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Relationships Among Dimensions of Information System Success and Benefits of Cloud

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This is to certify that the doctoral study by

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has been found to be complete and satisfactory in all respects,
and that any and all revisions required by
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Walden University
2021

Abstract

Relationships Among Dimensions of Information System Success and Benefits of Cloud

by

William H. Stanley

MS, Walden University, 2018

MS, University of Phoenix, 2007

BS, Southern University, 1994

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Information Technology

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August 2021

Abstract

Despite the many benefits offered by cloud computing's design architecture, there are many fundamental performance challenges for IT managers to manage cloud infrastructures to meet business expectations effectively. Grounded in the information systems success model, the purpose of this quantitative correlational study was to evaluate the relationships among the perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction, and net benefits of cloud computing services. The participants (*n* = 137) were IT cloud services managers in the United States, who completed the DeLone and McLean ISS authors' validated survey instrument. The multiple regression finding were signification, $F(5, 131) = 85.16$, $p < .001$, $R^2 = 0.76$. In the final model, perception of information quality ($\beta = .188$, $t = 2.844$, $p < .05$), perception of service quality ($\beta = .178$, $t = 2.102$, $p < .05$), and perception of user satisfaction ($\beta = .379$, $t = 5.024$, $p < .001$) were statistically significant; perception of system quality and perception of system use were not statistically significant. A recommendation is for IT managers to implement comprehensive customer evaluation of the cloud service(s) to meet customer expectations and afford satisfaction. The implications for positive social change include decision-makers in healthcare, human services, social services, and other critical service organizations better understand the vital predictors of attitude toward system use and user satisfaction of customer-facing cloud-based applications.

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Dedication

I dedicate this work to my Lord and Savior, Jesus Christ. Lord, I thank You for Your mercy and grace as You have seen me through so many trials and tribulations. But with You, all things are possible. You have been with me every step of my life, loving me unconditionally, protecting me, teaching me, and chastising me when I have gone off track. You are my everything, my Lord, and I love You with all that is in me!

I also want to dedicate this work in memory of Nobie and Emily Stanley, my dear and beloved parents. Although you are no longer with me, I want you to know how much I love you and how blessed I am to have had you as my parents. You taught me the value of family and how to remain positive, work hard, and focus on important life matters. You also instilled in me the importance of education and how no one can take it from me. Rest in peace, mom, and dad, as I will see you again someday.

Lastly, I want to contribute this work to my brother Darren Stanley. You have been a protector, a champion, and a valued friend. I am so grateful for your companionship, laughter, and emotional support. Man, we have been through many ups and downs together, but we have stuck together, stayed strong, and remained faithful brothers in Christ. I love you, and I thank you.

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Section 1: Foundation of the Study

Background of the Problem

Cloud computing has become a significant point of interest in the field of information technology (IT), as it allows enterprises to focus on their critical business activities to improve efficiencies (Ahmed, 2020). Because of its design architecture's ability to offer powerful capabilities of resource computation, storage, and elastic services, cloud computing has been viewed as the second generation of network computing and deemed amongst the most encouraging technologies in the 21st century (Ren et al., 2020). Despite the many advantages offered, there are several challenges related to cloud computing (i.e., availability and reliability of services, vendor lock-in, limited control, measuring return on investment) that need to be addressed to mitigate such common problems (Mallo & Ogwueleka, 2019).

Fundamentally, performance challenges have a direct impact on the quality of cloud services concerning system anomalies, instabilities, errors, and service level violations. (Fareghzadeh et al., 2019). Moreover, governance is a key discipline to address cloud computing challenges, and it provides IT leaders with the practices to effectively manage cloud infrastructures (Bounagui et al., 2019).

The purpose of this quantitative correlational study was to determine if the perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction, perception of system use, perception of user satisfaction are correlated with net benefits of cloud computing services from the viewpoint of IT cloud services managers. There was minimal quantitative evidence of the post-adoption use of cloud computing from a technical context. This study may fill the gap by focusing on technical measures that IT leaders use to attain the expected benefits of their cloud computing services.

Problem Statement

The paradigm shift to cloud computing business models has led to recent failures in cloud services implementations, which have raised several questions regarding cloud service sustainability and feasibility (Kathuria et al., 2018). Studies have shown that organizations have lost approximately $285 million annually because of cloud service failures, which limit providers to only achieving service levels of 99.91% availability rather than 99.999% (Mesbahi et al., 2018). The general IT problem is that some IT leaders do not have knowledge of the dependability and availability measures to ensure the attainment of the expected benefits of cloud computing services. The specific IT problem is that some IT cloud services managers have a limited understanding of the relationships among the perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction, and net benefits of cloud computing services from the viewpoint of IT cloud services managers.

Purpose Statement

The purpose of this quantitative correlation study was to evaluate the relationships among the perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction, perception of system use, perception of user satisfaction, and net benefits of cloud computing services from the viewpoint of IT cloud services managers. The independent variables used in the study were the perception of information quality, perception of system quality, perception of service quality, perception of system use, and perception of user satisfaction. The dependent variable was the net benefits of cloud computing services. The targeted population consisted of IT cloud services managers from small, medium, and large enterprises that subscribe to infrastructure-as-a-service (IaaS), platform-as-a-service (PaaS), and software-as-a-service (SaaS) in the United States. The results of this study may have potential positive social change implications such that it may help highlight the pervasive nature of cloud computing and provide further insight into the quality standards necessary to build more reliable cloud products and services. As a result, software developers may further leverage internet technologies to deliver more support for personal activities such as social media, online shopping, distance medicine, and Internet-based training programs to help serve the needs of individuals using more reliable, ubiquitous on-demand technology.

Nature of the Study

For this study, I used a quantitative design to evaluate the relationships among the perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction, and net benefits of cloud computing services. Considering the three discrete research design models, which include quantitative, qualitative, and mixed methods, the quantitative approach is used to test hypotheses, examine cause and effect, and make predictions (McCusker & Gunaydin, 2015). The quantitative design was most suitable because of its ability to perform hypothesis testing to draw a conclusion regarding the sample data. A qualitative design approach is used by researchers to understand and interpret social interactions while offering an in-depth exploration of a phenomenon (Jonsen et al., 2018; Korstjens & Moser, 2017). As I was not seeking to explore social experiences, a qualitative design was not the optimum method to analyze casual relationships. A mixed-methods approach integrates qualitative and quantitative practices to draw inferences from both quantitative and qualitative data in a single study (Alavi & Hąbek, 2016). Because of the mixed-methods use of qualitative strategies, it was not an ideal design for establishing relationships and causality. The selection of a research design hinges on the type of action applied by the researcher or why the phenomenon occurred. Because I was not searching for underlying motives that influence a phenomenon, a qualitative and mixed-methods approach was not a suitable method for this investigation.

For this quantitative study, I utilized a correlation design approach. A correlative design explores the relationship between two or more variables to establish the path or strength between them (Curtis et al., 2016). As I evaluated the relationships among the perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction, and net benefits of cloud computing services, I found a correlative design to be the most appropriate. There are three additional principal quantitative designs, which include descriptive, experimental, and quasi-experimental (Norris et al., 2015). A descriptive study is used to observe the behavior of the variables to create new measures or characterize a phenomenon in its natural environment (Loeb et al., 2017). Although descriptive designs offer an observation of the current state of variables, it does not assess relationships among variables. Thus, I did not elect to use a descriptive design. Furthermore, an experimental design is used to establish causal relationships through purposeful manipulation of the independent variables and randomly assigning participants to control groups to ensure the validity of the findings (McCarthy et al., 2017). Moreover, the quasi-experimental design differs from an experimental design such that it does not involve the assignment of participants to groups randomly (Haegele & Hodge, 2015). Neither an experimental or quasi-experimental was appropriate for this study due to my goal of establishing the cause and effect of variables instead of examining the relationship that exists between them.

Research Question

The primary research question (RQ) for this study was: Are there significant relationships among the perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction, and net benefits of cloud computing services from the viewpoint of IT cloud services managers?

Hypotheses

Null Hypothesis (H_0)**:** There are no significant relationships among the perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction, and net benefits of cloud computing services from the viewpoint of IT cloud services managers.

Alternative Hypothesis (H_a)**:** There is a significant relationship between the perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction, and net benefits of cloud computing services from the viewpoint of IT cloud services managers.

Theoretical or Conceptual Framework

In framing an analytical perspective for exploring the methods and standard approaches to measure cloud performance, I used the DeLone and McLean information system (IS) Success (ISS) model. Developed by William H. DeLone and Ephraim R. McLean in 1992 and later revised in 2003, the ISS model is a taxonomy and interactive structure designed to help researchers better understand the value and efficiency of ISS (DeLone & McLean, 2003). Moreover, the framework provides a multidimensional and integrated view of an IS and its impact by conceptualizing and operationalizing IS success (DeLone & McLean, 1992). Thus, this model can be used as a blueprint for examining the factors that influence IS success by providing an understanding of the relationships among the constructs and the measures for determining their impact on IS success.

My selection of the ISS model was grounded upon the framework's effectiveness in measuring the value realization of IS systems. ISS provides a wide range of understanding of the benefits of IS by identifying and describing the relationships among important dimensions of success. For example, Lal and Bharadwaj (2016) conducted a quantitative study to examine the performance of cloud-based customer relationship management systems (CRMS), where the researchers developed and validated a survey instrument to test the relationships in the ISS model as it relates to cloud-based CRMS. For my study, I examined the six dimensions of the ISS model to provide insight into the relationships among the perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction, and net benefits of cloud computing services. I used the ISS model to examine the associations among the variables and their relative impact on the perceived success amongst IT cloud service managers who utilize cloud computing systems on a daily basis.

Operational Definitions

Compound Annual Growth Rate: The compound annual growth rate (CAGR) is a method to measure the growth or weakening of specific indicators over a period of time by taking into account the initial and final invested financial contributions (De Melo Costa, 2019).

Cloud Service Providers: Cloud service providers (CSPs) are third-party suppliers who own a sizeable amount of physical resources and virtualization software to which customers request on-demand access at a fee per resource per time unit (Haghshenas et al., 2019).

IS Domain: Roles or resources associated with a functional area spanning the scope of an IT organization responsible for providing a specific IT service and defines how the resources within the IS should be configured, operated, and managed to support organizational activities and aid in the strategic or business and IT alignment (Avila et al., 2018).

Gartner, Inc.: Gartner, Inc. is one of the world's prominent research and advisory firms (Kietzmann & Archer-Brown, 2019) that offers an analysis of prevailing adoption forecasts and technologies that will face mainstream adoption (Kunz et al., 2019).

International Data Corporation: The International Data Corporation (IDC) is a prominent information technology and communication research and consultancy company that provides consulting and advisement for some of the worlds' largest IT vendors and services companies (Stott et al., 2016).

National Institute of Standards and Technology: The National Institute of Standards and Technology (NIST) is a non-regulatory agency of the United States Department of Commerce which mission is to promote innovation and industrial competitiveness through the advancement of measurements for science, standards, and technology by enhancing economic security and improving one's quality of life. The research conducted by NIST is shared with the scientific community to help establish the adoption of standards and best practices (Greene et al., 2019).

OpenStack: OpenStack is a prevalent and widely adopted open-source cloud software platform used by cloud service providers to build and manage cloud infrastructures for the provision of mostly infrastructure as a service (Da Silva et al., 2018).

Assumptions, Limitations, and Delimitations

Assumptions

An assumption is an unproven idea or belief accepted as actual, explicit, or implicit, which researchers often use to base their inferences concerning a theory of interest (Trafimow, 2019). In particular, design science, behavioral, and sociotechnical IS research vary in their assumptions concerning the function and significance of technology, awareness, or organizational context for research (Boell, 2017). I based my study on five assumptions. First, the inclusion criteria of the sample population were suitable for this study and ensured that the participants have the appropriate level of experience for the study's phenomenon. Second, the participants would truthfully respond to the survey questions. Third, the survey instrument was understandable, and those respondents efficiently completed it. Fourth, the sample was an appropriate representative of the population that the study wishes to make inferences. Fifth, the findings of this study were unbiased, valid, and reliable.

Limitations

A limitation is a weakness of a study that may influence the findings of research that cannot be prevented by the researcher (Apriwandi. & Pratiwi, 2019). Limitations identified in an investigation can be addressed through future research and identify future research directions (Chu et al., 2019). For this study, I recognized five limitations. First, improper representation of the target population could impede the investigation from attaining its desired objectives. A significant aspect of the sampling procedure for recruitment and a recommendation for ensuring the appropriate representation involves a clear definition of the population (Fielding et al., 2017). Thus, I clearly defined the sample population with explicit inclusion criteria.

Second, the structured closed-ended questions of the survey instrument presented narrow options of responses that may have led to constrained outcomes, which could have, in turn, affected the generalization of the findings. Although errors related to survey use cannot be circumvented, they can be lessened by evaluating the quality of survey items before use through pretesting to help ensure respondents understand questions, the questions are relevant to respondents, and the questions adequately address the topic or problems at hand (Colbert et al., 2019).

Third, the lack of responses for data collection could have presented nonresponse bias, which threatens the validity of the study results. Potential methods to avoid lack of survey responses included ensuring appropriate data collection periods, sending reminders to prospective respondents, use incentives (Yu et al., 2017), and use of re-contact data (Kopra et al., 2018). My strategy to minimize the risk of nonresponse bias included the use of methods such as employing reasonable data collection periods.

Fourth, the administration of an online web survey offered the potential for sampling bias as the survey will not reach individuals that do not have Internet access. Specifically, web surveys under-coverage due to populations without internet access can be overcome through the use of alternative platforms such as the telephone, smartphones, and email to reach a large number of respondents (Ha & Zhang, 2019). Nonetheless, I used web-based surveys as the tool to collect data from respondents.

Finally, the study was subject to participant bias as the respondents may have provided biased answers to support their positions as IT managers. Survey respondents frequently provide erroneous responses to questions they may perceive as harmful or detrimental as they lack trust in the agency conducting the survey will keep the information private (Rasinski et al., 1999). Therefore, I communicated to the participants my assurance of confidentiality, and their answers remained confidential to elicit better levels of cooperation to mitigate the risk of response bias.

Delimitations

A delimitation aids in establishing the scope of the research such that particular factors have a meaningful influence on the direction or outcome of the study (Welch, 2014). Delimitations establish the boundaries of the study to help constrain the research to make it more manageable and comprehensible to the reader (Ellis & Levy, 2009). For this study, I identified three delimitations. First, I had a set of geographical constraints to this study, where the sample population included states in the United States. Second, the sample population only included low-level, middle-level, and senior-level IT managers. The third delimitation consisted of the survey questionnaire, which contains questions focused on the technological characteristics of cloud computing services, excluding organizational or environmental aspects.

Significance of the Study

This study may be of value to IT practitioners or IT organizations such that it can add to the body of knowledge of the methods and standard approaches used by IT cloud services managers to measure cloud performance to substantiate the benefits return of cloud services. Understanding the rationale that drives customers to migrate to cloud services is essential; this examination of cloud success may also help business leaders strengthen their due diligence process as the findings may aid in supporting or repudiate some of the perceived benefits of cloud computing adoption. IT leaders may use the study’s conclusions to help establish processes to develop acceptable performance baselines for cloud services. Finally, with a better understanding of approaches to measure cloud performance, IT executives may gain better insight into whether modern cloud technologies can improve operational efficiencies and strengthen their organization's competitive position in the marketplace.

The results of this study may contribute to positive social change in several ways. For example, this study may bring awareness to future business leaders, entrepreneurs, and nonprofit organizations of ways in which cloud computing value management can facilitate business growth, improve services rendered to the community, and enhance communication between businesses and local communities. The exploration of cloud performance measures may help to confirm some perceived adoption benefits of cloud services and substantiate the attainment of cloud computing operational objectives. Consequently, this examination may improve the trust of day-to-day users of cloud services by divulging its performance benefits and availability limitations. Moreover, this examination of cloud performance may help demonstrate the ubiquitous capabilities of cloud services, which is a core delivery mechanism of e-services to the general populous.

A Review of the Professional and Academic Literature

Overview

The purpose of this quantitative correlation study was to evaluate the relationships among the perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction, perception of system use, perception of user satisfaction, and net benefits of cloud computing services from the viewpoint of IT cloud services managers. The purpose of a literature review is to offer a fair examination of a research topic through a trustworthy, rigorous, and repeatable methodology to perform a credible evaluation of the research topic (Cognini et al., 2018). A literature review methodology should consist of a thorough search for relevant studies on a specific topic that helps establish the extent to which existing research has advanced toward clarifying a particular problem (Cucari, 2019). Thus, I found, critically evaluated, and integrated the findings of all relevant, high-quality peer-reviewed studies that addressed my research topic and identified relations, contradictions, gaps, and inconsistencies in the literature.

In the subsequent subsections, I will review the relevant literature that discussed the definition of cloud computing, the concepts of virtualization and cloud services, cloud computing trends, the current state of cloud computing, and the adoption rationale of cloud computing. Furthermore, I will provide an exhaustive examination of the literature that defined the aspects of the theory for understanding the DeLone and McLean information system success (ISS) model, criticisms of the DeLone and McLean ISS model, supporting theories of the ISS model, contrasting theories of the ISS model, application of the ISS model, the relevance of the ISS model to this study, and literature regarding the study's variables. Lastly, I will examine other similar studies and discuss how they differ from my research.

I will conduct the literature review for this study by searching various research databases through the Walden University library and Google Scholar. Each library provided academic literature from databases such as Directory of Open Access Journals (DOAJ), EBSCO, Emerald Management, Education Resources Information Center

(ERIC), Expanded Academic ASAP, IEEE Xplore Digital Library, Journal of Computer Information Systems, Journal of Theoretical and Applied Information Technology, Pacific Asia Journal of the Association for Information Systems, ProQuest, SAGE Journals, ScienceDirect, and Taylor & Francis Online. I extended my search to confirm that, at a minimum, 85% of the sources used in my literature review were peer-reviewed and not more than 5 years old. This study included 684 references, of which 658 (96%) were from peer-reviewed sources, and 630 (92%) were published between 2016 and 2021, as shown in Table 1.

A primary component of the literature review included my selection of keywords relating to the main concepts of my research topic. I used phrases that might describe thoughts to ensure that identify any relevant information. Thus, for this study, I used the following keywords: *cloud computing, quantitative research, DeLone and McLean, information system success*, *cloud adoption, information technology adoption, information technology success, net benefits, information quality, system quality, service quality, system use, user satisfaction, SaaS, IaaS, PaaS, service models, delivery models, public cloud, private cloud, hybrid cloud, disruptive technology, elastic computing, on-demand service,* and *utility computing*. Lastly, I used Boolean operators such as AND, OR, and NOT and searched limiters to increase the search's specificity and ensured better exactness in finding relevant literature. The Boolean operators also helped to focus the search by joining various ideas related to cloud computing, information system success, and quantitative research to streamline the process to find what I sought.

Table 1

Rate of recurrence and Percentages of Peer-Reviewed Journals

Description	Occurrence	%
Total number of sources in the literature review	269	
*Total number of literature review sources that are peer-reviewed	265	99%
*The percentage of literature review sources used that are five or fewer years old	254	94%
Total number of sources used in this study	684	
*Total number of study sources that are peer-reviewed	658	96%
*Total number of study sources used that are five or fewer years old	630	92%

Note. The table demonstrates the rate of occurrence of source information of the study literature according to the criteria set in the Walden University Doctoral Study Checklist.

* Relates to the anticipated CAO approval date.

What is Cloud Computing?

Cloud computing consists of a sizable array of services. As characterized by the National Institute of Standards and Technology (NIST), cloud computing is a practice for delivering ubiquitous, on-demand hosted computer services over the internet which access is provided to a shared pool of configurable computing resources which the service provider can allocate and free with minimal management effort (Changchit & Chuchuen, 2018). Cloud computing offers a significant paradigm shift from which resources and services are allocated, provisioned, and accessed on-demand (Anisetti et al., 2018). Cloud's plug-and-play fashioned services offer commoditized services models delivered similarly to the standard utility services such as electricity, telephone, gas, and water (Bhardwaj et al., 2018). Moreover, cloud computing has several essential characteristics including broad network access, resource pooling, on-demand self-service, rapid elasticity, measured service, massive scaling, homogeneity, and virtualization (Caithness et al., 2017). Nevertheless, with cloud computing's inclusion of both traditional and nontraditional infrastructure technologies, an organization's ability to recognize its unique advantages is vital to understanding the value of cloud computing (Liu et al., 2018). From a value viewpoint, cloud computing empowers sense-and-respond strategies that facilitate organizational transformation through business process, network architecture, and scope analysis that can positively influence firm performance through enhanced quality, innovation, time savings, and reduction in cost (Kathuria et al., 2018). Thus, cloud computing can offer a dynamic array of service offerings in comparison to traditional on-premise services.

Despite the various service offerings of cloud computing, there are multiple ways to implement cloud services. The cloud deployment models are characterized by the specific type of holder of the cloud environment, level of security, scalability, and cost (Aryotejo et al., 2018). According to Baglai (2018), there are four primary deployment models: private cloud, public cloud, community cloud, and hybrid cloud. A private cloud deployment model provides a cloud infrastructure solely to a single organization, whereas a public cloud deployment model offers cloud infrastructure to the general public, and it is accessible to multiple tenants (Alvarez et al., 2019). A community cloud deployment model provides a cloud infrastructure solely to a particular group of organizations that share similar concerns or business needs (Attaran & Woods, 2019). A hybrid cloud deployment model consists of a combination of public and private cloud delivery models that permit the sharing of data and applications amongst the platforms (Helmi et al., 2018). The decision to adopt cloud services can be challenging and require significant time and resources to assess the feasibility and adoption readiness, perform migration analysis to identify the risks and benefits, and select suitable cloud services and deployment models (Alruwaili & Gulliver, 2018). Thus, each deployment model defines where cloud services will reside and who has control over the cloud infrastructure.

Cloud computing is further distinguished by the primary service models, which define the role that the provider fulfills and how it accomplishes its function. In particular, there are three primary models for cloud computing, namely IaaS, PaaS, and SaaS (Shee et al., 2018). Within an IaaS model, the vendor manages computing resources (i.e., networking, servers, storage, and virtual components), and the customer operates the operating system, data, and applications (Senyo et al., 2018). Within a PaaS model, the vendor manages computing resources as well as the operating system, and the customer controls the data and application(s (Gangwar et al., 2015). Whereas a SaaS model, the vendor manages each service layer, and the customer has access to a part of the software over the network (Hassan et al., 2017). Thus, the variances between the models hinge on the specific computing resources to which the consumer has access via the internet, its use or purpose, and with whom control of the resource resides (Steenkamp & Nel, 2016). To select the appropriate solution, managers must comprehend the strengths and weaknesses of the scope of available cloud computing models (Sohaib et al., 2019). Thus, the selection of the appropriate service model relies on the required level of control and the types of services the organization needs.

Virtualization and Cloud Services

Virtualization technologies are widely used in modern data centers that host cloud computing infrastructures. Virtualization is the process of abstracting physical server resources such as storage, memory, processor, and other input/output (I/O) devices to allow the partition of the operating system from the host computer (Asvija et al., 2019). Virtualization allows cloud service providers to increase IT agility, flexibility, and scalability by creating multiple software-simulated computer workloads, also known as virtual machines (VMs), which reside on a single host (Modi & Acha, 2017). Virtualization also has several characteristics to include partitioning (one-to-many servers to VMs) and isolation (each VM on the physical host is separate from one another) (Da Silva et al., 2017). Encapsulation, which prevents interference amid applications, is a vital element of virtualization (Levitin et al., 2017).

Virtualization is not limited to servers. Essential infrastructure components such as network devices, storage devices, desktops, applications, or complete data centers can be virtualized (Klement, 2017). The infrastructure of cloud services largely depends on virtualization technology, which controls the relationship between the operating system and the hardware (Nezarat & Shams, 2017). With the use of virtualization technologies, service providers can consolidate applications within individual services to avoid the proliferation of physical servers, which in turn can reduce the necessity for additional hardware, spending on power, and data center space (Sligh & Owusu, 2014). Similar to a physical server, the VMs are platform-independent containers that provide resource abstraction for resources such as memory, storage, and processing power, which is executed on software called the hypervisor that runs on the physical host (Tao et al., 2019). Through virtualization technology, cloud service providers rely on the abstraction of computing resources by logically dividing physical resources to facilitate multi-tenancy upon single machines securely and efficiently, which automates resource management and resource provisioning for individual applications (Jararweh et al., 2016). Thus, virtualization is the technology that enables cloud services to separate functions from hardware and provision them appropriately.

Cloud Computing Trends

There have been several growing trends in cloud computing in recent years regarding resource provisioning. As a foundational component of the cloud computing paradigm, applications, databases, infrastructure, and various computing platforms are used as services for computing processing, data storage, and system management to enable ubiquitous on-demand access to shared resources through the internet (Kobusinska et al., 2018). Research has shown that expectations are trending in the direction of expanded use of cloud computing, and it is likely to continue to increase exponentially (Garg et al., 2019). For example, the advancements in cloud computing have built the foundation for serverless PaaS, or function-as-a-service (FaaS), which is the next-generation cloud technology that allows third-party services, or as backend-as-a-service (BaaS), to run in transient containers to facilitate the execution of serverless applications tasks without building infrastructures (Sehrawat & Gill, 2018). The advancement of cloud technologies has led to an improvement in workflow scheduling strategies and emerging trends across distributed environments (Adhikari et al., 2019).

Furthermore, agent-based cloud computing is gaining traction as it involves the design and development of software agents' tools to autonomously manage cloud resources to support cloud service discovery, negotiation, and composition (De la Prieta et al., 2019). There is a rising interest in the use of container-based technologies that serve as lightweight virtualization solutions at IaaS and PaaS levels, which help to enhance the development and deployment of resources based on cloud-native platform services without the necessity for advanced orchestration support (Pahl et al., 2019). Although the premise of cloud computing is to provide on-demand access to computing resources, cloud service providers continue to seek new methods to enhance the provisioning process (Fabra et al., 2019). Consequently, the cloud industry is also witnessing new trends to improve the core infrastructure of the cloud.

The limitations of traditional cloud infrastructure are also leading to new trends regarding cloud architecture. Fog and edge computing are two reasonably new paradigms of computing that extend the bounds of cloud services that are proposed to tackle the issues related to geographically dispersed, heterogeneous endpoint devices, low latency constraints of IoT, and the magnitude of data processing and storage resources necessary to support the IoT requirements (Svorobej et al., 2019). In particular, fog computing is a computing paradigm presented to address the fundamental limitations of a traditional cloud by extending its architecture closer to the ground by permitting processing, networking, storage, and data management to occur near the end devices at designated locations of the network edge (Mouradian et al., 2018). Edge computing also enhances the management, storage, and processing of connected device data by providing computation resources as close as a single network hop through small data centers (Yousefpour et al., 2019).

Mist computing is a paradigm meant to leverage the compute and storage abilities of nodes, hubs, and gateways implemented in the intermediate layers at the extreme edge of a network environment by utilizing microcontrollers and sensors to overcome cloud and fog challenges and enhance storage capabilities, latency, location awareness, network overhead, and implementation costs (Linaje et al., 2019). There is cloud of things (CoT), which addresses the inadequate storage and computation resources available to IoT devices by storing data collected from physical devices to the cloud for computing power and storage (Eugster et al., 2019). IoT adoption process is emerging quickly through the integration of cloud computing technology as it uses the internet to extend the connection between any distant components through information sensing devices such as radio frequency identification, global positioning systems, infrared sensors, and laser scanners (Liu et al., 2019). Cloud computing is also seen as a chief technology to improve smart grids, which are power grids that integrate information technology into the power system infrastructure and allow two-way communication and control capabilities by aggregating all utility systems in a cloud environment (De Sousa et al., 2019).

The OpenStack open-source software platform is also rising in popularity. OpenStack has a substantial open-source community backing as it provides a collection of various loosely coupled components such as authentication, compute, data storage, image management, and networking components that can be accessed through RESTful web service calls that provide application programming interfaces to manage IaaS cloud environments (Krieger et al., 2017). Given the socially dispersed computing systems and rapid growth in smart devices, mobile technology, and sensors, cloud service providers are seeking advanced technologies to address low latency and reliability challenges posed by the vast number of devices that are now consuming cloud resources through technologies such as fog, edge, and mist computing (García-Valls et al., 2018).

The growth of cloud computing also presents opportunities surrounding security and cloud architecture. Due to the rapid emergence of cloud services and related security concerns, cloud service providers have come to realize that security has become an exceedingly vital attribute to the development of online-based applications and secure cloud platforms (Ramachandran, 2016). Because of the various deployment models, service models, cloud services, and tenants, a customer's security requirements and mechanisms can differ, resulting in the need to build a security architecture that appropriately considers the tenant's security requirements (Hawedi et al., 2018). Thus, security-as-a-service (SECaaS) models deliver security services via cloud services instead of on-premise security solutions, which enhances the functionality of existing on-premise deployments by working the cloud and on-premise systems in concert as part of the hybrid solution (Sharma, Dhote, et al., 2016). More organizations are looking toward the adoption of cloud security through managed cloud security services from cloud infrastructure and security vendors to strengthen its controlling mechanism(s) for cloud usage within their organizations by procuring services such as anti-virus, authentication mechanisms, antimalware, anti-spyware, security management and intrusion detection (Spanaki et al., 2019). Thus, SECaaS business models are available to potentially help organizations improve their security posture by outsourcing traditional on-premise security solutions.

Cloud providers are also seeking ways to improve the efficiencies of cloud services through artificial intelligence (AI). The infusion of AI into cloud computing, such as swarm intelligence, helps address changing workload dynamics and balance load among cloud environments based on honey bee behavior (Hashem et al., 2017). Cloud vendors are also looking toward AI to aid in their auto-scaling mechanisms by implementing machine learning techniques to achieve accurate prediction of the workload for elastic cloud service to adapt to workload dynamically changes through autonomously provisioning and de-provisioning of computing resources (Moreno-Vozmediano et al., 2019). The advancements of AI and the robust computing and storage capacity of cloud computing presents dynamic, flexible, virtual, shared, and efficient computing resources necessary for cognitive computing to provide accurate assistance in decision-making (Chen, Herrera, et al., 2018). Thus, the integration of AI in cloud computing presents promising advancements in cloud machine learning from experience as opposed to direct programming.

Cloud computing is also seeing advances in mobile technology. New methods are emerging by combining cloud computing, mobile devices, and wireless networks to augment the capacities of the resources of the mobile devices such as smartphones, tablets, and other portable devices to provide robust technology known as mobile cloud computing (MCC) (Annane & Ghazali, 2019). MCC is a cutting-edge architecture that mobile devices interact with a cloud service provider using native mobile software or embedded browser applications by integrating cloud computing into the mobile environment and using cloud computing to deliver applications to mobile devices (Zheng et al., 2018). Likewise, distributed computing paradigms such as MCC and mobile edge computing help to overcome the constraints of battery capacities of mobile devices that limit the use of computing resources by outsourcing portions of the computing tasks from weak mobile devices to the powerful cloud or fog (Fiandrino et al., 2019). The primary advantages to MCC include extended battery lifetime, unlimited data storage, increased processing power, dynamic resource provisioning, scalability, reliability, ease of integration, and offloading capabilities for mobile devices (Somula & Sasikala, 2018). Consequently, the combination of mobile computing, wireless communication, and cloud computing helps to extend the ubiquity of cloud computing and the capacity of mobile devices.

Current State of Cloud Computing

Over the past decade, cloud computing has significantly impacted today's information technology industry. The rapid adoption of cloud computing has fashioned a shift in the perspective toward IT operations and how cloud services provide critical business services to customers (Iqbal et al., 2016). Yet, the growth in cloud computing can be explained by its economic, scalable, innovative, and ubiquitous nature, wherein such benefits have led to cloud services' quick rise in popularity (Khalil, 2019). Although cloud computing has become a foundation of information technologies, its impact on the future of business is still tough to foresee (Stegaroiu, 2018). Nevertheless, cloud services have already been demonstrated to have a direct impact on organizations and the IT department's efficiencies by changing performance and economic activities (Schniederjans & Hales, 2016). Thus, the adoption of cloud computing will continue to impact IT and businesses globally for years to come.

As cloud adoption rises, research experts predict that cloud computing will continue to have a significant impact on global IT spend over the next several years. In 2018 the cloud market experienced earnings of US$127 billion with nearly a 25% annual increase resulting in almost 30% of worldwide enterprise applications (Kathuria et al., 2018). A forecast by Gartner suggests that the 2019 global IT spending is projected to total $3.79 trillion, which is about a 1.1% increase from 2018, where $1.48 trillion will occur in communication services, $1.01 billion in IT services, $655 billion in devices, $427 billion in enterprise software, and $204 billion in data center systems (Gartner, 2019). Gartner also predicts that IT spending will be impacted by cloud computing by over $1 trillion by the year 2020 (Vithayathil, 2018). Market Research Media reports that the cloud computing worldwide market forecast will see a 30% row by a compound annual growth rate (CAGR) through 2020, and the market will have a worth of approximately $270 billion (Alenezi et al., 2019).

Research data also offer insight into the IT spend distribution toward the various cloud service and deployment models. According to the source Righscale-2018, 82% of organizations subscribing to cloud services will utilize multi-cloud, 9% of organizations use a single public cloud, 4% of organizations use the single private cloud (Sugumar &

Rajesh, 2019). According to Liu and Li (2019), the total expenditure on cloud computing infrastructures reached $46.5 billion in 2017 and is expected to reach $51.9 billion in 2021, with Amazon Web Services leading cloud services platform revenue at $1.64 billion in sales in the second quarter of 2018. The growth within the public cloud services market is estimated to grow to $383 billion by 2020, and predictions indicated that cloud computing would impact nearly 50% of IT outsourcing deals (Werff et al., 2019). In terms of revenues of service models, the most significant cloud sectors are SaaS and IaaS, which make up approximately two-thirds of total cloud expenditure where the 2019 SaaS spend approximation totals $94.8 billion, cloud business process services (BPaaS) totaling $49.3 billion, IaaS totaling $38.9 billion, PaaS totaling $19 billion, and cloud management and security services totaling $12.2 billion (Coyle & Nguyen, 2019). The International Data Corporation (IDC) forecasts that in 2019 traditional data centers will share 50% of the market, private cloud will share 20% of the market, and public cloud will share roughly 30% of the market versus 52%, 18%, and 30% respectively in 2018 (International Data Corporation [IDC], 2019).

Cloud Adoption Rational

Cloud adoption rationale provides insight into the perceived benefits of cloud computing and the drives that lead organizations to embrace cloud services. A chief driver behind cloud adoption is to guarantee the attainability of the services by migrating from and augmenting the operation and maintenance of critical legacy systems (Fahmideh & Beydoun, 2018). A legacy system can be defined as an outdated system or application that is critical to the business but too expensive to maintain, unstable, difficult to extend and integrate with other systems, or difficult to change, upgrade or operate (Gholami et al., 2017). A significant number of the legacy systems today were implemented when computer processing and storage capacity were much more expensive in comparison to today, resulting in system efficiency taking priority over understanding or maintainability of the system leading to after-effects of degradation (Crotty & Horrocks, 2017).

The decommissioning of a legacy system is vital when the system limits the business for responding to changing environmental conditions, and the organization must prohibit the mechanisms that provide continuity to the system and no longer legitimize current information system selections (Rezazade Mehrizi et al., 2019). Legacy systems can cause significant challenges in organizations that are contemplating adopting cloud services as the re-architecture of such systems often present considerable barriers (Fahmideh, Beydoun, et al., 2019). Failures in legacy system migrations are often due to a lack of understanding of computing requirements, premature commitment to the technical implementation of a cloud solution, and confronting unanticipated problems that are beyond the control of consumers and providers (Fahmideh, Daneshgar, et al., 2019). Legacy systems characteristically must be refactored when migrating them to the cloud to help ensure that the system performs as expected and fully benefit from cloud properties (Zimmermann, 2017).

There are several perceived business and technical factors often associated with the adoption of cloud services. Adoption factors refer to the variables that are likely to influence or ease the acceptance of new technologies such as cloud computing (Qasem et al., 2019). Organizations adopt cloud computing to deal with internal operational and logistical problems. In particular, cloud adoption is perceived to be a promising way for organizations to reduce IT expenditure, save space, decrease the use of electricity, lessen the risks related to sustaining and retaining hardware infrastructure (Raut et al., 2017). Business factors focused on end-users associated with cloud adoption include organizational achievement, opportunity, creativity, independence, locus-of-control, and determination (Alam et al., 2018). Kristina and Andreja (2017) state that the potential benefits of cloud services include cost-effectiveness, reliability, service security and effectiveness, more effective and efficient IT governance, and improved service offerings to achieve maximum business value from the services. More importantly, organizations with exceptional cloud computing capability can leverage the cloud-enabled functionalities to improve information acquisition, dissemination, and sharing, expand the market reach, facilitate collaboration, improve decision making, inspire innovation, respond proactively to business environments challenges, and acquire a maintainable competitive advantage and superior business performance (Luo et al., 2018). Lastly, the perceived benefits of cloud adoption include minimal upfront investment, flexibility, scalability, speed of deployment, and access to quality software resulting in favorable perception by suppliers, customers, others in the industry (Oredo et al., 2019). Thus, there a plethora of business and technical drivers that attract organizations to the prospect of investing in cloud computing services.

Several studies also identify several factors that can impede the successful adoption of cloud computing. According to Mohammed et al. (2016), cloud services have seven primary barriers that can affect cloud adoption to include lacking IT infrastructure, absence of human capital, change management, strategy, policy issues, deficient leadership role and partnership, and lack of collaboration. Additional barriers to cloud adoption include lack of provider trust, service availability, and service contract issues, privacy policies, and lack of contingency plans (Branco et al., 2017). Cloud adoption challenges can include lack of standards, security and privacy, loss of data, issues with internet service providers between consumer and cloud service providers, and lack of leadership strategy (Lee, 2019b). Cons of cloud adoption availability and fault-tolerance, resource management and energy-efficiency, the confidentiality of information cloud providers compatibility with current business operations, and vendor lock-in (Assaf, 2019). Lastly, cloud adoption challenges may include mismanagement of data and services, cloud services interruption, adverse changes in work culture, business complexities, project management, lack of awareness regarding cloud services benefits, and usage (Rahi et al., 2017). Consequently, there are several adoption barriers that organizations should be aware of before, which may pose considerable threats to a successful cloud implementation.

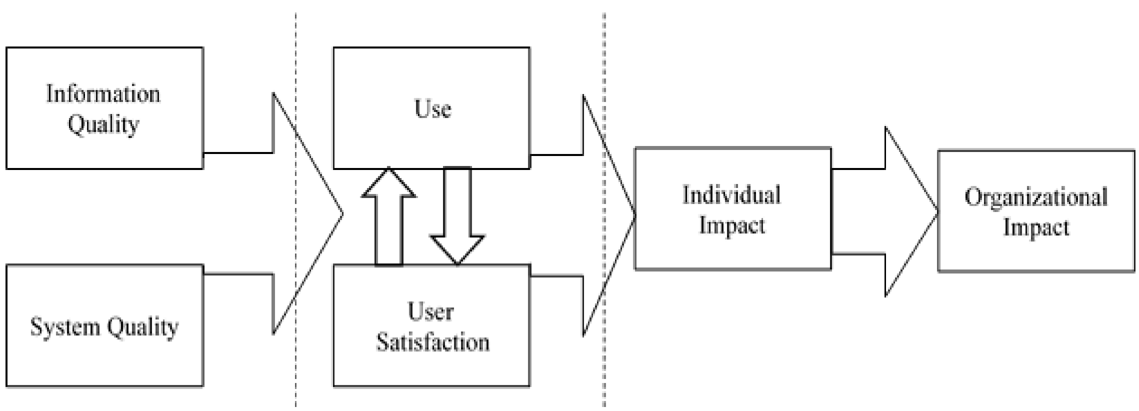
DeLone and McLean Information System Success Model

Several frameworks exist to examine the success of an information system. The concept of information system success (ISS) is utilized in research to measure the effectiveness of an information system or the quality output produced by ISs (Zaky & Naufal, 2017). Of the existing frameworks, the DeLone and McLean model are one of the most well-known frameworks used to assess ISS (Ebnehoseini et al., 2019). Developed in

1992, DeLone and McLean developed the model to measure ISS within organizations using six constructs, namely information quality, system quality, use, user satisfaction, individual impact, and organizational impact (Alzahrani et al., 2019). Figure 1 provides an illustration of the DeLone and McLean model proposed in 1992. Figure A1 in Appendix A includes confirmation of authorization to use and adapt the DeLone and McLean model. The ISS model was based on the modification of Shannon and Weaver's (1949) mathematical theory of communications by Mason (1978) that identified three levels of information which included the technical level that outlines the system's accuracy and efficiency, the semantic level that describes a systems ability to transfer the intended message, and the level of effectiveness the system impacts the receiver (Tam & Oliveira, 2016).

Figure 1

DeLone and McLean Information Success 1992 Model

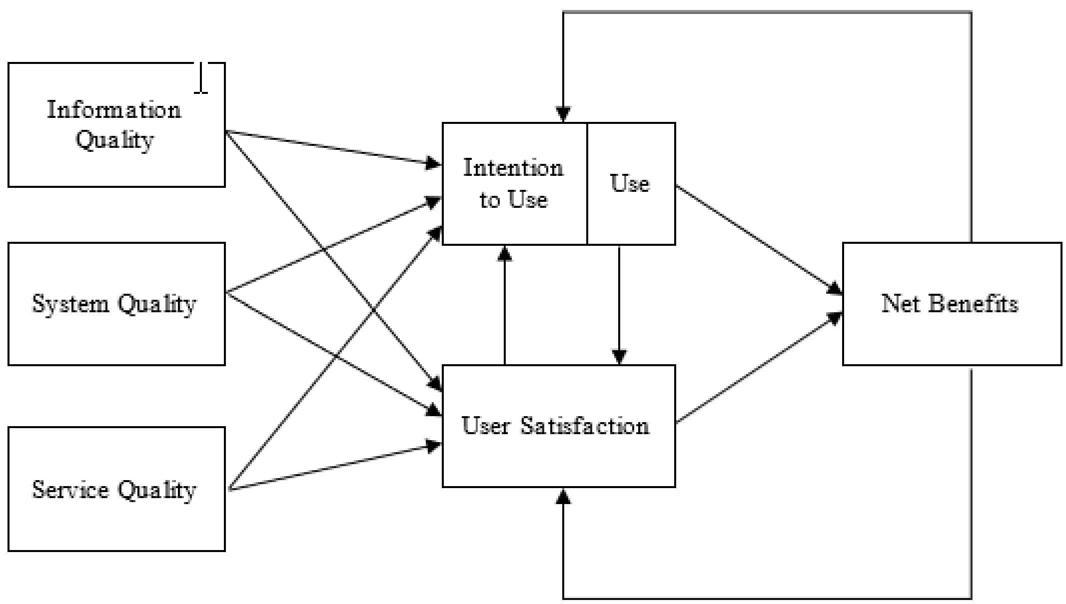


Note. The figure was produced by DeLone and McLean in 1992. From "Information systems success: The quest for the dependent variable," by W. H. DeLone and E. R. McLean, 1992, Information Systems Research, 3, p. 87. Reprinted with permission.

The ISS model suggests that a high-quality IS will be related to higher user satisfaction, added system use, which influences each other, and they both have a positive individual impact and organizational impact (Cheng, 2019). The model adds two meaningful contributions to earlier research on IS success to include the creation of a method to classify the variety of measures of IS success, as well as offer a model of causal interdependence between constructs (Al-Azawei, 2019). However, several researchers contended that the DeLone and McLean model did not comprise a vital measure of IS such as is service quality, as the researchers asserted that frequently used measures of IS effectiveness centered around products as opposed to systems of IS functions resulting in the absence of IS service quality (Rahi & Abd.Ghani, 2019). Studies indicated that there were problems in interpreting the multidimensional facets of use, be it mandatory vs. voluntary, informed vs. uninformed, or effective vs. ineffective (Nemeslaki et al., 2016). Thus, DeLone and McLean revised the model to address weaknesses identified by researchers such that they integrated the constructs individual and organizational to net benefits, added the construct service quality to depict the significance of service as a contributor to IS success (Yakubu & Dasuki, 2018). Figure 2 provides an illustration of the DeLone and McLean model proposed in 2003. Figure A1 in Appendix A includes confirmation of authorization to use and adapt the DeLone and McLean model. Furthermore, the impact constructs individual impact, and the organizational impact was grouped into a sole impact construct net benefits to a generalized construct that incorporates all levels and types of effects of IS (Yu & Qian, 2018). Thus, principal enhancements to the initial model comprise of the addition of service quality to exhibit the significance of service and support in successful IS and the collapsing of individual impacts and organizational impacts into the construct net benefits, which the model's developers find to be more parsimonious (DeLone & McLean, 2004).

