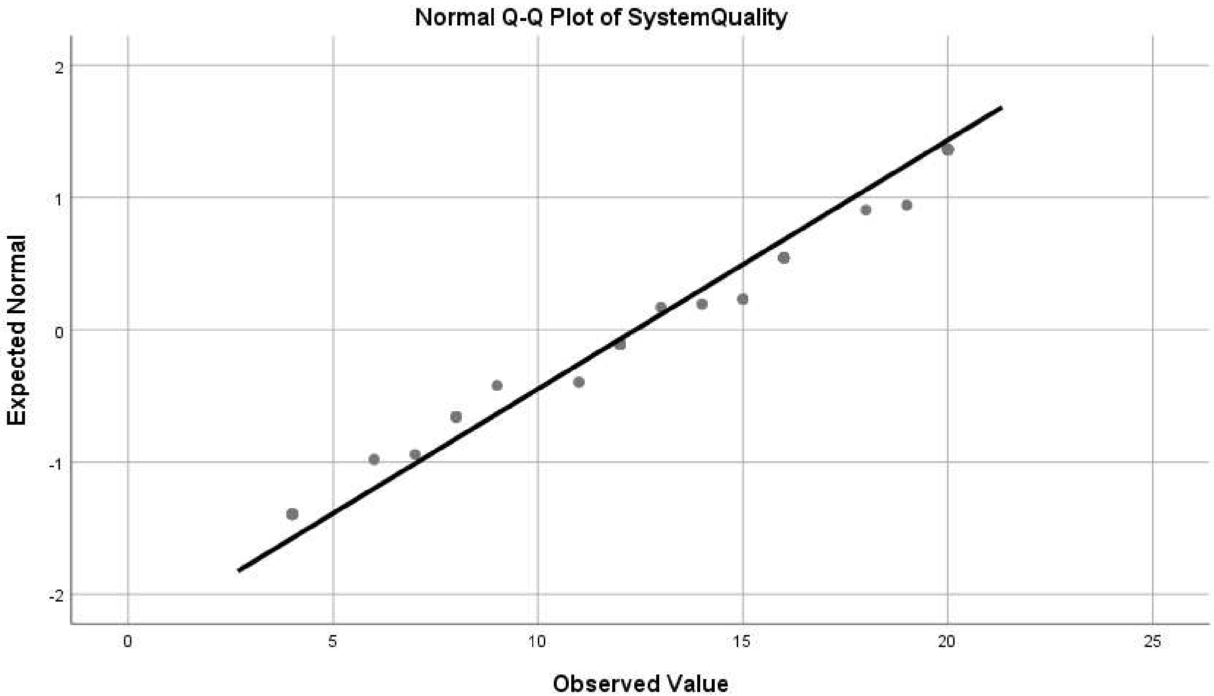
Inter-Item Correlation Matrix

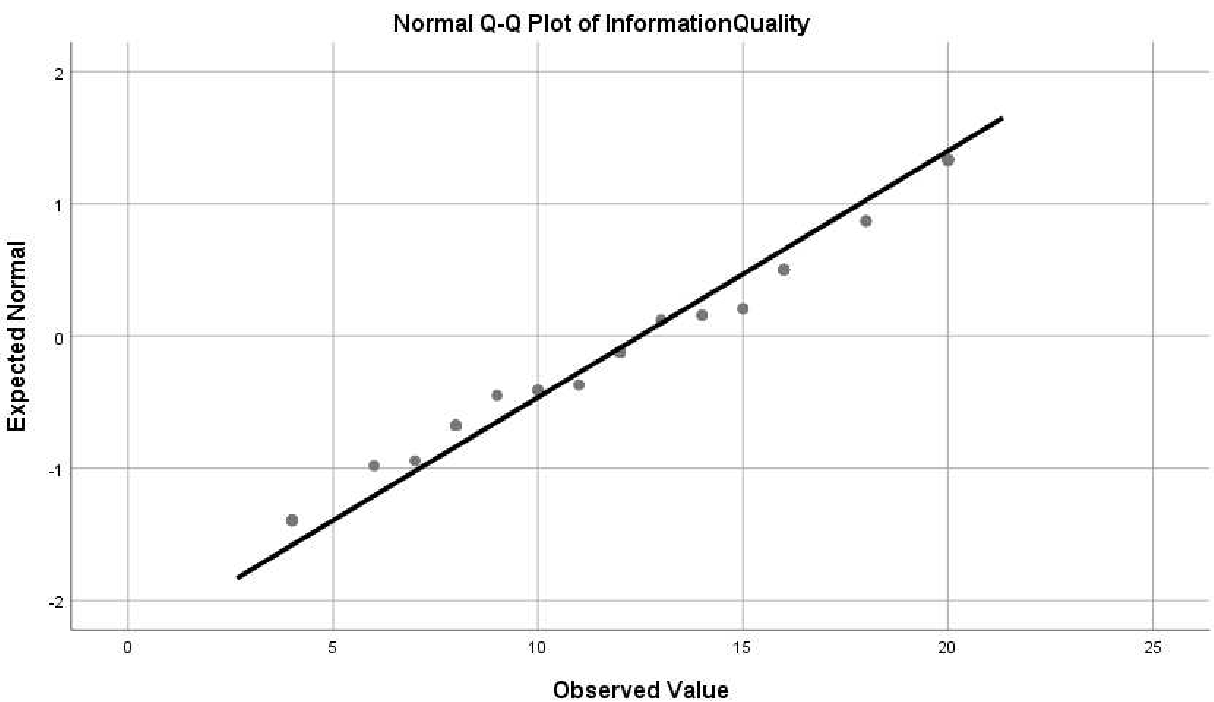
	ITU17-Intent To Use
IQ1-Information Quality	.981
IQ2-Information Quality	.990
IQ3-Information Quality	.985
IQ4-Information Quality	.990
SYQ5-System Quality	.990
SYQ6-System Quality	.978
SYQ7-System Quality	.992
SYQ8-System Quality	.987
SE9-Service Quality	.992
SE10-Service Quality	.992
SE11-Service Quality	.995
SE12-Service Quality	.976
SE13-Service Quality	.990
ITU14-Intent To Use	.992
ITU15-Intent To Use	.985
ITU16-Intent To Use	.992