Figure 2

DeLone and McLean Information Success 2003 Model



Note. The figure was produced by DeLone and McLean in 2003. From "The DeLone and McLean Model of Information Systems Success: A ten-year update," by W. H. DeLone and E. R. McLean, 2013, Journal of Management Information Systems, 19, p. 24. Reprinted with permission.

Alternative ISS Models

Supporting ISS Models

In addition to the DeLone and McLean IS success framework, several other models have been used to explain IS acceptance and success. For example, other studies have used the theory of reasoned action (TRA), technology acceptance model (TAM), and unified theory of acceptance and use of technology (UTAUT) to explain IS acceptance behavior (Lwoga & Sife, 2018). Moreover, the concept of understanding the significance of customers' expectations toward technology has been studied for several years, and acceptance frameworks are effective tools to help measure the attitude toward technology or the intentional behaviors to accept technology (Malik et al., 2017). Understanding the drivers that influence individuals to use technology has been a driving concern within management scholars and the professional community, leading to a wealth of literature that focused on comparing the predictive capability of the varying theories on technology adoption and use (Méndez-Aparicio et al., 2017). Because TRA, TAM, and UTAUT provide the ability to measure one's perceptions of the use benefits of technology, each model is considered to be viable frameworks to examine IS acceptance and success.

TRA

TRA was developed by Ajzen and Fishbein in 1975 to examine the relationship between attitudes and behavior (Tarabasz & Poddar, 2019). From a technology perspective, TRA helps to explain people's behavior and use intentions of IS and their influences by social pressures and attitudes (Merhi & Ahluwalia, 2019). Researchers have utilized TRA to examine user behavior and knowledge sharing to understand better end-user behavioral patterns and their impact on IS implementation outcomes (Allie & Ajiboye, 2019). Gashami et al. (2016) analyzed the cognitive mechanism which influenced user trust of SaaS and the acceptance of users in Korea grounded on TRA. Libaque-Saenz et al. (2016) employed TRA to examine the role of IS practices on the intention to authorize secondary use of personal data within Korean telecommunications companies. Bansal et al. (2016) utilized TRA to explore the critical roles regarding the sensitivity of and disclosure of private information and the customer's personality of students at a Midwestern university in Glendale, Arizona. However, TRA sets out to explain and predict behavior and maintains that attitudes regarding objects such as machines, people, or institutions are not essential to the theory and provides little to the forecast and rationalization of the development of intention and behavior (Hwang et al., 2016).

Despite TRA's recognition as a viable framework for examining the successes of IS, I did not select the model for my theoretical framework for this study. As indicated by Mi et al. (2018), many scholars consider TRA as the best indicator to predict and describe one's intention behind a particular behavior and human action. However, the emphasis of this study is to examine the acceptance perceptions based on the quality factors of the IS rather than the motivation of an individual to accept a system. Thus, I did not find the TRA model to the most appropriate framework for this study.

TAM

TAM was introduced by Davis (1989) as an adaption from TRA, and it is widely utilized for explaining the determinants of intended behaviors in several IS domains (Cheng, 2018). TAM model can be used to discover user's perspectives and behaviors regarding their preference in IS usage and help to explain the determinants of technology acceptance, which in turn can help describe their behavior in the inclusive range community that is adequate and acceptable (Amornkitpinyo & Piriyasurawong, 2017).

Moreover, TAM is based on the causal relationship amid belief, attitude, intention, and behavior within TRA and can be used to identify aspects that impact user acceptance of IS in organizations (Tripathi, 2017). For example, Zabukovšek et al. (2019) utilized the TAM model to examine the acceptance of enterprise resource planning (ERP) systems focused on its use in the maturity stage and different environments in Indian and European Union organizations. Sabi et al. (2018) conducted a study using TAM to examine the acceptance of cloud computing of university staff and students in western developed countries. Sharma, Al-Badi, et al. (2016) utilized TAM to examine the adoption of cloud computing services by IT professional's perceptions in the country of Oman. However, other researchers have others describe the DeLone and McLean mode to be a more sophisticated process wherein a causal and process relationship exists among different variables (Feng & Pan, 2016).

Although researchers recognize TAM as a feasible framework for examining the successes of IS, I did not select the model for my theoretical framework for this study. For example, criticism of TAM concerns the framework's subjective means to measure behavioral intention (BI), such as interpersonal influence (Ajibade, 2018). As a derivative of TRA, TAM emphasizes the conduct of the system user and behavior influences rather than the user's perceptions of the quality standards of the IS. Thus, I did not find the TAM model to the most appropriate framework for this study.

UTAUT

UTAUT framework was proposed by Venkatesh and other collaborators in 2013 (Mojarro Aliaño et al., 2019). UTAUT theory is used by many types of research to understand user behavior and intention to use IS which; the constructs and moderators were developed from the integration of eight models and approaches to included TRA, TAM, the social cognitive theory, motivational model, theory of planned behavior, innovation diffusion theory (IDT), the combination of TPB and TAM, and model of PC utilization (Persada et al., 2019). Deemed as a suitable tool for managers to evaluate the success of IS, the UTAUT model has improved performance than previous models and explains approximately 70% of the variance in the intent to employ technology, and researchers have successfully applied the model in numerous technology acceptance studies (Kalavani et al., 2018). For example, Rahi et al. (2019) utilized UTAUT to ascertain determinants of internet banking adoption of customers of commercial banks in the developing country of Pakistan. Yadegaridehkordi et al. (2018) explored the critical influencers of user adoption of cloud-based collaborative learning technology within Malaysian public universities grounded on UTAUT. Lastly, Alotaibi (2016) conducted a study to examine if UTAUT explains consumer decisions regarding the adoption of SaaS and belief factors that impact its acceptance. Although studies such as AL Athmay et al. (2016), Thongsri et al. (2019), and Wibowo et al. (2018) utilized the UTAUT model for variables such as social influence, perceived effectiveness, performance expectancy, effort expectancy, the researchers also employed the DeLone and McLean ISS model to examine technical constructs such as information quality and system quality.

The UTAUT framework is also deemed as a practical model to access IS acceptance and success. However, UTAUT suggests that effort expectancy and performance expectancy are critical technology influences of the attitude and behavior of

IS adopters (Alshare et al., 2019). Similar to TRA and TAM, UTAUT focus on predicting the behavior of the IS users rather than predicting perceptions of the user's acceptance of the IS based on its quality factors. Thus, I did not find the UTAUT model to be the most appropriate framework for this study.

Contrasting ISS Models

There are several well-known frameworks that contrast with the DeLone and McLean IS success framework that focuses on the adoption of new technology as an alternative to the acceptance and success of IS. In particular, the technology-environment-organization (TOE), the diffusion of innovations (DOI) theory, and innovation diffusion theory (IDT) are existing concepts that offer a comprehensive analysis of the criteria that are likely to influence the decisions regarding the adoption of innovation into an organization (Olufemi, 2019). A vital element for IT adoption is to comprehend the cultural context and practices of individuals and organizations, which in turn require the presence of different proficiencies for IT integration to be successful (Tarhini et al., 2019). Furthermore, understanding the factors that influence ones' intention to use technology can aid managers in employing strategies to boost the acceptance of technologies and advance the innovation adoption process (Mukred et al., 2019). Because the TOE, DOI, and IDT frameworks help to provide the bases to examine the factors that may impact the adoption tendencies of technology, the models are viewed as viable models to explore IS adoption behavior as opposed to the acceptance and success frameworks such as of TRA, TAM, and UTAUT's.

TOE

The TOE framework is a well-established technology adoption framework developed by Louis G Tornatzky and Mitchell Fleischer in 1990 (Cruz-Jesus et al., 2019). Fundamentally, TOE integrates characteristics of adopted technology, organizational factors that possibly have an impact on adoption, and factors that form the organization's environment, where together offers a complementary model of the determinants of technological adoption (Chen, Yin, et al., 2019). The technological context emphasizes the internal and external technologies relevant to the organization, such as infrastructure and processes that can already be in use within the organization or available but not currently in use (Ophoff & Miller, 2019). The organizational context emphasizes descriptive measurement elements such as the complexity of the company's size, centralization, quality, and quantity of human resources available internally and how the particular factors aid in the adoption decision-making process (Park & Choi, 2019). The environmental context emphasizes both the internal and external factors such as competition, business practice, government, and trading partners form the organization positively and undesirable to help understand how such factors and technology adoption decision-making process (Eze et al., 2019). Thus, TOE underscores the magnitude of technological resources and innovation, illustrates a strong influence on organizations, and provides a theoretical lens to investigate technology adoption where each context is a crucial antecedent of enterprise-level technology adoption (Bala & Feng, 2019).

Although the TOE framework is a feasible model for examining the adoption of new technology, I did not select the framework for this study. Notably, the TOE framework helps to describe the adoption of innovation, and numerous empirical studies applied the model to focus on technology adoption decisions within various IS domains from a technological, organizational, and environmental context (Lin, 2016). However, this study examined cloud computing services from a post-adoptive state. Furthermore, this study focused only on the technological characteristics of IS resulting in the organizational and environmental contexts being out of scope. As a result, I did not find the TOE model to be the most appropriate framework for this study.

DOI

Everett Rogers introduced the DOI theory in 1962 (Schoenbach et al., 2018). Diffusion is the process that communicates innovation across specific channels, over time, between individuals within a social system, and innovation is a perceived new concept, practice, or object by an individual or another group of adoption (Carreiro & Oliveira, 2019). Communication channels are the process where participants generate and distribute information to reach a common understanding, and a social system is a collection of interconnected units that are involved in collaborative problem-solving to achieve a common goal (Ho et al., 2019). Thus, DOI attempts to aid in the prediction of how decisions are made regarding the adoption of innovation by identifying adoption patterns and understanding its structure (Min et al., 2019). The DOI theory analyzes the phenomenon of technology adoption by helping to build an understanding of the psychological and sociological processes contributing to the adoption of innovation among the population (Ali et al., 2019). According to Kim and Amran (2018), the velocity of adoption of an innovation is centered on five factors to include perceived attributes of innovation, communication channels, nature of the social system, type of innovation-decision, and extent of change agents' promotion efforts.

My research aimed to examine the success of IS from a technical context using measures such as information, system, and service quality. Yet, the DOI theory measures innovative adoption through variables such as individual characteristics and internal and external organizational characteristics (Ali et al., 2018). Like the TOE model, the DOI theory also centers on an individual's degree of readiness to embrace innovation. As I investigated cloud computing services from a post-adoptive state and did not seek to measure internal and external organizational characteristics, I did not find that the DOI model is the most suitable framework for this study.

IDT

Everett Rogers developed the IDT model in 1962 as a means to predict and describe innovation adoption and diffusion behaviors (Wang & Lin, 2019). IDT can be characterized as the innovations that present advantages and perceived compatibility with current methods and ideas that also offers minimal complexity, possible trialability, and observability that will have a farther pervasive and precipitous rate of diffusion (Al-Rahmi et al., 2019). Rogers contends that innovation, acceptance, and diffusion might be directly related to each other, and the adoption of innovation may not happen instantaneously after an individual is exposed to it (Chen, Yen, et al., 2018). The velocity that diffusion occurs is based on the rate of adoption, which attribute to the speed at which individuals within the social system use the innovation, and the pace of adoption is, in effect, affected by numerous elements of the innovation (Hubert et al., 2019).

Additionally, the innovation-decision process facilitates (a) the persuasion or forming of an attitude toward the innovation based on one's acquiring of knowledge of the innovation, (b) the decision whether to accept or reject the innovation and (c) confirmation to continue using the innovation following the implementation of the new technology (Grover et al., 2019). Furthermore, the IDT model identifies five influential factors that influence the adoption of innovative technology that includes relative advantage, compatibility, complexity, trialability, and observability (AlBar & Hoque, 2017).

As the IDT model is a framework developed to examine the adoption of innovation, I did not find it appropriate for this study. According to Pantano and Vannucci (2019), researchers have primarily employed IDT to investigate the initial adoption of a particular innovation over time amongst the individuals in a specific social system. Understanding that the IDT model focuses on the diffusion or adoption of technology within an organization and its key measures focus more on environmental and organizational contexts, I did not find that the model was the most suitable framework for this study.

Application of Information System Success Model

Many studies have applied and maintained the validity of the DeLone and McLean ISS framework in various technical contexts. For example, Sharma and Sharma (2019) and Tam and Oliveira (2017) employed the ISS model to examine factors that influence the intention to use mobile banking systems. Wibowo and Sari (2018), Zainol et al. (2017), and Wijayanto and Haryono (2018) conducted studies to analyze the extent to which the implementation of ERPs are successful in academic and corporate environments. The DeLone and McLean ISS model was also used to examine the success of student ISs where Mashabela and Pillay (2017) investigated student acceptance of mobile student ISs during admission. Similarly, Ramírez-Correa et al. (2018) explored the user satisfaction of the visual aesthetics of student ISs.

Researchers also investigated electronic learning (e-learning) systems using the ISS model. For example, Aldholay, Isaac, Abdullah, Abdulsalam, et al. (2018) examine the impact on user satisfaction and actual usage of e-learning systems. Furthermore, Mtebe and Raphael (2018) set out to identify critical factors that influence e-learning satisfaction. Additionally, Gay (2016) examined online instructor readiness of e-learning, and Marjanovic et al. (2016) examined the success of e-learning from the employee perspective.

The DeLone and McLean framework has also been utilized to explore the success of hospital ISs (HIS). For instance, Kuo et al. (2018) investigated physicians' satisfaction levels using HIS. Novalendo et al. (2018) explored the success of prescription ISs and their effect on the performance of doctors to patients. Moreover, Cohen et al. (2016) investigated the satisfaction and productivity of nurses who used HIS in day-to-day clinical practice, and Mohd Salleh et al. (2016) assessed the performance of HIS from the perspective of health care providers.

Researchers also utilized the ISS model to investigate social networking applications (SNAs). For example, French et al. (2018) evaluated the success measures on social network sites (SNS). Shafawi and Hassan (2018) investigated the factors that influence users' engagement with social media, Ou et al. (2016) assessed the success of SNAs such as Facebook and Twitter. Lastly, Chen et al. (2016) examined the use of SNSs such as Facebook to conduct commercial activities.

Several recent studies examined knowledge management systems (KMS) success. For example, there is a study by Ali et al. (2017) that utilized ISS to develop a KMS success model for healthcare organizations. Karlinsky-Shichor and Zviran (2016) employed ISS to examine employees' and managers' perceived benefits and user satisfaction of KMS, and Budiardjo et al. (2017) leveraged ISS to investigate end-user satisfaction and continuance use intention of KMS. Negahban et al. (2016) grounded their study on the ISS model to investigate the effects of mCRM quality on business performance. Moreover, Agrifoglio et al. (2016) based their research on the ISS framework to examine the success factors for case management systems within Italian courtrooms.

Recent Similar Studies Using ISS for Cloud Computing Success

Several recent studies utilized the ISS model to examine various cloud-based services. For example, Lian (2017) used the ISS model to understand the essential factors that influence cloud computing success of electronic medical records (EMRs) systems. In particular, the researcher conducted a study to examine the quality-related elements that affect the cloud computing success of EMRs in Taiwan hospitals. Lian presented seven hypotheses in which information, system, service, and information quality of cloud computing would positively affect hospitals' trust toward the IS service providers and cloud computing satisfaction. He also hypothesized that hospitals' trust toward IS service providers would positively affect cloud computing satisfaction. The researcher also used a quantitative design model, and the research method consisted of a mail-based questionnaire survey for data collection and Cronbach's alpha and partial least squares (PLS) for data analysis and hypothesis testing. Differences between my study and Lian's begins with the researcher using an adaptation of the ISS model where he omitted the intention to use, user satisfaction, and net benefits constructs to use trust and cloud computing satisfaction constructs. Variations between our studies also include the researcher's sample population, included CIOs of the Taiwan hospitals versus IT managers.

Jiang and Wu (2016) conducted a study to examine the successful development of cloud-based mobile applications grounded on the ISS framework. The researchers presented seven hypotheses regarding the measures of system quality, information quality, user satisfaction, intention to use, user satisfaction, and how they positively affect the net benefits of the homestay application. The authors used a quantitative design, and the research method included an internet survey to collect data from the respondents. Jiang and Wu's research differs from my study in several ways. First, the researchers utilized the 1992 ISS model instead of the 2003 model, which did not include the service quality construct. Additionally, the researcher's sample population included end-users of the application instead of IT personnel who manage the software. The study also focused on a specific cloud SaaS solution, whereas I will not constrain this study by a particular cloud services model.

Chiu et al. (2016) sought to examine the success of the implementation of cloud ebookcases centered upon the ISS framework. The objective of the study was to implement a cloud ebookcase and adapt the ISS model so that it can successfully assess ebookcase systems. The researchers hypothesized that system quality, service quality, and information quality have a positive influence on end-users intention to use cloud ebookcase. Additionally, the authors hypothesized that system quality, service quality, and information quality positively influence users' satisfaction with the cloud ebookcase. One of the primary differences between Po-Sheng, I-Ching, Chih-Chien, K., Ying-Hung, and Yueh-Min's study and my research is their focus on a single SaaS-based solution instead of examining cloud services models from a broader perspective. Furthermore, the researchers elected to only explore the relationship from user satisfaction to intention to use and not examine the relationship from intention to use to user satisfaction. Moreover, the researchers' sample population students of three universities in southern Taiwan oppose to IT managers of cloud services within states in the United States. Lastly, the researchers' data analysis methods included partial least squares rather than regression and factor analysis.

Azeemi et al. (2013) utilized the IIS model to develop a new framework to support improved outcomes for cloud migration initiatives. The objective of Azeemi, Lewis, and Tryfonas' study is to propose a preliminary conceptual model of a holistic multi-leveled IS success model for migrating to the cloud. The researchers sought to answer the question of what are the newly presented challenges that go past the scope of existing IS models designed to measure the success of migrating traditional systems to a cloud? Azeemi, Lewis, and Tryfonas' based their research design on a qualitative case study. However, the researchers only presented the bases of their IS success model and did not carry out a complete case study. The chief difference between Azeemi, Lewis, and Tryfonas' research and my study centers around the research design as the researchers grounded their study on qualitative methods versus my quantitative approach. Although the authors did not specify a sample population, their study's target audience appeared to be consumers and providers of cloud services as opposed to IT managers of cloud services.

Cheng (2019) employed a hybrid model with ISS, confirmation model (ECM), and task-technology fit to examine the factors that may affect end-users continuance use intention of cloud ERP systems. The researcher sought to understand the factors that influenced users' continuance intention of cloud ERP following the acceptance of the system. The researchers hypothesized that system quality, task-technology fit, and information quality had positive effects on satisfaction, confirmation, and perceived usefulness, which ultimately leads to continuance user intentions to utilize cloud-based ERP systems. One of the significant distinctions between our studies involves the application of the ISS model. Cheng's theoretical framework was an adaptation of three models to include the confirmation model, DeLone and McLean ISS model, and task-technology fit model, where I will solely used the DeLone and McLean ISS framework. Furthermore, there exist differences in study participants where Cheng's population targeted 37 companies with end-users of cloud ERP in Taiwan, and my study targeted IT managers of cloud computing services within the United States. Cheng's data analysis included structural equation modeling (SEM) instead of a regression analysis. Lastly, Cheng specifically focused on ERP cloud SaaS solutions, whereas I did not constrain this study by a particular cloud services model.

Criticisms of the DeLone and McLean ISS Model

Despite the number of applications of the DeLone and McLean ISS Model, there are various criticisms of the framework within the research community. As indicated by DeLone and McLean (2003), IS success is a multidimensional and interdependent construct and requires that one studies the interrelationships among the six constructs information quality, system quality, service quality, intention to use, user satisfaction, and net benefits. However, Newman and Robey (1992) contend that the ISS model's process-model diagrams signify quite different concepts and cannot be represented appropriately in a single model. Seddon (1997) argues that the interpretations in the ISS model may lead to potentially unclear means. Sheldon also contends that the overall perception of IS benefit should be accounted for regarding the evaluation of IS success, where he defines perceived usefulness as the degree to which user's perceived that the use of an IS improves individual, group, or organizational job performance (Wang et al., 2016).

Moreover, the evaluation of the construct led the researchers to modify the construct because they speculated that the fundamentals of the success construct that researchers have been trying to measure *usefulness* instead of *use* (Petter et al., 2008). Mardiana et al. (2015) argued that the ISS model's construct *intent to use* is subject to internal consistency because behavioral intention to use is derived theoretically from psychology discipline, whereas information quality and system quality were derived from a technical aspect. Furthermore, Wani et al. (2017) argued that the ISS model focuses exclusively on the utilitarian facets of user satisfaction. Lastly, the ISS model does not take into account any social characteristics of systems such as the trust of users, social usefulness, or culture from a contextual aspect (Lashayo & Md Johar, 2018). Consequently, the literature demonstrates that the ISS framework is not an all-encompassing model, and researchers should give consideration to the measures for each of the framework's dimensions.

The Relevance of the ISS Model to this Study

The relevance of the ISS framework to this study was based on the model's appropriateness and its explanatory power to examine the potential attainment of the expected benefits of ISs from a technical context. In the investigation of the model, research has shown that ISS has a good descriptive power concerning the extent of IS success or failure (Van Cauter et al., 2017). Furthermore, the framework is effective toward helping to provide a view of IS as socio-technical systems that encompass both social and technical components that work together to produce, process, and warehouse data and information (Tilly et al., 2017). In particular, the ISS model fulfills three primary purposes to help strengthen this study by (a) offering the means to focus the examination on technical context using quality dimensions of IS such as information, system, and service quality, (b) provide the means to examine ISs from a post-adoption state, and (c) help to explain the attitude of individuals toward system satisfaction and use intentions. Furthermore, the model can help better understand if the net benefits of an IS are positively or negatively affected by user satisfaction and the continued use of the IS.

Thus, the ISS framework was especially significant to this study because it potentially aids in providing a comprehensive definition of IS success from a technical context while taking into consideration system use and an individual's satisfaction with the system from a post-adoption perspective.

Technical Context

One of the significant contributions of the ISS framework to this study is the model's ability to examine ISs from a technical context. In particular, a strength of the ISS framework is its capability to measure the success of IS using quality dimensions (i.e., system, information, and service) (Isaac et al., 2019). Nevertheless, there other popular frameworks such as TRA, TAM, and IDT that are effective models to study technology acceptance by measuring individuals' attitudes toward technology or behavioral intention (Malik et al., 2017). However, the ISS framework can be applied to a narrow IS use context as well as a broad range of technological systems, conceptions of systems, and system-related behaviors (Lange et al., 2016). Moreover, the technical aspects of the ISS model help to describe the accuracy and efficiency of the IS through its quality dimension measures, which are antecedents of user satisfaction and IS use (Agrifoglio et al., 2016). Thus, the ISS is a versatile model that provides measures to examine IS in terms of its technical qualities and its functional fit.

Post-Adoption Context

A strength of the ISS framework includes its ability to provides the basis to examine the perceived success of an IS from a post-adoption state. Earlier evidence conveys problems and significance of obtaining users' support during the transition phase of new IS, which includes the pre-adoption stage before the system implementation and the initial post-adoption stage immediately following the system implementation (Lu et al., 2020). Additionally, recent post-adoption studies have steered awareness to trust in technology as a driving factor toward attaining value-added IT usage behaviors associated with technology's specific attributes, such as IS functionality, effectiveness, and reliability. Consequently, as IS adoption literature has been prominent in offering guidance for attaining quality in technology use, the ISS framework is the foremost theory that examines IS acceptance use in a post-adoption context (Tam & Oliveira, 2017). Nonetheless, the ISS model is a widely recognized model to study innovation adoption success, and it has been successfully validated at the individual and organizational levels (Vatanasakdakul et al., 2017). As stated by Aparicio et al. (2016), DeLone and McLean's ISS model relates to a post-adoption stage where the independent variables are system quality, information quality, and service quality. Likewise, Lin et al. (2018) assert that researchers employ the ISS model to examine outcomes of IT adoption. Therefore, the ISS model provides measures to investigate the acceptance of IS from a post-implementation context at multiple levels of an organization.

Use and Satisfaction Context

The ISS framework can strengthen this study by helping to explain the user's attitude toward system satisfaction and use intentions to understand better IS acceptance. User satisfaction is perceived to be an essential variable between service perception and autonomy factors, it encourages customers to use services, and it has a powerful influence on self-determination stimulating factors (Rahi & Abd.Ghani, 2019). As suggested by the ISS model, the extent to which a user perceives that the use of an IS will increase individual, group, or organizational performance, the higher user satisfaction levels become (Wang et al., 2016). Because satisfaction signifies the usage of the IS in user decision-making, it could be challenging to refute that the success of a system that users value, which in turn results in satisfaction being regarded as the prevalent measure of IS success (Yu & Qian, 2018).

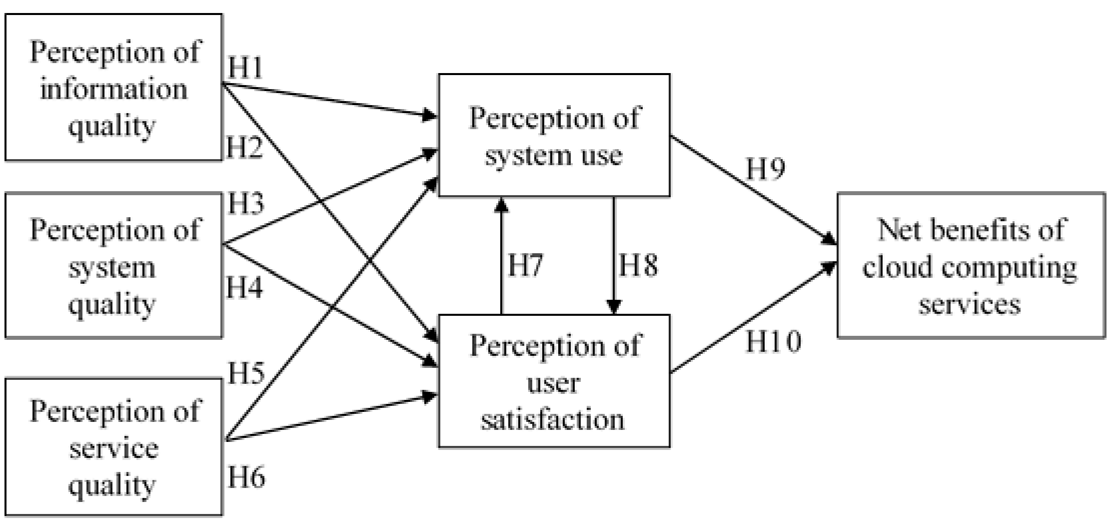
Additionally, the relationship between system usage and performance is a highly sought path for future research regarding the subject of technology usage, and in the context of ISs many studies measure usage through frequency and duration of use (Isaac et al., 2017). Subsequently, the 2003 ISS model includes the construct system usage or preferably intention to use as an essential measure of IS success to fit their model for volitional and non-volitional use contexts (Lin et al., 2017). Therefore, the literature demonstrates that the user's satisfaction with the IS and an individual's usage intention help to explain a user's attitude toward an IS. Thus, the constructs of the ISS can play a significant role in this study to describe the continued usage of an IS impact on the perceived benefits of the IS.

Research Model and Hypotheses Development

This study adopted the six constructs used in the updated ISS model to evaluate the relationships among the perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction, perception of system use, perception of user satisfaction, and net benefits of cloud computing services. Figure 3 presents the proposed model for this study. Figure A1 in Appendix A confirms the authorization was obtained to use and adapt the DeLone and McLean model. Perception can be defined as a working process in which an individual senses reality and draws a certain understanding of the same phenomenon (Fontes et al., 2016). Attributes such as age, gender, educational level, work experience, and culture are considered to possibly contribute to an individual's perception and the subsequent acceptance of technology (Naicker & Van Der Merwe, 2018). Moreover, perceptions are unique to every person and significantly affected by individual values and principles, life events, experiences, preconceived notions, and motivation (Jones & Seckman, 2018). Consequently, the underlying assumptions were that sufficient definitions for perception exist, and such factors can be measured.

Figure 3

Proposed ISS Research Model



Note. The figure illustrates the proposed ISS model. Adapted from "The DeLone and McLean Model of Information Systems Success: A ten-year update," by W. H. DeLone and E. R. McLean, 2013, Journal of Management Information Systems, 19, p. 24. Adapted with permission.

Information Quality

Information quality involves the quality of the information produced by the system (Gaardboe et al., 2017). Researchers have defined information quality as the extent to which IS users feel that the information provided by the system is current, precise, pertinent, comprehensive, and organized (Aldholay, Isaac, Abdullah, & Ramayah, 2018). The success criterion for a system's information quality is a vital aspect relative to the characteristics of its output, which may include accuracy, completeness, understandability, security, and usefulness (Daghouri et al., 2018). However, inadequate information quality can impact the reliability of the IS and lessens the desire to use the system (Thongsri et al., 2019). Nonetheless, Jiang and Wu (2016) indicated that information quality positively affected system use of the could-based operations application.

Researchers have previously demonstrated that information quality has a positive influence on user satisfaction by proving that various tangible benefits exist to help improve users' ability to perform their job functions (Yakubu & Dasuki, 2018). Similarly, a study by Hermawan (2019) showed that employees have a perception that the IS produced complete information to aid in their daily job activities, and the IS is relatively easy to comprehend. Furthermore, the Pawirosumarto (2017) findings were consistent with the researcher done by DeLone and McLean that information quality significantly influenced user satisfaction as the users felt satisfied using the IS. Thus, I posed the following questions:

Research Question 1 (RQ1): What is the relationship between the perception of information quality and the perception of system use of cloud computing services?

Null Hypothesis ($H_0$1): There is no significant relationship between the perception of information quality and the perception of system use of cloud computing services.

Alternative Hypothesis (H_a1): There is a significant relationship between the perception of information quality and the perception of system use of cloud computing services.

Research Question 2 (RQ2): What is the relationship between the perception of information quality and the perception of user satisfaction of cloud computing services?

Null Hypothesis **(**$H_0$2): There is no significant relationship between the perception of information quality and the perception of user satisfaction of cloud computing services.

Alternative Hypothesis (H_a2): There is a significant relationship between the perception of information quality and the perception of user satisfaction of cloud computing services.

System Quality

System quality is regarded to be the chief criterion for system success and mainly refers to system characteristics that focus on the system's technical facets such as stability, response time, and ease of use (Alksasbeh et al., 2019). Likewise, system quality involves whether the system has problems and if it is straightforward to use, which its characteristics may include ease of use, ease of learning, and user-friendliness (Mtebe & Raphael, 2018). Additionally, the ideals of system quality describe the performance of the IS regarding its reliability, convenience, functionality, and other system metrics (Ramírez-Correa et al., 2017). Accordingly, the study conducted by Marjanovic et al. (2016) found there to be a strong and significant relationship between system quality and system use. The findings of Tam and Oliveira (2017) also substantiate the existence of a relationship between system quality and system use. As described by the ISS model, the higher the system quality, the greater the level of user satisfaction will be obtained (Keikhosrokiani et al., 2018). Correspondingly, Yakubu and Dasuki (2018) corroborated that service quality has a significant relationship with user satisfaction. Yakubu and Dasuki (2018) findings are found to be consistent with other studies such as Nusantara et al. (2018) and Kuo et al. (2018). Thus, I posed the following questions:

Research Question 3 (RQ3): What is the relationship between the perception of system quality and the perception of system use of cloud computing services?

Null Hypothesis ($H_0$3): There is no significant relationship between the perception of system quality and the perception of system use of cloud computing services.

Alternative Hypothesis (H_a3): There is a significant relationship between the perception of system quality and the perception of system use of cloud computing services.

Research Question 4 (RQ4): What is the relationship between the perception of system quality and the perception of user satisfaction of cloud computing services?

Null Hypothesis ($H_0 4$): There is no significant relationship between the perception of system quality and the perception of user satisfaction of cloud computing services.

Alternative Hypothesis ($H_a 4$): There is a significant relationship between the perception of system quality and the perception of user satisfaction of cloud computing services.

Service Quality

Information quality involves the level of the service or support that system users receive (Assegaff et al., 2017). Similarly, one may view service quality as the general perceptions of assurance, understanding, and responsiveness of a service provider extending support to end-users (Thielsch et al., 2018). Additionally, service quality can be defined as the quality of system support by the IT function or third-party service providers to include technical competence, responsiveness, reliability, and empathy (Chaw & Tang, 2018). Moreover, Chiu et al. (2016) study demonstrated that service quality has a significant influence on system use and concludes that improvements in service quality are essential to enhance system use. Likewise, the notion of service quality is the point at which IS user interacts with the service deliverer, although the service may not be an interpersonal interaction (Nugroho & Prasetyo, 2018). Hence, Gay (2016) found that service quality was a significant predictor of user satisfaction in his examination of e-learning systems. Moreover, Rahi and Abd.Ghani (2019) also concluded that service quality had a positive and significant influence on user satisfaction. Thus, I posed the following questions:

Research Question 5 (RQ5): What is the relationship between the perception of service quality and the perception of system use of cloud computing services?

Null Hypothesis **(**$H_0$5): There is no significant relationship between the perception of service quality and the perception of system use of cloud computing services.

Alternative Hypothesis (H_a5): There is a significant relationship between the perception of service quality and the perception of system use of cloud computing services.

Research Question 6 (RQ6): What is the relationship between the perception of service quality and the perception of user satisfaction of cloud computing services?

Null Hypothesis **(**$H_0$6): There is no significant relationship between the perception of service quality and the perception of user satisfaction of cloud computing services.

Alternative Hypothesis (H_a6): There is a significant relationship between the perception of service quality and the perception of user satisfaction of cloud computing services.

System Use

System use involves the dependency that users may have on a particular system through the volitional usage of an IS (Gonzales & Wareham, 2019). System use is a prevalent literature success measure and relates to the effective use of a system, hence full adoption, the initial phase of success (Cidral et al., 2018). Furthermore, the ISS model incorporates system use as a proxy for mindsets toward systems use and contends that use should precede user satisfaction from a process perspective, although a user's positive experience with use will bring about further user satisfaction in a causal sense

(Iannacci & Cornford, 2018). Considering the definition of system use, Hermawan (2019) suggested that system use had a positive effect on user satisfaction, and system use positively affected net benefits. Furthermore, Pawirosumarto (2017) demonstrated that system use positively impacted user satisfaction. Yu and Qian (2018) study suggested that system use had a significant relationship between user satisfaction and net benefits. Thus, I posed the following questions:

Research Question 8 (RQ8): What is the relationship between the perception of system use and the perception of user satisfaction of cloud computing services?

Null Hypothesis ($H_0$8): There is no significant relationship between the perception of system use and the perception of user satisfaction of cloud computing services.

Alternative Hypothesis (H_a8): There is a significant relationship between the perception of system use and the perception of user satisfaction of cloud computing services.

Research Question 9 (RQ9): What is the relationship between the perception of system use and the net benefits of cloud computing services?

Null Hypothesis ($H_0$9): There is no significant relationship between the perception of system use and the net benefits of cloud computing services.

Alternative Hypothesis (H_a9): There is a significant relationship between the perception of system use and the net benefits of cloud computing services.

User Satisfaction

User satisfaction is a crucial determining factor of IS assessment, and organizations should be conscious of user satisfaction with the IS (Michel & Cocula, 2017). The general idea regarding user satisfaction centers around the users' attitude toward the system as it pertains to the system's ability to fulfilled expectations (Stefanovic et al., 2016). Furthermore, a user's attitude concerning an IS is a subjective principle of by what means an individual value the system, and the indicators for measuring user satisfaction may include one's satisfaction with the system, the information, and the service received from the IS (Arsyanur et al., 2019). The ISS model expresses that with the influence of various design qualities of ISs, both system use, and user satisfaction can be enhanced and lead to users' net benefits and success of an ISs (Chen, 2018). Hence, the findings from the studies of Chiu et al. (2016), Hermawan (2019), and Yu and Qian (2018) indicated that there was a significant relationship between user satisfaction and net benefits. Cidral et al. (2018) hypothesized and confirmed that there is a significant relationship between user satisfaction and system use, which is supported by the outcomes of Chiu et al. (2016) research. Thus, I posed the following questions:

Research Question 7 (RQ7): What is the relationship between perception of user satisfaction and perception of system use of cloud computing services?

Null Hypothesis **(**$H_0$7): There is no significant relationship between the perception of user satisfaction and the perception of system use of cloud computing services.

Alternative Hypothesis (H_a7): There is a significant relationship between the perception of user satisfaction and the perception of system use of cloud computing services.

Research Question 10 (RQ10): What is the relationship between the perception of user satisfaction and the net benefits of cloud computing services?

Null Hypothesis ($H_0$10): There is no significant relationship between the perception of user satisfaction and the net benefits of cloud computing services.

Alternative Hypothesis (H_a10): There is a significant relationship between the perception of user satisfaction and the net benefits of cloud computing services.

Net Benefits

Net benefits suggest that the primary gains attained by a user's increased use and satisfaction of an IS and the satisfaction of the users toward an IS make a significant contribution to the success and continued use of an IS (Mahmoodi et al., 2017). Additionally, net benefits are typically characterized within studies by applying perceived usefulness or a job impact as the utmost frequently adopted measure (Scott et al., 2016). The perceived benefits of an individual from using an IS in furthering to accomplish various aspects of their work achievements in the context of an organization (Sun & Teng, 2017). As proposed by DeLone and McLean's update, the ISS model denotes two feedback loops between net benefits and use and between net benefits and satisfaction (DeLone & McLean, 2003). The feedback loops show a potential influencing and subsequent reinforcing effect that occurs between the dimensions of use, user satisfaction, and net benefits if the IS or service continues (Vitari, 2011). Furthermore, the dynamic nature of IS reinforces the use of a process perspective in which the feedback loops *user satisfaction* and *use* constructs illustrate a new iteration of more or less user satisfaction and use contingent if there is a positive or negative impact on net benefits (DeLone & McLean, 2016). DeLone and McLean (2016) also indicate that the set of feedback loops provides allowances for maintenance changes and updates to the IS as such changes are necessary actions for an evolving process of the IS life cycle. As this study was not longitudinal, I did not examine the relationships between the dimensions of use, user satisfaction, and net benefits at different points in time. Therefore, I did not apply the feedback loops to system use and user satisfaction from net benefits into account, resulting in the omission of the hypothesis associated with their iterative relationships.

Construct Operational Measures

The measurement and conceptualization of variables in actual contexts are essential and somewhat absent in the literature as numerous studies have contended that the task of forming measures to assess IS is still relevant (Michel et al., 2019). Within the literature review of DeLone and McLean's study *Information Systems Success: The Quest for the Dependent Variable, Information Systems,* the researchers identified more than 100 measures utilized in over 180 studies (Van Cauter et al., 2017). The operational variables in this study include the independent variables perception of information quality, perception of system quality, and perception of service quality, and the dependent variable net benefits of cloud computing services. Thus the variables selected for the measures of the proposed constructs in this study were adapted from prior studies to ensure content validity.

Perception of Information Quality

For this study, the functional definition of perception of information quality included the measurements *trustworthy*, *accuracy*, *secure*, and *completeness*. The variable *trustworthy* describe an IS's reliability characteristic to include confidentiality and integrity such that it performs in the expected or required manner (Elshaafi & Botvich, 2016). The variable trustworthy was used by Kuo (2018) to measure the information quality of electronic health record systems (EMRS) and Jung and Jung (2019) to measure the impact of information quality on service-oriented architecture. The second variable, *accuracy,* concerns one's opinions of how well a system operates as it pertains to its ability to create and maintain the quality of the system's data (Mijin et al., 2019). Two examples of the application of the measurement accuracy include Rouibah et al. (2018), who examined the success of e-government systems, and Aldholay, Isaac, Abdullah, Abdulsalam, et al. (2018) to measure the accuracy of Online learning systems, and Veeramootoo et al. (2018), who measured the accuracy of e-filing systems. The third variable, *secure,* denotes an IS's ability to protect the organization's information and resources from disclosure from threat agents who attempt to access those resources without the appropriate authorization (Choi, 2016). Three examples of researchers who utilized the measure secure include Al-Azawei (2019), Daghouri et al. (2018), and Fan et al. (2016). The fourth variable *complete* describes an IS's information such that it possesses all necessary values to covers the needs of the desired tasks and sufficiently satisfies a user's needs (Shamala et al., 2017). Both Tam and Oliveira (2016) and Rahi and Abd.Ghani (2019) utilized the variable complete to examine internet banking systems. Table B1 in Appendix B provides a summary of the perception of information quality construct measures and the accompanying references.

Perception of System Quality

The functional definition of perception of system quality included the measurements reliable, ease of use, responsive (response time), accessibility, availability. The variable, *reliable,* entails the probability that the various components (i.e., hardware, firmware, and software) of an IS performs as designed for a defined time and within a particular environment (Tworek, 2018). Cheng (2019) applied the measure reliable to examine cloud ERP systems; Thielsch et al. (2018) employed the measure to investigate digitized workflow systems, and French et al. (2018) utilized the variable to study social networking applications. The second variable, *ease of use,* describes the extent that the user perceives that the use of the system will not necessitate much time and effort to complete a specific task (Xu & Du, 2018). Examples of the application of ease of use include Nusantara et al. (2018) and Sharma and Sharma (2019), who examined academic advisory systems and mobile banking systems, respectively. The third variable, *responsiveness,* describes the user's perception of how quickly the system responds to a specific request for information and execution of a command (Zhang, Liu, et al., 2016). In each of the studies, Jiang and Wu (2016), Al-Fraihat et al. (2020), and Ke and Su (2018) applied the variable responsiveness to examine the successful implementation of ISs. The fourth variable, *accessibility,* entails the level of effort required by a user to receive information from the system among various resources and, in turn, impact the user's selection of specific information resources (Zhang, Kwok et al., 2019).

Illustrations of the use of accessibility to measure system quality comprise of Assegaff et al. (2017), Negahban et al. (2016), and Chaw and Tang (2018). Lastly, the variable *availability* describes the continuance presence or existence of required technological resources to include hardware, software, and internet connection regarding essential aspects such as speed, access, and cost (Almaiah et al., 2019). Thongsri et al. (2019) applied the measure availability in their examination of online learning systems, where Ramírez-Correa et al. (2017) investigated learning management systems, and Rouibah et al. (2018) studied mobile government systems. Table B2 in Appendix B summarizes the perception of system quality construct measures and the accompanying references.

Perception of Service Quality

The functional definition of perception of service quality included the measurement responsiveness, assurance, empathy, effective solution, service level (customer service), knowledgeable (experts) as it pertains to the service provider. The first variable, *responsiveness,* refers to the willingness of the service provider to offer support to their consumers in an expeditious manner (Murray et al., 2019). Two examples of the application of responsiveness include Aldholay, Isaac, Abdullah, and Ramayah (2018) and Isaac et al. (2019), who studied the success of online learning systems in academic environments. The second variable, *assurance,* refers to the evidence of the service provider satisfying support requirements in terms of completeness and reportability (Islam et al., 2018). The studies of Arsyanur et al. (2019) and Wani et al. (2017) employed the variable assurance to study civil apparatus management systems and travel websites, respectively. The third variable, *empathy,* refers to the service provider's response to and their capability to understand what the user is undergoing during a service experience (Tan, Muskat, et al., 2019). Examples of the service quality variable empathy consist of Subiyakto et al. (2017) and Van Cauter et al. (2017). The fourth variable, *effective solution,* refers to the service provider's delivery capabilities and its ability to provide the expected level of technology solutions to its customers (Das & Bharadwaj, 2017). Applications of the variable, *effective solutions,* include Gonzales and Wareham (2019), who investigated the success of business intelligence systems, and Alzahrani et al. (2019), who studied the success of the digital library system. The fifth variable, *service level,* demonstrates the degree of customer service resulting from the service provider's IT capabilities and their ability to help the organization meet its IT needs (Faisal & Raza, 2016). Two examples of the application of the measure service level include Lwoga and Sife (2018) and Cohen et al. (2016). Lastly, the variable *knowledgeable* refers to the service provider's expert understanding of a particular subject matter and their relevant and valuable knowledge that enables the flow of new ideas and the formation of innovation (Nwagwu & Ibeku, 2016). Illustrations of researchers who employed the variable knowledgeable in their studies include Tam and Oliveira (2017) and Gay (2016). Table B3 in Appendix B provides a summary of the perception of service quality construct measures and the accompanying references.

Perception of System Use

The functional definition of perception of system use included the frequency of the measurements of use, duration of use, continuance use intentions, and system dependency. The first variable, *frequency of use,* refers to the rate of recurrence of the use of technology by a user to perform a particular task (Sox & Campbell, 2018). Isaac et al. (2017) applied the frequency of use to study organizational internet usage, and Harr et al. (2019) studied enterprise content management systems. The second variable, *duration of use,* describes the use patterns of an IS regarding the length a user interacts utilizes the system during a single session (Politi et al., 2017). Examples of the application of the variable duration of use include Marjanovic et al. (2016) and Al-Fraihat et al. (2020). The third variable, *continuance use intentions,* refers to the users' aim to use an IS repeatedly following the initial adoption of the system (Carillo et al., 2017). Both Lin et al. (2018) and Jiang and Wu (2016) applied *continuance use intentions* to examine the barcode medication administration IS and PMS. Lastly, the variable *system dependency* describes the factors that may influence an individual's rational system usage decisions, which is relevant in post-adoption and extended usage settings (Carillo et al., 2017). Examples of the application of system dependency comprise the studies of Agrifoglio et al. (2016) and Lin et al. (2017). Table B4 in Appendix B summarizes the perception of system use construct measures and the accompanying references.

Perception of User Satisfaction

The functional definition of perception of user satisfaction included the measurements satisfied (overall), expectations, adequacy, user attitude. The variable, *satisfied,* refers to a user's overall fulfillment of a system's usability, and their expectations for an ideal system have been met over time (Cillessen et al., 2017). Three examples of the use of the variable satisfied include Yakubu and Dasuki (2018), Harr et al. (2019), Budiardjo et al. (2017). The second variable, *expectations,* refers to the expanding belief in a system by the user regarding its ability to enhance work performance, which in turn affects the users' attitude toward the system (Lee et al., 2017). Stefanovic et al. (2016) applied the variable to examine e-government systems, and Keikhosrokiani et al. (2018) investigated EHRs. The third variable, *adequacy,* denotes a system's ability to reduce uncertainty and provide timely information, which in turn can reduce perceived risk (Domínguez-Escrig et al., 2018). Both Aparicio et al. (2016) and Cidral et al. (2018) utilized adequacy to study e-learning systems. Lastly, the variable, *user attitude,* refers to an individual's predisposition state of mind toward an IS regarding the system's overall effectiveness (Karlinsky-Shichor & Zviran, 2016). Suitable examines of the utilization of user attitude include Kuo et al. (2018) investigation of EHRs and Ramírez-Correa et al. (2017) study of learning management systems. Table B5 in Appendix B provides a summary of the perception of user satisfaction construct measures and the accompanying references.

Net Benefits of Cloud Computing Services

The functional definition of net benefits of cloud computing included the measurements improved communication, improved customer satisfaction, improved productivity, increased effectiveness, improved knowledge (or understanding) or increased knowledge, and improved decision making. The first variable, *improved communication,* can be defined as an IS ability to positively affect the transition of information and understanding through the use of technology between two or more team members (Tan, Ramayah, et al., 2019). Yu and Qian (2018) employed improved communication to examine EHRs, while Jiang and Wu (2016) investigated PMS. The second variable, *improved customer service,* defines how an IS positive impacts the ability to address customer issues, which in turn creates higher customer loyalty (Hesamamiri & Bourouni, 2016). Three studies that applied improved customer service include Wei et al. (2017), who examined the cleaning logistics system, Subiyakto et al. (2017), who studied the e-performance reporting system; and Lal and Bharadwaj (2016), who investigated cloud-based CRMs. The third variable, *improved productivity,* refers to an IS's ability to improve a user or firm's ability to raise the level of output on a day-to-day basis (Baker et al., 2017). Two applications of the measure improved productivity comprise Borena and Negash's (2016) study of banking systems and Monika and Gaol's (2017) study of airline e-cargo systems. The fourth variable, *increased effectiveness,* refers to the IS's ability to help an individual or a firm heighten their ability to achieve business objectives and the extent to which they can solve problems (Glava & Malakhov, 2018). Arsyanur et al. (2019) employed the measure *increased effectiveness* to examine civil apparatus management ISs, and Nusantara et al. (2018) investigated academic advisory systems, and Tilahun and Fritz (2015) examined EHRs. The fifth variable, *improved knowledge,* refers to an IS ability to support the knowledge creation process, transfer, or retention of knowledge to enhance one's skills or the firm's capabilities (Kaschig et al., 2016). Two examples of the use of improved knowledge to examine IS include Marjanovic et al. (2016) and Chiu et al. (2016), who studied e-learning systems and cloud-based ebook systems, respectively. The final variable, *improved decision-making,* refers to an IS to enhance an individual or a firm's capacity to increase its effectiveness in organizational culpability to achieve its goals (Aydiner et al., 2019).

Fitting examples of the utilization of the variable improved decision-making include Fadhilah et al. (2015) study of accounting management systems and Ghobakhloo and Tang's (2015) study of manufacturing systems. Table B6 in Appendix B provides a summary of the net benefits of cloud computing services construct measures and the accompanying references.

Transition and Summary

In Section 1, I discussed the IT problem that some IT cloud service managers do not have knowledge of the service, system, and information quality measures of cloud computing to ensure the attainment of the expected benefits of cloud services. I presented the purpose statement, which in turn precedes the research question and hypotheses. Additionally, I introduced the theoretical framework, nature of the study, and significance of the study, operational definitions, and the study's assumptions, limitations, and delimitations. Lastly, I presented a professional and academic literature review, in which I briefly discussed the content of the literature, its organization, and the strategy that I employed for searching the literature. Furthermore, my review of academic literature addressed the definition and current state of cloud computing and the trending of cloud computing about the problem statement. Additionally, I compared and contrasted different points of view of cloud computing services, the relationship of the study to previous research and findings, and provided insight into the cloud adoption rationale.

The literature review also included a critical analysis and synthesis of the DeLone and McLean ISS model. The analysis of the information success model included an examination of the literature that defines the aspects of the theory for understanding ISS as well as a literature-based description of its research variables. I discussed alternatives to the ISs success model, which included TRA, TAM, and UTAUT. Furthermore, I identified literature regarding well-known contrasting theories of the ISS model to include the DOI theory, TOE, and IDT. Lastly, I examined recent similar studies that employed the ISS model for cloud computing success, as well as various criticisms of the ISS model and the relevance of the ISS model to this study. The conclusion of the literature review included an analysis of the research model, hypotheses development, as well as the operationalization of the research constructs.

In Section 2, I will present my role as the researcher, and I will review my plan for obtaining access and establishing a working relationship with my participants. I will also expound on my use of a quantitative method and correlation design approach and justified both over other design methods. Additionally, I will describe and explain my sample population and sample size, as well as discuss the various strength and weaknesses associated with my chosen sampling method. Furthermore, I will address any ethical considerations about my study, instrumentation, data collection and analysis technique, and external and internal study validation methods.

In Section 3, I will offer a detailed presentation of my study's findings to include descriptions of statistical tests and reports of descriptive and inferential statistics and evaluation of statistical assumptions. I also will provide a detailed analysis of the applicability of my findings regarding the professional practice of IT and its implications for social change. Additionally, I will provide recommendations for action as it pertains to my study findings and give suggestions for further research. Lastly, I will reflect on my research experience of the DIT doctoral study process and present my closing statement.

Section 2: The Project

Purpose Statement

The purpose of this quantitative correlation study was to evaluate the relationships among the perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction, perception of system use, perception of user satisfaction, and net benefits of cloud computing services from the viewpoint of IT cloud services managers. The independent variables that I used in the study were the perception of information quality, perception of system quality, perception of service quality, perception of system use, and perception of user satisfaction. The dependent variable was the net benefits of cloud computing services. The targeted population consisted of IT cloud services managers from small, medium, and large enterprises that subscribe to IaaS, PaaS, and SaaS in the United States. The results of this study may have potential positive social change implications such that it may help highlight the pervasive nature of cloud computing and provide further insight into the quality standards necessary to build more reliable cloud products and services. As a result, software developers may further leverage internet technologies to deliver more support for personal activities such as social media, online shopping, distance medicine, and internet-based training programs to help serve the needs of individuals using more reliable, ubiquitous on-demand technology.

Role of the Researcher

As the researcher for this quantitative correlative study, my role was to ensure that the research design suited the research question that the investigation addressed and specified the context in which I carried out the study (Köhler et al., 2017). In particular, a researcher of a quantitative study emphasizes the concepts of objectivity and validity by utilizing mathematical models and statistical estimation to examine a phenomenon with expectations that the effort produces unbiased outcomes that can be generalized to a larger population (Zyphur & Pierides, 2019). Moreover, a quantitative study researcher must accurately conceptualize the research problem by (a) describing one's concepts on the research problem, (b) defining the concept formed, (c) selecting the dimensions and indicators that the concept will imply, (d) providing an operational definition of the concept, and (e) identifying by what means the concept will be measured (Onen, 2016). Primarily, the data collection process of a quantitative study is driven by the researcher's research question. After the question is formed, the investigator selects a data collection method (e.g., using a survey or assessment), chooses and executes a statistical analysis approach, examines the *p*-value, and derives a conclusion (Hjalmarson & Moskal, 2018). Furthermore, the questionnaire involves the researcher developing a list of questions in an appropriate format in which the data collection starts when the researcher issues the surveys to participants and ends when the researcher chooses to accept questionnaires no longer (Zahle, 2018). Thus, as the researcher, I used a validated instrument that aligned with my study and administered an appropriate web-based survey as my research instrument to collect and analyze the data and report the research findings.

My relationship as the researcher with the topic of attaining the net benefits of cloud computing services stemmed from extending my professional growth in the IT industry and my experiences with cloud services professionally. As stated by

Nieuwenhuis et al. (2018), the rapid diffusion of cloud computing has influenced how organizations develop, distribute, and implement enterprise systems, and cloud services present profound implications for the IT industry, subscribers of cloud services, service provider's business models, and other actors in the business ecosystem. Consequently, I devoted my efforts to becoming a subject matter expert in cloud services, which has led to acquiring the CompTIA Cloud+ certification and fueled my pursuit of the AWS Certified Solutions Architect and Cisco Certified Network Associate Cloud certifications.

From a professional perspective, I have worked with local small businesses as an advisor regarding cloud adoption. Furthermore, I have participated on a task force to help a federal government agency draft a request for a proposal to acquire cloud-based hosting and transition support to help plan, implement, and manage a PaaS within a private cloud for their non-mainframe and mainframe payroll and personnel hardware and applications. My current organization is undergoing an AWS cloud transformation, in which we are migrating all of our corporate systems to an IaaS platform. We have also migrated our email system to the Microsoft Office 365 cloud services, our project management system, to a PaaS platform. From a corporate perspective, we have implemented several PaaS solutions such as construction documents management and collaboration, portable document format management, hotel point of sales and property management system services, and residential property management system.

For this quantitative study, I did not have any type of relationship with the participants. When conducting survey-based studies, it is vital to ensure that participants maintain their anonymity during the research study as many respondents will not give truthful information if they believe that they can be linked back to their responses (Rice et al., 2017). To maintain anonymity, I did not link the participant's name to the survey. Thus, I did not know who the survey respondents were. Consequently, I did not know if I had a relationship with any of the study participants.

My ethical considerations regarding this study hinged on the *Belmont Report* protocol, which helps to lead the current day human subject protection (Cassel & Bindman, 2019). The *Belmont Report* outlines the fundamental ethical principles characterized by the National Commission for the Protection of Human and make the principles easily accessible to researchers, members of IRBs, and Federal employees (U.S. Department of Health & Human Services [HHS.gov], 1979). Furthermore, the *Belmont Report* is built upon the Nuremberg Code, Declaration of Helsinki, and other laws, and it is grounded on three primary ethical research guiding principles: (a) respect for persons, (b) beneficence, and (c) justice (Miracle, 2016). Therefore, my role as the researcher was to ensure that I follow the *Belmont Report* protocol and had consent from my participants. Likewise, I made sure that the participants understood and were comfortable with the survey questions and ensured that I demonstrated respect for the participants' autonomy.

As a researcher, I implemented measures to minimize bias. Notably, the means that a researcher uses to design, construct, and execute a study can influence the research outcomes and is an essential factor regarding bias (Bloomfield & Fisher, 2019). There are several common biases associated with quantitative research: the effects of confounding, participation bias, selection bias, and bias in measurement outcomes (Benton et al., 2016). A bias created from confounding results from an alternative factor that misrepresents the association between variables (Lewis & Kyriacou, 2016). Effects concerning confounding can be addressed through the appropriate statistical analysis, such as regression modeling (Arah, 2017). Furthermore, a common challenge to survey research is participation bias that can occur due to the unwillingness of participants to partake in the survey (Gray et al., 2019). I mitigated participation bias by providing information to the participant, such as the duration and the number of questionnaire pages to help win or encourage a respondent (Pecáková, 2016). Sselection bias can also result from the lack of proper randomization in the selection of research participants (Wadgave et al., 2018). The risk associated with selection bias can be reduced by employing statistical analysis methods such as regression testing (Trutschel et al., 2017). Lastly, changes in measured behavior and other outcomes because of measurement outcome could present systematic error or bias (Miles et al., 2018). Any bias associated with outcome measures can be mitigated by the selection of an appropriate measurement instrument (Chiarotto et al., 2016). Considering the various bias associated with quantitative studies, I effectively mitigated bias through my research design methods by developing an effective communication plan for potential respondents, employ the appropriate statistical analysis methods, and selecting a suitable research instrument.

Participants

In quantitative designs, participants play a role in the quantitative approach in which the researcher measures and addresses in some way a performative action (Martí, 2016). Common barriers in the recruitment of participants include the lack of access to the target group and obstacles in identifying participants who satisfy the inclusion and exclusion criteria (Lai & Afseth, 2019). Additionally, conveying key participant characteristics that are pertinent to the study outcomes is essential for evaluating generalizability and because of their relevance to research results (Motschman et al., 2016). As I took into consideration the significance of the eligibility criteria, the conditions for this study consisted of four characteristics that must be shared by all participants. The first eligibility criterion required that the participant's organization must subscribe to an IaaS, SaaS, or PaaS cloud service model. The second criterion necessitated that the participant's organization subscribed to the cloud service for a minimum of 1 year. Thirdly, the participant was a cloud services manager within the IT department, such as a chief information officer (CIO), vice president, director-level, or manager-level. Fourth, the organization had a presence in the United States.

In addition to establishing eligibility criteria for study participants, I also developed a strategy for gaining access to participants. Obtaining access and the recruitment of study participants is a vital element to research, and researchers have indicated that it is one of the most challenging aspects of the research process (Williams, 2019). Access to proprietary business databases is also considered an essential element of successful study for academic business researchers (Kim & Wyckoff, 2016). Equally, the design decisions concerning the response rate of web surveys include the selection of contact method used to distribute the survey invitation, shown in Appendix I, and studies have shown that email and paper are the most universally used communication methods for delivering web survey invitations and reminders (Sakshaug et al., 2018). Additionally, contact and response rates for surveys can be improved using methods such as prenotification and different approaches to follow-up contact (Smith et al., 2019). Accordingly, my strategy for gaining access to participants included enlisting the marketing research company Centiment to aid in recruiting volunteer survey respondents.

The panel research organization Centiment (n.d.-c) provides marketing panel services for researchers to collect responses for a specific target audience. Web panels are a commonly used source of survey samples where candidate panel members are recruited through numerous methods such as an address-based probability sample and vetted to evaluate eligibility (Stanley et al., 2020). Centiment's survey panel is compatible will major survey tools such as SurveyMoney. In particular, Centiment sends a link to the respondent via email, which they recruit using resources comprising of social media platforms such as Facebook and LinkedIn, directing them to the researcher's survey URL. The respondent is tagged on embedded data to aid Centiment in identifying the respondent once they are redirected back to Centiment upon the participant completion of the survey. For security reassurance, the Centiment survey panel provider uses digital characteristics, which couples the respondent's IP address, device type, screen size, and cookies to safeguard unique panelists enters the survey as outlined by Krista Reuther, Project Manager at Centiment, shown in Figure F1, Appendix F. As specified by Hart (2019), Centiment passes custom variables that represent respondent's identification which ensures confidentiality as the respondent is forwarded from Centiment to the researcher's survey tool. Furthermore, Centiment sends an email to panel participants through anonymous links to participate in the study (Clouse, 2018). Moreover, Walden

University students that used Centiment's survey panel services in recent years include Pickett (2018) and Mitchell (2020). I discussed Centimen's methodology of safeguarding participant's privacy in the Ethical Research subsection.

In addition to Centiment's survey panel services, several other Walden students used survey panel services from other providers. For example, Gavlas (2018), Plaushin (2019), and Preiksaitis (2016) utilized survey panel services from SurveyGizmo. Additionally, Arowolo (2017), Buck (2018), DeGraffe (2017), and Foster (2017) procured panel services from SurveyMonkey. Lastly, Anye (2019), Graves (2019), Judd (2019), Murvin (2019), Roman (2017), and Walton (2019) purchased panel services for Qualtrics.

Considering the development of eligibility criteria and access strategies for study participants, I did not know if I have a direct working relationship with participants. From an objectivist perspective, relationships with research participants could be relevant for access to information, but not for how the relationships can form their substance (Charmaz & Belgrave, 2018). Nevertheless, building a relationship with participants entails instilling a sense of motivation through exhibiting personal benefits for potential candidates, altruism, and ensuring trust (Berrios et al., 2017). A sincere trust relationship occurs when the researcher has invited confidence by some means, and it is essential to guarantee that the information statement works to (a) explicitly inform what the participant can trust and (b) what the researcher and the institution can and cannot do (Guillemin et al., 2018). Thus, my strategy for forming a working relationship with participants centered around my invitation to participate in the study. In particular, my message included language to describe how the research will benefit not only them as an IT manager of cloud services but also others' well-being. Lastly, I guaranteed the confidentiality of the data, the concealment of their identity, and ensured that Walden University, as an institution, was trustworthy.

Research Method and Design

Research Method

For this study, I used a quantitative design to examine the relationships among the perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction, and net benefits of cloud computing services. As research designs and methods ought to shape the structure on which all research is built, there are three theoretical research design approaches, namely quantitative, qualitative, and mixed-method (Tuan et al., 2019). Specific labels have been assigned to research methods that are perceived to be useful anchors for providing a helpful working definition (Leppink, 2017). In particular, each method consists of three interrelated elements, which include philosophical worldviews, strategies of inquiry, and research technique (Abutabenjeh & Jaradat, 2018). Consequently, my understanding of the various characteristics of each research method contributed to my selection of the appropriate research method.

Based on the various characteristics of quantitative, qualitative, and mixed-methods research methods, I believed that a quantitative methodology was most appropriate for my study. For example, quantitative research emphasizes statistical techniques to explain better or describe a particular event, idea, or action (Knaub et al., 2019). Quantitative research is most closely associated with a positivist philosophy that argues that reality is definable, perceptible, and unchanging that emphasizes measurement and the creation of law-like certainties (Nield, 2019). Quantitative inquiry entails a research design that permits researchers to approximate the likelihood that a relationship exists for a given population and provide an estimate of the confidence level that a causal relationship exists in a populace of interest (Newman & Houchins, 2018). Moreover, the characteristics of quantitative research include being objective, assessing outcomes using statistical analysis, measurable and quantifiable data, signifying complex problems through variables, findings that can be summarized, compared, or generalized (Goertzen, 2017), and test prespecified hypotheses (Murshed & Zhang, 2016). Consequently, the quantitative method was best suited for this study because of my goals to examine relationships between my various variables, test the proposed hypothesis using statistical means to draw inferences, and use a survey instrument to collect data and measure the research findings.

The qualitative method had unique defining characteristics that I did not find suitable for this study. For instance, qualitative research emphasizes direct personal experience to gain a deep understanding of an event through cognitive means and the application of a mindset of exploration to embrace the notion that reality is socially constructed (Peterson, 2019). Qualitative research is most closely associated with an interpretivist philosophy or naturalistic approach, in which realities are constructed from the collected data, and often no single truth exists, resulting in the lack of control for variables, nor the forming of hypotheses regarding the research outcomes (Schliep et al., 2017). Qualitative inquiry is an interpretive paradigm that entails a research design that encompasses the use of explanatory techniques to pursue an understanding of a phenomenon through participants' observations and experiences, and the findings are typically derived inductively from data gathered through themes, concepts, or theories (Gordy et al., 2018). Likewise, the characteristics of qualitative research include observations of the participants, focus group, open and in-depth interviews, multiple data sources, triangulation of data, and the assurance of data trustworthiness through aspects of credibility, transferability, dependability, and confirmability (Chatchumni et al., 2019). Consequently, the qualitative method was inappropriate because my study was not exploratory in nature, I did not conduct in-depth interviews or focus groups, my data collection utilized close-ended inquiries, and I did not seek to assess the personal observations and experiences of the participants.

Mixed-methods research shares the characteristics of quantitative and qualitative methods. Specifically, mixed methods possess a quantity-quality dichotomy by integrating different approaches and diverse analytical methods (Piccioli, 2019). Mixed-methods research takes a pragmatist approach that allows investigators to embrace a multitude of research methods and circumvent the contentious issues of truth and reality by not proposing normative advice and reserving its verdict until resulting utilities are compared (Baškarada & Koronios, 2018). When considering mixed-methods inquiry, the quantitative data and the qualitative findings are not presented separately but equal components of a study, and there is a concentrated effort to merge the findings to produce new and deeper understandings of the findings to the questions fashioned to guide the study (Stahl et al., 2019). Equally, the characteristics of mixed-methods research include triangulation and verification of results, elaboration and clarification of findings, the establishment of new methods, uncovering new or contradictive viewpoints, and expansion of the scope of inquiry (Brown et al., 2017). Because of the mixed-methods incorporation of qualitative methodologies, I found that this method was also inappropriate for this study.

Research Design

For this quantitative study, I utilized a correlational design approach. The fundamental quantitative design approaches can be classified mainly into experimental (interventional) and non-experimental (observational) studies (Indu & Vidhukumar, 2019). More specifically, there are four major types of quantitative research designs that include descriptive designs, correlational designs, quasi-experimental designs, and experimental designs (Jorrín Abellán, 2019). The experimental quantitative design includes experimental and quasi-experimental designs (Miller et al., 2020), where non-experimentation includes descriptive and correlational research (Garcia & Cuevas, 2019). Furthermore, quantitative design attributes include a structured environment that permits the investigator to have control of study variables, environment, and research questions to describe an expected result or determine relationships among variables and outcomes (Rutberg & Bouikidis, 2018). As a result, my understanding of the various attributes of each quantitative design contributed to my selection of the appropriate design approach.

The experimental quantitative research designs had unique attributes that I did not find suitable for this study. In particular, experimental designs best align with studies concentrating on cause-and-effect relationships by trying to account for or control all possible causes in an environment except the intervention to remove or reduce alternative rationalizations for an observed result (Pattison et al., 2019). Moreover, experimental designs are statistical analysis of causal hypotheses concerning three causality criteria to include (a) association which suggests that cause and effect can be statistically associated, (b) isolation that suggests that confounders that potentially disguise the effects are eliminated, randomized, or (experimentally) controlled, and (c) direction that suggests that the mechanism being examined originates in the independent variable (cause) and moves to the dependent variable (effect) (Von Eye & Wiedermann, 2017). In true experimental and quasi-experimental designs, the researcher is the active driver of the study, but the chief distinction between the two is the level of control the investigator has on the study's participants and variables (Krishnan, 2019). For example, true experiment designs entail the random assignment of participants to the experimental and control groups and impose control over all other variables apart from the dependent variables (Flannelly et al., 2018). However, the quasi-experimental design uses partial or nonrandomized assignments of participants to pre-existing groups, and the researcher does not control the independent variables (Handley et al., 2018). Nevertheless, I did not find either of the experimental research designs appropriate for this study because I did not implement experimental control groups. Additionally, I did not take part in any manipulation of the research variables, and this study did not seek to determine causality.

There also are unique attributes related to a descriptive non-experimental quantitative research design versus a correlative design that I did not find suitable for this study. For example, the objective of descriptive research is to classify the characteristics of events and serves as a beneficial starting point when there is minimal understanding of a phenomenon (Johansson & Silén, 2018). Descriptive research is not a hypothesis testing design as there are no independent or dependent variables such that the study only examines variables of interest (Siedlecki, 2020). Furthermore, descriptive research lacks predictive capabilities (O'Keefe, 2011).

However, correlational research characterizes the nature and extent of the association between two variables, which in turn provides an understanding regarding the theory-based, hypothetical relationship of the variables. However, correlational designs are fundamentally adaptable and allow various insights into the research variables, and have a significant capability to further research and understanding regarding a target variable (Martin et al., 2019). Moreover, correlational studies assess the relationship between two or more variables without the intervention of the variables (Onel & Firat Durdukoca, 2019). Additionally, correlative studies facilitate the prediction and explanation of the relationship among variables to examine the magnitude of the relationship between the variables (Seeram, 2019). Accordingly, I found that a correlational design was more appropriate than a descriptive design because the descriptive method lacked because of its inability to examine and predict the degree of association between the variables. Likewise, a descriptive study did not provide the means for hypothesis testing. Thus, I did not find the descriptive design to be a suitable research method for this study.

Population and Sampling

The population for this quantitative correlational study included IT cloud services managers within organizations' IT departments to include frontline-line managers, middle managers, and executives who subscribe to cloud computing services. In particular, front-line supervisors are structurally arranged between nonsupervisory workers and higher supervisory levels of organizations and provide direct supervision of employees at the bottom levels of the organizations (Magee & Upenieks, 2017). Middle managers, described as a department or unit head (Heyden et al., 2018), are supervised by executive managers, carry out implementation duties such as planning, coordination, facilitation, motivation, and evaluation, and must operate within the constraints established by upper management (Urquhart et al., 2018). Additionally, the CIO (executive manager) is frequently required to ensure the availability of IT, implement technology strategy and innovation, assist in the shaping of the organization's strategy, and bring about a more holistic, strategic, or transformational viewpoint to the C-level of the organization (Jones et al., 2019).

For this correlative study, I sought to address the question: Are there significant relationships among the perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction, and net benefits of cloud computing services from the viewpoint of IT cloud services managers. IT managers can examine the benefits, challenges, and business impacts of cloud computing adoption (Tripathi, 2018). The role of IT managers also includes tasks such as improving process and system development, ensure compliance with cybersecurity requirements, enhancing operational efficiencies and customer service, developing information policies, promote innovation, and provide strategic planning (Damyanov, 2019). Thus, I found that the selected population aligns with the overarching research questions based on the role of IT cloud services managers within an organization. Besides, cloud services managers are a subgroup of IT managers. For example, IT managers are meant to have a unique set of skills and expertise about various business segments, IT (i.e., cybersecurity, software development, cloud technologies, and web design), and the law such as labor and IT regulations (Horetko, 2018). Additionally, studies have shown the role of IT managers has evolved to exhibit both skills in technology and organizational strategy to face challenges successfully surround digital transformation (Manfreda & Indihar Štemberger, 2019). Similarly, IT managers are frequently expected to support business service innovation initiatives, and having a managerial process in place capable of guiding them in adopting strategies and managerial postures will make sure the successful adoption of open technology (Hsu et al., 2019).

For this quantitative correlational study, I employed a non-probabilistic sampling method. Non-probability sampling is based on the researcher's selection of a population that is accessible and available (Setia, 2016). Non-probability sampling methods consist of enlisting participants in a non-random manner for a research study resulting in the study population not having an equal selection opportunity (El-Masri, 2017a). Non-probability studies mostly rely on purposive selection to accomplish the desired sample makeup, while data collection is continuing through quotas, where the researcher specifies a specific distribution across one or more variables (Mercer et al., 2017b). One reason for using a non-probability sample is because low response rate probability surveys do not present any significant thing to offer versus a well-built nonprobability sample (Dutwin & Buskirk, 2017). Thus, low response rates realized by probability-based surveys over the past years have caused some to deem that the theoretical benefits of probability-based studies no longer obtain (MacInnis et al., 2018).

The specific non-probabilistic sampling method that I employed for this study entailed purposive sampling. Purposive sampling is a methodology for enrolling participants who are deemed champions or authorities on the subject matter of interest (Nguyen et al., 2016). Furthermore, purposive sampling approaches are very different from probabilistic methods, pursuing not generalization or randomness, but the knowledgeable selection of particular cases, adept at increasing the likelihood of examining the phenomena of interest (Serra et al., 2018). Specifically, purposive sampling allows the researcher to seek a pre-determined target group hinged on various criteria such a specialist knowledge of the research problem, willingness to participate in the research, and the ability to contribute appropriate data (Apostolopoulos & Liargovas, 2016). Hence, a purposeful sampling method facilitates the investigator to select only the participants who are interested in the study and understand the research variables (Sokip, 2019).

There are several challenges associated with non-probability, such as purposive sampling. The main problem with non-probability sampling is that the data-producing process is unknown and probably selective concerning the intended target population

(Buelens et al., 2018). Non-probability sampling is thought to lack the essential properties of randomization theory to include the capability to measure the uncertainty of sample-based estimates (Sakshaug et al., 2019). Furthermore, the group of people who participate in studies using non-probability sampling methods could be an unrepresentative part of the target population of concern, and measures of data quality are also often problematic to achieve from many non-probability designs (Link, 2018). Moreover, nonprobability sampling is subject to selection bias (Mercer et al., 2017a). Although selection bias cannot be precluded entirely, a mitigation strategy to minimize its impact includes confirming that the sample shares the characteristics of the population (El-Masri, 2017b).

To identify the sample size for this study, I conducted a statistical method called a power analysis. In practice, power analysis is perhaps the commonly used sample size planning approach (Liu & Wang, 2019). Power is the likelihood of determining if the population effect sought by the researcher is in the sample, and the sample size is big enough to have the necessary power to detect the desired effect (Phillips & Jiang, 2016). The primary factors in determining the sample size include (a) the population effect α (Type 1 error rate), which is the probability of rejecting a true null hypothesis; (b) the statistical power $1 - \beta$ (where β is the probability of a Type II error), which is the probability of rejecting a false null hypothesis; and (c) the population effect size expressed as the separation between the null and alternative hypothesis distribution (Chen & Liu, 2019). Cohen (1988,1992) submitted that the failure to detect a true effect (β) is approximately four times as significant as uncovering an effect that is not true (α), hence a β of .80 was recommended in combination with the conventional error probability α of .05 (Paterson et al., 2016). For the effect size, Cohen's definitions of a small, medium, and large vary as a function of the researcher's analysis method, which he defines a multiple regression, medium as $f^2 = 0.15$ (Correll et al., 2020). Additionally, the lower acceptable statistical target level of power is defined at .80 or more, which one should seek to achieve (Arend & Schäfer, 2019). However, a 90% power is highly recommended considering that 80% power has the likelihood of missing a true difference is 20%, but a 90% power is only 10%, which is a 50% improvement (Mascha & Vetter, 2018). Similarly, Taylor and Spurlock (2018) suggest that the power of .80 is inadequate, and researchers should consider power levels as high as .90 and .95.

To perform the power analysis, I used the statistical analysis software G*Power version 3.1.9.6. G*Power, the most known and widely used free software, allows approximating power parameters for the research design by applying different methods and various user interfaces (Perugini et al., 2018). G*Power includes statistical power analyses for several statistical tests to include f-test, t-test, $\chi 2$-test, z-test, and some exact tests while offering a distribution-based and a design-based input mode (Balogh & Golea, 2016). Computing the necessary sample size in G*Power is a function of user-specified values for the required significance level (α), the desired statistical power (1 - β), and the population effect size (Faul et al., 2009). Thus, to calculate the sample size using multiple linear regression with a fixed model, R^2 deviation from zero statistical tests, I used an effect size $f^2 = 0.15$, error probability $\alpha =.05$, number of predictors 5, and power $(1 - \beta) = .80$ (for the minimal sample size) and .95 (the maximum sample size). As a result, G*Power indicated a participant range of 92 to 138, as shown in Figure H1 and Figure H2 in Appendix H.

Ethical Research

The ethical principles that are the foundation of research can, at times, be challenging to implement during the planning and execution of a research study (Biros, 2018). A common rule to the ethical research principles includes the informed consent of participants which the permission sought for the study participation is voluntary, and the prospective research subjects are provided with the information that a reasonable person requires to make an informed decision whether to partake in the study (King, 2019). The idea of a reasonableness standard for disclosure of information throughout the informed consent process encompasses specific inclusion of a reasonable person guideline for disclosure is unmatched in U.S. federal human subject’s protection regulations (Odwazny & Berkman, 2017). Thus, erroneous information, including incorrectly misattributed risks, diminishes the validity of informed consent for, by definition, a choice cannot be informed if it is contingent on dishonesty, which in turn, understanding which risks are appropriately attributed to the study is critical for valid informed consent (Lantos, 2017). For this study, I integrated an informed consent form at the beginning of the questionnaire to ensure that the participants were aware of their rights and understand the benefits of participating in the study. With the approval, Walden University’s IRB approval number is 11-18-20-0674936.

There are several recommended practices to mitigate the ethical challenges associated with survey-based research in addition to obtaining informed consent.

Through the guidance of the United States Common Rule, research ethics committees such as institutional review boards assess privacy and security safeguards to minimize risks to participants and ensure that researchers appropriately adopt consent, coordination, and accountability ethical best practices (Thorogood & Knoppers, 2017). According to Dimitrios and Antigoni (2018), there are several basic ethical principles to include respect for autonomy, full disclosure, participant withdrawal from the study with no consequences, beneficence, and fidelity. Moreover, ethical best practices for survey-based studies should include transparency during the recruitment process and provide participants with the opportunity to withdraw from the research (Gupta, 2017). Thus, I incorporated into the various components of my questionnaire such as (a) language to acknowledge the individual's independence to make decisions for themselves, (b) language specifying full disclosure of the purpose, risks, and benefits of the study, (c) options on each page of the questionnaire to opt-out of the study, (d) the implementation of encryption and a data management plan to securely process, store, and handle the participant's data.

For this quantitative study, I enlisted in the use of a panel survey service by Centiment. As part of the services, Centiment used incentives to recruit participants using resources comprising of social media platforms such as Facebook and LinkedIn. Respondents received 25% to 60% of the quoted price per completed response as payment for their participation in the study, as outlined by Krista Reuther (K. Reuther, personal communication, June 8, 2020, krista@centiment.co), shown in Figure F1, Appendix F. Krista Reuther explained that the percentage level depends on the need to offer a higher reward as participation invites are sent in waves. Considering the incentive estimate range and the contract cost of $8.75 per response, each participant expected an enticement of approximately $2.19 to $5.25, as outlined by Krista Reuther (K. Reuther, personal communication, June 21, 2020, krista@centiment.co), shown in Figure F2, Appendix F. Furthermore, the participants had the preference to be directly compensated via accounts such as PayPal or donate the proceeds to their choice of a local school or nonprofit. The contractual agreement, shown in Figure G1, Appendix G, shows the proposed cost for the panel services, which is based on the sample size, survey length, and targeted demographics.

Web-based survey research enables participants to feel a heightened sense of comfort and autonomy and decreased inhibitions to partaking in research studies by recognizing that they can privately take the survey, and their responses will remain confidential (McInroy, 2016). According to a study conducted by Robertson et al. (2018), participants reported significantly higher mean comfort levels with anonymous methods of survey methodology versus non-anonymous modes resulting in substantially higher comfort levels with self-administered means versus interviewer-administered research methods. Likewise, ensuring the confidentiality and anonymity of participants can be achieved by taking careful steps by researchers such that no collected information can potentially identify the participant, such as not gathering gender or age and using subject-generated identification code to association data while protecting participant anonymity (Lippe et al., 2019). Similarly, Ripper et al. (2017) suggest the use of a secret code to ensure anonymity and confidentiality of survey data, the promotion of unbiased reporting, and retaining the capability to align participant data over time. Thus, I did not collect any identifying information, and with the passing of custom variables between Centiment and SurveyMonkey, the participant identities will be maintained. Lastly, as mandated by Walden University, I will maintain the data for a period of at least five years on an encrypted disk or Universal Serial Bus drive, which I locked in a secure cabinet. Once the five-year retention period elapses, I will physically destroy the storage device to prevent anyone from retrieving the data.

As the panel survey provider, Centiment provided secure passing of respondents to SurveyMonkey through the use of SurveyMonkey's survey design and logic workflow capabilities (Centiment, n.d.-b). Centiment's integration into SurveyMonkey consisted of four steps to include passing custom variables, setting up of Centiment redirect URL, setting up a disqualified respondent URL, and sending a copy of the survey to "centiment.co" through Hypertext Transfer Protocol Secure. The passing of custom variables provided the means to send a respondent to the SurveyMonkey survey anonymously. The custom variables used embedded data to help Centiment identify the respondent when they are redirected back to the Centiment portal at the end of the survey. The completion redirect URL ensured that participants who complete the survey study were compensated by passing on the variable data back to Centiment. Likewise, respondents that were disqualified were forwarded to a specific URL to prevent charges. Lastly, a test survey link was sent to Centiment to validate integration, and Centiment set up a soft launch by collecting an initial 10–20 responses for review.

From a compliance perspective, Centiment conforms with General Data Protection Regulation and California Consumer Privacy Act requirements (Centiment, n.d.-a). Per their legal and security statement, Centiment deleted any methodology and data sets collected upon the completion of the project. Furthermore, Centiment did not permit researchers to require Personally Identifiable Information from the study respondents. As measures to ensure unique panelist participation, Centiment used digital identification methods such as Internet Protocol (IP) address, device type, and screen size, and cookies. Furthermore, Centiment did not store any project data upon the delivery of study results. When the researcher uses a third-party survey tool such as SurveyMonkey, the third-party tool stores the data, and it is subject to encryption/security set-up. Lastly, all of Centiment data centers reside in the United States, and all of our servers are secured through firewalls and encompass distributed denial-of-service preventive measures.

Data Collection

Instruments

For my data collection process, I utilized a survey questionnaire as my research instrument. Questionnaires are a common preference for acquiring information in the social sciences and online platforms such as SurveyMonkey, Google Forms, and research electronic data capture can help to raise self-disclosure by assisting participants in feeling more comfortable by anonymously completing questionnaires, which could facilitate disclosing their experiences and opinions more openly (Goegan et al., 2018). The application of questionnaires based on adequate procedural criteria could add to the validity, reliability, and reproducibility of the study results (Silva et al., 2019). Furthermore, the use of web-based surveys presents several advantages to include cost-effectiveness, ease of application, data storing, and data encryption, and the advancements in internet access have made web-based questionnaires the most utilized survey method in quantitative research globally (Cantuaria & Blanes-Vidal, 2019). Thus, my data collection method relied on a web-based online survey tool.

My questionnaire was an adaptation, with the author's permission (as shown in Appendix C), from the ISS model survey instrument of Lal and Bharadwaj Survey Instrument published by Skyline Business Journal 2016. The researchers used the original survey in a study that concentrated on the performance of cloud-based CRM systems within organizations in India. Their instrument utilizes 29 nominal variables to measure the six latent constructs system quality, service quality, information quality, use of cloud-based CRM, user satisfaction, and organizational benefits. Latent variables are not directly observed and do not have any interpretation associated with them but are used to make inferences through a mathematical model from other directly measured and observed variables (Taeb & Chandrasekaran, 2018). The authors also used closed-ended questions to collect data from the participants, as shown in Appendix D. Closed-ended questions have single fixed answers, do not provide an in-depth exploration and understanding of data (Säre et al., 2017), and better for gathering quantitative data (Zhou et al., 2017). Additionally, the researchers demonstrated the instrument's high reliability and validity for each construct using the statistical methods Cronbach's alpha greater than 0.7, discriminant validity with the square root of AVE with a cut-off value of 0.50, and composite reliability greater than 0.8 (Di Martino et al., 2018). Di Martino et al. also demonstrated the models fit with values of $\chi2/df = 1.53$, comparative fit index (CFI) =0.96, Tucker Lewis Index (TFI) =0.96, Incremental fit index (IFI) = 0.95, Standardized root mean residual (SRMR) = 0.034, and root mean square error of approximation (RMSEA) = 0.026. Acceptable values for IFI and CFI are at least 0.90, RMSEA less than.08, $\chi2/df$ less than 4 (Hou & Pereira, 2017), TLI greater than 0.95, and SRMR less than .08 (Rakotoasimbola & Blili, 2019).

The Lal and Bharadwaj (2016) model were appropriate for this study as the researchers developed the instrument on the foundation of the updated ISS Model, and they conducted the study using a questionnaire survey method. The ISS model was updated by DeLone and Ephraim in 2003 to help researchers better understand the value and the model's efficiencies (DeLone & McLean, 2003). Lal and Bharadwaj used a Likert scale to capture the point of view of the participants regarding ISS six constructs. Furthermore, Lal and Bharadwaj used similar populations of IT executives who manage a cloud-based system(s).

For this study, I collected data using a closed-ended questionnaire that measured the six ISS latent ISS constructs perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction, and net benefits of cloud computing services. I measured the constructs using the 29 variables detailed in Section 1. The survey consisted of eight parts with 40 questions, and 29 of the questions were used by Lal and Bharadwaj (2016) to measure the six latent variables. Furthermore, I used two measures of scale for this study to include nominal and ordinal. In statistics, there are four levels of scale to include nominal, ordinal, interval, and ratio (Kim, 2017). Nominal and ordinal represent data on the lower level of the scale and numerical, and data expressed as nominal or ordinal does not have the standard for natural numbers analysis, and they are coded for distinguishing and positioning intent (Foryś & Gaca, 2016). However, a nominal measurement scale (e.g., Europe; Africa; Asia) provides a way of categorizing the variables and an ordinal measurement scale (e.g., good; medium; bad); the order of the variable is what's significant (Sudmanns, 2019). In measuring the level of agreement with a statement, the answer options are frequently given in a Likert-type scale with a specific number of ordinal response options (Kuhlmann et al., 2017). Thus, I used a five-point Likert scale (1) Strongly disagree, (2) Disagree, (3) Neither agree nor disagree, (4) Agree and (5) Strongly agree for the ordinal variables.

Part 1 of the questionnaire consisted of three qualifying questions 1–3 of a nominal scale, as shown in Appendix E Tables E1. The qualifying questions were presented at the start of the survey, and if the participant answers yes to any of the questions, they were omitted from the study. Additionally, the questions in the section of the questionnaire were not part of the study analysis. Part 2 of the survey included nine demographic questions 4–11 of a nominal scale to gain a better understanding of the participant's characteristics, as shown in Appendix E Tables E2– E4. Part 3 of the questionnaire included four Likert scale questions 12–15 of an ordinal scale to measure the latent variable perception of information quality, as shown in Appendix E Table E5. Part 4 of the questionnaire included five Likert scale questions 16–20 of an ordinal scale to measure the latent variable perception of system quality, as shown in Appendix E Table E6. Part 5 of the questionnaire included six Likert scale questions 21–26 of an ordinal scale to measure the latent variable perception of service quality, as shown in Appendix E Table E7. Part 6 of the questionnaire included four Likert scale questions 27 –30 of an ordinal scale to measure the latent variable perception of system use, as shown in Appendix E Table E8. Part 7 of the questionnaire included four Likert scale questions 31 –34 of an ordinal scale to measure the latent variable perception of user satisfaction, as shown in Appendix E Table E9. Lastly, part 8 of the questionnaire included six Likert scale questions 35 –40 of an ordinal scale to measure the latent variable net benefits of cloud computing services, as shown in Appendix E Table E10 –Table E11.

There were two primary adjustments made to Lal and Bharadwaj Survey Instrument. Research instruments are adapted to allow the capturing of the requested information specific for the intended respondents and best suited for a particular study (Kaltenbrunner et al., 2017). As illustrated by Pegoraro et al. (2018), adaptations to an instrument could include rephrasing of writing, replacement of terms, combining questions, and completing questions with additional terms. First, the instrument required the necessary adaptation of the questions to suit my study. For instance, the researchers' study focused on cloud-based CRM systems, which were evident as 24 of the 29 survey questions explicitly stated cloud-based CRM systems. However, my research focused on cloud services as a whole, resulting in my altering of the researchers' questions, where they stated cloud-based CRM systems, I specified cloud-based service(s). Furthermore, I altered many of the question's variables to align with my research model. For example, the researchers' variables for system use included satisfaction, high quality, meeting expectations, and enhances employees' performance. However, my variables for the perception of system use included frequency of use, duration of use, continuance use intention, system dependency.