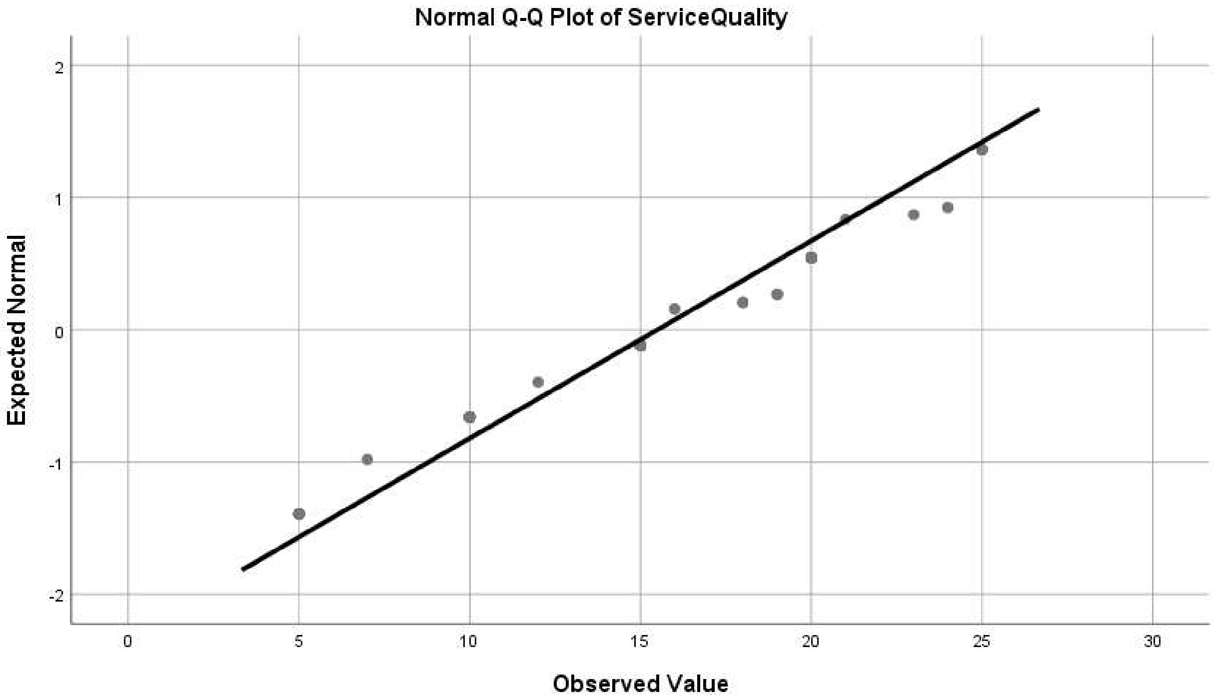
ITU17-Intent To Use	1.000

Appendix H: Normal QQ Plot




Normal Q-Q Plot of SystemQuality
Expected Normal
Observed Value
2
1
0
-1
-2
0
5
10
15
20
25


Normal Q-Q Plot of InformationQuality
Expected Normal
Observed Value
2
1
0
-1
-2
0
5
10
15
20
25



Normal Q-Q Plot of ServiceQuality
Expected Normal
Observed Value
2
1
0
-1
-2
0
5
10
15
20
25
30

Appendix I: Correlations Among Predictors

Correlations

		ServiceQuality	IntentToUse
ServiceQuality	Pearson Correlation	1	.996**
	Sig. (2-tailed)		.000
	N	103	103
IntentToUse	Pearson Correlation	.996**	1
	Sig. (2-tailed)	.000	
	N	103	103

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

Correlations

		IntentToUse	SystemQuality
IntentToUse	Pearson Correlation	1	.993**
	Sig. (2-tailed)		.000
	N	103	103
SystemQuality	Pearson Correlation	.993**	1
	Sig. (2-tailed)	.000	
	N	103	103

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

Correlations

		IntentToUse	InformationQuality
IntentToUse	Pearson Correlation	1	.997**
	Sig. (2-tailed)		.000
	N	103	103
InformationQuality	Pearson Correlation	.997**	1
	Sig. (2-tailed)	.000	
	N	103	103

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