Second, I added demographic questions to the instrument, shown in Appendix E Tables E2 – E4. Demographic questions are fundamental for researchers to explain or characterize their samples to help explain similarities and differences across studies (Hughes et al., 2016). Demographic information is the core of many social science examinations, and researchers should utilize the information to investigate differential patterns in attitudes and behaviors (McCormick et al., 2017). The demographics measures included level of education, managerial role, length in the managerial role, years of experience, organizational size, primary cloud service model strategy, primary cloud deployment model strategy, and organization's primary industry.

My data collection method included the use of the web-based surveying tool Survey Monkey. Survey Monkey is a cloud-based system used to administer and collect survey data (Arentz et al., 2014). Through the marketing research firm Centiment, the respondent will be directed to the Survey Monkey uniform resource locator. The survey remained available until enough valid responses were received to reach the required sample size objective. Once the data collection process was complete, the results from Survey Monkey were exported in IBM SPSS Version 27.0 Windows 64-bit for analysis.

Data Collection Technique

For this quantitative correlational study, I used a web-based self-administered questionnaire to collect research data. Typical data sources in research studies include surveys and questionnaires, transcripts, pre-tests, post-tests, interviews, observations, and field notes (Hartwick, 2018). Moreover, survey methodologies included employing questionnaires either directly through face-to-face or indirectly through telephone, mail, and web surveys (Čehovin et al., 2019). With the growing access to the internet globally and the drop in the price of technology devices and software, internet-based data collection methods such as online questionnaire surveys have grown to be popular in recent years (Regmi et al., 2016). According to Zhu et al. (2018), survey research is the most prominent approach used for quantitative studies.

There are several benefits and challenges associated with web-based surveys. From a general perspective, a web-based survey involves the respondent engaging with the survey through an internet browser from a personal computer, tablet, or smart device with access to the internet (Žmuk, 2018). Web-based surveys have several benefits over conventional data collection methods, such as considerable savings in cost and time, more flexibility, convenience, and anonymity for respondents (Roster et al., 2015). Web-based surveys can also offer higher quality data, minimize data entry errors, provide real-time data tracking and immediate survey delivery (Sebo et al., 2017). However, limitations to online surveys include possibly low response rates, demographic biases, limited computer literacy of participants, and lack of internet availability (Maymone et al., 2018). Nevertheless, recruitment partners can help expand recruitment and maximize response rates at a reasonable cost (Karlsen et al., 2018). Thus, I leveraged the cost, administrative, and anonymity advantages of web-based surveys and minimized the risk of low response rates by using the market search firm Centiment as a recruitment partner to aid in the recruitment process.

Pre-testing or pilot testing allows the screening for the measurement of the items under development, which in turn allows additional evaluation and refinement of the measures to ensure their content validity (Alzoubi et al., 2018). Moreover, pre-testing can aid in the assessment of the usability of the survey for researchers and its appropriateness for respondents (Genereaux et al., 2016). However, Bulgurcu et al. (2010) established that an instrument that has previously demonstrated acceptable validity and reliability does not necessitate pilot testing. Thus, I elected not to conduct a pilot test.

Data Analysis Technique

Overarching Research Question and Hypotheses

The overarching aim of this study was to evaluate the relationships among the perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction, perception of system use, perception of user satisfaction, and net benefits of cloud computing services from the viewpoint of IT cloud service managers. Thus, the research questions (RQ) presented in this study inquired about the relationships among variables defined in the proposed ISS theoretical model.

RQ: Are there significant relationships among the perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction, and net benefits of cloud computing services?

H_0: There are no significant relationships among the perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction, and net benefits of cloud computing services.

H_a: There is a significant relationship between the perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction, and net benefits of cloud computing services.

Testable Questions and Hypotheses

Moreover, I sought to address the overarching research question and hypotheses by exploring ten subordinate research questions (RQ1–RQ10), ten corresponding null hypotheses ($H_01 - H_010$), and ten corresponding alternative hypotheses ($H_a1 - H_a10$).

RQ1: What is the relationship between the perception of information quality and the perception of system use of cloud computing services?

H_01: There is no significant relationship between the perception of information quality and the perception of system use of cloud computing services.

H_a1: There is a significant relationship between the perception of information quality and the perception of system use of cloud computing services.

RQ2: What is the relationship between the perception of information quality and the perception of user satisfaction of cloud computing services?

*H_0*2: There is no significant relationship between the perception of information quality and the perception of user satisfaction of cloud computing services.

*H_a*2: There is a significant relationship between the perception of information quality and the perception of user satisfaction of cloud computing services.

RQ3: What is the relationship between the perception of system quality and the perception of system use of cloud computing services?

*H_0*3: There is no significant relationship between the perception of system quality and the perception of system use of cloud computing services.

*H_a*3: There is a significant relationship between the perception of system quality and the perception of system use of cloud computing services.

RQ4: What is the relationship between the perception of system quality and the perception of user satisfaction of cloud computing services?

*H_0*4: There is no significant relationship between the perception of system quality and the perception of user satisfaction of cloud computing services.

*H_a*4: There is a significant relationship between the perception of system quality and the perception of user satisfaction of cloud computing services.

RQ5: What is the relationship between the perception of service quality and the perception of system use of cloud computing services?

*H_0*5: There is no significant relationship between the perception of service quality and the perception of system use of cloud computing services.

*H_a*5: There is a significant relationship between the perception of service quality and the perception of system use of cloud computing services.

RQ6: What is the relationship between the perception of service quality and the perception of user satisfaction of cloud computing services?

$H_0$6: There is no significant relationship between the perception of service quality and the perception of user satisfaction of cloud computing services.

H_a6: There is a significant relationship between the perception of service quality and the perception of user satisfaction of cloud computing services.

RQ7: What is the relationship between perception of user satisfaction and perception of system use of cloud computing services?

$H_0$7: There is no significant relationship between the perception of user satisfaction and the perception of system use of cloud computing services.

H_a7: There is a significant relationship between the perception of user satisfaction and the perception of system use of cloud computing services.

RQ8. What is the relationship between the perception of system use and the perception of user satisfaction of cloud computing services?

$H_0$8. There is no significant relationship between the perception of system use and the perception of user satisfaction of cloud computing services.

H_a8 There is a significant relationship between the perception of system use and the perception of user satisfaction of cloud computing services.

RQ9. What is the relationship between the perception of system use and the net benefits of cloud computing services?

$H_0$9. There is no significant relationship between the perception of system use and the net benefits of cloud computing services.

H_a9. There is a significant relationship between the perception of system use and the net benefits of cloud computing services.

RQ10. What is the relationship between the perception of user satisfaction and the net benefits of cloud computing services?

$H_0 10$. There is no significant relationship between the perception of user satisfaction and the net benefits of cloud computing services.

$H_a 10$. There is a significant relationship between the perception of user satisfaction and the net benefits of cloud computing services.

Statistical Analysis

For this study, I utilized a multiple regression statistical approach to examine the relationship between variables. There were several statistical analyses used in research to examine the relationship between variables. In particular, most researchers assessed their research hypotheses using methods such as analysis of variance (ANOVA), t-tests, correlation, and multiple regression (Counsell & Harlow, 2017). Furthermore, statistical methodologies such as inferential and predictive statistics play a vital role in quantitative research, where inferential statistical methods, such as t-test and ANOVA, focus on hypothesis testing and predictive methods concentrate on correlation analysis and regression analysis (Zhang, Zhao, et al., 2016). The ANOVA statistical method provides testing of the hypothesis for comparison of means amongst two groups where the testing or dependent variable ought to be on a continuous scale and approximately normal distribution (Mishra, Singh, et al., 2019). Likewise, a t-test provides a one-sample, and a two paired test where a one-sample t-test compares one group's average value to a single known population mean, and a two paired t-test determines if there is a significant difference amongst the means of two groups (Feng et al., 2017). Moreover, the theoretical presumption of t-test, one can only apply t-test to the quantitative data of single-factor design; hence it is unsuitable to perform a t-test for multifactor independent variables/factors design (Liang et al., 2019). A single factor design shows the independent effect of one causal variable, and it can not estimate the causal role of the other variables versus multifactor models where at least two variables are allowed to vary independently (Reiss & Wyatt, 1975). Consequently, the t-test was not best suited for this study because I tested multiple independent variables. Lastly, an ANOVA analysis was not appropriate because I did not have multiple test groups.

Regression analysis is an essential statistical instrument for examining the relationships between one dependent variable and one or more independent variable(s) with the primary aim of determining and estimating factors of a function that explain the best fit for a particular data set (Korkmaz, 2019). Simple and multiple linear regression models explore the relationship between a single continuous dependent variable and one or several independent variables (Bangdiwala, 2018a). Simple regression models explore the relationship between a single dependent variable and one independent variable versus multiple linear regression examines the relationship between more than one independent variable (Bangdiwalaa, 2018b). Similarly, a correlation analysis examines the strength of the relationship between two variables, which are assumed to be both be random, thus not denoting if the variable is dependent and independent (Hazra & Gogtay, 2016b). Therefore, the multiple regression analysis was the most appropriate data analysis model since I tested the relationship between five independent variables and a single dependent variable.

I also used descriptive statistics to capture the respondents' educational level, managerial role, time in a managerial position, years of experience with cloud computing, organization's size, organization's primary cloud computing service model strategy, organization's primary cloud computing primary deployment model strategy, and organization's primary business or industry. Descriptive statistics helps to summarize the study's sample in the form of simple quantitative measures without drawing any inferences based on probability theory (Kaliyadan & Kulkarni, 2019). When reported sufficiently, descriptive statistics can provide alternatives to both raw data for various analyses and assessing the reproducibility and robustness of preceding research (Nimon et al., 2019). Furthermore, researchers report descriptive statistics numerically in the manuscript text tables, graphs, and figures and aids in answering the questions of who, what, where, when, why, how much, and so what concerning a data set (Vetter, 2017b). Since a study lacks access to an entire population, descriptive statics provides the details to depict a given sample of data to help make inferential conclusions and generalization past the observed data to a larger population (Halfens & Meijers, 2013). Thus, I used descriptive statistics to describe the IT managers' sample group participating in the study to help draw inferences about a population.

As part of my statistical analysis, I also performed cross-tabulations and Chi-square tests to better understand the relationships between the various ISS variables. Cross tabulation, or contingency tables (Avinash et al., 2017), is a quantitative methodology that examines the relationship between multiple variables (Kharub & Sharma, 2018). As a fundamental data analysis procedure of applied survey research, a cross-tabulation separates the sample into subgroups to discover how an explained factor differs from one subgroup to another subgroup to help reveal associations between variables not readily evident (Mohn, 1990). Furthermore, through the chi-square test, cross-tabulations can aid in determining whether there are significant relationships between categorical independent and dependent variables to distinguish if differences exist between demographic categories (Hess, 2020). Moreover, cross-tabulation can help to identify the intervening effects (Kim et al., 2003) and moderating effects (Nagy, 2017) between variables.

Data Cleaning, Screening, and Handling Missing Data

During the research process, the research must perform data cleaning and editing to identify and correct errors that may occur from data entry to ensure that the study results are accurate (Kulkarni, 2016). The problem of data quality is pivotal, and researchers should not ignore the issue either in data production or analysis (Morselli et al., 2019). Yet, a low proportion of untrustworthy survey data may significantly bias statistical outcomes, which can be misleading and can produce results that obstruct scientific progress (Hyman et al., 2019). For survey research, a data screening method for detecting low-quality data includes the use of self-report indicators that tags the respondent, which is typically undetectable and does not require modifying the survey to identify incorrect items or failure to follow instructions (DeSimone & Harms, 2018).

Additionally, researchers frequently experience nonresponse or missing data is in survey research, in which the most evident consequence is a decline in the sample size and subsequent loss of statistical power (Madden et al., 2017). Subsequently, it is common practice to disregard missing data and utilize methods that delete all instances that have some missing data on any variables measured in the analysis (Pampaka et al., 2016). Thus, I implemented procedures in the survey to screen and tag respondents with erroneous or incomplete data. Furthermore, I removed any respondents with missing data from the study before I deemed the data analysis process complete. Consequently, the survey remained active until the receipt of 92 to 138 completed surveys as specified by the G*Power participant calculations.

Testing Assumptions

For this study, I considered several assumptions concerning the statistical method regression analyses. Testing the fundamental assumptions of regression analysis is a process, and infringements of the principle assumptions can lead to biases and obscure forecasts, confidence intervals, and scientific understandings (Flatt & Jacobs, 2019). For example, researchers commonly assume that all of the variables are multivariate normally distributed, permitting non-zero covariance (Deresa & Van Keilegom, 2020). Testing for multivariate normal distribution can be achieved by plotting the data, and diagnostics can be performed by calculating the goodness of fit (Marchant et al., 2016). Researchers can calculate goodness-of-fit using a statistical test such as chi-squared to test the extent to which the sample data fit the distribution of normal population distribution (Quessy et al., 2018). The value of the chi-square test, $X^2 = \sum(y - p)^2/p$ where y is the observed value, and p is the expected value, is based on a fitness function that minimizes the distance between the model implied and observed values (Qiu et al., 2019). The model is believed to have a good fit when X^2 is less than (or less extreme) the critical chi-square value, which indicates strong evidence against the null hypothesis with a significance level of .05 (Yuan & Chan, 2016). Mitigation of violations of the goodness of fit assumption includes model adjustments by isolating the violation and misspecification of the variable producing the misfit (Nagelkerke et al., 2016).

An assumption is that the data is linear for mediator and outcome (Loeys et al., 2016). The normal distribution of the are preferred because of its continuous variables, and researchers are most comfortable when handling normally distributed continuous variables because it impacts the accuracy estimation of confidence intervals and the calculation of p-values (Jupiter, 2017). The confidence interval describes the level of uncertainty associated with a sample estimate and helps to interpret the potential for error (Calin-Jageman & Cumming, 2019). Thus, the desired 95% confidence interval meant that there is a certainty that 95% of the value range encompasses the true mean of the population (Ialongo, 2019). Researchers can use graphical tests to explore the normality of the distribution and the appropriateness of the model, homoscedasticity, and independence of errors (Schmidt & Finan, 2018). Presentation methods such as graphs provide meaningful and compact summarization of data without troubling the reader with a plethora of information and allow the deriving of inferences by examining the summarized data (Hazra & Gogtay, 2016a). Consequently, if there is a violation of the linear data assumption, the researcher can use nonlinear or monotonic regression analyses as a mitigation strategy (Regenwetter & Cavagnaro, 2019).

Linear regression assumes that there is minimal multicollinearity in the data, which happens when there is a high level of correlation between independent variables, which can lead to inaccurate results of regression analysis (Kim, 2019). Although multicollinearity does not affect the model's goodness of fit, it can result in the wrong conclusion and the contribution of each predictor being unrealistic due to the overlapping of variables (Gwelo, 2019). Researchers can identify multicollinearity by calculating the variance inflation factors using the formula $V = 1/(1- R^2)$ where R^2 denotes the regression index and values $V > 10$ results in serious multicollinearity and $V < 5$ is the suggested threshold criteria (Marcoulides & Raykov, 2019). The mitigation strategy to avoid multicollinearity is for the researcher to remove the contributing variable(s) or use alternative regression analysis, such as partial least squares regression (Thompson et al., 2017).

Interpreting Inferential Results

Inferential statistics, which include conventional measures such as effect size, p-values, standard errors, and confidence intervals, is an analytical procedure whereby researchers interpret information concerning a sample data into intelligent inferences or guesses about a population (White & Gorard, 2017). Researchers who use significance testing should follow the best practices in applying inferential statistical methods (Rouse, 2016). For example, an effect size reveals the magnitude of the difference between two means such that if a statistically significant difference exists, the effect size describes the magnitude of the associations between variables (Lininger & Riemann, 2016). Using Cohen's d method for calculating effect size, 0.2 indicates a small effect size, 0.5 indicates a medium effect size, and 0.8 indicates a large effect size (Perdices, 2018). Additionally, odds ratios from standard regression techniques are used to quantify and exhibit variable effects to measure the relationship between them (Uanhoro et al., 2019). Thus, the odds ratio $OR = [p_A(1 - p_A)]/[p_B(1 - p_B)]$, where p is the population, can be interpreted as OR = 1 means that there is no effect, OR > 1 there is a higher odds of effect, and OR < 1 there is a lower odd of effect (Sheldrick et al., 2017).

The probability value or p-value represents the probability of obtaining results at least as extreme as the observed outcomes due to random chance to help ascertain the significance of the study results assuming the null hypothesis is correct (Prasad, 2019). A p-value < 0.05 indicates to reject the null hypothesis and accept the null hypothesis when P > .05 for a one-sample, two-tailed t-test (Goodman et al., 2019). The degrees of freedom, df = n - 1, where n is the number of data points to calculate the standard deviation, is a key parameter estimate that refers to the number of values in a data set that is allowed to vary (Sutrick, 2017). In particular, the degrees of freedom are necessary for calculating one-sample t procedures, the chi-square procedure for one-sample variance studies, and the sample variances applied in the F test for equality of two variances (Cashing, 2018).

Statistical Software

For this study, I used IBM SPSS Version 27.0 Windows 64-bit to perform my data analysis and inferential interpretations. SPSS is one of the most commonly used software packages used to perform statistical analysis on data quicker, simpler, and with fewer errors (Davidson et al., 2019). Principally, statistical inference provides frequentist techniques for generalizing from a sample to the population, and it is geared to the conduct of enumerative studies, as well as deriving causal inferences in scientific experiments (Hubbard et al., 2019).

Study Validity

As an aspect of this quantitative correlational study, I examined various risks associated with validity to include threats to external validity, threats to internal validity, and threats to statistical conclusion validity. Furthermore, I discussed the extent to which research results can be generalized to larger populations and employed in disparate environments. Validity indicates the extent that the results of the study's instrument measure represent what it is meant to measure (Enemark Larsen et al., 2020). Examining the validity in quantitative studies is a vital analysis as it can deem the effectiveness of the research instrument, which computes the research objectives (Elas et al., 2019). The validity of research studies includes several methods, such as external validity, internal validity, and statistical conclusion validity (Kenny, 2019). Thus, the subsequent paragraphs described the approach taken to ensure the validity of the study.

Threats to External Validity

For this study, I assessed the external validity of the research instrument and addressed any potential threats. External validity measures the extent to which study outcomes can be generalized to a specific broader population (Hütter & Tigges, 2019). It is essential to establish strong external validity by producing convincing evidence that the results will generalize in an intended manner (Loyka et al., 2020). Assessing the external validity of a survey study can be achieved by examining measurement characteristics such as construct validity (Clark & Watson, 2019). Conclusions concerning the external validity of a study hinge on the reporting of essential attributes of sufficient information regarding the participants, settings, the factors tested, and the assessed outcomes (Brænd et al., 2017). Moreover, research findings are externally valid under the condition that the effect of the study sample is unbiased for the effect of the target population (Westreich et al., 2019). Thus, it was essential as the researcher that I understood the methods needed to assess and control threats to external validity, which can hinder the generalizability of study outcomes.

As the researcher, there are several threats associated with external validity that I considered while conducting a correlational study. For example, selection bias can pose a threat to external validity such that the study's sample population does not represent the population that the researcher wants to generalize (Brincks et al., 2018). In addition, poorly operationalize variables pose a significant threat to external validity and the possibility to generalize results to other settings (Garavan et al., 2019). Furthermore, survey research is subject to the Hawthorne effect, where the participants may alter their responses, knowing they are in a study (Fekjær, 2018). Thus, I carefully considered the various mitigation factors such as selection bias, poorly operationalize variables, and the Hawthrone effect to address and minimize the impact of external validity.

There are techniques that I employed to control external validity threats such as selection bias, poorly operationalize variables and the Hawthorne effect. For instance, the threat of selection bias can be mitigated by implementing screening methods to ensure that the recruitment process includes only the desired sample population (Yang et al., 2017). Additionally, the threat of poorly operationalize variables can be addressed by demonstrating construct validity, which indicates that the appropriateness of the research variables measurements (Francis et al., 2016). Construct validity can be measured by assessing convergent validity and discriminant validity (Zinbarg et al., 2018).

Convergent validity refers to how closely measures correlate with other measures of the same constructs (Castilla-Earls & Fulcher-Rood, 2018). Discriminant validity refers to how closely measures do not correlate to ensure that the measures are not measuring the same entity (Matthes & Ball, 2019). Researchers can measure convergent validity using construct reliability (CR) (Liu et al., 2016b). The critical limit for construct reliability is CR >= 0.70 (Saptono, 2017). A standard method for measuring discriminant validity includes Average Variance Extracted (AVE) (Lee, 2019a). Researchers consider values above .70 to be very good, and the measure of .50 is acceptable for discriminant validity (Liu et al., 2016a). Thus, I utilized measures such as AVE and CR to test the degree of convergent and discriminant validity of my research instrument.

Lastly, the Hawthorne Effect becomes more prevalent with the visual presence of the researcher administering the survey, potentially skewing the results (Lowe & Hynes, 2016). Because of the lack of an interviewer, completion of online survey questionnaires is often preferred by respondents, resulting in participants answering at their convenience and pace, which can reduce social desirability bias, increase response rates (Ball, 2019), and maintain anonymity to protect participants and their environment (Vacek et al., 2017). Thus, as the researcher, I managed external validity threats by implementing methods such as screening techniques during recruitment, demonstrating construct validity, and ensuring that the survey instrument provided anonymity.

Threats to Internal Validity

For this study, I appraised the internal validity of the research instrument and addressed any potential threats. Internal validity refers to the level of confidence one has that the observed cause produces the desired effect (Bernstein, 2018). As experimental designs are quite vulnerable to internal validity, internal validity is considered as the extent to which the experimental composition of a study rein in specious variables that could expose the integrity of the causal relationship between independent and dependent variables (Lee, 2012). Furthermore, the internal validity assesses if the study appropriately answers the research questions devoid of systematic error that can arise through selection, performance, detection, and attrition bias (Andrade, 2018). Consequently, threats to internal validity can make it difficult to rationalize and discuss findings as well as genuinely know if there are significant or nonsignificant findings between intervention and control groups (Siedlecki, 2018).

There are several threats associated with internal validity. Specifically, factors that jeopardize internal validity are termed confounding factors, and there are generally nine perceived threats to include selection, history, maturation, testing, instrumentation, regression to the mean, interactions with selection, causal ambiguity, and mortality (Cook & Rumrill, 2005). Yet, internal validity threats such as history, maturation, testing, instrumentation, regression to the mean, interactions with selection, causal ambiguity, and mortality are generally associated with experimental studies (Torre & Picho, 2016). However, longitudinal non-experimental studies are subject to threats such as maturation and attritions (Behie & O'Donnell, 2015). Nevertheless, non-experimental studies such as surveys and field studies are passive in observations and conducted in the natural environment (no interventions) (Kluge et al., 2019). Because this study employed a correlational non-experimental design, there was no manipulation of the study variables. Thus, internal validity was not a significant threat to this study.

Threats to Statistical Conclusion Validity

For this correlational study, I addressed the various threat to statistical conclusion validity and factors that influence the Type I error rate. Statistical conclusion validity refers to the extent to which inferences regarding the relationships between variables are correct or acceptable, centered on the sampling techniques, measurement methods, and statistical tests employed during the study (Grigsby & McLawhorn, 2019). Statistical conclusion validity describes the likelihood of making the mistakes of concluding that (a) intervention effects, when it doesn't, or (b) that the intervention has no effect when it does (Tengstedt et al., 2018). Furthermore, statistical conclusion validity seeks to address the general questions concerned about the appropriateness of the employed statistical techniques; thus, detailed explanations of the issues are not required (Cor, 2016). Moreover, the quality of research findings is, to some extent, relies on the validity of the resulting statistical conclusions, which Type 1 or Type 2 errors can make measurement conclusions inconsequential (Koziol & Bovaird, 2018).

As the researcher, there were several threats associated with statistical conclusion validity to consider. Specifically, threats to statistical conclusion validity include low statistical power, violated assumptions of statistical tests, unreliable measures, and inaccurate effect size (Rankupalli & Tandon, 2010). Low statistical power can occur from low sample size or small effects, which heightens the likelihood that a statistically significant finding signifies a false-positive result (Dumas-Mallet et al., 2017). Strengthening the statistical power of a study raises the probability of uncovering true positives while reducing the likelihood of combatting false negatives, increasing the informational value of research (LeBel et al., 2017). Consequently, a study with low statistical power has a diminished possibility of identifying a true effect, and it is less appreciated that low power also decreases the probability that a statistically significant outcome reveals an actual effect (Munafò, 2016). Accordingly, there are multiple measures researchers can employ to increase statistical power, such as using a higher significance level (α), increase the effect size, and increase the sample size (Goulet & Cousineau, 2019). Thus, I applied methods such as using a higher significance level, boosting effect, and sample size to increase statistical power if necessary.

Numerous models are resilient to small and large violations of their assumptions, but researchers should determine whether the model assumptions are not violated beyond an acceptable limit (Tijmstra, 2018). When the data extensively depart underlying assumptions, elevated risks may exist, causing statistical Type I and Type II errors, and violations of the assumptions often occur due to non-normality, severely skewed data, and inaccurate sample sizes (Theodore & Gatchel, 2008). Moreover, the researcher should consider how the underlying assumptions should be evaluated and what are the appropriate actions if there are violations of the underlying assumptions (Nielsen et al., 2019). Furthermore, as the investigator, one should substantiate the study's assumptions by ensuring the careful development of an adequate model, and the instrument has been determined to exhibit sufficiently high validity by the researcher (Raykov & Marcoulides, 2016). Thus, I utilized an acceptable model and survey instrument that demonstrated to satisfy model assumptions and exhibit adequately high validity.

Unreliable measures pose a threat to statistical conclusion validity because it presents false conclusions concerning covariation of variables based on statistical evidence; thus, creating more random errors into the scores and the test relationships between variables (Strickland, 2005). Very often, the definition of the constructs of the measurement of outcome variables, or instrument, experiences variations in definitions that can lead to different conclusions (Suter & Suter, 2015). Additionally, an unreliable measure is important to statistical conclusion validity because the estimated relationships concerning variables can be biased in both directions (Breitsohl & Steidelmüller, 2018). As a means to prevent or detect the treat, researchers typically put a strong emphasis on furnishing unambiguous operational definitions to examine and assess measures throughout the study (Petursdottir & Carr, 2018). Thus, I adequately defined my model's constructs of the measurement using clear definitions of the variables.

The effect size refers to the measurement of the magnitude of a phenomenon and the size of the expected effect produced by the event through the lens of the instrument that the researcher aims to identify the event (Oleson et al., 2019). A larger effect size results in a more powerful statistical test assuming a constant significance level and sample size (Ottenbacher, 1989). However, an exaggerated effect size estimates can lead to an underestimation of the needed replication sample size resulting in the failure of replication (Mattsson et al., 2016). Additionally, a priori power analyses are only accurate when the effect size estimate is accurate, and inaccuracies to effect size estimates might unknowingly increase the Type II error rate of their studies (Albers & Lakens, 2018). Some researchers consider that indiscriminate responses to questionnaires weaken effect sizes yielding Type II errors that can potentially produce Type I errors where presumably significant results are artifactual (Holden et al., 2019). Moreover, researchers can mitigate the risk of erroneous effect size by increasing the size of the effect, employing appropriate data cleaning techniques, or more powerful research designs and investigational procedures (Meyvis & Van Osselaer, 2018). Thus, I utilized proper size effects, applied suitable data cleaning techniques, and grounded my model on robust study designs and investigational procedures.

Rationale for Generalization Findings to Larger Populations

Generalizability refers to extending research findings from a study sample to the population wherefrom the researcher selected that sample (Stuart et al., 2018). The ability to generalize a study's outcomes is determined by the extent of applicability of its findings to any observable circumstances in general, and it is associated with the idea of external validity of study results (Khayat et al., 2020). The challenges related to generalizability are of significant importance across many disciplines in the research community, emphasizing the significance of creating guidelines and approaches for dealing with poor external validity (Ackerman et al., 2019). Whereas internal validity often has a high priority in primary research, external validity factors such as generalization across populations and settings are often neglected (Berggren et al., 2018). Even with the preeminence statistical prediction over human judgment, statistical prediction models such as linear and logistic regression have encountered only partial success when validated on external data, mostly when the models comprise multiple predictor variables (Menton, 2020).

Replication research serves a pivotal role in systemically examining if the effects of an intervention are valid and able to be generalized throughout various settings, participants, and other appropriate dimensions (Coyne et al., 2016). The adequacy of generalizations based on research data is a prevalent source of controversy as researchers perceive that it is vulnerable to error when the target population is different differs from the study's participant pool (Kern et al., 2016). Nevertheless, generalizability is clear-cut with a strong assumption but often implausible that predictor impacts are constant (Tipton & Olsen, 2018). It is more probable that the generalizability of an effect will be ascertained by replicating studies employing methodically sampled settings and participants (Dzewaltowski et al., 2004).

With the application of the appropriate statistical methods, research outcomes can be generalized to larger populations and employed in other settings. For instance, statistical methods for assessing and improving generalizability include producing pertinent population data sets and making precise measure comparability between study and population data sets (Stuart & Rhodes, 2017). Identifying study recruitment disparities is essential to recognize the boundaries of the evidence concerning generalizability and also to help in planning studies (Kerry et al., 2018). Moreover, researchers can take approaches to extend causal generalizations such as (a) assess similarities between studies concerning the target of generalization, (b) exclude irrelevant attributes that do not alter generalization, (c) recognize attributes that constrain generalization, (d) interpolate unsampled data within and extrapolate beyond a sample range, and (e) develop effective program theories (Leviton, 2017).

Transition and Summary

In Section 2, I discussed the role of the researcher, where I described my role in the data collection process, as well as any relationship I had regarding the participants. I also described the eligibility criteria, strategies for access, and my working relationship with the study participants. Furthermore, I expanded on my discussion of the nature of the study and elaborated further on my approach to my research method and key design elements. Additionally, I described my population and sampling techniques and justified my sample size via power analysis. Section 2 also conversed the study's ethical elements to include the informed consent process, procedures for withdrawing from the study, and measures to safeguard the protection of participants.

Moreover, I discussed the parameters of my survey instrument by identifying the publisher's name, concepts measured by the instrument, scale of measurement, its appropriateness to the study, administrative procedures, scoring methods, published reliability, and validity properties. Section 2 contained considerations regarding my data collection techniques to include its advantages and disadvantage, as well as data analysis and statistical analysis that I employed in this study. Lastly, I described the various validity threats and mitigation methods associated with quantitative studies to include external validity threats, internal validity threats, statistical conclusion validity threats, and rationale to justify why research outcomes can be generalized to larger populations and employed in other sceneries.

In Section 3, I will present an introduction to include the study's purpose and a brief summary of the findings. Furthermore, I will give a comprehensive report on the study findings, offer a detailed discussion regarding the finding's applicability to the IT profession, and consider the finding's implications for social change. To conclude, I review my recommendations for action, suggestions for further research, reflection on my experience within the Doctor of Information Technology process, and share my closing thoughts.

Section 3: Application to Professional Practice and Implications for Change

Introduction

The purpose of this quantitative, correlational study was to examine the relationship between (a) perception of information quality, (b) perception of system quality, (c) perception of service quality, (d) perception of system use, (e) perception of user satisfaction, and net benefits of cloud computing service. I gathered data from 143 IT managers via a Centiment panel, which satisfied the sample size requirements. With 143 participants, the power achieved was .99. The response rate was 87%. I used Multiple linear regression analysis to examine the presence of the relationship between the independent and dependent variables.

The results of the multiple regression were significant, $F(5,131) = 85.16$, $p <.001$, $R^2 = .76$, indicated that approximately 76% of the variance in net benefits of cloud computing service could be explained by (a) perception of information quality, (b) perception of system quality, (c) perception of service quality, (d) perception of system use, and (e) perception of user satisfaction. Perception of information quality ($\beta = .188$, $t = 2.844$, p < .05), perception of service quality ($\beta = .178$, $t = 2.102$, $p < .05$), and perception of user satisfaction ($\beta = .379$, $t = 5.024$, $p < .001$), were significant at .05 level as predictors of net benefits of cloud computing service. Two of the five independent variables, perception of information quality and perception of user satisfaction, were the most significant factors influencing net benefits of cloud computing service. Hence, I rejected the null hypothesis for overarching RQ because the study results confirmed a relationship between the independent variables and the net benefits of cloud computing service.

Presentation of the Findings

I used descriptive and inferential statistics to draw conclusions from the sample collected. Furthermore, I applied multiple regression analysis to examine the research question and hypotheses. The research question was:

Are there significant relationships among the (a) perception of information quality, (b) perception of system quality, (c) perception of service quality, (d) perception of system use, (e) perception of user satisfaction, and net benefits of cloud computing services?

The null and alternative hypothesis addressed in the study were:

H_0: There are no significant relationships among (a) perception of information quality, (b) perception of system quality, (c) perception of service quality, (d) perception of system use, (e) perception of user satisfaction, and net benefits of cloud computing services.

H_a: There is a significant relationship among (a) perception of information quality, (b) perception of system quality, (c) perception of service quality, (d) perception of system use, (e) perception of user satisfaction, and net benefits of cloud computing services.

As a precondition to data analysis, I assessed the collected data for missing data, outliers, normality, linearity, homoscedasticity, and multicollinearity. Thereafter, I performed a multiple regression analysis to ascertain if there were any significant relationships between the variables of interest. Described below are the outcomes of the data analysis.

Data Cleaning

Before examining the research question, I cleansed the research data from missing values and extreme distribution values. The cleansing of data, which includes checking for extreme scores, missing data, and abnormalities, is a significant step in assessing the quality or reliability of quantitative finings (Osborne, 2010). I identified missing data using frequency counts. There was a total of 165 respondents to the survey. However, the frequency count found 22 participants that missed or skipped items on the survey. I removed the data with incomplete answers from the data set, resulting in 143 records for analysis. Additionally, I tested the research data for univariate outliers using boxplots and scatter plots. Common outlier detection techniques include applying boxplots to uncover potential outliers from total scores or subscale scores, where extreme z-scores are considered to be ±3.0 standard deviations from the mean (Felt et al., 2017). Univariate outliers were identified and withdrawn from the regression analysis, which included perception of information quality has one outlier (case: 141), perception of service quality had two outliers (case: 133, 141), perception of system use had two outliers (record 58, 59), perception of user satisfaction had one outlier (case: 141), and net benefits of cloud computing services had three outliers (case: 33, 133, and 141). Lastly, results from Cook's Distance analysis provides a method for detecting influential observations in a set of predictor variables when performing regression analysis (Leone et al., 2019). I used Cook's Distance analysis to identify a single data point of influence (case: 100).

Descriptive Statistics

I examined the descriptive statistics from a sample of 137 IT cloud services managers from small, medium, and large enterprises that subscribe to IaaS, PaaS, and SaaS in the United States. (*N* = 137). Descriptive statistics provide a means of collecting and presenting data concisely through tables and graphs, measures of central tendency, location, and dispersion to provide simple summaries about the sample and measures (Dewi et al., 2020). Table 2 displays the descriptive statistics to examine the research questions, where n represents the sample size. The mean, or mathematical average, is a unique value for a set of data useful when comparing groups and central tendency measures (Mishra, Pandey, et al., 2019). Yet, the standard deviation (*SD*) shows the variation in the data's dispersion (Keser et al., 2016). The mean ranges from 0.39 to 0.45, and the standard deviation range is 0.40 to 0.42. The standard error of the mean (SE_M), $SD/\sqrt{n}$, estimates the proximity of the sample's mean to the population's mean, where the smaller the standard error, the closer it is to the population mean (Andrade, 2020). With a range of 0.03 to 0.04, the SE_M suggests that the sample is close to the population's mean.

Table 2

Descriptive Statistics of Dependent and Independent Variables

Variable	*n*	Mean	Std. Deviation	SE_M	Skew ness	Kurtosis
Perception of information quality	137	0.39	0.40	0.03	0.64	-0.85
Perception of system quality	137	0.45	0.42	0.04	0.84	0.31
Perception of service quality	137	0.46	0.40	0.03	0.35	-1.05
Perception of system use	137	0.48	0.45	0.04	0.80	0.09

Perception of user satisfaction	137	0.46	0.42	0.04	0.63	-0.67
Net benefits of cloud computing services	137	0.45	0.42	0.04	0.69	-0.34

Skewness and kurtosis provide a means to examine the characteristics of distributions of the data. Skewness measures the symmetry of the data distribution, and kurtosis measures if the data is heavily or lightly tailed relative to the normal distribution (Neethling et al., 2020). A normal distribution has a skewness of zero, which means that any symmetric data skewness should approach zero (Soberón & Stute, 2017). A normal distribution has a kurtosis of three, where (a) positive value implies heavy-tails, (b) negative value implies light-tails, (c) values greater than three are leptokurtic, and (d) values less than three are platykurtic (McAlevey & Stent, 2018). The skewness ranges from 0.35 to 0.80, which suggests that the distributions are relatively free of skewness. However, none of the measures approach a kurtosis of thee, which indicates the presence of kurtosis. Furthermore, each measure appears to be platykurtic with the variables perception of system quality and perception of system use have heavy-tails. The variables perception of information quality, perception of service quality, perception of user satisfaction, and net benefits of cloud computing services have light-tails.

Tables 3-6 provide a summary of the descriptive statistics. Illustrated in Table 3 are the frequency and percent statistics for participants' education, job position, and organization size. The most frequently observed category of education level is graduate degree (*n* = 91, 66.4%), while bachelor's accounted for (*n* = 41, 29.4%). Job position frequency ranged from 32 to 86. The most frequently observed job position category was senior manager (*n* = 83, 60.6%). In contrast, front-line manager was the second most observed category (n = 31, 22.6%, and middle manager was the least observed category (n = 23, 16.8%). The most frequently observed category of organization size was more than 1000 employees (n = 39, 28.5%) and the least observed category was less than 100 employees (n = 9, 6.6%).

Table 3

Frequency and Percent Statistics of Participants' Education, Job Position, and Organization Size

Demographic	Frequency (n)	%
Education Level		
High School/GED	1	0.7
Some College	1	0.7
Associates	3	2.2
Bachelor's degree	41	29.9
Graduate Degree	91	66.4
Total	137	100.0
Job Position		
Front-line manager (manage nonsupervisory workers)	31	22.6
Middle manager (manage front-line managers)	23	16.8
Senior manager (department manager or executive, i.e., director or CIO)	83	60.6
Total	137	100.0
Organization Size		
less than 100 employees	9	6.6
between 100 and 500 employees	37	27.0
between 500 and 1000 employees	52	38.0
more than 1000 employees	39	28.5
Total	137	100.0

Note. Total N = 137. Due to rounding errors, percentages may not equal 100%.

Table 4 demonstrates the frequency of distribution of demographics years in managerial position and experience. The most frequently observed category of managerial position is 5 years and above (*n* = 61, 44.5%), where the category at least 3 but less than 5 years accounted for (*n* = 43, 31.4%), at least 1 but less than 3 years accounted for (*n* = 26, 19.0%). The category less than 1 year was the least frequently observed (*n* = 7, 5.1%). Additionally, the most frequently observed category of experience was 5 years and above (*n* = 48, 35.0%). The least observed category of experience was less than 6 months (*n* = 10, 7.3%).

Table 4

Frequency and Percent Statistics of Participants' Managerial Position and Experience

Demographic	Frequency (*n*)	%
Managerial Position		
Less than 1 year	7	5.1
at least 1 –but less than 3 years	26	19.0
at least 3 –but less than 5 years	43	31.4
5 years and above	61	44.5
Total	137	100.0
Experience		
Less than 6 months	10	7.3
at least 6 months but less than 1 Year	19	13.9
at least 1 – but less than 2 years	27	19.7
at least 2 – but less than 5 years	33	24.1
5 years and above	48	35.0
Total	137	100.0

Note. Total *N* = 137. Due to rounding errors, percentages may not equal 100%.

Table 5 shows the frequency of distribution of demographics of the primary cloud service model and deployment model. The most frequently observed service model was hybrid (*n* = 57, 41.6%, with the second most observed model was SaaS (*n* = 49, 35.8%). While the least observed service model was unknown (*n* = 5, 3.6%), the IaaS and PaaS models had low frequencies with (*n* = 12, 8.8%) and (*n* = 14, 10.2%) respectively. Moreover, the most frequently observed deployment model was private cloud (*n* = 57, 41.6%). The next greatest observed category for the deployment model included hybrid cloud (*n* = 38, 27.7%) with the next public cloud (*n* = 31, 22.6%) and community cloud (*n* = 10, 7.3%). The least observed deployment model category was unknown (*n* = 1, 0.7%).

Table 5

Frequency and Percent Statistics of Participants' Service Model and Deployment Model

Demographic	Frequency (*n*)	%
Service Model		
IaaS	12	8.8
SaaS	49	35.8
PaaS	14	10.2
Hybrid	57	41.6
Unknown	5	3.6
Total	137	100.0
Deployment Model		
Public Cloud	31	22.6
Private Cloud	57	41.6
Community Cloud	10	7.3
Hybrid Cloud	38	27.7
Unknown	1	0.7
Total	137	100.0

Note. Total *N* = 137. Due to rounding errors, percentages may not equal 100%.

Table 6 demonstrates the frequency and percent statistics of participants' industry. The most frequently observed category was cloud server prover and IT services (*n* = 79, 57.7%). The category other was the second most distributed (*n* = 31, 22.6%). Lastly, the categories energy, utilities, and gas; government and military; and nonprofit were the least observed (*n* = 1, 0.7).

Table 6

Frequency and Percent Statistics of Participants' Industry

Demographic	Frequency (*n*)	%
Industry		
Agriculture, Forestry, & Wildlife	7	5.1
Automotive, Sales, & Marketing	3	2.2
Cloud Service Provider & IT Services	79	57.7
Construction, Real Estate, & Housing	5	3.6
Education	3	2.2
Energy, Utilities, & Gas	1	0.7
Financial, Insurance, Banking, & Legal	3	2.2
Government & Military	1	0.7
Health Care & Pharmaceutical	3	2.2
Non-profit	1	0.7
Other	31	22.6
Total	137	100.0

Note. Total $N = 143$. Due to rounding errors, percentages may not equal 100%.

Validity and Reliability Assessment

As reviewed in Section 2, the measurement instrument I used depended on a validated scale from a previous study. While Lal and Bharadwaj (2016) tested and validated the constructs used in this study, I further assessed the construct scales' validity and reliability because I adapted the DeLone and McLean ISS instrument by replacing the instrument's 29 nominal variables to align with the context of my study.

Reliability Analysis

I computed Cronbach alpha coefficient for the dependent and each independent variable to test for reliability. The reporting of the reliability coefficients for data collection instruments and tests is a vital component of research as common practice dictates that an instrument's reliability must be high enough to make an informed decision regarding the study outcomes (Gugiu & Gugiu, 2018). A measure is considered reliable if independent measures yield the same result under identical conditions versus the outcomes resulting in heavily different measures, which exhibits mistrust in the measurement method (Schrepp, 2020). I assessed the Cronbach's alpha coefficient based on the parameters proposed by Di Martino et al. (2018), where the measure is considered to be reliable where Cronbach's alpha coefficient greater than 0.70 with a cutoff value of 0.5. As shown in Table 7, perception of information quality, perception of system quality, perception of system quality, and net benefits of cloud computing services all demonstrated good reliability. Perception of system use and perception of user satisfaction indicates questionable reliability. Nevertheless, none of the measures fell below the acceptable threshold of .50. Thus, all the measures were found to be sufficiently reliable.

Table 7

Cronbach's Alpha Summary of Reliability for the Dependent and Independent Variables

Scale	No. of Items	α
Perception of information quality	4	0.76
Perception of system quality	5	0.70
Perception of service quality	6	0.75
Perception of system use	4	0.67
Perception of user satisfaction	4	0.66
Net benefits of cloud computing services	6	0.75

Note. The table provides a summary of Cronbach's alpha reliability testing for each of the model's constructs.

Validity Analysis

The composite reliability and AVE were computed for the dependent and each independent variable to test for validity. A study's validity refers to the extent to which the observed data measures what is meant to measure and whether a study's methods allow for generalization to a population (Zyphur & Pierides, 2017). The complexities of sampling can have significant implications for external validity in that study is incapable of generalizing from small, nonrepresentative samples, while there are studies that conclude with broad-based generalizations grounded on small, specific samples (Laher, 2016). Demonstrating that measures are valid necessitates studies to determine the degree to which measures reflect the phenomena of interest, which is essential in selecting, understanding limitations, and determining where further research is needed for the measures (Frongillo et al., 2019). For this study, I used composite reliability to measure the instrument's convergent validity and AVE to measure its discriminant validity.

The convergent validity and discriminant validity were analyzed using the outcomes from a factor analysis in SPSS for each construct's indicator variables. The indicator loadings from the factor analysis were used to calculate the composite reliability and AVE in Microsoft Excel. Composite reliability was calculated using the formula $(\Sigma \lambda_i)^2 / ([\Sigma \lambda i]^2 + \Sigma\delta_{ii})$ where λ_i is the factor loadings and δ_{ii} the error variances (Sánchez-Oliva et al., 2017). I calculated AVE using the formula $(\Sigma \lambda_i^2)/n$ where λ_i is the factor loadings, and n is the number of factor loadings (dos Santos & Cirillo, 2021). For convergent validity, the suggested equivalences included AVE greater than 0.50, composite reliability greater than 0.70, and composite reliability greater than AVE (Canbulat et al., 2020). A construct is deemed valid if the AVE value is above 0.50 (Suyudi et al., 2020). Moreover, the indicator variable's standardized factor loading should be greater than 0.50 (Lee et al., 2020). Additionally, when the value of the factor loading in conjunction with a construct is higher, the item plays a more significant role in explaining the constructs, and a factor loading less than 3.0 lacks significance and should be disregarded (Farzandipour et al., 2021).

Table 8 summarizes the outcomes of the validity analysis based on the factor loadings. All of the factor loadings were greater than 0.50. The lowest factor loadings were found in the dependent variable net benefits of cloud computing services' indicators NET2 with a value of 0.594 and NET6 with a value of 0.629. The composite reliability ranged between 0.81–0.86, demonstrating a good convergent validity. The AVE scores were between 0.47– 0.58. Thus, all of the AVE values were acceptable except for the construct net benefits of cloud computing services with a value of 0.47. Although AVE's ideal thresholds greater than or equal to 0.5, lower values can be accepted when the composite reliability is well over 0.6 (Iyer & DoraiswamyIyer, 2020). Thus, with the net benefits of cloud computing services having composite reliability of 0.84, the AVE can be accepted.

Table 8

Test for Criterion Validity

Construct	Indicator Variables	*n*	λ_i	Composite Reliability	AVE
Perception of information quality	INF1	4	0.779	0.85	0.58
	INF2		0.739		
	INF3		0.781		
	INF4		0.743		
Perception of system quality	SYS1	5	0.773	0.83	0.50
	SYS2		0.642		
	SYS3		0.731		
	SYS4		0.688		
	SYS5		0.689		
Perception of service quality	SER1	6	0.767	0.86	0.50
	SER2		0.675		
	SER3		0.699		
	SER4		0.661		
	SER5		0.695		
	SER6		0.761		
Perception of system use	USE1	4	0.711	0.82	0.53
	USE2		0.803		
	USE3		0.682		
	USE4		0.698		
Perception of user satisfaction	SAT1	4	0.683	0.81	0.52
	SAT2		0.724		
	SAT3		0.712		
	SAT4		0.759		
Net benefits of cloud computing services	NET1	6	0.718	0.84	0.47
	NET2		0.594		
	NET3		0.739		
	NET4		0.725		
	NET5		0.713		
	NET6		0.629		

Note. The table provides a summary of the factor loadings for each variable and the composite reliability and average variance extracted for each construct.

Evaluations of Statistical Assumptions

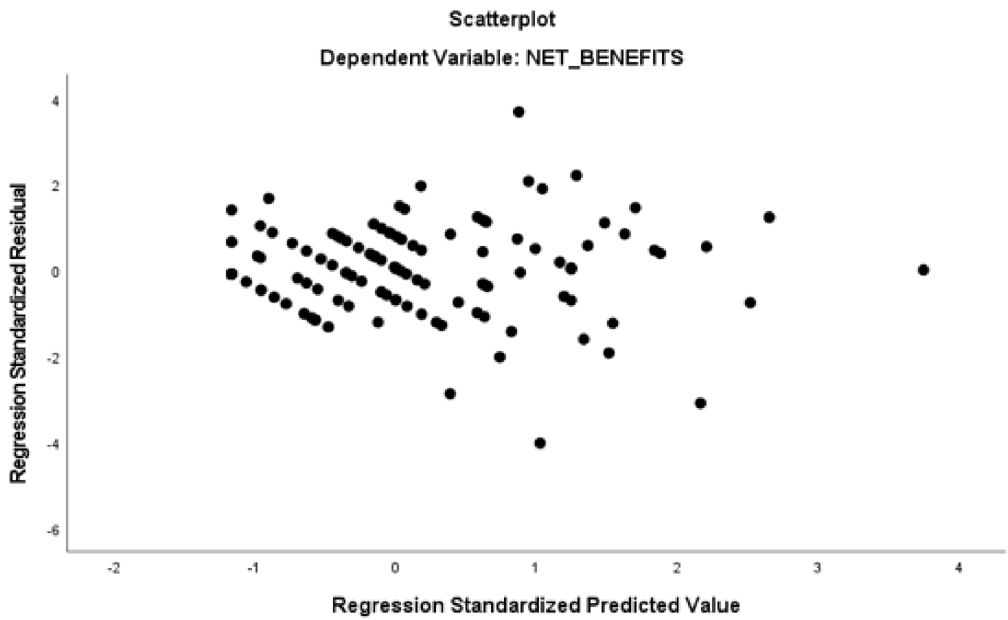
The assumptions of homoscedasticity, outliers, multicollinearity, normality, linearity, standard residuals, and Cook's distance were assessed. I analyzed homoscedasticity, normality, linearity, standard residuals, and Cook's distance using scatter plots. Additionally, a histogram was used to examine normality and normal distribution further. Potential outliers were examined using boxplots. The following section offers the result of the test of assumptions.

Homoscedasticity

Linear regression analysis necessitates the assumption involving homoscedasticity, which means all observed measures are equally dispersed from the estimated regression line (Lee, 2020). The regression model is homoscedastic when the residuals are roughly equal for the predicted values of the dependent variable, no distinctive patterns appear in the scatter plots, and the standardized residuals seem random (Kong et al., 2019). Additionally, the Durbin-Watson test, varying between zero and four, can help test for homoscedasticity, which measures the correlation between residual errors (Osei-Kyei & Chan, 2019). A Durbin-Watson statistic near two indicates non-autocorrelation, and a fit model versus a value toward zero or four suggests positive and negative autocorrelation and an unfit model (Hossein-Zadeh, 2016). Figure 4 demonstrates a random displacement of scores absent clustering or systematic pattern, which suggests that the assumption of homoscedasticity was met. The Durbin-Watson score is 2.217, which approaches the value of two and further suggests that the model is fit.

Figure 4

Residuals Standardized Predicted Value Testing for Homoscedasticity



Note. The figure illustrates the standardized residuals' variance distribution for the independent variable net benefits of cloud computing services.

Multicollinearity

I analyzed the assumption of multicollinearity by examining the tolerance and variance inflation factor (VIF). The assumption of multicollinearity refers to a lack of strongly correlated predictor variables that cause poor estimation of individual parameters of such variables and adversely affect the constructed model's generalizability (Tsao, 2019). A tolerance less than 0.10 signifies a severe issue with collinearity (Marcoulides & Raykov, 2019). A VIF greater than 10 indicates the existence of collinearity among the independent variables (Arabameri et al., 2019). Table 9 shows that the independent variable's tolerance ranges from 0.206 to 0.342, and the VIF ranges from 2.855 to 4.866.

Thus, the data reflects that there are no evidence of a violation of the assumption of multicollinearity.

Table 9

Multicollinearity Statistics

Variable	Tolerance	VIF
Perception of information quality	0.342	2.922
Perception of system quality	0.264	3.785
Perception of service quality	0.206	4.865
Perception of system use	0.350	2.855
Perception of user satisfaction	0.280	3.570

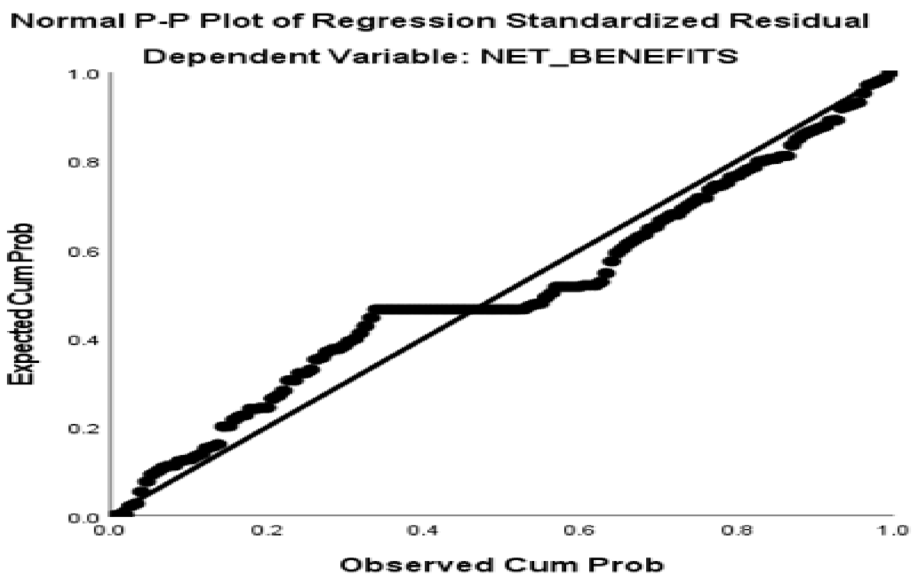
Note. The table provides a summary of the tolerance and VIF outcomes toward the evidence of a violation of the assumption of multicollinearity.

Normality

I examined the assumption of normality using a P-P scatter plot and histogram plot. Graphical methods such as histograms and normal probability plots are used to check for normality to compare their goodness of fit with the data (Wooluru et al., 2016). When data are normally distributed, the histogram or frequency distribution data will shape a bell curve (Vetter, 2017a). Furthermore, if the data are consistent with a normal distribution, the normality plot will roughly follow a straight line and not deviate systematically from a straight line (Curran-Everett, 2017). The frequency distribution of the continuous data set, shown in Figure 5 P-P plot and Figure 6 histogram, indicated an approximately normal distribution that supported normality.

Figure 5

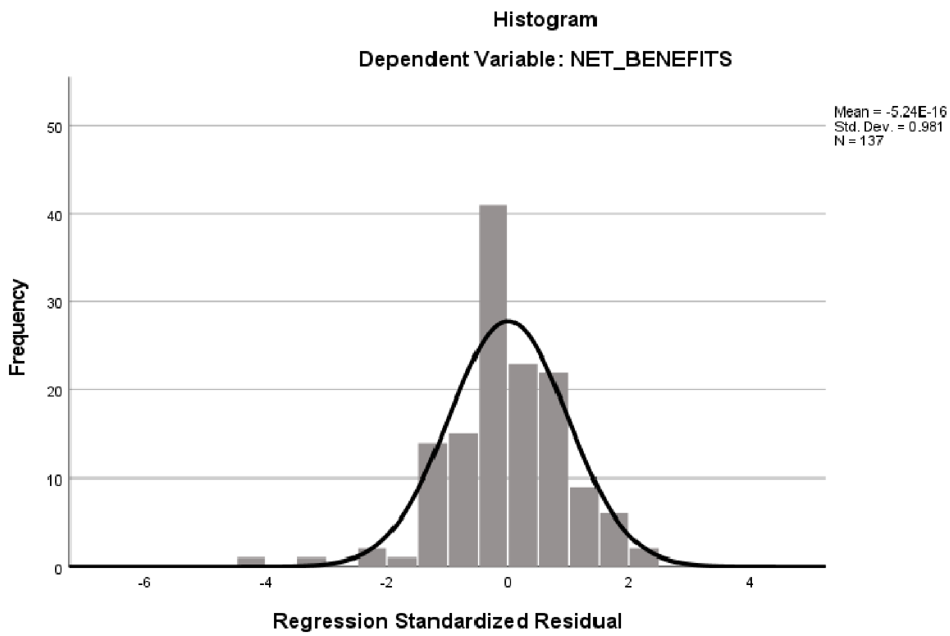
The Normal P-P Plot of Regression Standardized Residual



Note. The figure illustrates a Normal P-P plot, which illustrates the skewness of net benefits of cloud computing services variable.

Figure 6

Histogram Showing Normality of Distribution



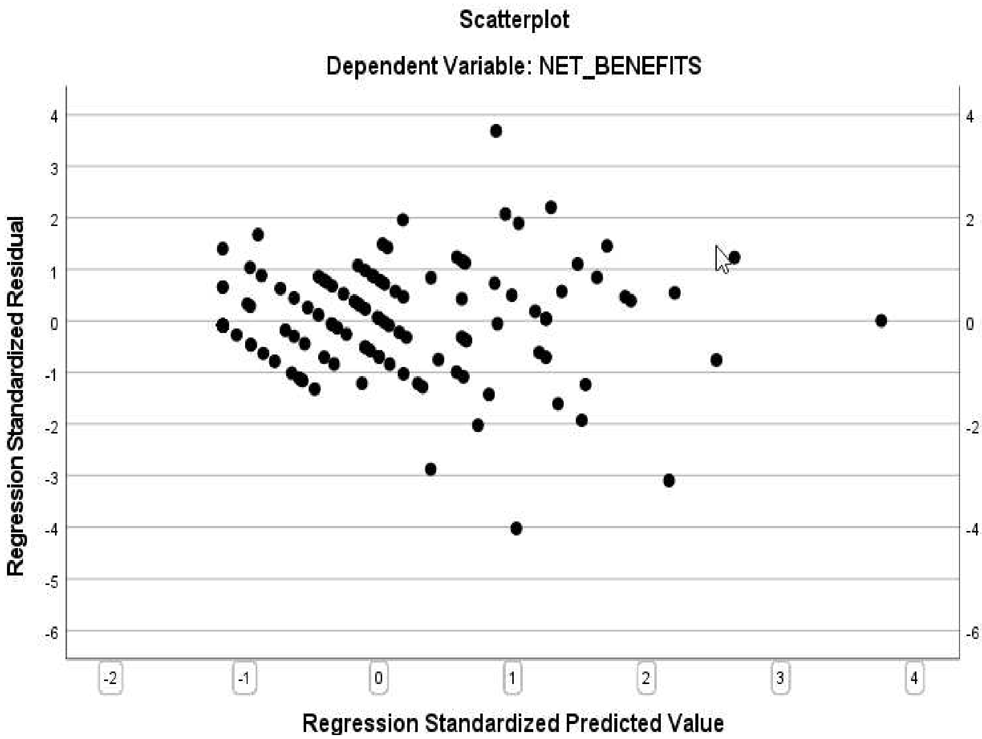
Note. The figure illustrates the range of data of the net benefits of cloud computing services variable.

Standard Residuals

I examined the assumption of standard residuals through the visual inspection of a scatter plot. Residuals signify the difference between the actual and predicted values with the confidence of being normally distributed (Chang et al., 2017). The observation of large residuals greater than +/- 3 are possible outliers (Imon & Hadi, 2008). The lack of an obvious or systematic pattern in Figure 7, the scatterplot of the standardized residuals, supports the reasonableness of standardized residuals' assumptions being met. However, there are several cases (case: 33, 115, 141) that may require further investigation for outliers.

Figure 7

Scatterplot of the Standardized Residuals



Note. The figure illustrates the regression model's standard residuals' plotting toward the dependent variable net benefits of cloud computing services.

Outliers

I examined the assumption of outliers through the visual inspection of boxplots. Boxplots are a highly utilized exploratory data analysis instrument in statistical practice for outlier judgment (Li et al., 2016). An observation is deemed as possible irregular data when its value does not fit into the interval (Zhao & Yang, 2019). There were five potential univariate outliers identified from the observation of boxplots. For instance, Figure J1, in Appendix J, illustrates potential outliers for the independent variable perception of information quality, indicating one outlier (case: 141). Figure J2 displays potential outliers for the independent variable perception of system quality, indicating no outliers. Figure J3 illustrates potential outliers for the independent variable perception of service quality, which had two outliers (case: 133, 141). Figure J4 illustrates potential outliers for the independent variable perception of system use, which had two outliers (case: 58, 59). Figure J5 illustrates potential outliers for the independent variable perception of user satisfaction which had one outlier (case: 141). Figure J6 illustrates potential outliers for the dependent variable net benefits of cloud computing services with three outliers (case: 33, 133, and 141). Each of the identified outliers was tagged for removal from the inferential analysis.

Cook's Distance

I assessed the assumption of influential data points using visual inspection of Cook's Distance scatterplot versus the maximum cutoff value derived from the SPSS residual statistics. Cook's distance measures how distant the independent variable values of a specific observation from those of the other observations where the uppermost leveraged points are those observations that might be perceived as extreme or outlying values (Padron-Hidalgo et al., 2020). Cook's distance is calculated by fitting a multiple regression model for n observations based on the independent variables, which the observations above the cutoff distance are considered to be belonging to an influential cluster (Jayakumar & Sulthan, 2015). As shown in Table 10, the cutoff value for Cook's Distance is 0.111. The examination of Figure 8 shows that the three cases (case: 33, 0.1074), (case: 45, 0.1016), and (case: 100, 0.1108) approached the cutoff value. However, only case 100 exceeded the cutoff value and was tagged for removal.

Table 10

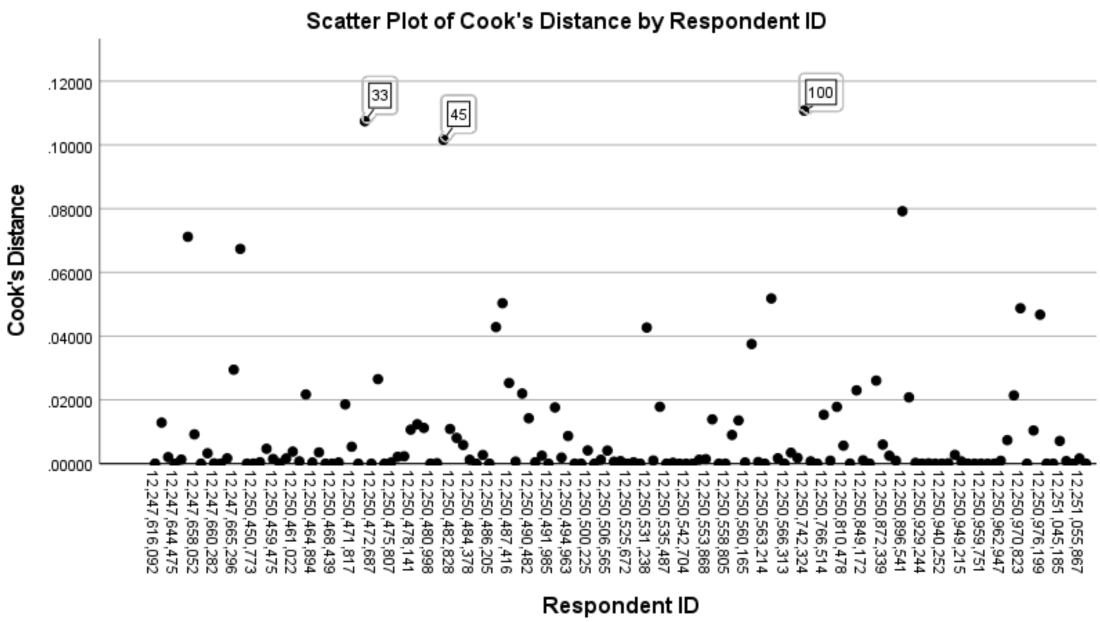
Cook's Distance Measure

Distance Measure	Minimum	Maximum	*n*
Cook's Distance	0.000	0.111	143

Note. The table provides the residual statistics outcome for Cook's D, in which the maximum value sets the cutoff baseline of influence.

Figure 8

Cook's Distance Scatter Plot by Respondent ID



Note. The figure illustrates Cook's Distance model's influence plotting toward the dependent variable net benefits of cloud computing services.

Inferential Analysis

I tested the hypothesis using multiple regression analysis to determine if there were any significant relationship between (a) perception of information quality, (b) perception of system quality, (c) perception of service quality, (d) perception of system use, (e) perception of user satisfaction, and net benefits of cloud computing services. I calculated the composite scores for the independent and dependent variables by averaging survey scores related to each construct.

Effect Size

I examined the effect size for this study using a Cohen's F analysis. The effect size is used in quantitative research to evaluate the correlation between two or more variables where the independent variable's influence on the dependent variable can be measured (Nikpeyma et al., 2020). The larger the effect size measures, the stronger the relationship between two variables (Moeyaert, 2019). A common method of calculating effect size is Cohen's F for regression analysis (Correll et al., 2020). Cohen's F is calculated by the formula r^2/ (1 - r^2), where r is the regression variance explained (Clugston et al., 2019). Cohen's F values ranging from 0.1 to 0.24 indicates a small effect, values ranging from 0.25 to 0.39 indicate a moderate effect, and values greater than 0.4 show a large effect (Knowlden & Conrad, 2018). As shown in Table 11, the variance explained for the regression model is 0.87, which computes an effect size of 3.25. Thus, one can conclude that the model has a high effect size, which means that the five independent variables as a whole significantly affected the dependent variable net benefits of cloud computing services.

Table 11

Cohen's F Summary

Model	r	r^2	Cohen's F
1	0.87	0.76	3.25

Note. The table summarizes the variance explained and Cohen's F value for the regression model with the five independent variables perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction.

Goodness-of-Fit

I examined the goodness-of-fit for this study using the chi-square analysis. A goodness of fit test is based upon establishing how well the observed sample data match a population's expected distribution under the applicable model (Veazie & Ye, 2020). A null hypothesis test for goodness-of-fit tests can indicate that the model fits the data well, such that the alternative hypothesis suggests that there is an unspecific problem with the model's fit (Fagerland & Hosmer, 2017). The chi-square statistic is a method to assess that the model conforms with the covariance structure of the observed variables (Yildiz & Güngörmüş, 2016). The chi-square goodness of fit test requires the analyst to state a null and an alternative hypothesis, where the p-value ≤ alpha suggests the variable is likely to come from a specified distribution and the p-value > alpha indicates that the variable is unlikely to come from a specified distribution (McNeish, 2020). Tables K1– K5, in Appendix K, summarizes the chi-square analysis for each of the independent indicator variables versus each dependent indicator variable, where X^2 is the chi-square value, df is the degrees of freedom, and p is the p-value.

Examining the data, I found that only one of the 138 pairs NET2 and SER1, shown in Table K3, was not significant, $X^2(4, N = 137) = 7.88$, $p = .096$. Thus, using the goodness of fit test I failed to reject the null hypothesis for each of the independent variables (a) perception of information quality, (b) perception of system quality, (c) perception of service quality, (d) perception of system use, (e) perception of user satisfaction. Additionally, one can conclude that the tests held their 5% nominal level well under the null hypothesis. Additionally, one may observe that some of the tests were more powerful when df = 6 or 9 compared to 2 and 3.

Multiple Regression Analysis

I performed the multiple linear regression analysis, $\alpha = 0.5$, to examine the relationship between perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction, and net benefits of cloud computing services. The independent variables were perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction. The dependent variable was net benefits of cloud computing services

RQ: Are there significant relationships among the (a) perception of information quality, (b) perception of system quality, (c) perception of service quality, (d) perception of system use, (e) perception of user satisfaction, and net benefits of cloud computing services?

$H_{0:}$ There are no significant relationships among (a) perception of information quality, (b) perception of system quality, (c) perception of service quality, (d) perception of system use, (e) perception of user satisfaction, and net benefits of cloud computing services.

H_a: There is a significant relationship among (a) perception of information quality, (b) perception of system quality, (c) perception of service quality, (d) perception of system use, (e) perception of user satisfaction, and net benefits of cloud computing services.

The results of the linear regression model are shown in Table 12–14. In Table 12, *R* is the correlation between the observed and predicted values of the dependent variable (Armstrong, 2019). R-squared indicates the proportion of spread or variance (Mondal & Mondal, 2017). The adjusted R-squared measures the proportion of the variation of regression models as a number of predictors are added to the model (Gouda & El-Hoshy, 2020). The standard error of the estimate is the standard deviation of the linear regression model's residuals, which measures the accuracy or magnitude of prediction errors (Hammers & Duff, 2019). The significance (Sig.) is the p-value that indicates the evidence that the null hypothesis is true (Di Leo & Sardanelli, 2020).

Table 12

Multiple Linear Regression Analysis Model Summary

R	R-Square	Adjusted R-Square	Std. Error of the Estimate	Sig.
0.874	0.765	0.756	0.205	0.000

Note. The table provides the model summary data. a. Predictors: (Constant), perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction. b. Dependent Variable: net benefits of cloud computing services.

In Table 13, the sum of squares measures the degree of the spread between each value and the mean (LaMotte, 2018). The degree of freedom (df) is the number of independent observations in the model's sample data (Rodgers, 2019). The mean square is the sum of squares divided by the degrees of freedom (Choe et al., 2017). The F statistic is the mean square regression divided by the mean square residual (Mehrens et al., 2005). The Sig. indicates the p-value associated with the F statistic (Zhang, Cheng, et al., 2019).

Table 13

Multiple Linear Regression Analysis ANOVA of Research Model

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	17.969	5	3.594	85.16	0.000
Residual	5.53	131	0.042		
Total	22.50	136			

Note. The table provides the ANOVA summary data. a. Predictors: (Constant), perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction. b. Dependent Variable: net benefits of cloud computing services.

In Table 14, the value B indicates the unstandardized coefficients, which are the regression values predicting the dependent variable from the independent variable (van Ginkel, 2020). The standard error (SE) signifies the observed values' variance from the regression line (Kurniawan, 2016). Additionally, the standardized coefficients (β) indicate the coefficients if the regression variables are standardized (Lu & Westfall, 2019). The t-value (t) is the coefficient divided by the standard error, which measures the difference in the means (Edwards & Mee, 2008). Moreover, Sig. provides the two-tailed p-value used to test the null hypothesis with an alpha of 0.05 (Peskun, 2020).

Table 14

Multiple Linear Regression Analysis Coefficients of Research Model

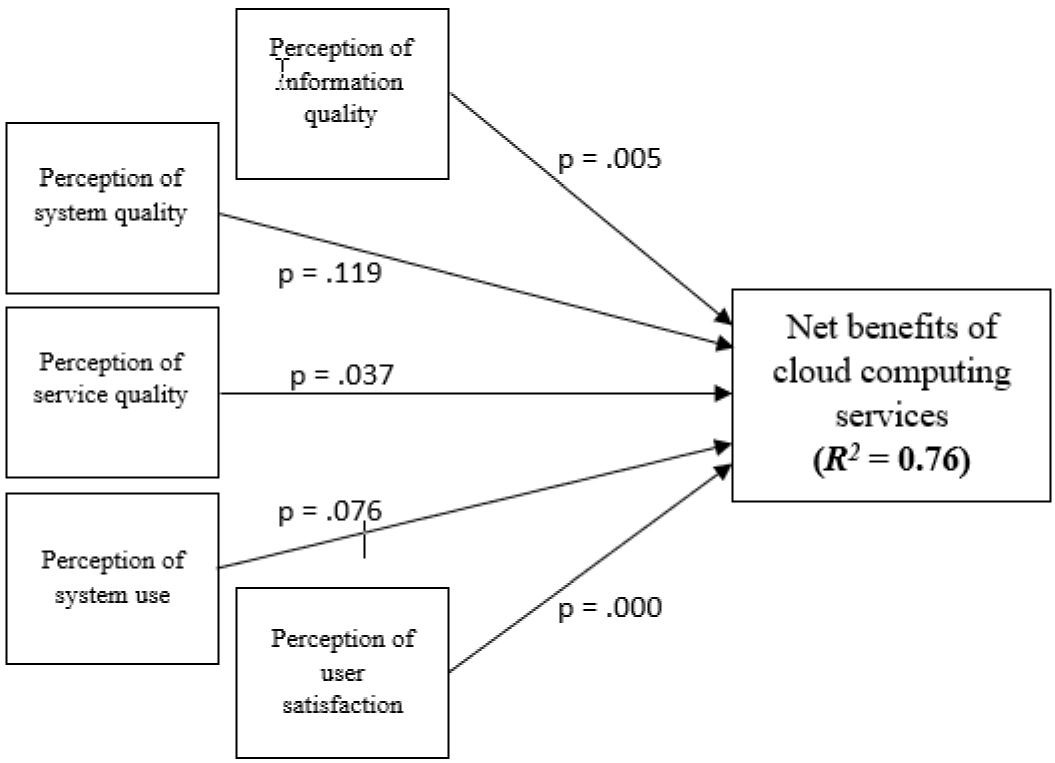
Variable	Unstandardized coefficients B	Unstandardized coefficients Standard Error (SE)	Standardized Coefficients Beta β	t	Sig.
Perception of information quality	0.20	0.07	0.19	2.84	0.005
Perception of system quality	0.11	0.07	0.12	1.57	0.119
Perception of service quality	0.19	0.09	0.18	2.10	0.037
Perception of system use	0.11	0.06	0.12	1.79	0.076
Perception of user satisfaction	0.37	0.07	0.38	5.02	0.000

Note. The table provides the multiple liner regression analysis summary data. Results: $F(5, 131) = 85.16$, $p < .001$, $R^2 = 0.76$ a. Dependent Variable: net benefits of cloud computing services.

Examining Tables 12–14, I concluded that the model was significant, $F(5, 131) = 85.16$, $p < .001$, $R^2 = 0.76$. The R^2 (0.76) indicated that approximately 76% of the variance in net benefits of cloud computing services could be explained by the linear combination of the independent variables. I examined the individual predictors further, shown in Table 20, which revealed that perception of system quality ($t = 1.57$, $p =.119$) and perception of system use ($t = 1.79$, $p = .076$) did not have a statistically significant relationship with net benefits of cloud computing services ($p > .05$). Thus, I accepted the null hypothesis. However, individual predictors results revealed a statistically significant relationship between perception of information quality ($t = 2.84$, $p = .005$), perception of service quality ($t = 2.10$, $p = .037$), and perception of user satisfaction ($t = 5.02$, $p = .000$), at .05 level, with net benefits of cloud computing services. Thus, I rejected the null hypothesis. Figure 9 illustrates the results of the model's p-value and R^2 outcomes.

Figure 9

ISS Research Model Results of Multiple Linear Regression Analysis



Note. The figure illustrates the results of the overarching hypothesis test of the ISS model, where *p* indicates the significance (p-value) for each hypothesis and R^2 indicates the r-squared value.

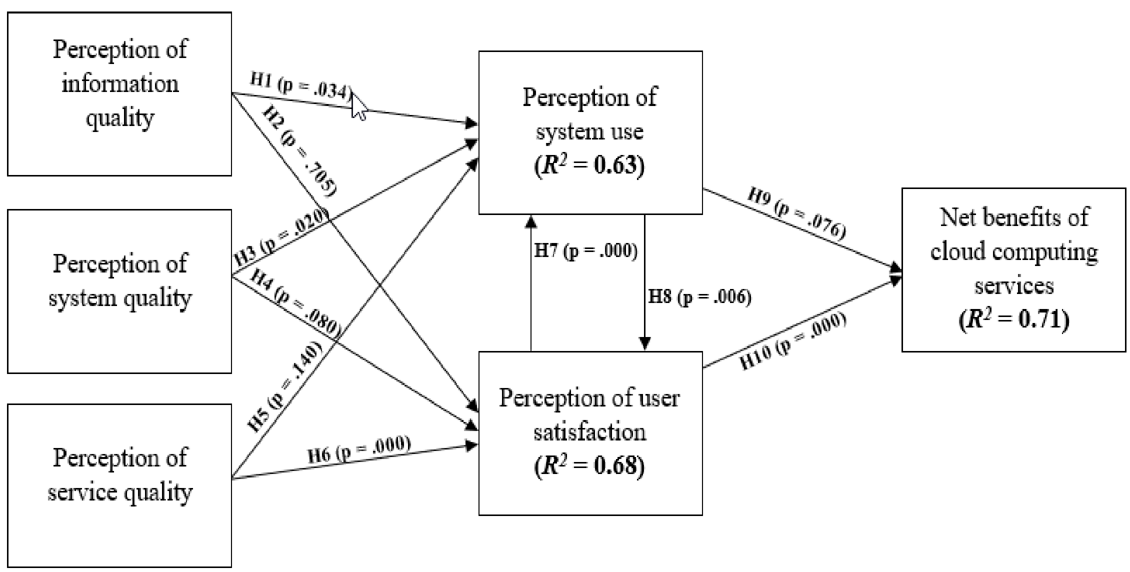
Subordinate Questions and Hypotheses

I addressed the overarching research question and hypotheses by exploring ten subordinate research questions (RQ1–RQ10), ten corresponding null hypotheses ($H_0 1$–$H_0 10$), and ten corresponding alternative hypotheses ($H_a 1$– $H_a 10$), illustrated in Figure

10. To examine the subordinate research questions *H*1, *H*3, *H*5, and *H*7, I performed a multiple linear regression analysis, $\alpha = 0.5$, to investigate the relationship between (a) perception of information quality, (b) perception of system quality, (c) perception of service quality, (d) perception of user satisfaction, and perception of system use. The independent variables were perception of information quality, perception of system quality, perception of service quality, perception of user satisfaction. The dependent variable was the perception of system use. Table 15–17 summarizes the linear regression model results for the subordinate research questions *H*1, *H*3, *H*5, and *H*7.

Figure 10

ISS Research Model Results of Subordinate Hypothesis Testing



Note. The figure illustrates the results of the subordinate hypothesis testing of the ISS model, where *p* indicates the significance (p-value) for each hypothesis and R^2 indicates the r-squared value.

Table 15

Multiple Linear Regression Analysis Model Summary of Subordinate Research Questions H1, H3, H5, and H7

R	R-Square	Adjusted R-Square	Std. Error of the Estimate	Sig.
.792	0.627	0.615	0.281	0.000

Note. The table provides the model summary data. a. Predictors: (Constant), perception of information quality, perception of system quality, perception of service quality, perception of user satisfaction. b. Dependent Variable: perception of system use.

Table 16

Multiple Linear Regression Analysis ANOVA of Research Model of Subordinate Research Questions H1, H3, H5, and H7

Model	Sum of Squares	df	Mean Square	*F*	Sig.
Regression	17.582	4	4.396	85.16	0.000
Residual	10.48	132	0.0		
Total	28.06	136			

Note. The table provides the ANOVA summary data. a. Predictors: (Constant), perception of information quality, perception of system quality, perception of service quality, perception of user satisfaction. b. Dependent Variable: perception of system use.

Table 17

Multiple Linear Regression Analysis of Subordinate Research Questions H1, H3, H5, and H7

Variable	*B*	*SE*	Standardized Coefficients Beta *β*	*t*	Sig.
Perception of information quality	0.20	0.09	0.17	2.14	0.03
Perception of system quality	0.23	0.10	0.22	2.36	0.02
Perception of service quality	0.18	0.12	0.16	1.48	0.14
Perception of user satisfaction	0.36	0.10	0.34	3.76	0.00

Note. The table provides the multiple liner regression analysis summary data. Results: $F(4, 132) = 55.38$, $p < .001$, $R^2 = 0.63$ a. Dependent Variable: perception of system use.

I performed a multiple linear regression analysis, $\alpha = 0.5$, for subordinate research questions *H*2, *H*4, *H*6, and *H*8, which examines the relationship between (a) perception of information quality, (b) perception of system quality, (c) perception of service quality, (d) perception of system use, and perception of user satisfaction. The independent variables were perception of information quality, perception of system quality, perception of service quality, perception of system use. The dependent variable was the perception of user satisfaction. Table 18–20 summarizes the linear regression model results for the subordinate research questions *H*2, *H*4, *H*6, and *H*8.

Table 18

Multiple Linear Regression Analysis Model Summary of Subordinate Research Questions H2, H4, H6, and H8

R	R-Square	Adjusted R-Square	Std. Error of the Estimate	Sig.
.827	0.684	0.675	0.241	0.000

Note. The table provides the model summary data. a. Predictors: (Constant), perception of information quality, perception of system quality, perception of service quality, perception of system use. b. Dependent Variable: perception of user satisfaction.

Table 19

Multiple Linear Regression Analysis ANOVA of Research Model of Subordinate Research Questions H2, H4, H6, and H8

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	16.646	4	4.162	71.58	0.000
Residual	7.67	132	0.058		
Total	24.32	136			

Note. The table provides the ANOVA summary data. a. Predictors: (Constant), perception of information quality, perception of system quality, perception of service quality, perception of system use. b. Dependent Variable: perception of user satisfaction.

Table 20

Multiple Linear Regression Analysis of Subordinate Research Questions H2, H4, H6, and H8

Variable	B	SE	Standardized Coefficients Beta β	t	Sig.
Perception of information quality	0.03	0.08	0.03	0.38	0.71
Perception of system quality	0.15	0.08	0.15	1.76	0.08
Perception of service quality	0.47	0.10	0.44	4.95	0.00
Perception of system use	0.27	0.07	0.29	3.76	0.00

Note. The table provides the multiple liner regression analysis summary data. Results: $F(4, 132) = 71.58$, $p < .001$, $R^2 = 0.68$ a. Dependent Variable: perception of user satisfaction.

Lastly, I assessed the subordinate research questions *H*9 and *H*10 from the regression analysis of the research model and the data collected in Table 20. However, I performed a regression analysis, $\alpha = 0.5$, to examine the amount of variance that (a) perception of system use and (b) perception of user satisfaction had on net benefits of cloud computing services. The independent variables were perception of system use and perception of user satisfaction. The dependent variable was the net benefits of cloud computing services. Table 21 and 22 summarizes the linear regression model results for the subordinate research questions *H*9 and *H*10.

Table 21

Multiple Linear Regression Analysis Model Summary of Subordinate Research Questions H9 and H10

R	R-Square	Adjusted R-Square	Std. Error of the Estimate	Sig.
.840	0.706	0.701	0.227	0.000

Note. The table provides the model summary data. a. Predictors: (Constant), perception of system use and perception of user satisfaction. b. Dependent Variable: net benefits of cloud computing services.

Table 22

Multiple Linear Regression Analysis ANOVA of Research Model of Subordinate Research Questions H9 and H10

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	16.582	2	8.291	160.65	0.000
Residual	6.91	134	0.052		
Total	23.50	136			

Note. The table provides the ANOVA summary data. a. Predictors: (Constant), perception of system use and perception of user satisfaction. b. Dependent Variable: net benefits of cloud computing services.

RQ1: RQ1 pertained to what was the relationship between the perception of information quality and perception of system use of cloud computing services. One can conclude that there was a significant relationship between perception of information quality (t = 2.14, p = .034) and perception of system use. Thus, I rejected the null hypothesis.

RQ2: RQ2 pertained to what was the relationship between perception of information quality and perception of user satisfaction of cloud computing services. One can conclude that there was not a significant relationship between perception of information quality ($t = 0.38$, $p = .705$) and perception of user satisfaction. Thus, I accepted the null hypothesis.

RQ3: RQ3 pertained to what was the relationship between perception of system quality and perception of system use of cloud computing services. One can conclude that there was a significant relationship between perception of system quality ($t = 2.36$, $p = .020$) and perception of system use. Thus, I rejected the null hypothesis.

RQ4: RQ4 pertained to what was the relationship between perception of system quality and perception of user satisfaction of cloud computing services. One can conclude that there was not a significant relationship between perception of system quality ($t = 1.76$, $p = .080$) and perception of user satisfaction. Thus, I accepted the null hypothesis.

RQ5: RQ5 pertained to what was the relationship between perception of service quality and perception of system use of cloud computing services. One can conclude that there was not a significant relationship between perception of service quality ($t = 1.48$, $p = .140$) and perception of system use. Thus, I accepted the null hypothesis.

RQ6: RQ6 pertained to what was the relationship between the perception of service quality and perception of user satisfaction of cloud computing services. One can conclude that there was a significant relationship between perception of service quality ($t = 4.95$, $p = .000$) and perception of user satisfaction. Thus, I rejected the null hypothesis.

RQ7: RQ7 pertained to what was the relationship between perception of user satisfaction and perception of system use of cloud computing services. One can conclude that there was a significant relationship between perception of user satisfaction (t = 3.76, p = .000) and perception of system use. Thus, I rejected the null hypothesis.

RQ8: RQ8 pertained to what was the relationship between perception of system use and perception of user satisfaction of cloud computing services. One can conclude that there was a significant relationship between perception of system use (t = 3.76, p = .000) and perception of user satisfaction. Thus, I rejected the null hypothesis.

RQ9: RQ9 pertained to what was the relationship between the perception of system use and net benefits of cloud computing services. One can conclude that there was not a significant relationship between perception of system use (t = 1.79, p = .076) and net benefits of cloud computing services. Thus, I accepted the null hypothesis.

RQ10: RQ10 pertained to what was the relationship between perception of user satisfaction and net benefits of cloud computing services. One can conclude that there was a significant relationship between perception of user satisfaction (t = 5.02, p = .000) and net benefits of cloud computing services. Thus, I rejected the null hypothesis.

Theoretical Discussion of the Findings

Using the DeLeon and McLean ISS framework as guidance, I applied a quantitative instrument to survey IT leaders in the United States to gain an understanding of their perspective of what determinants influence the realization of cloud computing services' expected benefits. DeLone and McLean (1992) developed the IIS framework to comprehensively understand information systems' success, explaining the relationships among six critical dimensions of success in which information systems are assessed. The DeLone and McLean ISS model has been extensively used in prior studies of IS success using the multidimensional measures information quality, system quality, service quality, system use, user satisfaction, and net benefits (Jeyaraj, 2020).

This study's empirical evidence supported accepting the alternative hypotheses for the independent variables perception of information quality, perception of service quality, and perception of user satisfaction. I concluded that the model was significant, $F(5, 131) = 85.16$, $p < .001$, $R^2 = 0.76$. The results from the overarching research question indicated that approximately 76% of the variance in net benefits of cloud computing services could be explained by the independent variables (a) perception of information quality, (b) perception of system quality, (c) perception of service quality, (d) perception of system use, and (e) perception of user satisfaction ($R^2 = 0.76$).

I evaluated the study's model results with the findings of Lal and Bharadwaj (2016), summarized in Table 23, which the researchers' model exhibited the independent variables accounted for 54% of the total variance to the ISS model versus 76% of this study's model. Further, Lal and Bharadwaj construct systems use and user satisfaction account for 75% of the total variance toward net benefits compared to the study findings of 70%. The researchers found that *H*2 (system quality → user satisfaction), *H*3 (service quality → system use), *H*5 (information quality → system use), *H*6 (information quality → user satisfaction), *H*7a (system use → user satisfaction), *H*7b (user satisfaction → system use), *H*8 (system use → net benefits), and *H*9 (user satisfaction → net benefits) were statistically significant. However, the study found *H*1 (information quality →

system use), *H*3 (system quality → system use), *H*6 (service quality → user satisfaction), *H*7 (user satisfaction → system use), *H*8 system use → user satisfaction), and *H*10 (user satisfaction → net benefits) were statistically significant.

Table 23

Research Model & Lal & Bharadwaj (2016) Outcomes Comparison

Measure	Study Findings	Lal and Bharadwaj (2016) Findings
Model Proportion of Variance (R^2) of IVs	0.76	0.54
System Use Proportion of Variance (R^2)	0.63	0.54
User Satisfaction Proportion of Variance (R^2)	0.68	0.67
Net Benefits Proportion of Variance (R^2)	0.71	0.75
p-values		
information quality → system use	p < 0.05 (H1)	p < 0.05 (H5)
information quality → user satisfaction	.705 (H2)	p < 0.001 (H6)
system quality → system use	p < 0.05 (H3)	.515 (H1)
system quality → user satisfaction	.080 (H4)	p < 0.001 (H2)
service quality → system use	.140 (H5)	p < 0.001 (H3)
service quality → user satisfaction	p < 0.001 (H6)	0.364 (H4)
user satisfaction → system use	p < 0.001 (H7)	p < 0.05 (H7b)
system use → user satisfaction	p < 0.05 (H8)	p < .001 (H7a)
system use → net benefits	.076 (H9)	p < .001 (H8)
user satisfaction → net benefits	p < 0.001 (H10)	p < .05 (H9)

Note. The table provides a comparison summary of the research model's R^2 statistics and subordinate hypothesis p-values with the Bharadwaj (2016) ISS model.

As applied to this study, the DeLone and McLean ISS model suggested that the independent variables information quality, system quality, service quality, user satisfaction, and system use impacted the net benefits of an information system. The statistical model supported the notion that information quality, service quality, and user satisfaction influence the net benefits of cloud computing services. However, the model did not support the perception that system quality and system use affect the net benefits of cloud computing services. Furthermore, I performed an analysis of the theoretical framework and relationship(s) among variables by comparing the study findings with other scholarly literature, described in Table 24.

Table 24

Scholarly Studies Utilized in Theoretical Framework Comparative Analysis

Analysis Resource List	Information System
Van Cauter et al. (2017)	Cultural event database, library information, monitoring system, and geographic information system
Yakubu and Dasuki (2018)	eLearning systems
Widiastuti et al. (2019)	Information expense systems
Arsyanur et al. (2019)	Civil apparatus management information system
Wang and Liao (2008)	eGovernment systems
Khayun et al. (2012)	Excise tax payment (e-excise) system
Salam and Farooq (2020)	Web-based collaborative learning information system
Shim and Jo (2020)	online health information sites
Bradford et al. (2020)	Audit software
Khand and Kalhoro (2020)	ERP systems
Mkinga and Mandari (2020)	Students information systems

Note. The table provides a listing of the scholarly literature used in the theoretical framework comparative analysis.

Information Quality

I defined information quality by the four variables trustworthy, accuracy, secure, and completeness. The outcome analysis of the perception of information quality indicated a significant relationship with the net benefits of cloud computing services. Furthermore, the examination of the subordinate hypothesis *H*1 found that information quality had a significant relationship with system use. The outcomes of hypothesis *H*2 indicated that information quality did not have a significant relationship with user satisfaction.

The research of Yakubu and Dasuki (2018), Shim and Jo (2020), Wang and Liao (2008), and Bradford et al. (2020) also concluded that a significant relationship existed between information quality and system use. However, Van Cauter et al. (2017), Widiastuti et al. (2019), Arsyanur et al. (2019), Khayun et al. (2012), Salam and Farooq (2020), Khand and Kalhoro (2020), and Mkinga and Mandari (2020) all found that a significant relationship did not exist between information quality and system use. One possible reason for the stark contrast in the importance of information quality regarding system use is that the sample population included end-users and students. Thus, most participants did not find that the system's fitness impacted their desire to use the information system as opposed to that of IT managers.

The studies of Yakubu and Dasuki (2018), Salam and Farooq (2020), and Bradford et al. (2020) also concluded that a significant relationship did not exist between information quality and user satisfaction. Whereas the findings of Van Cauter et al. (2017), Widiastuti et al. (2019), Arsyanur et al. (2019), Wang and Liao (2008), Khayun et al. (2012), Shim and Jo (2020), Khand and Kalhoro (2020), and Mkinga and Mandari (2020) all suggested that a significant relationship existed between information quality and user satisfaction. Consequently, the findings of these studies indicated that the students and end-users who participated in the research found that the system's informational fitness had a more considerable impact on their contentment with the systems.

System Quality

I defined system quality by the five variables reliable, ease of use, responsiveness (response time), accessibility, and availability (high). The outcome analysis of the perception of system quality indicated no significant relationship with the net benefits of cloud computing services. Additionally, the review of the subordinate hypothesis H3 found that system quality had a significant relationship with system use. However, the results of H4 indicated that system quality did not have a significant relationship with user satisfaction.

The studies of Yakubu and Dasuki (2018), Khayun et al. (2012), Khand and Kalhoro (2020), and Mkinga and Mandari (2020) also found system quality to have a significant relationship with system use. However, Van Cauter et al. (2017), Widiastuti et al. (2019), Arsyanur et al. (2019), Wang and Liao (2008), Salam and Farooq (2020), Shim and Jo (2020), and Bradford et al. (2020) all found that there was no significant relationship between system quality and system use. One can conclude from the data that IT managers found that a systems performance and accessibility are more critical to their desire to utilize a system than an end-user of a system.

Similar to the study results, Yakubu and Dasuki (2018), Khayun et al. (2012), Shim and Jo (2020), Khand and Kalhoro (2020), and Mkinga and Mandari (2020) found that there was no significant relationship between system quality and user satisfaction. Conversely, Van Cauter et al. (2017), Widiastuti et al. (2019), Arsyanur et al. (2019), Wang and Liao (2008), Salam and Farooq (2020), Shim and Jo (2020), and Bradford et al. (2020) found that a significant relationship existed between system quality and user satisfaction. A possible explanation could include that most end-users surveyed believed that the system's integrity has a greater impact on their contentment with the system than IT managers. Additionally, one may conclude that an end-user's satisfaction with a system is not necessarily measured by their use of a system.

Service Quality

I defined service quality by the six variables responsiveness, assurance, empathy, effective solution, service level (customer service), and knowledgeable (experts). The outcome analysis of the perception of service quality indicated a significant relationship with the net benefits of cloud computing services. Furthermore, examining the subordinate hypotheses H5, the study's outcomes revealed that service quality did not have a significant relationship with system use. However, the results of hypothesis H6 indicated a significant relationship between service quality and user satisfaction.

Yakubu and Dasuki (2018), Van Cauter et al. (2017), Wang and Liao (2008), Salam and Farooq (2020), Shim and Jo (2020), and Bradford et al. (2020) concurred that service quality and system use did not have a significant relationship. However, Widiastuti et al. (2019), Arsyanur et al. (2019), and Khayun et al. (2012) findings showed that service quality had a significant relationship with system use. Consequently, the findings suggest that service quality, or level of support, does not substantially impact the majority of either IT managers or end-users surveyed desire to utilize a system.

Comparable to the study results, the research of Yakubu and Dasuki (2018), Van Cauter et al. (2017), Widiastuti et al. (2019), Arsyanur et al. (2019), Khayun et al. (2012), Salam and Farooq (2020), Shim and Jo (2020), Khand and Kalhoro (2020), and Mkinga and Mandari (2020) all found that there was a significant relationship between service quality and user satisfaction. On the contrary, the studies of Wang and Liao (2008) and Bradford et al. (2020) concluded that service quality did not have a significant relationship with user satisfaction. As a result, the findings suggested that both IT managers and end-users surveyed found that service quality, or level of support, has a more significant impact on one's contentment with an information system.

System Use

I defined system use by the four variables frequency of use, duration of use, continuance use intentions, and system dependency. The outcome analysis of the perception of system use indicated no significant relationship with net benefits of cloud computing services, which also addressed the subordinate hypotheses H9. Moreover, examining the subordinate hypothesis H8, the findings showed that system use had a significant relationship with user satisfaction.

The studies of Van Cauter et al. (2017), Widiastuti et al. (2019), Wang and Liao (2008), Khayun et al. (2012), Khand and Kalhoro (2020), and Mkinga and Mandari (2020) also found that the relationship between system use and user satisfaction was significant. But, Arsyanur et al. (2019) did not find the relationship between system use and user satisfaction to be significant. The studies of Yakubu and Dasuki (2018), Salam and Farooq (2020), Shim and Jo (2020), and Bradford et al. (2020) did not test the relationship between system use and user satisfaction. The findings supported that both IT managers and end-users surveyed found that continued usage of a system contributed to the overall satisfaction of a system.

The studies of Van Cauter et al. (2017), Widiastuti et al. (2019), and Khayun et al. (2012) also found that there was not a significant relationship between system use and net benefits. Conversely, the findings of Yakubu and Dasuki (2018), Arsyanur et al. (2019), Wang and Liao (2008), Salam and Farooq (2020), Shim and Jo (2020), Bradford et al. (2020), Khand and Kalhoro (2020), and Mkinga and Mandari (2020) all observed that there was a significant relationship between system use and net benefits. The findings suggest that IT managers were at a minatory to those survey that the continued use of a system contributed to the overall net benefits of a system. Thus, one can conclude the ultimate success of a system was reflected by the commitment of an end-user to employ the system.

User Satisfaction

I defined user satisfaction by the four variables satisfied (overall), expectations, adequacy, and user attitude. The outcome analysis of the perception of user satisfaction indicated a significant relationship with the net benefits of cloud computing services, which also addressed the subordinate hypotheses H10. Additionally, examining the subordinate hypothesis H7, the findings showed that user satisfaction had a significant relationship with system use.

The researchers Khayun et al. (2012), Salam and Farooq (2020), and Shim and Jo (2020) found that user satisfaction had a significant relationship with system use. However, the studies of Yakubu and Dasuki (2018), Van Cauter et al. (2017), Widiastuti et al. (2019), and Bradford et al. (2020) found that user satisfaction did not have a significant relationship with system use. Additionally, Arsyanur et al. (2019), Wang and

Liao (2008), Khand and Kalhoro (2020), Khand and Kalhoro (2020), and Mkinga and Mandari (2020) did not test the relationship between user satisfaction and system use. Thus, the findings indicated that a proportionate number of end-users surveyed shared the notion that their overall gratification of a system influences their use. A possible explanation for the conclusions of this study is that satisfied patrons may tend to be repeated users.

The studies of Yakubu and Dasuki (2018), Yakubu and Dasuki (2018), Widiastuti et al. (2019), Arsyanur et al. (2019), Wang and Liao (2008), Khayun et al. (2012), Salam and Farooq (2020), Bradford et al. (2020), Khand and Kalhoro (2020), and Mkinga and Mandari (2020) all concurred with the study that there was a significant relationship between user satisfaction and net benefits. Only the study Shim and Jo (2020) concluded that there was not a significant relationship between user satisfaction and net benefits. The findings suggest that user satisfaction was a priority for both IT managers and end-users. A possible justification for the conclusion is that the surveyed participants, both technical and end-user, found that the system helped meet the collective needs.

Net Benefits

I defined net benefits by the six variables improved communication, improved customer satisfaction, improved productivity, increasing effectiveness, improved knowledge (or understanding), and improved decision making. The outcomes of the study summary indicated that there was a significant relationship between the perception of user satisfaction and the net benefits of cloud computing services. However, the results showed no significant relationship between perception of system use and net benefits of cloud computing services. The lack of relation between perception of system use and net benefits of cloud computing services can be explained by the IT managers who did not experience a personal benefit for the cloud system.

Furthermore, the total effect of perception of user satisfaction on net benefits was stronger than the perception of system use. Likewise, amongst all related constructs, perception of user satisfaction had the strongest total effect on net benefits of cloud computing services. The studies Van Cauter et al. (2017), Yakubu and Dasuki (2018), Arsyanur et al. (2019), Widiastuti et al. (2019), Khayun et al. (2012), Bradford et al. (2020), and Khand and Kalhoro (2020) corroborated the study findings that user satisfaction had the strongest effect on net benefits. However, Wang and Liao (2008), Salam and Farooq (2020), and Mkinga and Mandari (2020) refuted the study findings. Thus, this study suggests that perception of user satisfaction can offer more to net benefits of cloud computing services as opposed to system use.

Applications to Professional Practice

The purpose of this correlational study was to examine the relationships among the perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction, perception of system use, perception of user satisfaction, and net benefits of cloud computing services. For this study, I utilized the DeLone and McLean information system success to assess the realization of cloud computing services through the eyes of IT managers centered on the six success dimensions information quality, system quality, service quality, system use, user satisfaction, and net benefits. DeLone and McLean (2003) suggested that an IS can be described as demonstrating various levels of quality, which users and managers experienced such characteristics by utilizing the system where they are satisfied or dissatisfied with the system. Very few studies were found in the literature that examined the impact of the six success dimensions in a post-adoption cloud environment. This study is significant to IT practice as it may offer IT managers a practical model of understanding what characteristics of an IS that influence the subsequent net benefits of a system when designing, provisioning, and supporting cloud computing services. Thus, future practitioners can adopt the model and the instrument presented in this study for further information system success studies.

As the use of ISs has increased over the last two decades, studies revealed that many organizations have successful ISs while others have failing systems that cannot be associated with the type of technology or system used (Hamdan & Al-Hajri, 2021). The success of an IS can be observed by the system's quality, the given information, the degree of use and satisfaction gained by use, and other facets that indicate how much influence is attained by the existence of the IS (Hayati et al., 2021). As Khayer et al. (2020) maintained, the success of technology can be measured by the benefits that an organization gains after adopting that technology and the degree of end-user satisfaction from using that technology. Moreover, users may use only portions of a system or not use the system, which affects the system's capability, efficiency, and overall condition and ultimately weakens returns from its value perspective (Davidson et al., 2020). The analysis results led to rejecting the null hypothesis of the overarching research question for the perception of information quality, perception of service quality, and perception of user satisfaction. With the variables explaining 76% of the variation in the model, this study demonstrates the importance of enhancing information quality, service quality, and user satisfaction and its influences on the net benefits of the IS. Furthermore, the results suggest that system quality and system use had no direct influence on the net benefits of the IS. Therefore, this study can conceivably aid future practitioners in developing success measurement instruments to assess better the characteristics that explain IS success.

The quality of an IS seems to have essential attributes that form user behaviors (Abdul Rahman & Mohezar, 2020). The success in an IS can be appraised in terms of the quality antecedents *information quality*, *system quality*, and *service quality* which can further influence user satisfaction and subsequent use (Albelbisi et al., 2021). Ideally, an IS with high quality will be linked with greater user satisfaction, additional subsequent use, and more significant net benefits (Cheng, 2020). Itthiphone et al. (2020) expressed that information quality frequently plays a crucial dimension in user satisfaction apparatuses as the use of information accentuates that the information output yields value to the user. Knauer et al. (2020) highlight that the conceptualization of system quality is challenging as IS quality depends on end-user needs, subject to ongoing technological and innovation changes requiring specific technical and managerial IT skills to implement, operate, and maintain the IS. In their study, Mathew et al. (2020) asserted that system failures often affect customers' service quality perceptions, influencing their overall satisfaction, causing their tolerance levels toward service failures to reduce drastically.

The findings indicated that information quality and system quality affected system use but not user satisfaction. Specifically, in the context of the quality antecedents, opinions concerning information quality and system quality are better predictors of system use than user satisfaction. The findings imply that IT leaders should pay much more attention to furthering the information quality and service quality of the use of cloud computing services. Additionally, the findings revealed that service quality had a significant relationship with user satisfaction but not system use. The empirical results emphasized the importance of service support capabilities as it pertains to end-user satisfaction. The model developed in this study can assist IT managers in analyzing cloud systems in terms of the quality of the system and services provided by the vendor. Thus, this study can contribute to the IT-related body of knowledge regarding possible distinct quality antecedents to increase an IS perceived effectiveness and organizational benefit.

Ample empirical findings support the idea that *system use* and *user satisfaction* as perceived values are considered two major factors for the benefit of enterprises concerning IS success (Tsai, 2021). According to Mekawie and Yehia (2021), understanding the human factor is an essential aspect of gaining insight into individual perspectives concerning the challenges and opportunities of cloud computing. Likewise, understanding the customer experience plays a crucial role in delivering cloud services as it aids in an organization's ability to provide products and services according to the customer's values (Tabrizchi & Kuchaki Rafsanjani, 2020). According to Qasem et al. (2020), post-adoption expectations are vital in IS services and products because expectations tend to change over time, impacting perceived usefulness and subsequent IS continuance use decisions. Furthermore, Hornyak et al. (2020) suggested that acceptance and use of an IS has revealed that user perceptions regarding a new system can predict the behavioral intention to use the IS and, in turn, system use.

Based on the findings, user satisfaction had a more significant effect on net benefits than system use. This study can offer IT managers the measures to better evaluate user satisfaction, as it can be a key indicator or predictor of the effective use of the system. The IT managers in this study generally agreed that user satisfaction contributes more to the net benefits of their cloud system(s) than system use. The finding should be helpful for IT managers in highlighting the importance of user satisfaction and encourage the establishment of strategies to understand better user expectations and measures to assess user attitude toward the effectiveness of cloud ISs.

N*et benefits* have been used to describe IS technology characteristics and overall system success (Hammood et al., 2020). As described by Abdul Rahman et al. (2020), the net benefit is the effect of an IS on an individual, group, business, or industry influenced by both continuous usage intention and user satisfaction. Saghaeiannejad-Isfahani and Salimian-Rizi (2020) highlighted that net benefits are experienced after implementing ISs, and the decision of where effects are quantified depends on the system(s) type and purposes. The study findings suggested that net benefits should arise if information quality, service quality, and user satisfaction are appropriately managed. Consequently, the research implies that IT management's attention should focus on developing methods to measure the technological characteristics. To increase net benefits, managers need to build IS with good information quality and service quality. While the model proposed that system use and user satisfaction are applicable IS measures, the results validated that uses-satisfaction is the most appropriate predictor of net benefits. Thus, to increase net benefits, IT managers must increase user satisfaction by implementing strategies to enhance information quality and service quality. Furthermore, the findings highlight that the five constructs, information quality, system quality, service quality, system use, and user satisfaction defined by the DeLeon and McLean ISS model are not always appropriate predictors of the net benefits of an IS.

Implications for Social Change

The study results may add to the body of knowledge by offering insight into how organizations that provide vital user-based services may successfully leverage the positive attributes of cloud services that influence the continuing use and user satisfaction to realize its net benefits. For instance, the COVID-19 global pandemic has intensified the need for rapid development and provisioning of technological tools such as cloud computing for critical science research (Kaplan et al., 2020). The continued emergence of cloud computing innovations has underscored its benefit, which has led to a better understanding of the human factors that influence the acceptance, use, and satisfaction of cloud computing services (Amron et al., 2021). Thus, the findings of this study may help decision-makers in healthcare, human services, social services, and other critical service organizations better understand the vital predictors of attitude toward system use and user satisfaction of customer-facing cloud-based applications. As a result, providers may leverage the knowledge of building secure and reliable cloud-based services while end-users may expect simple, immediate, and relevant experiences.

The research findings may also bring about positive change to education, non-profit, and community-based organizations. According to Ye and Yang (2020), the mobile platform is regarded as an innovative and effective tool to diminish the social and economical digital divide that disparately limits access to and usage of information and communication technologies amongst individuals, households, businesses, and geographic areas. Cloud technology has expanded mobile network computing by facilitating rapid improvements of shared assets involving mobile application development and delivery (Guo et al., 2020). Reavis (2019) underlines that mobile cloud applications may help address the challenges that non-profit and smaller organizations face regarding the limited resources available to them for technology investments to ensure that investments have a positive impact. Moreover, cloud computing has become a vital tool in delivering mobile learning environments, providing mobile education software, building rich learning resources platforms, collaborative learning environments, and collaborative learning opportunities (Hu, 2021).

Implications for social change may be expressed in developing cloud-based mobile applications that emphasize robust information quality, excellent service quality, and user interfaces that guarantee a high degree of user satisfaction. The study results highlighted the influence of information quality and system quality on user satisfaction, ultimately resulting in a significant link with net benefits. Thus, this study may aid education, non-profit, and community-based organizations in identifying common barriers of mobile cloud applications that contribute to low user satisfaction. Offering quality user experience is a vital component of a user's perception, and interaction with an IS. Thus, assisting business leaders in understanding the relationship between system quality factors, user satisfaction, and net benefits may help to improve the design, content, and other elements that empower users to achieve their goals within the application.

The findings of this study may also affect social change and behaviors of individual entrepreneurship and small businesses. According to Roberts et al. (2016), IT innovation plays an essential role in sensing opportunities where understanding an IS's routine and innovative usage behaviors may help initiate new ventures. Ferri et al. (2020) maintained that there is increasing adoption of cloud technologies by startups, giving birth to a new generation of startups for new markets with a stout direction toward product innovation and sales strategies. Accordingly, individuals, intrapreneurs, and small business owners may leverage the findings of this study to help gain a deeper understanding of what potential clients perceive as the most critical factors that drive system use and satisfaction. Such knowledge may aid in developing systems that create unique and compelling client experiences, which may generate successful new ventures.

Recommendations for Action

The review of the results of this study offered a basis for recommendations of actions for IT managers of cloud computing services. The findings led to accept the alternative hypothesis, which connotes a statistically significant relationship between the predictors perception of information quality, perception of service quality, and perceptions of user satisfaction and the dependent variable net benefits of cloud computing services. Thus, IT managers who oversee cloud computing services should implement strategies that help develop an understanding of end-user sentiment toward their cloud ISs. Such methods should include evaluating the core capabilities of the cloud systems and highlighting key functionality where improvements are needed.

Another critical action is to adopt programs to assess how the user community periodically views how the cloud IS can help them perform their jobs more efficiently. Thus, IT managers should identify opportunities to improve the reputation of the system and the IT department. Such programs may ensure that end-users believe they are being heard and given the proficiencies to use cloud technology that IT delivers. Additionally, IT leaders should implement strategies to measure and enhance the quality of services using comprehensive customer evaluation of the cloud service(s) to meet customer expectations and affords satisfaction. Lastly, IT leaders should examine their measures of information quality and the dimensions used to assess and report quality metrics. Such quality dimensions should include various categories of appropriate data attributes to classify the degree to which information is fit for purpose.

There are several viable platforms available to disseminate the study results. For example, I plan to publish my study findings in national journals and statewide publications. I will also distribute the outcomes through various technology research and advisory groups such as Gartner, International Data Corporation (IDC), Peer Insights, and Forrester. Furthermore, I plan to leverage IT governance organizations such as ISACA, the project management Institute (PMI), the International Information System Security Certification Consortium $(ISC)^2$, and the Information Technology Infrastructure Library (ITIL) as vehicles for the publication and distribution of the study results. Moreover, I will utilize social media and organizations' websites such as LinkedIn and various cloud-based forums to disseminate the study findings.

Additionally, I will invite cloud service providers such as AWS, Microsoft, IBM, Oracle Cloud, and Google Cloud to publish the study findings in their case studies. Furthermore, I will share the study conclusions as part of my customer consultancy service to organizations that currently subscribe or consider migrating to cloud services. Lastly, I plan to include the study results as part of my training toolkits, curricula materials centered around cloud computing, and cloud program materials such as flyers, guides, and pamphlets to guide customers through the cloud migration adoption process.

Recommendations for Further Study

The outcomes of this study lead to several recommendations for further research related to improved practice in IT. For instance, the DeLone and McLean (2003) ISS model proposes an association between the dimension information quality, system quality, service quality, system use, and user satisfaction that certain net benefits are achieved. However, this study's results indicated no correlation between system use and net benefits or system quality and net benefits. The failure to confirm a significant relationship between the dimensions may be accredited to the variables used to operationalize the constructs. As a result, I suggest that future studies be conducted, which select alternative variables to define the model's dimension may more accurately describe the constructs. Furthermore, other boundary conditions may deserve consideration, such as the type of IS and the timing of success measurement versus implementation time. Last, the failure to confirm any significant relationship between the variables could result from possible distortion or sidedness from the posed survey questions. Although the questions appeared to be relevant when they were administered, they may require modifications in further research to better express the meaning and intent of the questions.

Further considerations for future research should also focus on the selected population. For this study, the sample population included IT managers who supervised cloud-based ISs. Therefore, future studies' sample population should comprise service providers and subject matter experts who have experience designing, implementing, and supporting cloud services to validate the ISS model further. Moreover, the study outcomes also revealed that the research model validity and correlational results varied as cases were removed during the data cleansing process. As a result, future studies should ensure that the sample size is large enough to tolerate the exclusion of cases post data cleaning such that the removal of any cases does not negatively impact the model's validity or reporting of tests of assumptions.

The DeLone and McLean model identified loopback relationships between net benefits and use and between net benefits and satisfaction to provide allowances for maintenance changes and updates to the IS over time, which not I did not examine in this study. Thus, I suggest that future studies focus on such feedback to explore the relationships and to understand the success model better more completely. Additionally, the DeLone and McLean model also primarily concentrates on the technical aspects of an IS. Consequently, the variables used to define the constructs may not accurately reflect the participant's organization(s). Thus, future studies should consider variables from alternative contexts such as organizational, environmental, and financial for businesses that identify with non-technical measures to define IS success.

Many of the studies identified in this study, which applied the ISS model, selected only parts of the model. Only a few models utilized the entire model. As a result, more research using the model as a whole is necessary to help extend IT managers' understanding of the ISS model's overall validity. As a result, the additional data created should be used in fieldwork to evaluate, select, implement, and support new IS. Additionally, such studies may help determine if the model's propositions can effectively aid practitioners in handling the IS(s) more effectively in practice.

The study participants were obtained through the Centiment panel, which offered them incentives to participate in the survey. As a result, the participants may not fully represent the views of all IT leaders who manage cloud computing services which may impact the generalizability of results. Therefore, future studies should target participants' responses through other voluntary data collection methods, such as LinkedIn and direct invitations, where the participants do not receive incentives for participation.

In the proposal for this study, I recognized five limitations. The first limitation highlighted the potential improper representation of the target population could impede the investigation from attaining its desired objectives. Thus, future studies should employ the research instrument to more extensive samples, allowing for more precise effect studies with the design model. Second, the structured closed-ended questions of the survey instrument may present limited responses that lead to constrained outcomes that affect the generalization of the findings. As a result, future research should include a mixed-methods design to offer a more holistic perspective of IS success.

The third limitation acknowledged that a lack of responses for data collection could have produced non-response bias which threatens the validity of the study results. For this study, I utilized a research panel to minimize the risk of non-response bias. However, the panel members required internet access, and the survey required appropriate screener questions to diminish bias or low-quality responses. Hence, future studies should consider alternative survey distribution methods and expand participant screening methods. The fourth limitation noted the risk of sampling bias due to online web surveys. Thus, future researchers may employ additional survey distribution methods to augment the web-based survey, including email, random device engagement, and assisted crowdsourcing. The final limitation recognized the potential impact of participant bias from the IT managers as the respondents may have offered biased answers to support their managerial positions. Researchers may address participant bias in future research by placing a higher emphasis on the survey structure by avoiding emotionally charged terms, allowing participants to state if they "don't know" or "undecided," and carefully phrasing questions to receive an unbiased response.

Reflections

Though the Doctor of Information Technology (DIT) process presented several challenges, I found that the doctoral process at Walden University to have been a life-altering experience. The DIT process has changed how I consume information when reading, listening or watching the news. I now constantly question the origin of information and the credibility of the reporting source. I also gained a passion for research with my newfound knowledge, which has motivated me to research areas such as information technology, business management, social science, and humanities. Moreover, I have a new level of respect for the individuals who carry the title "doctor" as I now understand the rigorous journey required to earn such a designation. Lastly, the DIT program has elevated my ability to persevere, my capacity for patience, and heightened my enthusiasm to learn.

Before I started conducting this study, I had some preconceived ideas of what influenced the benefit returns of cloud services. Having spent nearly 30 years in information technology, I have subconsciously believed that system use was a vital factor in IS adoption and acceptance. However, as I began to understand the research process and proceed through the various phases of the DIT process, my preconceived biases started to weaken. Moreover, as my understanding of the DeLone and McLean ISS framework grew, I eventually realized that my biases were misplaced as I came to grips with my inexperience in the research process. As a result, I maintained an open mind as I conducted the data collection and analysis process. Nevertheless, I was intrigued by the finding that there was no significant relationship between perception of system use and net benefits of cloud computing services.

Due to the experience gained from the DIT program, I now realize that my initial biases toward cloud computing benefits realization were obscured. Consequently, I gained an acute appreciation of the research process and the importance of a researcher's objectivity when conducting research. As a whole, the experience I gained from the

Walden doctoral program is invaluable to my growth as an IT professional. Likewise, the program made me more socially aware and informed me of my responsibility to leverage my technology skills to improve the lives of others and help bridge the technology gaps that exist today.

Summary and Study Conclusions

Cloud computing is an innovative technology trend that has played a significant role in how computing resources and applications are delivered to customers in today's on-demand computing culture. Cloud service providers advertise the many perceived advantages offered by cloud services (i.e., costs savings, flexibility, mobility, sustainability, and high availability). However, many challenges are associated with cloud computing (i.e., security issues, cost management and containment, lack of resources and expertise, vendor lock-in, and governance/control), affecting end-user continuance use and satisfaction in the IS, and ultimately impacting its benefits return. Consequently, models such as the DeLone and McLean ISS were developed to provide technology practitioners with the ability to define and measure success for ISs such as cloud computing.

As our reliance on information systems, many driven through technologies such as cloud computing, continues to grow in our daily lives, we must understand how to quantify the return on IT investments. IT practitioners, business leaders, and service providers need to understand how to yield consistent measures to identify (a) the quality antecedents and dimensions, (b) the factors that influence the continuance, and (c) the aspects that inspire user satisfaction of an IS. The findings of this study can help IT managers, business leaders, and service providers develop strategies to measure the benefit returns of ISs more effectively. Thus, by using established frameworks and instruments to measure IS success, we can ensure that our technology has the positive impact that we expect on every facet of society, be it in business, health care, human services, or our social activities.

References

Abdul Rahman, A. R., & Mohezar, S. (2020). Ensuring continued use of a digital library: A qualitative approach. *The Electronic Library*, *38*(3), 513–530. https://doi.org/10.1108/el-12-2019-0294

Abdul Rahman, A. R., Mohezar, S., Habidin, N. F., & Mohd Fuzi, N. (2020). Critical success factors of the continued usage of digital library successful implementation in military-context. *Digital Library Perspectives*, *36*(1), 38–54. https://doi.org/10.1108/dlp-10-2019-0038

Abutabenjeh, S., & Jaradat, R. (2018). Clarification of research design, research methods, and research methodology: A guide for public administration researchers and practitioners. *Teaching Public Administration*, *36*(3), 237–258. https://doi.org/10.1177/0144739418775787

Ackerman, B., Schmid, I., Rudolph, K. E., Seamans, M. J., Susukida, R., Mojtabai, R., & Stuart, E. A. (2019). Implementing statistical methods for generalizing randomized trial findings to a target population. *Addictive Behaviors*, *94*, 124–132. https://doi.org/10.1016/j.addbeh.2018.10.033

Adhikari, M., Amgoth, T., & Srirama, S. N. (2019). A survey on scheduling strategies for workflows in cloud environment and emerging trends. *ACM Computing Surveys*, *52*(4), 1–36. https://doi.org/10.1145/3325097

Agrifoglio, R., Metallo, C., & Lepore, L. (2016). Success factors for using case management system in Italian courts. *Information Systems Management*, *33*(1), 42–54. https://doi.org/10.1080/10580530.2016.1117871

Ahmed, I. (2020). Technology organization environment framework in cloud computing. *Telkomnika*, *18*(2), 716–725. https://doi.org/10.12928/telkomnika.v18i2.13871

Ajibade, P. (2018). Technology acceptance model limitations and criticisms: Exploring the practical applications and use in technology-related studies, mixed-method, and qualitative researches. *Library Philosophy & Practice*, 1–13.

Alam, S. S., Nor, N. G., Ali, M. H., Omar, N. A., & Wel, C. A. (2018). Relationship between entrepreneur's traits and cloud computing adoption among Malay-owned SMEs in Malaysia. *Cuadernos de Gestión*, *18*(2), 115–132. https://doi.org/10.5295/cdg.140515ss

AL Athmay, A. A., Fantazy, K., & Kumar, V. (2016). E-government adoption and user's satisfaction: An empirical investigation. *EuroMed Journal of Business*, *11*(1), 57–83. https://doi.org/10.1108/emjb-05-2014-0016

Alavi, H., & Hąbek, P. (2016). Addressing research design problem in mixed methods research. *Management Systems in Production Engineering*, *21*(1), 62–66. https://doi.org/10.12914/MSPE-10-01-2016

Al-Azawei, A. (2019). What drives successful social media in education and e-learning? A comparative study on Facebook and Moodle. *Journal of Information Technology Education: Research*, *18*, 253–274. https://doi.org/10.28945/4360

AlBar, A. M., & Hoque, M. R. (2017). Factors affecting cloud ERP adoption in Saudi Arabia: An empirical study. *Information Development*, *35*(1), 150–164. https://doi.org/10.1177/0266666917735677

Albelbisi, N. A., Al-Adwan, A. S., & Habibi, A. (2021). Impact of quality antecedents on satisfaction toward MOOC. *Turkish Online Journal of Distance Education*, *22*(2), 164–175. https://doi.org/10.17718/tojde.906843

Albers, C., & Lakens, D. (2018). When power analyses based on pilot data are biased: Inaccurate effect size estimators and follow-up bias. *Journal of Experimental Social Psychology*, *74*, 187–195. https://doi.org/10.1016/j.jesp.2017.09.004

Aldholay, A., Isaac, O., Abdullah, Z., Abdulsalam, R., & Al-Shibami, A. H. (2018). An extension of DeLone and McLean IS success model with self-efficacy: Online learning usage in Yemen. *International Journal of Information and Learning Technology*, *35*(4), 285–304. https://doi.org/10.1108/ijilt-11-2017-0116

Aldholay, A. H., Isaac, O., Abdullah, Z., & Ramayah, T. (2018). The role of transformational leadership as a mediating variable in DeLone and McLean information system success model: The context of online learning usage in Yemen. *Telematics and Informatics*, *35*(5), 1421–1437. https://doi.org/10.1016/j.tele.2018.03.012

Alenezi, A., Atlam, H. F., & Wills, G. B. (2019). Experts reviews of a cloud forensic readiness framework for organizations. *Journal of Cloud Computing: Advances, Systems and Applications*, *8*(1), 1–14. https://doi.org/10.1186/s13677-019-0133-z

Al-Fraihat, D., Joy, M., Masa'deh, R., & Sinclair, J. (2020). Evaluating e-learning systems success: An empirical study. *Computers in Human Behavior*, *102*, 67–86. https://doi.org/10.1016/j.chb.2019.08.004

Ali, M., Raza, S. A., Puah, C. H., & Amin, H. (2019). Consumer acceptance toward takaful in Pakistan: An application of diffusion of innovation theory.

International Journal of Emerging Markets, *14*(4), 620–638. https://doi.org/10.1108/ijoem-08-2017-0275

Ali, N., Tretiakov, A., Whiddett, D., & Hunter, I. (2017). Knowledge management systems success in healthcare: Leadership matters. *International Journal of Medical Informatics*, *97*, 331–340. https://doi.org/10.1016/j.ijmedinf.2016.11.004

Ali, O., Soar, J., & Shrestha, A. (2018). Perceived potential for value creation from cloud computing: A study of the australian regional government sector. *Behaviour & Information Technology*, *37*(12), 1157–1176. https://doi.org/10.1080/0144929x.2018.1488991

Alksasbeh, M., Abuhelaleh, M., Almaiah, M. A., AL-Jaafreh, M., & Abu Karaka, A. (2019). Towards a model of quality features for mobile social networks apps in learning environments: An extended information system success model. *International Journal of Interactive Mobile Technologies*, *13*(5), 75–93. https://doi.org/10.3991/ijim.v13i05.9791

Allie, A., & Ajiboye, S. (2019). Lead user adaptation within information systems: Human behavior as a predictor of enterprise resource planning systems implementation outcomes. *Journal of Organizational Psychology*, *19*(2), 18–37. https://doi.org/10.33423/jop.v19i2.2041

Almaiah, M. A., Alamri, M. M., & Al-Rahmi, W. (2019). Applying the UTAUT model to explain the students' acceptance of mobile learning system in higher education. *IEEE Access*, *7*, 174673–174686. https://doi.org/10.1109/access.2019.2957206

Alotaibi, M. B. (2016). Antecedents of software-as-a-service (saas) adoption: A structural equation model. *International Journal of Advanced Computer Research*, *6*(25), 114–129. https://doi.org/10.19101/ijacr.2016.626019

Al-Rahmi, W. M., Yahaya, N., Aldraiweesh, A. A., Alamri, M. M., Aljarboa, N. A., Alturki, U., & Aljeraiwi, A. A. (2019). Integrating technology acceptance model with innovation diffusion theory: An empirical investigation on students' intention to use e-learning systems. *IEEE Access*, *7*, 26797–26809. https://doi.org/10.1109/access.2019.2899368

Alruwaili, F. F., & Gulliver, T. A. (2018). Secure migration to compliant cloud services: A case study. *Journal of Information Security and Applications*, *38*, 50–64. https://doi.org/10.1016/j.jisa.2017.11.004

Alshare, K. A., Alomari, M. K., Lane, P. L., & Freeze, R. D. (2019). Development and determinants of end-user intention: Usage of expert systems. *Journal of Systems and Information Technology*, *21*(2), 166–185. https://doi.org/10.1108/jsit-08-2018-0108

Alvarez, R., Mirzoev, T., Gowan, A., Henderson, B., & Kruck, S. E. (2019). Learning laboratories as services in private cloud deployment. *Journal of Computer Information Systems*, *59*(4), 354–362. https://doi.org/10.1080/08874417.2017.1368422

Alzahrani, A. I., Mahmud, I., Ramayah, T., Alfarraj, O., & Alalwan, N. (2019). Modelling digital library success using the DeLone and McLean information system success model. *Journal of Librarianship and Information Science*, *51*(2), 291–306. https://doi.org/10.1177/0961000617726123

Alzoubi, Y. I., Gill, A. Q., & Moulton, B. (2018). A measurement model to analyze the effect of agile enterprise architecture on geographically distributed agile development. *Journal of Software Engineering Research and Development*, *6*(1), 1-24. https://doi.org/10.1186/s40411-018-0048-2

Amornkitpinyo, T., & Piriyasurawong, P. (2017). The concept framework of structural equation model of mobile cloud learning acceptance for higher education students in the 21st century. *TEM Journal*, *6*(3), 464–468. https://doi.org/10.18421/TEM63-05

Amron, M. T., Ibrahim, R., & Bakar, N. A. (2021). Cloud computing acceptance among public sector employees. *Telkomnika*, *19*(1), 124–133. https://doi.org/10.12928/telkomnika.v19i1.17883

Andrade, C. (2018). Internal, external, and ecological validity in research design, conduct, and evaluation. *Indian Journal of Psychological Medicine*, *40*(5), 498-499. https://doi.org/10.4103/ijpsym.ijpsym_334_18

Andrade, C. (2020). Understanding the difference between standard deviation and standard error of the mean, and knowing when to use which. *Indian Journal of Psychological Medicine*, *42*(4), 409–410. https://doi.org/10.1177/0253717620933419

Anisetti, M., Ardagna, C. A., Damiani, E., El Ioini, N., & Gaudenzi, F. (2018). Modeling time, probability, and configuration constraints for continuous cloud service certification. *Computers & Security*, *72*, 234–254. https://doi.org/10.1016/j.cose.2017.09.012

Annane, B., & Ghazali, O. (2019). Virtualization-based security techniques on mobile cloud computing: Research gaps and challenges. *International Journal of Interactive Mobile Technologies*, *13*(4), 20–32. https://doi.org/10.3991/ijim.v13i04.10515

Anye, E. T. (2019). *Factors affecting employee intentions to comply with password policies* (13900175) [Doctoral dissertation, Walden University]. ProQuest Dissertations & Theses Global.

Aparicio, M., Bacao, F., & Oliveira, T. (2016). Cultural impacts on e-learning systems' success. *The Internet and Higher Education*, *31*, 58–70. https://doi.org/10.1016/j.iheduc.2016.06.003

Apostolopoulos, N., & Liargovas, P. (2016). Regional parameters and solar energy enterprises: Purposive sampling and group AHP approach. *International Journal of Energy Sector Management*, *10*(1), 19–37. https://doi.org/10.1108/ijesm-11-2014-0009

Apriwandi. & Pratiwi, Y. M. (2019). The influence of social pressure, responsibility and procedural fairness toward the creation of budgetary slack: An experimental research. *Global Business & Management Research*, *11*(1), 9–21.

Arabameri, A., Cerda, A., Rodrigo-Comino, J., Pradhan, B., Sohrabi, M., Blaschke, T., & Tien Bui, D. (2019). Proposing a novel predictive technique for gully erosion susceptibility mapping in arid and semi-arid regions (Iran). *Remote Sensing*, *11*(21), 2577. https://doi.org/10.3390/rs11212577

Arah, O. A. (2017). Bias analysis for uncontrolled confounding in the health sciences.

Annual Review of Public Health, *38*, 23–38. https://doi.org/10.1146/annurev-publhealth-032315-021644

Arend, M. G., & Schäfer, T. (2019). Statistical power in two-level models: A tutorial based on Monte Carlo simulation. *Psychological Methods*, *24*(1), 1–19. https://doi.org/10.1037/met0000195

Arentz, S., Smith, C. A., Abbott, J. A., & Bensoussan, A. (2014). A survey of the use of complementary medicine by a self-selected community group of australian women with polycystic ovary syndrome. *BMC Complementary and Alternative Medicine*, *14*(1), 128–141. https://doi.org/10.1186/1472-6882-14-472

Armstrong, R. A. (2019). Should pearson's correlation coefficient be avoided? *Ophthalmic and Physiological Optics*, *39*(5), 316–327. https://doi.org/10.1111/opo.12636

Arowolo, O. M. (2017). *Strategic cyber-risk implications of cloud technology adoption in the U.S. financial services sector* (10639600) [Doctoral dissertation, Walden University]. ProQuest Dissertations & Theses Global.

Arsyanur, M. R., Suroso, A. I., & Sukmawati, A. (2019). Analysis of success factors implementation of state civil apparatus management information system. *Jurnal Aplikasi Manajemen*, *17*(3), 479–488. https://doi.org/10.21776/ub.jam.2019.017.03.12

Aryotejo, G., Kristiyanto, D. Y., & Mufadhol. (2018). Hybrid cloud: Bridging of private and public cloud computing. *Journal of Physics: Conference Series*, *1025*(1), 1. https://doi.org/10.1088/1742-6596/1025/1/012091

Assaf, R. (2019). Adoption of cloud computing in Palestinian Ministry of Telecommunication and Information Technology: A framework development. *I-Manager's Journal On Cloud Computing*, *6*(1), 19–26. https://doi.org/10.26634/jcc.6.1.15491

Assegaff, S., Hendri, H., Sunoto, A., Yani, H., & Kisbiyanti, D. (2017). Social media success model for knowledge sharing (scale development and validation). *Telkomnika*, *15*(3), 1335–1343. https://doi.org/10.12928/telkomnika.v15i3.5569

Asvija, B., Eswari, R., & Bijoy, M. B. (2019). Security in hardware assisted virtualization for cloud computing—State of the art issues and challenges. *Computer Networks*, *151*, 68–92. https://doi.org/10.1016/j.comnet.2019.01.013

Attaran, M., & Woods, J. (2019). Cloud computing technology: Improving small business performance using the internet. *Journal of Small Business & Entrepreneurship*, *31*(6), 495–519. https://doi.org/10.1080/08276331.2018.1466850

Avila, O., Goepp, V., & Kiefer, F. (2018). Addressing alignment concerns into the design of domain-specific information systems. *Journal of Manufacturing Technology Management*, *29*(5), 726–745. https://doi.org/10.1108/jmtm-07-2017-0136

Avinash, B., Shivalinga, B. M., Balasubramanian, S., Ravikumar, M., Shekar, S., Chandrashekar, B. R., & Avinash, B. S. (2017). Geographic information system and index of orthodontic treatment need: Tools to assess orthodontic treatment needs of 12-year-old children of Mysuru district. *Journal of Indian Association of Public Health Dentistry*, *15*(4), 348–353.

https://doi.org/10.4103/jiaphd.jiaphd_33_17

Aydiner, A. S., Tatoglu, E., Bayraktar, E., & Zaim, S. (2019). Information system capabilities and firm performance: Opening the black box through decision-making performance and business-process performance. *International Journal of Information Management*, *47*, 168–182. https://doi.org/10.1016/j.ijinfomgt.2018.12.015

Azeemi, I. K., Lewis, M., & Tryfonas, T. (2013). Migrating to the cloud: Lessons and limitations of 'traditional' IS success models. *Procedia Computer Science*, *16*, 737–746. https://doi.org/10.1016/j.procs.2013.01.077

Baglai, R. (2018). Research of deployment models of cloud technologies for banking information systems. *Technology Audit & Production Reserves*, *3*(4(41)), 47–52. https://doi.org/10.15587/2312-8372.2018.134981

Baker, J., Song, J., & Jones, D. R. (2017). Closing the loop: Empirical evidence for a positive feedback model of it business value creation. *Journal of Strategic Information Systems*, *26*(2), 142–160. https://doi.org/10.1016/j.jsis.2016.12.001

Bala, H., & Feng, X. (2019). Success of small and medium enterprises in Myanmar: Role of technological, organizational, and environmental factors. *Journal of Global Information Technology Management*, *22*(2), 100–119. https://doi.org/10.1080/1097198x.2019.1603511

Ball, H. L. (2019). Conducting online surveys. *Journal of Human Lactation*, *35*(3), 413–417. https://doi.org/10.1177/0890334419848734

Balogh, P., & Golea, P. (2016). Analysis training staff using statistical hypothesis testing.

Quality - Access to Success, *17*, 255–262.

Bangdiwala, S. I. (2018a). Regression: Binary logistic. *International Journal of Injury Control & Safety Promotion*, *25*(3), 336–338. https://doi.org/10.1080/17457300.2018.1486503

Bangdiwalaa, S. I. (2018b). Regression: Multiple linear. *International Journal of Injury Control and Safety Promotion*, *25*(2), 232–236. https://doi.org/10.1080/17457300.2018.1452336

Bansal, G., Zahedi, F. M., & Gefen, D. (2016). Do context and personality matter? Trust and privacy concerns in disclosing private information online. *Information & Management*, *53*(1), 1–21. https://doi.org/10.1016/j.im.2015.08.001

Baškarada, S., & Koronios, A. (2018). A philosophical discussion of qualitative, quantitative, and mixed methods research in social science. *Qualitative Research Journal*, *18*(1), 2–21. https://doi.org/10.1108/qrj-d-17-00042

Behie, A. M., & O'Donnell, M. H. (2015). Prenatal smoking and age at menarche: Influence of the prenatal environment on the timing of puberty. *Human Reproduction*, *30*(4), 957–962. https://doi.org/10.1093/humrep/dev033

Benton, J. S., Anderson, J., Hunter, R. F., & French, D. P. (2016). The effect of changing the built environment on physical activity: A quantitative review of the risk of bias in natural experiments. *International Journal of Behavioral Nutrition & Physical Activity*, *13*, 1–18. https://doi.org/10.1186/s12966-016-0433-3

Berggren, S., Fletcher-Watson, S., Milenkovic, N., Marschik, P. B., Bölte, S., & Jonsson, U. (2018). Emotion recognition training in autism spectrum disorder: A systematic review of challenges related to generalizability. *Developmental Neurorehabilitation*, *21*(3), 141–154. https://doi.org/10.1080/17518423.2017.1305004

Bernstein, J. L. (2018). Unifying SoTL methodology: Internal and external validity. *Teaching & Learning Inquiry*, *6*(2), 115–126. https://doi.org/10.20343/teachlearninqu.6.2.9

Berrios, C., James, C. A., Raraigh, K., Bollinger, J., Murray, B., Tichnell, C., Applegate, C. D., & Bergner, A. L. (2017). Enrolling genomics research participants through a clinical setting: The impact of existing clinical relationships on informed consent and expectations for return of research results. *Journal of Genetic Counseling*, *27*(1), 263–273. https://doi.org/10.1007/s10897-017-0143-2

Bhardwaj, A., Rama Krishna, C., Srivastava, S., Malik, H., & Sharma, R. (2018). Efficient multistage bandwidth allocation technique for virtual machine migration in cloud computing. *Journal of Intelligent & Fuzzy Systems*, *35*(5), 5365–5378. https://doi.org/10.3233/JIFS-169819

Biros, M. (2018). Capacity, vulnerability, and informed consent for research. *Journal of Law, Medicine & Ethics*, *46*(1), 72–78. https://doi.org/10.1177/1073110518766021

Bloomfield, J., & Fisher, M. J. (2019). Quantitative research design. *Journal of the Australasian Rehabilitation Nurses' Association*, *22*(2), 27–30. https://doi.org/10.33235/jarna.22.2.27-30

Boell, S. K. (2017). Information: Fundamental positions and their implications for information systems research, education and practice. *Information and Organization*, *27*(1), 1–16. https://doi.org/10.1016/j.infoandorg.2016.11.002

Borena, B., & Negash, S. (2016). IT infrastructure role in the success of a banking system: The case of limited broadband access. *Information Technology for Development*, *22*(2), 265–278. https://doi.org/10.1080/02681102.2014.979392

Bounagui, Y., Mezrioui, A., & Hafiddi, H. (2019). Toward a unified framework for cloud computing governance: An approach for evaluating and integrating it management and governance models. *Computer Standards & Interfaces*, *62*, 98–118. https://doi.org/10.1016/j.csi.2018.09.001

Bradford, M., Henderson, D., Baxter, R. J., & Navarro, P. (2020). Using generalized audit software to detect material misstatements, control deficiencies and fraud: How financial and IT auditors perceive net audit benefits. *Managerial Auditing Journal*, *35*(4), 521–547. https://doi.org/10.1108/maj-05-2019-2277

Brænd, A. M., Straand, J., & Klovning, A. (2017). Clinical drug trials in general practice: How well are external validity issues reported?. *BMC Family Practice*, *18*(1), 1–11. https://doi.org/10.1186/s12875-017-0680-7

Branco, T., Jr., de Sá-Soares, F., & Rivero, A. L. (2017). Key issues for the successful adoption of cloud computing. *Procedia Computer Science*, *121*, 115–122. https://doi.org/10.1016/j.procs.2017.11.016

Breitsohl, H., & Steidelmüller, C. (2018). The impact of insufficient effort responding detection methods on substantive responses: Results from an experiment testing parameter invariance. *Applied Psychology*, *67*(2), 284–308.

https://doi.org/10.1111/apps.12121

Brincks, A., Montag, S., Howe, G. W., Huang, S., Siddique, J., Ahn, S., Sandler, I. N., Pantin, H., & Brown, C. H. (2018). Addressing methodologic challenges and minimizing threats to validity in synthesizing findings from individual-level data across longitudinal randomized trials. *Prevention Science*, *19*(S1), 60–73. https://doi.org/10.1007/s11121-017-0769-1

Brown, G., Strickland-Munro, J., Kobryn, H., & Moore, S. A. (2017). Mixed methods participatory GIS: An evaluation of the validity of qualitative and quantitative mapping methods. *Applied Geography*, *79*, 153–166. https://doi.org/10.1016/j.apgeog.2016.12.015

Buck, V. B. (2018). *The impact of transformational leadership on nonprofit volunteer engagement and commitment* (10826973) [Doctoral dissertation, Walden University]. ProQuest Dissertations & Theses Global.

Budiardjo, E. K., Pamenan, G., Hidayanto, A. N., Meyliana., & Cofriyanti, E. (2017). The impact of knowledge management system quality on the usage continuity and recommendation intention. *Knowledge Management & E-Learning: An International Journal*, *9*(2), 200–224. https://doi.org/10.34105/j.kmel.2017.09.012

Buelens, B., Burger, J., & van den Brakel, J. A. (2018). Comparing inference methods for non-probability samples. *International Statistical Review*, *86*(2), 322–343. https://doi.org/10.1111/insr.12253

Bulgurcu, B., Cavusoglu, H., & Benbasat, I. (2010). Information security policy compliance: An empirical study of rationality-based beliefs and information security awareness. *MIS Quarterly*, *34*(3), 523–A7. https://doi.org/10.2307/25750690

Caithness, N., Drescher, M., & Wallom, D. (2017). Can functional characteristics usefully define the cloud computing landscape and is the current reference model correct?. *Journal of Cloud Computing: Advances, Systems and Applications*, *6*(1), 1–13. https://doi.org/10.1186/s13677-017-0084-1

Calin-Jageman, R. J., & Cumming, G. (2019). The new statistics for better science: Ask how much, how uncertain, and what else is known. *American Statistician*, *73*, 271–280. https://doi.org/10.1080/00031305.2018.1518266

Canbulat, M., Direkci, B., Çorapçıgil, A., Şimşek, E. E., Asma, B., Tezci, İ. H., Akbulut, S., & Şimşek, B. (2020). The psychometric properties of school belonging scale for primary school students: A validity and reliability study. *İlköğretim Online*, *19*(3), 1422–1438. https://doi.org/10.17051/ilkonline.2020.730754

Cantuaria, M. L., & Blanes-Vidal, V. (2019). Self-reported data in environmental health studies: Mail vs. web-based surveys. *BMC Medical Research Methodology*, *19*(1), 1–13. https://doi.org/10.1186/s12874-019-0882-x

Carillo, K., Scornavacca, E., & Za, S. (2017). The role of media dependency in predicting continuance intention to use ubiquitous media systems. *Information & Management*, *54*(3), 317–335. https://doi.org/10.1016/j.im.2016.09.002

Carreiro, H., & Oliveira, T. (2019). Impact of transformational leadership on the diffusion of innovation in firms: Application to mobile cloud computing.

Computers in Industry, *107*, 104–113. https://doi.org/10.1016/j.compind.2019.02.006

Cashing, D. (2018). An informal justification for selected degree-of-freedom formulae. *Teaching Statistics*, *40*(1), 12–15. https://doi.org/10.1111/test.12143

Cassel, C., & Bindman, A. (2019). Risk, benefit, and fairness in a big data world. *JAMA: Journal of the American Medical Association*, *322*(2), 105. https://doi.org/10.1001/jama.2019.9523

Castilla-Earls, A., & Fulcher-Rood, K. (2018). Convergent and divergent validity of the grammaticality and utterance length instrument. *Journal of Speech, Language, and Hearing Research*, *61*(1), 120-129. https://doi.org/10.1044/2017_jslhr-l-17-0152

Čehovin, G., Bosnjak, M., & Manfreda, K. L. (2019). Meta-analyses in survey methodology: A systematic review. *Public Opinion Quarterly*, *82*(4), 641-660. https://doi.org/10.1093/poq/nfy042

Centiment. (n.d.-a). *Legal & security*. Retrieved June 22, 2020, from https://help.centiment.co/surveymonkey/required-setup

Centiment. (n.d.-b). *Link a SurveyMonkey survey*. Retrieved June 22, 2020, from https://help.centiment.co/surveymonkey/required-setup

Centiment. (n.d.-c). *Our approach*. Retrieved June 10, 2020, from https://www.centiment.co/

Chang, C.-H., Pal, N., & Lin, J.-J. (2017). A revisit to test the equality of variances of several populations. *Communications in Statistics - Simulation and Computation*, *46*(8), 6360–6384. https://doi.org/10.1080/03610918.2016.1202277

Changchit, C., & Chuchuen, C. (2018). Cloud computing: An examination of factors impacting users' adoption. *Journal of Computer Information Systems*, *58*(1), 1-9. https://doi.org/10.1080/08874417.2016.1180651

Charmaz, K., & Belgrave, L. L. (2018). Thinking about data with grounded theory. *Qualitative Inquiry*, *25*(8), 743–753. https://doi.org/10.1177/1077800418809455

Chatchumni, M., Namvongprom, A., Eriksson, H., & Mazaheri, M. (2019). Exploring the different management structures in nurses responses and treating of patients' postoperative pain: A qualitative triangulation study. *Electronic physician*, *11*(2), 7536–7543. https://doi.org/10.19082/7536

Chaw, L. Y., & Tang, C. M. (2018). What makes learning management systems effective for learning?. *Journal of Educational Technology Systems*, *47*(2), 152–169. https://doi.org/10.1177/0047239518795828

Chen, H.-J. (2018). What drives consumers' mobile shopping? 4ps or shopping preferences?. *Asia Pacific Journal of Marketing and Logistics*, *30*(4), 797–815. https://doi.org/10.1108/apjml-08-2017-0167

Chen, J. V., Su, B., & Widjaja, A. E. (2016). Facebook C2C social commerce: A study of online impulse buying. *Decision Support Systems*, *83*, 57–69. https://doi.org/10.1016/j.dss.2015.12.008

Chen, L.-T., & Liu, L. (2019). Content analysis of statistical power in educational technology research: Sample size matters. *International Journal of Technology in Teaching & Learning*, *15*(1), 49–75.

Chen, M., Herrera, F., & Hwang, K. (2018). Cognitive computing: Architecture, technologies and intelligent applications. *IEEE Access*, *6*, 19774–19783. https://doi.org/10.1109/ACCESS.2018.2791469

Chen, S.-C., Yen, D. C., & Peng, S.-C. (2018). Assessing the impact of determinants in e-magazines acceptance: An empirical study. *Computer Standards & Interfaces*, *57*, 49–58. https://doi.org/10.1016/j.csi.2017.11.004

Chen, Y., Yin, Y., Browne, G. J., & Li, D. (2019). Adoption of building information modeling in Chinese construction industry: The technology-organization-environment framework. *Engineering, Construction and Architectural Management*, *26*(9), 1878–1898. https://doi.org/10.1108/ecam-11-2017-0246

Cheng, Y.-M. (2018). What drives cloud ERP continuance? An integrated view. *Journal of Enterprise Information Management*, *31*(5), 724–750. https://doi.org/10.1108/jeim-02-2018-0043

Cheng, Y.-M. (2019). A hybrid model for exploring the antecedents of cloud ERP continuance. *International Journal of Web Information Systems*, *15*(2), 215–235. https://doi.org/10.1108/ijwis-07-2018-0056

Cheng, Y.-M. (2020). Quality antecedents and performance outcome of cloud-based hospital information system continuance intention. *Journal of Enterprise Information Management*, *33*(3), 654–683. https://doi.org/10.1108/jeim-04-2019-0107

Chiarotto, A., Terwee, C. B., & Ostelo, R. W. (2016). Choosing the right outcome measurement instruments for patients with low back pain. *Best Practice &*

Research Clinical Rheumatology, *30*(6), 1003–1020. https://doi.org/10.1016/j.berh.2017.07.001

Chiu, P.-S., Chao, I.-C., Kao, C.-C., Pu, Y.-H., & Huang, Y.-M. (2016). Implementation and evaluation of mobile e-books in a cloud bookcase using the information system success model. *Library Hi Tech*, *34*(2), 207–223. https://doi.org/10.1108/lht-12-2015-0113

Choe, H.-M., Kim, M., & Lee, E.-K. (2017). Emsaov: An r package for the analysis of variance with the expected mean squares and its shiny application. *The R Journal*, *9*(1), 252–261. https://doi.org/10.32614/rj-2017-011

Choi, M. (2016). Leadership of information security manager on the effectiveness of information systems security for secure sustainable computing. *Sustainability*, *8*(7), 638. https://doi.org/10.3390/su8070638

Chu, X., Luo, X., & Chen, Y. (2019). A systematic review on cross-cultural information systems research: Evidence from the last decade. *Information & Management*, *56*(3), 403–417. https://doi.org/10.1016/j.im.2018.08.001

Cidral, W. A., Oliveira, T., Di Felice, M., & Aparicio, M. (2018). E-learning success determinants: Brazilian empirical study. *Computers & Education*, *122*, 273–290. https://doi.org/10.1016/j.compedu.2017.12.001

Cillessen, F. H., Robbé, P. D., & Biermans, M. C. (2017). A hospital-wide transition from paper to digital problem-oriented clinical notes. *Applied Clinical Informatics*, *8*(2), 502–514. https://doi.org/10.4338/aci-2016-08-ra-0137

Clark, L., & Watson, D. (2019). Constructing validity: New developments in creating objective measuring instruments. *Psychological Assessment*, *31*(12), 1412–1427. https://doi.org/10.1037/pas0000626

Clouse, M. (2018). *Predicting u.s. adolescents' purchasing of denim jeans using quality attributes, behavioral characteristics, and sociodemographics* (13424342) [Doctoral dissertation, Utah State University]. ProQuest Dissertations and Theses Global.

Clugston, J. R., Houck, Z. M., Asken, B. M., Boone, J. K., Kontos, A. P., Buckley, T. A., Schmidt, J. D., Chrisman, S. D., Hoffman, N. L., Harmon, K. G., Kaminski, T. W., Collins, M. W., McAllister, T. W., McCrea, M. A., Broglio, S. P., & Ortega, J. D. (2019). Relationship between the king-devick test and commonly used concussion tests at baseline. *Journal of Athletic Training*, *54*(12), 1247–1253. https://doi.org/10.4085/1062-6050-455-18

Cognini, R., Corradini, F., Gnesi, S., Polini, A., & Re, B. (2018). Business process flexibility - A systematic literature review with a software systems perspective. *Information Systems Frontiers*, *20*(2), 343–371. https://doi.org/10.1007/s10796-016-9678-2

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112*, 155–159. https://dor.org/10.1037/14805-018

Cohen, J. F., Coleman, E., & Kangethe, M. J. (2016). An importance-performance analysis of hospital information system attributes: A nurses' perspective.

International Journal of Medical Informatics, *86*, 82-90. https://doi.org/10.1016/j.ijmedinf.2015.10.010

Colbert, C. Y., French, J. C., Arroliga, A. C., & Bierer, S. B. (2019). Best practice versus actual practice: An audit of survey pretesting practices reported in a sample of medical education journals. *Medical Education Online*, *24*(1), 1673596. https://doi.org/10.1080/10872981.2019.1673596

Cook, L., & Rumrill, P. D., Jr. (2005). Internal validity in rehabilitation research. *Work*, *25*(3), 279-283.

Cor, M. K. (2016). Trust me, it is valid: Research validity in pharmacy education research. *Currents in Pharmacy Teaching and Learning*, *8*(3), 391-400. https://doi.org/10.1016/j.cptl.2016.02.014

Correll, J., Mellinger, C., McClelland, G. H., & Judd, C. M. (2020). Avoid Cohen's 'small', 'medium', and 'large' for power analysis. *Trends in Cognitive Sciences*, *24*(3), 200–207. https://doi.org/10.1016/j.tics.2019.12.009

Counsell, A., & Harlow, L. L. (2017). Reporting practices and use of quantitative methods in Canadian journal articles in psychology. *Canadian Psychology/Psychologie canadienne*, *58*(2), 140–147. https://doi.org/10.1037/cap0000074

Coyle, D., & Nguyen, D. (2019). Cloud computing, cross-border data flows and new challenges for measurement in economics. *National Institute Economic Review*, *249*(1), R30–R38. https://doi.org/10.1177/002795011924900112

Coyne, M. D., Cook, B. G., & Therrien, W. J. (2016). Recommendations for replication research in special education: A framework of systematic, conceptual replications. *Remedial and Special Education*, *37*(4), 244–253. https://doi.org/10.1177/0741932516648463

Crotty, J., & Horrocks, I. (2017). Managing legacy system costs: A case study of a meta-assessment model to identify solutions in a large financial services company. *Applied Computing and Informatics*, *13*(2), 175–183. https://doi.org/10.1016/j.aci.2016.12.001

Cruz-Jesus, F., Pinheiro, A., & Oliveira, T. (2019). Understanding crm adoption stages: Empirical analysis building on the TOE framework. *Computers in Industry*, *109*, 1–13. https://doi.org/10.1016/j.compind.2019.03.007

Cucari, N. (2019). Qualitative comparative analysis in corporate governance research: A systematic literature review of applications. *Corporate Governance: The International Journal of Effective Board Performance*, *19*(4), 717–734. https://doi.org/10.1108/CG-04-2018-0161

Curran-Everett, D. (2017). Explorations in statistics: The assumption of normality. *Advances in Physiology Education*, *41*(3), 449–453. https://doi.org/10.1152/advan.00064.2017

Curtis, E. A., Comiskey, C., & Dempsey, O. (2016). Importance and use of correlational research. *Nurse Researcher*, *23*(6), 20–25. https://doi.org/10.7748/nr.2016.e1382

Daghouri, A., Mansouri, K., & Qbadou, M. (2018). Enhanced model for evaluating information system success: Determining critical criteria. *Engineering, Technology & Applied Science Research*, *8*(4), 3194–3198.

Damyanov, I. (2019). Corporate information infrastructure - Management aspects. *TEM Journal*, *8*(1), 102–106. https://doi.org/10.18421/TEM81-14

Das, A. K., & Bharadwaj, S. S. (2017). Framework for alignment of service provider value drivers with client expectations in IT services outsourcing. *Journal of Information Technology Case and Application Research*, *19*(1), 34–61. https://doi.org/10.1080/15228053.2017.1317161

Da Silva, C. E., Diniz, T., Cacho, N., & de Lemos, R. (2018). Self-adaptive authorisation in openstack cloud platform. *Journal of Internet Services and Applications*, *9*(1), 1–17. https://doi.org/10.1186/s13174-018-0090-7

Da Silva, M. P., Obelheiro, R. R., & Koslovski, P. G. (2017). Adaptive Remus: Adaptive checkpointing for Xen-based virtual machine replication. *International Journal of Parallel, Emergent & Distributed Systems*, *32*(4), 348–367. https://doi.org/10.1080/17445760.2016.1162302

Davidson, B., Dewan, M. A., Kumar, V. S., Chang, M., & Liggett, B. (2020). Visualizing benefits: Evaluating healthcare information system using IS-impact model. *IEEE Access*, *8*, 148052–148065. https://doi.org/10.1109/access.2020.3015467

Davidson, H., Jabbari, Y., Patton, H., O'Hagan, F., Peters, K., & Cribbie, R. (2019). Statistical software use in Canadian university courses: Current trends and future directions. *Teaching of Psychology*, *46*(3), 246–250. https://doi.org/10.1177/0098628319853940

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340.

https://doi.org/10.2307/249008

DeGraffe, H. J., Jr. (2017). *The relationship between athletic development personality factors and decision making* (10261486) [Doctoral dissertation, Walden University]. ProQuest Dissertations & Theses Global.

De la Prieta, F., Rodríguez-González, S., Chamoso, P., Corchado, J. M., & Bajo, J. (2019). Survey of agent-based cloud computing applications. *Future Generation Computer Systems*, *100*, 223–236. https://doi.org/10.1016/j.future.2019.04.037

DeLone, W. H., & McLean, E. R. (1992). Information systems success: The quest for the dependent variable. *Information Systems Research*, *3*(1), 60–95. https://doi.org/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. https://doi.org/10.1080/07421222.2003.11045748

DeLone, W. H., & McLean, E. R. (2004). Measuring e-commerce success: Applying the DeLone & Mclean information systems success model. *International Journal of Electronic Commerce*, *9*(1), 31–47. https://doi.org/10.1080/10864415.2004.11044317

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

De Melo Costa, D. (2019). Efficiency of public policies for higher education: The case of people's republic of China. *Revista Organizações em Contexto*, *15*(29), 155–190. https://doi.org/10.15603/1982-8756/roc.v15n29p155-190

Deresa, N. W., & Van Keilegom, I. (2020). A multivariate normal regression model for survival data subject to different types of dependent censoring. *Computational Statistics & Data Analysis*, *144*, 106879. https://doi.org/10.1016/j.csda.2019.106879

DeSimone, J. A., & Harms, P. D. (2018). Dirty data: The effects of screening respondents who provide low-quality data in survey research. *Journal of Business and Psychology*, *33*(5), 559–577. https://doi.org/10.1007/s10869-017-9514-9

De Sousa, J. V., Reche, E. A., Coury, D. V., & Fernandes, R. A. (2019). Cloud computing in the smart grid context: An application to aid fault location in distribution systems concerning the multiple estimation problem. *IET Generation, Transmission & Distribution*, *13*(18), 4222–4232. https://doi.org/10.1049/iet-gtd.2018.6651

Dewi, N., Trisnawati, T., & Kristina, M. (2020). The drill method with realistic approach to improve learning outcomes of descriptive statistics in higher education. *JINOP (Jurnal Inovasi Pembelajaran)*, *6*(2), 215–226. https://doi.org/10.22219/jinop.v6i2.13010

Di Leo, G., & Sardanelli, F. (2020). Statistical significance: P value, 0.05 threshold, and applications to radiomics—reasons for a conservative approach. *European Radiology Experimental*, *4*(1), 1–8. https://doi.org/10.1186/s41747-020-0145-y

Di Martino, S., Di Napoli, I., Esposito, C., Prilleltensky, I., & Arcidiacono, C. (2018).

Measuring subjective well-being from a multidimensional and temporal perspective: Italian adaptation of the I COPPE scale. *Health and Quality of Life Outcomes*, *16*(1), 1–11. https://doi.org/10.1186/s12955-018-0916-9

Dimitrios, T., & Antigoni, F. (2018). Ethics and deontology in nursing research: A discussion paper. *International Journal of Caring Sciences*, *11*(3), 1982–1989.

Domínguez-Escrig, E., Broch, F. F., Lapiedra, R., & Chiva, R. (2018). Promoting radical innovation through end-user computing satisfaction. *Industrial Management & Data Systems*, *118*(8), 1629–1646. https://doi.org/10.1108/imds-06-2017-0256

dos Santos, P., & Cirillo, M. (2021). Construction of the average variance extracted index for construct validation in structural equation models with adaptive regressions. *Communications in Statistics - Simulation and Computation*, 1–13. https://doi.org/10.1080/03610918.2021.1888122

Dumas-Mallet, E., Button, K. S., Boraud, T., Gonon, F., & Munafò, M. R. (2017). Low statistical power in biomedical science: A review of three human research domains. *Royal Society Open Science*, *4*(2), 160254. https://doi.org/10.1098/rsos.160254

Dutwin, D., & Buskirk, T. D. (2017). Apples to oranges or gala versus golden delicious? Comparing data quality of nonprobability internet samples to low response rate probability samples. *Public Opinion Quarterly*, *81*, 213–239. https://doi.org/10.1093/poq/nfw061

Dzewaltowski, D. A., Estabrooks, P. A., Klesges, L. M., Bull, S., & Glasgow, R. E. (2004). Behavior change intervention research in community settings: How generalizable are the results?. *Health Promotion International*, *19*(2), 235–245. https://doi.org/10.1093/heapro/dah211

Ebnehoseini, Z., Tabesh, H., Deldar, K., Mostafavi, S. M., & Tara, M. (2019). Determining hospital information system (HIS) success rate: Development of a new instrument and case study. *Open Access Macedonian Journal of Medical Sciences*, *7*(9), 1407–1414. https://doi.org/10.3889/oamjms.2019.294

Edwards, D. J., & Mee, R. W. (2008). Empirically determined p-values for lenth t-statistics. *Journal of Quality Technology*, *40*(4), 368–380. https://doi.org/10.1080/00224065.2008.11917743

Elas, N. I., Majid, F. B., & Narasuman, S. A. (2019). Development of technological pedagogical content knowledge (TPACK) for English teachers: The validity and reliability. *International Journal of Emerging Technologies in Learning*, *14*(20), 18–33. https://doi.org/10.3991/ijet.v14i20.11456

Ellis, T. J., & Levy, Y. (2009). Towards a guide for novice researchers on research methodology: Review and proposed methods. *Issues in Informing Science & Information Technology*, *6*, 323–337. https://doi.org/10.28945/1062

El-Masri, M. M. (2017a). Non-probability sampling. *The Canadian Nurse*, *113*(3), 17.

El-Masri, M. M. (2017b). Non-probability sampling: The process of selecting research participants non-randomly from a target population. *Canadian Nurse*, *113*(3), 17.

Elshaafi, H., & Botvich, D. (2016). Optimisation-based collaborative determination of component trustworthiness in service compositions. *Security and Communication Networks*, *9*(6), 513–527. https://doi.org/10.1002/sec.985

Enemark Larsen, A., Wehberg, S., & Christensen, J. R. (2020). The validity of the Danish version of the Canadian occupational performance measure. *Occupational Therapy International*, 1–11. https://doi.org/10.1155/2020/1309104

Eugster, P., Kumar, S., Savvides, S., & Stephen, J. J. (2019). Ensuring confidentiality in the Cloud of Things. *IEEE Pervasive Computing*, *18*(1), 10–18. https://doi.org/10.1109/MPRV.2018.2877286

Eze, S. C., Olatunji, S., Chinedu-Eze, V. C., Bello, A. O., Ayeni, A., & Peter, F. (2019). Determinants of perceived information need for emerging ICT adoption: A study of UK small service businesses. *Bottom Line: Managing Library Finances*, *32*(2), 158–183. https://doi.org/10.1108/bl-01-2019-0059

Fabra, J., Ezpeleta, J., & Álvarez, P. (2019). Reducing the price of resource provisioning using EC2 spot instances with prediction models. *Future Generation Computer Systems*, *96*, 348–367. https://doi.org/10.1016/j.future.2019.01.025

Fadhilah, A., Harahap, S. N., & Setyaningrum, D. (2015). Investigating the role of management accountants in Indonesia. *International Research Journal of Business Studies*, *8*(2), 81–96. https://doi.org/10.21632/irjbs.8.2.81-96

Fagerland, M. W., & Hosmer, D. W. (2017). How to test for goodness of fit in ordinal logistic regression models. *The Stata Journal*, *17*(3), 668-686. https://doi.org/10.1177/1536867x1701700308

Fahmideh, M., & Beydoun, G. (2018). Reusing empirical knowledge during cloud computing adoption. *Journal of Systems and Software*, *138*, 124–157. https://doi.org/10.1016/j.jss.2017.12.011

Fahmideh, M., Beydoun, G., & Low, G. (2019). Experiential probabilistic assessment of cloud services. *Information Sciences*, *502*, 510–524. https://doi.org/10.1016/j.ins.2019.06.027

Fahmideh, M., Daneshgar, F., Rabhi, F., & Beydoun, G. (2019). A generic cloud migration process model. *European Journal of Information Systems*, *28*(3), 233–255. https://doi.org/10.1080/0960085x.2018.1524417

Faisal, M. N., & Raza, S. A. (2016). IT outsourcing intent in academic institutions in GCC countries. *Journal of Enterprise Information Management*, *29*(3), 432–453. https://doi.org/10.1108/jeim-05-2015-0042

Fan, J., Gao, L., & Gao, J. (2016). Study on the diffusion performance of standard e-government information systems. *China Communications*, *13*(5), 182–202. https://doi.org/10.1109/cc.2016.7489986

Fareghzadeh, N., Seyyedi, M. A., & Mohsenzadeh, M. (2019). Toward holistic performance management in clouds: Taxonomy, challenges and opportunities. *Journal of Supercomputing*, *75*(1), 272–313. https://doi.org/10.1007/s11227-018-2679-9

Farzandipour, M., Mohamadian, H., Akbari, H., Safari, S., & Sharif, R. (2021). Designing a national model for assessment of nursing informatics competency. *BMC Medical Informatics and Decision Making*, *21*(1), 1–12. https://doi.org/10.1186/s12911-021-01405-0

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior*

Research Methods, *41*(4), 1149–1160. https://doi.org/10.3758/brm.41.4.1149

Fekjær, S. B. (2018). Old and new methods in police research. *Nordisk Politiforskning*, *5*(2), 104-123. https://doi.org/10.18261/issn.1894-8693-2018-02-02

Felt, J. M., Castaneda, R., Tiemensma, J., & Depaoli, S. (2017). Using person fit statistics to detect outliers in survey research. *Frontiers in Psychology*, *8*, 1–9. https://doi.org/10.3389/fpsyg.2017.00863

Feng, X., & Pan, W. (2016). Determinants of user acceptance of electronic recordkeeping systems: A user-focused empirical study of system characteristics. *Canadian Journal of Information & Library Sciences*, *40*(2), 124–151.

Feng, Y., Huang, Y., & Ma, X. (2017). The application of student’s t -test in internal quality control of clinical laboratory. *Frontiers in Laboratory Medicine*, *1*(3), 125–128. https://doi.org/10.1016/j.flm.2017.09.002

Ferri, L., Spanò, R., & Tomo, A. (2020). Cloud computing in high tech startups: Evidence from a case study. *Technology Analysis & Strategic Management*, *32*(2), 146–157. https://doi.org/10.1080/09537325.2019.1641594

Fiandrino, C., Allio, N., Kliazovich, D., Giaccone, P., & Bouvry, P. (2019). Profiling performance of application partitioning for wearable devices in mobile cloud and fog computing. *IEEE Access*, *7*, 12156–12166. https://doi.org/10.1109/ACCESS.2019.2892508

Fielding, E., Beattie, E., O’Reilly, M., & McMaster, M. (2017). Achieving a national sample of nursing homes: Balancing probability techniques and practicalities. *Research in Gerontological Nursing*, *10*(2), 58–65.

https://doi.org/10.3928/19404921-20151019-03

Flannelly, K. J., Flannelly, L. T., & Jankowski, K. R. (2018). Threats to the internal validity of experimental and quasi-experimental research in healthcare. *Journal of Health Care Chaplaincy*, *24*(3), 107–130. https://doi.org/10.1080/08854726.2017.1421019

Flatt, C., & Jacobs, R. L. (2019). Principle assumptions of regression analysis: Testing, techniques, and statistical reporting of imperfect data sets. *Advances in Developing Human Resources*, *21*(4), 484–502. https://doi.org/10.1177/1523422319869915

Fontes, A., Rodrigues, L. L., & Craig, R. (2016). A theoretical model of stakeholder perceptions of a new financial reporting system. *Accounting Forum*, *40*(4), 300–315. https://doi.org/10.1016/j.accfor.2016.10.002

Foryś, I., & Gaca, R. (2016). Application of the Likert and Osgood scales to quantify the qualitative features of real estate properties. *Folia Oeconomica Stetinensia*, *16*(2), 7–16. https://doi.org/10.1515/foli-2016-0021

Foster, T. A. (2017). *Budget planning, budget control, business age, and financial performance in small businesses* (10272755) [Doctoral dissertation, Walden University]. ProQuest Dissertations & Theses Global.

Francis, D. O., McPheeters, M. L., Noud, M., Penson, D. F., & Feurer, I. D. (2016). Checklist to operationalize measurement characteristics of patient-reported outcome measures. *Systematic Reviews*, *5*(1), 129. https://doi.org/10.1186/s13643-016-0307-4

French, A. M., Shim, J. P., Otondo, R. F., & Templeton, G. T. (2018). An empirical study evaluating social networking continuance and success. *Journal of Computer Information Systems*, *58*(4), 353–362. https://doi.org/10.1080/08874417.2017.1281075

Frongillo, E. A., Baranowski, T., Subar, A. F., Tooze, J. A., & Kirkpatrick, S. I. (2019). Establishing validity and cross-context equivalence of measures and indicators. *Journal of the Academy of Nutrition and Dietetics*, *119*(11), 1817-1830. https://doi.org/10.1016/j.jand.2018.09.005

Gaardboe, R., Nyvang, T., & Sandalgaard, N. (2017). Business intelligence success applied to healthcare information systems. *Procedia Computer Science*, *121*, 483–490. https://doi.org/10.1016/j.procs.2017.11.065

Gangwar, H., Date, H., & Ramaswamy, R. (2015). Understanding determinants of cloud computing adoption using an integrated TAM-TOE model. *Journal of Enterprise Information Management*, *28*(1), 107–130. https://doi.org/10.1108/JEIM-08-2013-0065

Garavan, T., McCarthy, A., Sheehan, M., Lai, Y., Saunders, M. N., Clarke, N., Carbery, R., & Shanahan, V. (2019). Measuring the organizational impact of training: The need for greater methodological rigor. *Human Resource Development Quarterly*, *30*(3), 291–309. https://doi.org/10.1002/hrdq.21345

Garcia, J., & Cuevas, E. (2019). Perceptions on workplace safety and work engagement of teachers in the public elementary school setting. *University of Mindanao International Multidisciplinary Research Journal*, *4*(1), 87–94.

García-Valls, M., Dubey, A., & Botti, V. (2018). Introducing the new paradigm of social dispersed computing: Applications, technologies and challenges. *Journal of Systems Architecture*, *91*, 83–102. https://doi.org/10.1016/j.sysarc.2018.05.007

Garg, D., Sidhu, J., & Rani, S. (2019). Emerging trends in cloud computing security: A bibliometric analyses. *IET Software*, *13*(3), 223–231. https://doi.org/10.1049/iet-sen.2018.5222

Gartner. (2019, April 17). *Gartner says global IT spending to grow 1.1 percent in 2019*. Gartner, Inc.. https://www.gartner.com/

Gashami, J. P., Chang, Y., Rho, J. J., & Park, M.-C. (2016). Privacy concerns and benefits in SaaS adoption by individual users: A trade-off approach. *Information Development*, *32*(4), 837–852. https://doi.org/10.1177/0266666915571428

Gavlas, J. T. (2018). *Psychometric properties of the modern homonegativity scale in the southern United States* (10747601) [Doctoral dissertation, Walden University]. ProQuest Dissertations & Theses Global.

Gay, G. H. (2016). An assessment of online instructor e-learning readiness before, during, and after course delivery. *Journal of Computing in Higher Education*, *28*(2), 199–220. https://doi.org/10.1007/s12528-016-9115-z

Genereaux, D., Bansback, N., & Birch, P. (2016). Development and pilot testing of a tool to calculate parental and societal costs of raising a child with intellectual disability. *Journal of Intellectual and Developmental Disability*, *41*(1), 11–20. https://doi.org/10.3109/13668250.2015.1087479

Ghobakhloo, M., & Tang, S. H. (2015). Information system success among manufacturing SMEs: Case of developing countries. *Information Technology for Development*, *21*(4), 573–600. https://doi.org/10.1080/02681102.2014.996201

Gholami, M. F., Daneshgar, F., Beydoun, G., & Rabhi, F. (2017). Challenges in migrating legacy software systems to the cloud — an empirical study. *Information Systems*, *67*, 100–113. https://doi.org/10.1016/j.is.2017.03.008

Glava, M., & Malakhov, V. (2018). Information systems reengineering approach based on the model of information systems domains. *International Journal of Software Engineering and Computer Systems*, *4*(1), 95–105. https://doi.org/10.15282/ijsecs.4.1.2018.8.0041

Goegan, L. D., Radil, A. I., & Daniels, L. M. (2018). Accessibility in questionnaire research: Integrating universal design to increase the participation of individuals with learning disabilities. *Learning Disabilities: A Contemporary Journal*, *16*(2), 177–190.

Goertzen, M. J. (2017). Chapter 3: Introduction to quantitative research and data. *Library Technology Reports*, *53*(4), 12–18.

Gonzales, R., & Wareham, J. (2019). Analysing the impact of a business intelligence system and new conceptualizations of system use. *Journal of Economics, Finance and Administrative Science*, *24*(48), 345–368. https://doi.org/10.1108/jefas-05-2018-0052

Goodman, W. M., Spruill, S. E., & Komaroff, E. (2019). A proposed hybrid effect size plus p-value criterion: Empirical evidence supporting its use. *The American Statistician*, *73*, 168–185. https://doi.org/10.1080/00031305.2018.1564697

Gordy, X. Z., Jones, E. M., & Bailey, J. H. (2018). Technological innovation or educational evolution? A multi-disciplinary qualitative inquiry into active learning classrooms. *Journal of the Scholarship of Teaching and Learning*, *18*(2), 1–23. https://doi.org/10.14434/josotl.v18i2.23597

Gouda, O. E., & El-Hoshy, S. H. (2020). Diagnostic technique for analysing the internal faults within power transformers based on sweep frequency response using adjusted r-square methodology. *IET Science, Measurement & Technology*, *14*(10), 1057–1068. https://doi.org/10.1049/iet-smt.2020.0048

Goulet, M.-A., & Cousineau, D. (2019). The power of replicated measures to increase statistical power. *Advances in Methods and Practices in Psychological Science*, *2*(3), 199–213. https://doi.org/10.1177/2515245919849434

Graves, N. K. (2019). *Thinking about engaging in charitable behaviors and its influence on loneliness* (27543968) [Doctoral dissertation, Walden University]. ProQuest Dissertations & Theses Global.

Gray, L., Gorman, E., White, I. R., Katikireddi, S. V., McCartney, G., Rutherford, L., & Leyland, A. H. (2019). Correcting for non-participation bias in health surveys using record-linkage, synthetic observations and pattern mixture modelling. *Statistical Methods in Medical Research*, *29*(4), 1212–1226. https://doi.org/10.1177/0962280219854482

Greene, G., Plante, R., & Hanisch, R. (2019). Building open access to research (OAR) data infrastructure at NIST. *Data Science Journal*, *18*(1), 1–7. https://doi.org/10.5334/dsj-2019-030

Grigsby, T. J., & McLawhorn, J. (2019). Missing data techniques and the statistical conclusion validity of survey-based alcohol and drug use research studies: A review and comment on reproducibility. *Journal of Drug Issues*, *49*(1), 44–56. https://doi.org/10.1177/0022042618795878

Grover, P., Kar, A. K., & Janssen, M. (2019). Diffusion of blockchain technology: Insights from academic literature and social media analytics. *Journal of Enterprise Information Management*, *32*(5), 735–757. https://doi.org/10.1108/jeim-06-2018-0132

Gugiu, C., & Gugiu, M. (2018). Determining the minimum reliability standard based on a decision criterion. *The Journal of Experimental Education*, *86*(3), 458–472. https://doi.org/10.1080/00220973.2017.1315712

Guillemin, M., Barnard, E., Allen, A., Stewart, P., Walker, H., Rosenthal, D., & Gillam, L. (2018). Do research participants trust researchers or their institution?. *Journal of Empirical Research on Human Research Ethics*, *13*(3), 285–294. https://doi.org/10.1177/1556264618763253

Guo, Z., Ren, X., & Ren, F. (2020). Better realization of mobile cloud computing using mobile network computers. *Wireless Personal Communications*, *111*(3), 1805–1819. https://doi.org/10.1007/s11277-019-06958-y

Gupta, S. (2017). Ethical issues in designing internet-based research: Recommendations for good practice. *Journal of Research Practice*, *13*(2), 1–14.

Gwelo, A. S. (2019). Principal components to overcome multicollinearity problem. *Oradea Journal of Business and Economics*, *4*(1), 79–91.

Ha, L. S., & Zhang, C. (2019). Are computers better than smartphones for web survey responses?. *Online Information Review*, *43*(3), 350–368. https://doi.org/10.1108/oir-11-2017-0322

Haegele, J. A., & Hodge, S. R. (2015). Quantitative methodology: A guide for emerging physical education and adapted physical education researchers. *Physical Educator*, *72*(5), 59–75. https://doi.org/10.18666/TPE-2015-V72-I5-6133

Haghshenas, H., Habibi, J., & Fazli, M. A. (2019). Parasite cloud service providers: On-demand prices on top of spot prices. *Heliyon*, *5*(11), e02877. https://doi.org/10.1016/j.heliyon.2019.e02877

Halfens, R. J., & Meijers, J. M. (2013). Back to basics: An introduction to statistics. *Journal of Wound Care*, *22*(5), 248–251. https://doi.org/10.12968/jowc.2013.22.5.248

Hamdan, M. N., & Al-Hajri, N. J. (2021). The effect of information systems success factors on user satisfaction in accounting information systems. *Management Science Letters*, 2045–2052. https://doi.org/10.5267/j.msl.2021.3.005

Hammers, D. B., & Duff, K. (2019). Application of different standard error estimates in reliable change methods. *Archives of Clinical Neuropsychology*, 1–8. https://doi.org/10.1093/arclin/acz054

Hammood, W. A., Asmara, S. M., Arshah, R. A., Hammood, O. A., Halbusi, H. A., Al-Sharafi, M. A., & Khaleefah, S. H. (2020). Factors influencing the success of information systems in flood early warning and response systems context. *Telkomnika*, *18*(6), 2956–2961. https://doi.org/10.12928/telkomnika.v18i6.14666

Handley, M. A., Lyles, C. R., McCulloch, C., & Cattamanchi, A. (2018). Selecting and improving quasi-experimental designs in effectiveness and implementation research. *Annual Review of Public Health*, *39*, 5–25. https://doi.org/10.1146/annurev-publhealth-040617-014128

Harr, A., vom Brocke, J., & Urbach, N. (2019). Evaluating the individual and organizational impact of enterprise content management systems. *Business Process Management Journal*, *25*(7), 1413–1440. https://doi.org/10.1108/bpmj-05-2017-0117

Hart, V. R. (2019). *Perceived racism and perceived leadership from subordinates based on race and gender differences* (13887128) [Doctoral dissertation, Capella University]. ProQuest Dissertations and Theses Global.

Hartwick, P. (2018). Investigating research approaches: Classroom-based interaction studies in physical and virtual contexts. *ReCALL*, *30*(2), 161–176. https://doi.org/10.1017/s0958344017000386

Hashem, W., Nashaat, H., & Rizk, R. (2017). Honey bee based load balancing in cloud computing. *KSII Transactions on Internet & Information Systems*, *11*(12), 5694–5711. https://doi.org/10.3837/tiis.2017.12.001

Hassan, H., Nasir, M. H., Khairudin, N., & Adon, I. (2017). Factors influencing cloud computing adoption in small and medium enterprises. *Journal of Information & Communication Technology*, *16*(1), 21–41.

Hawedi, M., Talhi, C., & Boucheneb, H. (2018). Security as a service for public cloud tenants (SaaS). *Procedia Computer Science*, *130*, 1025–1030.

https://doi.org/10.1016/j.procs.2018.04.143

Hayati, U., Sukarsa, D. E., Mulyani, S., & Winarningsih, S. (2021). Information system's implementation and its Impact on university organization performance in west Java. *Utopia y Praxis Latinoamericana*, *26*, 343–357. https://doi.org/10.5281/zenodo.4556291

Hazra, A., & Gogtay, N. (2016a). Biostatistics series module 1: Basics of biostatistics. *Indian Journal of Dermatology*, *61*(1), 10–20. https://doi.org/10.4103/0019-5154.173988

Hazra, A., & Gogtay, N. (2016b). Biostatistics series module 6: Correlation and linear regression. *Indian Journal of Dermatology*, *61*(6), 593–601. https://doi.org/10.4103/0019-5154.193662

Helmi, A. M., Farhan, M. S., & Nasr, M. M. (2018). A framework for integrating geospatial information systems and hybrid cloud computing. *Computers and Electrical Engineering*, *67*, 145–158. https://doi.org/10.1016/j.compeleceng.2018.03.027

Hermawan, H. (2019). Successful implementation of enterprise resource planning. *Journal the Winners: Economics, Business, Management, and Information System Journal*, *20*(1), 19–31. https://doi.org/10.21512/tw.v20i1.5359

Hesamamiri, R., & Bourouni, A. (2016). Customer support optimization using system dynamics: A multi-parameter approach. *Kybernetes*, *45*(6), 900–914. https://doi.org/10.1108/k-10-2015-0257

Hess, A. N. (2020). Academic librarians' teaching identities and work experiences:

Exploring relationships to support perspective transformation in information literacy instruction. *Journal of Library Administration*, *60*(4), 331–353. https://doi.org/10.1080/01930826.2020.1721939

Heyden, M. L., Sidhu, J. S., & Volberda, H. W. (2018). The conjoint influence of top and middle management characteristics on management innovation. *Journal of Management*, *44*(4), 1505–1529. https://doi.org/10.1177/0149206315614373

Hjalmarson, M. A., & Moskal, B. (2018). Quality considerations in education research: Expanding our understanding of quantitative evidence and arguments. *Journal of Engineering Education*, *107*(2), 179–185. https://doi.org/10.1002/jee.20202

Ho, T.-Y., Tsai, H.-T., & Lin, P.-H. (2019). The effects of technology innovation and network presence on Otaku identity. *Technological Forecasting and Social Change*, *144*, 82–92. https://doi.org/10.1016/j.techfore.2019.04.008

Holden, R. R., Marjanovic, Z., & Troister, T. (2019). Indiscriminate responding can increase effect sizes for clinical phenomena in nonclinical populations: A cautionary note. *Journal of Psychoeducational Assessment*, *37*(4), 464–472. https://doi.org/10.1177/0734282918758809

Horetko, T. (2018). Trends in professional training of IT managers in the global educational space. *Comparative Professional Pedagogy*, *8*(2), 143–147. https://doi.org/10.2478/rpp-2018-0031

Hornyak, R., Rai, A., & Dong, J. Q. (2020). Incumbent system context and job outcomes of effective enterprise system use. *Journal of the Association for Information Systems*, *21*(2), 364–387. https://doi.org/10.17705/1jais.00605

Hossein-Zadeh, N. G. (2016). Modelling lactation curve for fat to protein ratio in Holstein cows. *Animal Science Papers & Reports*, *34*(3), 233–245. http://www.ighz.edu.pl/

Hou, S.-I., & Pereira, V. (2017). Measuring infusion of service-learning on student program development and implementation competencies. *Journal of Experiential Education*, *40*(2), 170–186. https://doi.org/10.1177/1053825917699518

Hsu, H.-Y., Liu, F.-H., Tsou, H.-T., & Chen, L.-J. (2019). Openness of technology adoption, top management support and service innovation: A social innovation perspective. *Journal of Business & Industrial Marketing*, *34*(3), 575–590. https://doi.org/10.1108/jbim-03-2017-0068

Hu, L. (2021). The construction of mobile education in cloud computing. *Procedia Computer Science*, *183*, 14–17. https://doi.org/10.1016/j.procs.2021.02.024

Hubbard, R., Haig, B. D., & Parsa, R. A. (2019). The limited role of formal statistical inference in scientific inference. *American Statistician*, *73*, 91–98. https://doi.org/10.1080/00031305.2018.1464947

Hubert, M., Blut, M., Brock, C., Zhang, R. W., Koch, V., & Riedl, R. (2019). The influence of acceptance and adoption drivers on smart home usage. *European Journal of Marketing*, *53*(6), 1073–1098. https://doi.org/10.1108/ejm-12-2016-0794

Hughes, J. L., Camden, A. A., & Yangchen, T. (2016). Rethinking and updating demographic questions: Guidance to improve descriptions of research samples. *Psi Chi Journal of Psychological Research*, *21*(3), 138–151.

Hütter, M., & Tigges, D. (2019). On the external validity of evaluative conditioning: Evaluative responses generalize to modified instances of conditioned stimuli. *Journal of Experimental Social Psychology*, *84*, 1–12. https://doi.org/10.1016/j.jesp.2019.103824

Hwang, Y., Al-Arabiat, M., & Shin, D.-H. (2016). Understanding technology acceptance in a mandatory environment. *Information Development*, *32*(4), 1266–1283. https://doi.org/10.1177/0266666915593621

Hyman, M. R., Kostyk, A., Zhou, W., & Paas, L. (2019). Novel approaches for improving data quality from self-administered questionnaires. *International Journal of Market Research*, *61*(5), 552–555. https://doi.org/10.1177/1470785319870622a

Ialongo, C. (2019). Confidence interval for quantiles and percentiles. *Biochemia Medica*, *29*(1), 1–13. https://doi.org/10.11613/bm.2019.010101

Iannacci, F., & Cornford, T. (2018). Unravelling causal and temporal influences underpinning monitoring systems success: A typological approach. *Information Systems Journal*, *28*(2), 384–407. https://doi.org/10.1111/isj.12145

Imon, A., & Hadi, A. S. (2008). Identification of multiple outliers in logistic regression. *Communications in Statistics - Theory and Methods*, *37*(11), 1697–1709. https://doi.org/10.1080/03610920701826161

Indu, P. V., & Vidhukumar, K. (2019). Research designs - An overview. *Kerala Journal of Psychiatry*, *32*(1), 64–67. https://doi.org/10.30834/KJP.32.1.2019.179

International Data Corporation. (2019, June 20). *Cloud IT infrastructure revenues* *continue to expand despite slow down in spending in 2019, According to IDC*. IDC. https://www.idc.com/

Iqbal, S., Kiah, M. L., Anuar, N. B., Daghighi, B., Wahab, A. W., & Khan, S. (2016). Service delivery models of cloud computing: Security issues and open challenges. *Security and Communication Networks*, *9*(17), 4726–4750. https://doi.org/10.1002/sec.1585

Isaac, O., Abdullah, Z., Ramayah, T., & Mutahar, A. M. (2017). Internet usage, user satisfaction, task-technology fit, and performance impact among public sector employees in Yemen. *International Journal of Information and Learning Technology*, *34*(3), 210–241. https://doi.org/10.1108/ijilt-11-2016-0051

Isaac, O., Aldholay, A., Abdullah, Z., & Ramayah, T. (2019). Online learning usage within Yemeni higher education: The role of compatibility and task-technology fit as mediating variables in the is success model. *Computers & Education*, *136*, 113–129. https://doi.org/10.1016/j.compedu.2019.02.012

Islam, S., Ouedraogo, M., Kalloniatis, C., Mouratidis, H., & Gritzalis, S. (2018). Assurance of security and privacy requirements for cloud deployment models. *IEEE Transactions on Cloud Computing*, *6*(2), 387–400. https://doi.org/10.1109/tcc.2015.2511719

Itthiphone, V., Jo, D., & Kwon, C. (2020). Determinants of continuance intention in mobile payment services: Based on the IS success model. *Journal of Korean Society for Internet Information*, *21*(5), 87–95. https://doi.org/10.7472/jksii.2020.21.5.87

Iyer, G., & DoraiswamyIyer, R. (2020). Internet addiction in freshmen engineering students in India. *Journal of Management & Public Policy*, *12*(1), 45–58. https://doi.org/10.47914/jmpp.2020.v12i1.004

Jararweh, Y., Al-Ayyoub, M., Darabseh, A., Benkhelifa, E., Vouk, M., & Rindos, A. (2016). Software defined cloud: Survey, system and evaluation. *Future Generation Computer Systems*, *58*, 56–74. https://doi.org/10.1016/j.future.2015.10.015

Jayakumar, D. S., & Sulthan, A. (2015). A new procedure of regression clustering based on cook's d. *Electronic Journal of Applied Statistical Analysis*, *8*(1), 13–27. https://doi.org/10.1285/i20705948v8n1p13

Jeyaraj, A. (2020). Delone & Mclean models of information system success: Critical meta-review and research directions. *International Journal of Information Management*, *54*, 102139. https://doi.org/10.1016/j.ijinfomgt.2020.102139

Jiang, S.-J., & Wu, C.-T. (2016). Utilization of cloud computing app for homestay operation - design and analysis. *International Journal of Organizational Innovation*, *11*(2), 31–44.

Johansson, L., & Silén, M. (2018). Research methods in nursing students' bachelor's theses in sweden: A descriptive study. *Nurse Education Today*, *66*, 187–193. https://doi.org/10.1016/j.nedt.2018.04.006

Jones, M. C., Kappelman, L., Pavur, R., Nguyen, Q. N., & Johnson, V. L. (2019). Pathways to being CIO: The role of background revisited. *Information & Management*, 1–14. https://doi.org/10.1016/j.im.2019.103234

Jones, N. T., & Seckman, C. (2018). Facilitating adoption of an electronic documentation system. *CIN: Computers, Informatics, Nursing*, *36*(5), 225–231. https://doi.org/10.1097/cin.0000000000000410

Jonsen, K., Fendt, J., & Point, S. (2018). Convincing qualitative research: What constitutes persuasive writing?. *Organizational Research Methods*, *21*(1), 30–67. https://doi.org/10.1177/1094428117706533

Jorrín Abellán, I. M. (2019). Hopscotch 2.0: An enhanced version of the model for the generation of research designs in social sciences and education. *Georgia Educational Researcher*, *16*(1), 5–22. https://doi.org/10.20429/ger.2019.160103

Judd, J. A. (2019). *Organizational culture's moderating relationship on surface acting and psychological distress* (22624049) [Doctoral dissertation, Walden University]. ProQuest Dissertations & Theses Global.

Jung, E., & Jung, E. J. (2019). Service-oriented architecture of environmental information systems to forecast the impacts of natural disasters in South Korea. *Journal of Enterprise Information Management*, *32*(1), 16–35. https://doi.org/10.1108/jeim-03-2015-0022

Jupiter, D. C. (2017). Assumptions of statistical tests: What lies beneath. *Journal of Foot and Ankle Surgery*, *56*(4), 910–913. https://doi.org/10.1053/j.jfas.2017.05.022

Kalavani, A., Kazerani, M., & Shekofteh, M. (2018). Acceptance of evidence based medicine (EBM) databases by Iranian medical residents using unified theory of acceptance and use of technology (UTAUT). *Health Policy and Technology*, *7*(3), 287–292. https://doi.org/10.1016/j.hlpt.2018.06.005

Kaliyadan, F., & Kulkarni, V. (2019). Types of variables, descriptive statistics, and sample size. *Indian Dermatology Online Journal*, *10*(1), 82–86. https://doi.org/10.4103/idoj.IDOJ_468_18

Kaltenbrunner, M., Bengtsson, L., Mathiassen, S. E., & Engström, M. (2017). A questionnaire measuring staff perceptions of Lean adoption in healthcare: Development and psychometric testing. *BMC Health Services Research*, *17*, 1–11. https://doi.org/10.1186/s12913-017-2163-x

Kaplan, M., Kneifel, C., Orlikowski, V., Dorff, J., Newton, M., Howard, A., Shinn, D., Bishawi, M., Chidyagwai, S., Balogh, P., & Randles, A. (2020). Cloud computing for covid-19: Lessons learned from massively parallel models of ventilator splitting. *Computing in Science & Engineering*, *22*(6), 37–47. https://doi.org/10.1109/mcse.2020.3024062

Karlinsky-Shichor, Y., & Zviran, M. (2016). Factors influencing perceived benefits and user satisfaction in knowledge management systems. *Information Systems Management*, *33*(1), 55–73. https://doi.org/10.1080/10580530.2016.1117873

Karlsen, M. C., Lichtenstein, A. H., Economos, C. D., Folta, S. C., Rogers, G., Jacques, P. F., Livingston, K. A., Rancaño, K. M., & McKeown, N. M. (2018). Web-based recruitment and survey methodology to maximize response rates from followers of popular diets: The adhering to dietary approaches for personal taste (adapt) feasibility survey. *Current Developments in Nutrition*, *2*(5), 1–11. https://doi.org/10.1093/cdn/nzy012

Kaschig, A., Maier, R., & Sandow, A. (2016). The effects of collecting and connecting activities on knowledge creation in organizations. *Journal of Strategic Information Systems*, *25*(4), 243–258. https://doi.org/10.1016/j.jsis.2016.08.002

Kathuria, A., Mann, A., Khuntia, J., Saldanha, T. J., & Kauffman, R. J. (2018). A strategic value appropriation path for cloud computing. *Journal of Management Information Systems*, *35*(3), 740–775. https://doi.org/10.1080/07421222.2018.1481635

Ke, P., & Su, F. (2018). Mediating effects of user experience usability: An empirical study on mobile library application in China. *The Electronic Library*, *36*(5), 892–909. https://doi.org/10.1108/el-04-2017-0086

Keikhosrokiani, P., Mustaffa, N., & Zakaria, N. (2018). Success factors in developing iheart as a patient-centric healthcare system: A multi-group analysis. *Telematics and Informatics*, *35*(4), 753–775. https://doi.org/10.1016/j.tele.2017.11.006

Kenny, D. A. (2019). Enhancing validity in psychological research. *American Psychologist*, *74*(9), 1018–1028. https://doi.org/10.1037/amp0000531

Kern, H. L., Stuart, E. A., Hill, J., & Green, D. P. (2016). Assessing methods for generalizing experimental impact estimates to target populations. *Journal of Research on Educational Effectiveness*, *9*(1), 103–127. https://doi.org/10.1080/19345747.2015.1060282

Kerry, S. M., Morgan, K. E., Limb, E., Cook, D. G., Furness, C., Carey, I., DeWilde, S., Victor, C. R., Iliffe, S., Whincup, P., Ussher, M., Ekelund, U., Fox-Rushby, J., Ibison, J., & Harris, T. (2018). Interpreting population reach of a large, successful physical activity trial delivered through primary care. *BMC Public Health*, *18*(1), 1–10. https://doi.org/10.1186/s12889-018-5034-4

Keser, İ. K., Kocakoç, İ. D., & Şehirlioğlu, A. K. (2016). A new descriptive statistic for functional data: Functional coefficient of variation. *Alphanumeric Journal*, *4*(2), 1–10. https://doi.org/10.17093/aj.2016.4.2.5000185408

Khalil, S. (2019). Adopting the cloud: How it affects firm strategy. *Journal of Business Strategy*, *40*(4), 28–35. https://doi.org/10.1108/jbs-05-2018-0089

Khand, Z. H., & Kalhoro, M. R. (2020). Testing and validating Delone and Maclean is model: ERP system success in higher education institutions of Pakistan. *Engineering, Technology & Applied Science Research*, *10*(5), 6242–6248. https://doi.org/10.48084/etasr.3762

Kharub, M., & Sharma, R. K. (2018). Quantifying the relationship between latent variables after successful implementation of QM practices in MSMEs. *International Journal of Quality & Reliability Management*, *35*(4), 875–896. https://doi.org/10.1108/ijqrm-12-2016-0221

Khayat, M., Karimzadeh, M., Ebert, D. S., & Ghafoor, A. (2020). The validity, generalizability and feasibility of summative evaluation methods in visual analytics. *IEEE Transactions on Visualization and Computer Graphics*, *26*(1), 353–363. https://doi.org/10.1109/tvcg.2019.2934264

Khayer, A., Bao, Y., & Nguyen, B. (2020). Understanding cloud computing success and its impact on firm performance: An integrated approach. *Industrial Management & Data Systems*, *120*(5), 963–985. https://doi.org/10.1108/imds-06-2019-0327

Khayun, V., Ractham, P., & Firpo, D. (2012). Assessing e-excise sucess with DeLone and McLean's model. *Journal of Computer Information Systems*, *52*(3), 31–40. https://doi.org/10.1080/08874417.2012.11645556

Kietzmann, J., & Archer-Brown, C. (2019). From hype to reality: Blockchain grows up. *Business Horizons*, *62*(3), 269–271. https://doi.org/10.1016/j.bushor.2019.01.001

Kim, J. H. (2019). Multicollinearity and misleading statistical results. *Korean Journal of Anesthesiology*, *72*(6), 558–569. https://doi.org/10.4097/kja.19087

Kim, K., & Wyckoff, T. (2016). What's in your list?: A survey of business database holdings and funding sources at top academic institutions. *Journal of Business & Finance Librarianship*, *21*(2), 135–151. https://doi.org/10.1080/08963568.2016.1140548

Kim, L. L., & Amran, A. (2018). Factors leading to the adoption of business continuity management (BCM) in Malaysia. *Global Business and Management Research: An International Journal*, *10*(1), 179–196.

Kim, M. M., Rhoades, G., & Woodard, D. B., Jr. (2003). Sponsored research versus graduating students? Intervening variables and unanticipated findings in public research universities. *Research in Higher Education*, *44*(1), 51–81. https://doi.org/10.1023/a:1021365528640

Kim, T. K. (2017). Practical statistics in pain research. *Korean Journal of Pain*, *30*(4), 243–249. https://doi.org/10.3344/kjp.2017.30.4.243

King, N. M. (2019). Key information in the new common rule: Can it save research consent?. *Journal of Law, Medicine & Ethics*, *47*(2), 203–212. https://doi.org/10.1177/1073110519857276

Klement, M. (2017). Models of integration of virtualization in education: Virtualization technology and possibilities of its use in education. *Computers & Education*, *105*, 31–43. https://doi.org/10.1016/j.compedu.2016.11.006

Kluge, A., Schüffler, A. S., Thim, C., Haase, J., & Gronau, N. (2019). Investigating unlearning and forgetting in organizations: Research methods, designs and implications. *The Learning Organization*, *26*(5), 518–533. https://doi.org/10.1108/tlo-09-2018-0146

Knaub, A. V., Aiken, J. M., & Ding, L. (2019). Two-phase study examining perspectives and use of quantitative methods in physics education research. *Physical Review Physics Education Research*, *15*(2), 1–20. https://doi.org/10.1103/physrevphyseducres.15.020102

Knauer, T., Nikiforow, N., & Wagener, S. (2020). Determinants of information system quality and data quality in management accounting. *Journal of Management Control*, *31*(1-2), 97–121. https://doi.org/10.1007/s00187-020-00296-y

Knowlden, A. P., & Conrad, E. (2018). Two-year outcomes of the enabling mothers to prevent pediatric obesity through web-based education and reciprocal determinism (empower) randomized control trial. *Health Education & Behavior*, *45*(2), 262–276. https://doi.org/10.1177/1090198117732604

Kobusinska, A., Leung, C., Hsu, C.-H., Raghavendra, S., & Chang, V. (2018). Emerging trends, issues and challenges in internet of things, big data and cloud computing. *Future Generation Computer Systems*, *87*, 416–419. https://doi.org/10.1016/j.future.2018.05.021

Köhler, T., Landis, R. S., & Cortina, J. M. (2017). From the editors: Establishing methodological rigor in quantitative management learning and education research: The role of design, statistical methods, and reporting standards. *Academy of Management Learning & Education*, *16*(2), 173–192. https://doi.org/10.5465/amle.2017.0079

Kong, Y. S., Abdullah, S., Schramm, D., Omar, M. Z., & Haris, S. M. (2019). Development of multiple linear regression-based models for fatigue life evaluation of automotive coil springs. *Mechanical Systems and Signal Processing*, *118*, 675–695. https://doi.org/10.1016/j.ymssp.2018.09.007

Kopra, J., Härkänen, T., Tolonen, H., Jousilahti, P., Kuulasmaa, K., Reinikainen, J., & Karvanen, J. (2018). Adjusting for selective non-participation with re-contact data in the finrisk 2012 survey. *Scandinavian Journal of Public Health*, *46*(7), 758–766. https://doi.org/10.1177/1403494817734774

Korkmaz, M. (2019). A study over the formulation of the parameters 5 or less independent variables of multiple linear regression. *Journal of Function Spaces*, 1–14. https://doi.org/10.1155/2019/1526920

Korstjens, I., & Moser, A. (2017). Series: Practical guidance to qualitative research. Part 2: Context, research questions and designs. *European Journal of General Practice*, *23*(1), 274–279. https://doi.org/10.1080/13814788.2017.1375090

Koziol, N. A., & Bovaird, J. A. (2018). The impact of model parameterization and estimation methods on tests of measurement invariance with ordered polytomous data. *Educational and Psychological Measurement*, *78*(2), 272–296.

https://doi.org/10.1177/0013164416683754

Krieger, M. T., Torreno, O., Trelles, O., & Kranzlmüller, D. (2017). Building an open source cloud environment with auto-scaling resources for executing bioinformatics and biomedical workflows. *Future Generation Computer Systems*, *67*, 329–340. https://doi.org/10.1016/j.future.2016.02.008

Krishnan, P. (2019). A review of the non-equivalent control group post-test-only design. *Nurse Researcher*, *26*(2), 37–40. https://doi.org/10.7748/nr.2018.e1582

Kristina, B. H., & Andreja, P. (2017). The importance of business model factors for cloud computing adoption: Role of previous experiences. *Organizacija*, *50*(3), 255–272. https://doi.org/10.1515/orga-2017-0013

Kuhlmann, T., Dantlgraber, M., & Reips, U.-D. (2017). Investigating measurement equivalence of visual analogue scales and Likert-type scales in internet-based personality questionnaires. *Behavior Research Methods*, *49*(6), 2173–2181. https://doi.org/10.3758/s13428-016-0850-x

Kulkarni, D. K. (2016). Interpretation and display of research results. *Indian Journal of Anaesthesia*, *60*(9), 657–661. https://doi.org/10.4103/0019-5049.190622

Kunz, W. H., Heinonen, K., & Lemmink, J. G. (2019). Future service technologies: Is service research on track with business reality?. *Journal of Services Marketing*, *33*(4), 479–487. https://doi.org/10.1108/jsm-01-2019-0039

Kuo, K.-M., Liu, C.-F., Talley, P. C., & Pan, S.-Y. (2018). Strategic improvement for quality and satisfaction of hospital information systems. *Journal of Healthcare Engineering*, 1–14. https://doi.org/10.1155/2018/3689618

Kuo, R.-Z. (2018). Emrs adoption: Exploring the effects of information security management awareness and perceived service quality. *Health Policy and Technology*, *7*(4), 365–373. https://doi.org/10.1016/j.hlpt.2018.10.012

Kurniawan, M. H. (2016). Bootstrapping residuals to estimate the standard error of simple linear regression coefficients. *Jurnal Eksakta*, *16*(2), 64–69. https://doi.org/10.20885/eksakta.vol16.iss2.art1

Laher, S. (2016). Ostinato rigore: Establishing methodological rigour in quantitative research. *South African Journal of Psychology*, *46*(3), 316–327. https://doi.org/10.1177/0081246316649121

Lai, Y. S., & Afseth, J. D. (2019). A review of the impact of utilising electronic medical records for clinical research recruitment. *Clinical Trials*, *16*(2), 194–203. https://doi.org/10.1177/1740774519829709

Lal, P., & Bharadwaj, S. S. (2016). Assessing the performance of cloud-based customer relationship management systems. *Skyline Business Journal*, *11*(1), 89–100.

LaMotte, L. R. (2018). Proportional subclass numbers in two-factor ANOVA. *Statistics*, *52*(1), 228–238. https://doi.org/10.1080/02331888.2017.1319834

Lange, M., Mendling, J., & Recker, J. (2016). An empirical analysis of the factors and measures of enterprise architecture management success. *European Journal of Information Systems*, *25*(5), 411–431. https://doi.org/10.1057/ejis.2014.39

Lantos, J. D. (2017). Informed consent for comparative effectiveness research should not donsider the risks of the standard therapies that are being studied as risks of the research...22nd annual Thomas A. Pitts memorial lectureship, April 7–8, 2016, Charleston, South Carolina. *Journal of Law, Medicine & Ethics*, *45*(3), 365–374. https://doi.org/10.1177/1073110517737537

Lashayo, D. M., & Md Johar, M. G. (2018). Instructor adoption of e-learning systems in Tanzania's universities: A proposed multi-factors adoption model (MFAM11). *JOIV: International Journal on Informatics Visualization*, *2*(2), 76–80. https://doi.org/10.30630/joiv.2.2.117

LeBel, E. P., Campbell, L., & Loving, T. J. (2017). Benefits of open and high-powered research outweigh costs. *Journal of Personality and Social Psychology*, *113*(2), 230–243. https://doi.org/10.1037/pspi0000049

Lee, D. (2019a). The convergent, discriminant, and nomological validity of the depression anxiety stress scales-21 (DASS-21). *Journal of Affective Disorders*, *259*, 136–142. https://doi.org/10.1016/j.jad.2019.06.036

Lee, D. K. (2020). Data transformation: A focus on the interpretation. *Korean Journal of Anesthesiology*, *73*(6), 503–508. https://doi.org/10.4097/kja.20137

Lee, J. H. (2012). Experimental methodology in English teaching and learning: Method features, validity issues, and embedded experimental design. *English Teaching: Practice & Critique*, *11*(2), 25–43.

Lee, K., Jung, S. Y., Hwang, H., Yoo, S., Baek, H. Y., Baek, R.-M., & Kim, S. (2017). A novel concept for integrating and delivering health information using a comprehensive digital dashboard: An analysis of healthcare professionals' intention to adopt a new system and the trend of its real usage. *International Journal of Medical Informatics*, *97*, 98–108.

https://doi.org/10.1016/j.ijmedinf.2016.10.001

Lee, S.-L., Lin, S.-Y., Ko, H.-K., & Liu, Y.-Y. (2020). Construct validity and reliability of the Chinese version personal adjustment and role skills scale iii for adolescents with chronic disease. *Journal of Pediatric Nursing*, *53*, e136–e141. https://doi.org/10.1016/j.pedn.2020.03.008

Lee, Y.-C. (2019b). Adoption intention of cloud computing at the firm level. *Journal of Computer Information Systems*, *59*(1), 61–72. https://doi.org/10.1080/08874417.2017.1295792

Leone, A. J., Minutti-Meza, M., & Wasley, C. E. (2019). Influential observations and inference in accounting research. *The Accounting Review*, *94*(6), 337–364. https://doi.org/10.2308/accr-52396

Leppink, J. (2017). Revisiting the quantitative-qualitative-mixed methods labels: Research questions, developments, and the need for replication. *Journal of Taibah University Medical Sciences*, *12*(2), 97–101. https://doi.org/10.1016/j.jtumed.2016.11.008

Levitin, G., Xing, L., & Dai, Y. (2017). Optimal data partitioning in cloud computing system with random server assignment. *Future Generation Computer Systems*, *70*, 17–25. https://doi.org/10.1016/j.future.2016.12.025

Leviton, L. C. (2017). Generalizing about public health interventions: A mixed-methods approach to external validity. *Annual Review of Public Health*, *38*, 371–391. https://doi.org/10.1146/annurev-publhealth-031816-044509

Lewis, R. J., & Kyriacou, D. N. (2016). Confounding by indication in clinical research.

Journal of the American Medical Association, *316*(17), 1818–1819. https://doi.org/10.1001/jama.2016.16435

Li, A., Feng, M., Li, Y., & Liu, Z. (2016). Application of outlier mining in insider identification based on boxplot method. *Procedia Computer Science*, *91*, 245–251. https://doi.org/10.1016/j.procs.2016.07.069

Lian, J.-W. (2017). Establishing a cloud computing success model for hospitals in Taiwan. *Journal of Health Care Organization, Provision, and Financing*, *54*, 1–6. https://doi.org/10.1177/0046958016685836

Liang, G., Fu, W., & Wang, K. (2019). Analysis of t-test misuses and SPSS operations in medical research papers. *Burns & Trauma*, *7*(1), 1–5. https://doi.org/10.1186/s41038-019-0170-3

Libaque-Saenz, C. F., Chang, Y., Kim, J., Park, M.-C., & Rho, J. J. (2016). The role of perceived information practices on consumers' intention to authorise secondary use of personal data. *Behaviour & Information Technology*, *35*(5), 339–356. https://doi.org/10.1080/0144929x.2015.1128973

Lin, H.-H., Wang, Y.-S., Li, C.-R., Shih, Y.-W., & Lin, S.-J. (2017). The measurement and dimensionality of mobile learning systems success: Two-stage development and validation. *Journal of Educational Computing Research*, *55*(4), 449–470. https://doi.org/10.1177/0735633116671324

Lin, J.-C., Lee, T.-T., & Mills, M. (2018). Evaluation of a barcode medication administration information system. *Computers, Informatics, Nursing*, *36*(12), 596–602. https://doi.org/10.1097/cin.0000000000000459

Lin, S.-W. (2016). Identifying the critical success factors and an optimal solution for mobile technology adoption in travel agencies. *International Journal of Tourism Research*, *19*(2), 127–144. https://doi.org/10.1002/jtr.2092

Linaje, M., Berrocal, J., & Galan-Benitez, A. (2019). Mist and edge storage: Fair storage distribution in sensor networks. *IEEE Access*, *7*, 123860–123876. https://doi.org/10.1109/ACCESS.2019.2938443

Lininger, M., & Riemann, B. L. (2016). Statistical primer for athletic trainers: Using confidence intervals and effect sizes to evaluate clinical meaningfulness. *Journal of Athletic Training*, *51*(12), 1045–1048. https://doi.org/10.4085/1062-6050-51.12.14

Link, M. (2018). New data strategies: Nonprobability sampling, mobile, big data. *Quality Assurance in Education*, *26*(2), 303–314. https://doi.org/10.1108/qae-06-2017-0029

Lippe, M., Johnson, B., & Carter, P. (2019). Protecting student anonymity in research using a subject-generated identification code. *Journal of Professional Nursing*, *35*(2), 120–123. https://doi.org/10.1016/j.profnurs.2018.09.006

Liu, S., Chan, F. T., Yang, J., & Niu, B. (2018). Understanding the effect of cloud computing on organizational agility: An empirical examination. *International Journal of Information Management*, *43*, 98–111. https://doi.org/10.1016/j.ijinfomgt.2018.07.010

Liu, S., Guo, L., Webb, H., Ya, X., & Chang, X. (2019). Internet of Things monitoring system of modern eco-agriculture based on cloud computing. *IEEE Access*, *7*, 37050–37058. https://doi.org/10.1109/ACCESS.2019.2903720

Liu, X., & Wang, L. (2019). Sample size planning for detecting mediation effects: A power analysis procedure considering uncertainty in effect size estimates. *Multivariate Behavioral Research*, *54*(6), 822–839. https://doi.org/10.1080/00273171.2019.1593814

Liu, Y., & Li, S. (2019). An analysis of promotional programs for cloud computing: Coupons or free trials?. *International Journal of Electronic Commerce*, *23*(3), 405–426. https://doi.org/10.1080/10864415.2019.1619910

Liu, Z., Tian, L., Chang, Q., Sun, B., & Zhao, Y. (2016a). A competency model for clinical physicians in China: A cross-sectional survey. *PLoS One*, *11*(12), 1–17. https://doi.org/10.1371/journal.pone.0166252

Liu, Z., Yuan, L., Huang, Y., Zhang, L., & Luo, F. (2016b). Development of the Chinese version of the hospital autonomy questionnaire: A cross-sectional study in Guangdong Province. *BMJ Open*, *6*(2), e010504. https://doi.org/10.1136/bmjopen-2015-010504

Loeb, S., Dynarski, S., McFarland, D., Morris, P., Reardon, S., & Reber, S. (2017). Descriptive analysis in education: A guide for researchers (NCEE 2017-4023). *National Center for Education Evaluation and Regional Assistance*, i–B5.

Loeys, T., Talloen, W., Goubert, L., Moerkerke, B., & Vansteelandt, S. (2016). Assessing moderated mediation in linear models requires fewer confounding assumptions than assessing mediation. *British Journal of Mathematical & Statistical Psychology*, *69*(3), 352–374. https://doi.org/10.1111/bmsp.12077

Lowe, K., & Hynes, F. (2016). Recruitment into forensic psychiatry, a cross sectional survey to identify attitudes and opinions of core trainees of this speciality. *Journal of Mental Health Training, Education and Practice*, *11*(3), 144–155. https://doi.org/10.1108/jmhtep-06-2015-0026

Loyka, C. M., Ruscio, J., Edelblum, A. B., Hatch, L., Wetreich, B., & Zabel, A. (2020). Weighing people rather than food: A framework for examining external validity. *Perspectives on Psychological Science*, *15*(2), 483–496. https://doi.org/10.1177/1745691619876279

Lu, Y., & Westfall, P. (2019). Simple and flexible Bayesian inferences for standardized regression coefficients. *Journal of Applied Statistics*, *46*(12), 2254–2288. https://doi.org/10.1080/02664763.2019.1584609

Lu, Z., Cui, T., Tong, Y., & Wang, W. (2020). Examining the effects of social influence in pre-adoption phase and initial post-adoption phase in the healthcare context. *Information & Management*, *57*(3), 1–11. https://doi.org/10.1016/j.im.2019.103195

Luo, X., Zhang, W., Li, H., Bose, R., & Chung, Q. B. (2018). Cloud computing capability: Its technological root and business impact. *Journal of Organizational Computing and Electronic Commerce*, *28*(3), 193–213. https://doi.org/10.1080/10919392.2018.1480926

Lwoga, E. T., & Sife, A. S. (2018). Impacts of quality antecedents on faculty members' acceptance of electronic resources. *Library Hi Tech*, *36*(2), 289–305. https://doi.org/10.1108/lht-01-2017-0010

MacInnis, B., Krosnick, J. A., Ho, A. S., & Cho, M.-J. (2018). The accuracy of measurements with probability and nonprobability survey samples: Replication and extension. *Public Opinion Quarterly*, *82*(4), 707–744. https://doi.org/10.1093/poq/nfy038

Madden, G., Vicente, M. R., Rappoport, P., & Banerjee, A. (2017). A contribution on the nature and treatment of missing data in large market surveys. *Applied Economics*, *49*(22), 2179–2187. https://doi.org/10.1080/00036846.2016.1234699

Magee, W., & Upenieks, L. (2017). "Stuck in the middle with you?" Supervisory level and anger about work. *Canadian Review of Sociology*, *54*(3), 309–330. https://doi.org/10.1111/cars.12152

Mahmoodi, Z., Esmaelzadeh- Saeieh, S., Lotfi, R., Baradaran Eftekhari, M., Akbari Kamrani, M., Mehdizadeh Tourzani, Z., & Salehi, K. (2017). The evaluation of a virtual education system based on the DeLone and McLean model: A path analysis. *F1000Research*, *6*, 1–11. https://doi.org/10.12688/f1000research.12278.1

Malik, A., Suresh, S., & Sharma, S. (2017). Factors influencing consumers' attitude toward adoption and continuous use of mobile applications: A conceptual model. *Procedia Computer Science*, *122*, 106–113. https://doi.org/10.1016/j.procs.2017.11.348

Mallo, S., & Ogwueleka, F. (2019). Impacts and challenges of cloud computing for small and medium scale businesses in Nigeria. *Journal of Advances in Computer Engineering and Technology*, *5*(3), 169–180.

Manfreda, A., & Indihar Štemberger, M. (2019). Establishing a partnership between top and IT managers. *Information Technology & People*, *32*(4), 948–972. https://doi.org/10.1108/itp-01-2017-0001

Marchant, C., Leiva, V., Cysneiros, F. J., & Vivanco, J. F. (2016). Diagnostics in multivariate generalized Birnbaum-Saunders regression models. *Journal of Applied Statistics*, *43*(15), 2829–2849. https://doi.org/10.1080/02664763.2016.1148671

Marcoulides, K. M., & Raykov, T. (2019). Evaluation of variance inflation factors in regression models using latent variable modeling methods. *Educational and Psychological Measurement*, *79*(5), 874–882. https://doi.org/10.1177/0013164418817803

Mardiana, S., Tjakraatmadja, J. H., & Aprianingsih, A. (2015). Validating the conceptual model for predicting intention to use as part of information system success model: The case of an indonesian government agency. *Procedia Computer Science*, *72*, 353–360. https://doi.org/10.1016/j.procs.2015.12.150

Marjanovic, U., Delić, M., & Lalic, B. (2016). Developing a model to assess the success of e-learning systems: Evidence from a manufacturing company in transitional economy. *Information Systems & e-Business Management*, *14*(2), 253–272. https://doi.org/10.1007/s10257-015-0282-7

Martí, J. (2016). Measuring in action research: Four ways of integrating quantitative methods in participatory dynamics. *Action Research*, *14*(2), 168–183. https://doi.org/10.1177/1476750315590883

Martin, A. J., Collie, R. J., Durksen, T. L., Burns, E. C., Bostwick, K. C., & Tarbetsky, A. L. (2019). Growth goals and growth mindset from a methodological-synergistic perspective: Lessons learned from a quantitative correlational research program. *International Journal of Research & Method in Education*, *42*(2), 204–219. https://doi.org/10.1080/1743727x.2018.1481938

Mascha, E. J., & Vetter, T. R. (2018). Significance, errors, power, and sample size: The blocking and tackling of statistics. *Anesthesia & Analgesia*, *126*(2), 691–698. https://doi.org/10.1213/ane.0000000000002741

Mashabela, F., & Pillay, A. S. (2017). Effectiveness of an integrated tertiary software mobile information system for student registration and admission at a university in Gauteng. *Expert Journal of Business and Management*, *5*(1), 32–49.

Mason, R. O. (1978). Measuring information output: A communication systems approach. *Information & Management*, *1*(4), 219–234. https://doi.org/10.1016/0378-7206(78)90028-9

Mathew, S., Jose, A., G, R., & Chacko, D. P. (2020). Examining the relationship between e-service recovery quality and e-service recovery satisfaction moderated by perceived justice in the banking context. *Benchmarking: An International Journal*, *27*(6), 1951–1980. https://doi.org/10.1108/bij-07-2019-0323

Matthes, J. M., & Ball, A. D. (2019). Discriminant validity assessment in marketing research. *International Journal of Market Research*, *61*(2), 210–222. https://doi.org/10.1177/1470785318793263

Mattsson, C. M., Wheeler, M. T., Waggott, D., Caleshu, C., & Ashley, E. A. (2016).

Sports genetics moving forward: Lessons learned from medical research. *Physiological Genomics*, *48*(3), 175–182. https://doi.org/10.1152/physiolgenomics.00109.2015

Maymone, M. B., Venkatesh, S., Secemsky, E., Reddy, K., & Vashi, N. A. (2018). Research techniques made simple: Web-based survey research in dermatology: Conduct and applications. *Journal of Investigative Dermatology*, *138*(7), 1456–1462. https://doi.org/10.1016/j.jid.2018.02.032

McAlevey, L. G., & Stent, A. F. (2018). Kurtosis: A forgotten moment. *International Journal of Mathematical Education in Science and Technology*, *49*(1), 120–130. https://doi.org/10.1080/0020739x.2017.1357848

McCarthy, C. J., Whittaker, T. A., Boyle, L. H., & Eyal, M. (2017). Quantitative approaches to group research: Suggestions for best practices. *Journal for Specialists in Group Work*, *42*(1), 3–16. https://doi.org/10.1080/01933922.2016.1264520

McCormick, T. H., Lee, H., Cesare, N., Shojaie, A., & Spiro, E. S. (2017). Using twitter for demographic and social science research: Tools for data collection and processing. *Sociological Methods & Research*, *46*(3), 390–421. https://doi.org/10.1177/0049124115605339

McCusker, K., & Gunaydin, S. (2015). Research using qualitative, quantitative or mixed methods and choice based on the research. *Perfusion*, *30*, 537–542. https://doi.org/10.1177/0267659114559116

McInroy, L. B. (2016). Pitfalls, potentials, and ethics of online survey research: LGBTQ and other marginalized and hard-to-access youths. *Social Work Research*, *40*(2), 83–93. https://doi.org/10.1093/swr/svw005

McNeish, D. (2020). Should we use f-tests for model fit instead of chi-square in overidentified structural equation models? *Organizational Research Methods*, *23*(3), 487–510. https://doi.org/10.1177/1094428118809495

Mehrens, S. M., Kale, U. J., & Qu, X. (2005). Statistical analysis of differences in the Raman spectra of polymorphs. *Journal of Pharmaceutical Sciences*, *94*(6), 1354–1367. https://doi.org/10.1002/jps.20355

Mekawie, N., & Yehia, K. (2021). Challenges of deploying cloud computing in ehealth. *Procedia Computer Science*, *181*, 1049–1057. https://doi.org/10.1016/j.procs.2021.01.300

Méndez-Aparicio, M. D., Izquierdo-Yusta, A., & Jiménez-Zarco, A. I. (2017). Consumer expectations of online services in the insurance industry: An exploratory study of drivers and outcomes. *Frontiers in Psychology*, *8*, 1–14. https://doi.org/10.3389/fpsyg.2017.01254

Menton, W. H. (2020). Generalizability of statistical prediction from psychological assessment data: An investigation with the MMPI-2-RF.. *Psychological Assessment*, *32*(5), 473–492. https://doi.org/10.1037/pas0000808

Mercer, A. W., Kreuter, F., Keeter, S., & Stuart, E. A. (2017a). Reply. *Public Opinion Quarterly*, *81*, 277–279. https://doi.org/10.1093/poq/nfx004

Mercer, A. W., Kreuter, F., Keeter, S., & Stuart, E. A. (2017b). Theory and practice in nonprobability surveys: Parallels between causal inference and survey inference.

Public Opinion Quarterly, *81*, 250–271. https://doi.org/10.1093/poq/nfw060

Merhi, M. I., & Ahluwalia, P. (2019). Examining the impact of deterrence factors and norms on resistance to information systems security. *Computers in Human Behavior*, *92*, 37–46. https://doi.org/10.1016/j.chb.2018.10.031

Mesbahi, M. R., Rahmani, A. M., & Hosseinzadeh, M. (2018). Reliability and high availability in cloud computing environments: A reference roadmap. *Human-Centric Computing and Information Sciences*, *8*(1), 1–31. https://doi.org/10.1186/s13673-018-0143-8

Meyvis, T., & Van Osselaer, S. M. (2018). Increasing the power of your study by increasing the effect size. *Journal of Consumer Research*, *44*(5), 1157–1173. https://doi.org/10.1093/jcr/ucx110

Mi, C., Chang, F., Lin, C., & Chang, Y. (2018). The theory of reasoned action to CSR behavioral intentions: The role of CSR expected benefit, CSR expected effort and stakeholders. *Sustainability*, *10*(12), 4462. https://doi.org/10.3390/su10124462

Michel, S., & Cocula, F. (2017). Impact of the three IS qualities on user satisfaction in an information-intensive sector. *Electronic Journal of Information Systems Evaluation*, *20*(2), 85–101.

Michel, S., Michaud-Trévinal, A., & Cocu la, F. (2019). Net Impacts in front office IS: A first operationalization of DeLone and McLean model in the banking sector. *The Electronic Journal of Information Systems Evaluation*, *22*(2), 92–112. https://doi.org/10.34190/ejise.19.22.2.003

Mijin, N., Jang, H., Khongorzul, G., & Choi, B. (2019). Attitude toward the use of electronic medical record systems: Exploring moderating effects of self-image. *Information Development*, *35*(1), 67–79. https://doi.org/10.1177/0266666917729730

Miles, L. M., Elbourne, D., Farmer, A., Gulliford, M., Locock, L., McCambridge, J., Sutton, S., & French, D. P. (2018). Bias due to measurement reactions in trials to improve health (MERIT): Protocol for research to develop MRC guidance. *Trials*, *19*(1), 1–8. https://doi.org/10.1186/s13063-018-3017-5

Miller, C. J., Smith, S. N., & Pugatch, M. (2020). Experimental and quasi-experimental designs in implementation research. *Psychiatry Research*, *283*, 112452. https://doi.org/10.1016/j.psychres.2019.06.027

Min, S., So, K. K., & Jeong, M. (2019). Consumer adoption of the Uber mobile application: Insights from diffusion of innovation theory and technology acceptance model. *Journal of Travel & Tourism Marketing*, *36*(7), 770–783. https://doi.org/10.1080/10548408.2018.1507866

Miracle, V. A. (2016). The Belmont Report: The triple crown of research ethics. *Dimensions of Critical Care Nursing*, *35*(4), 223–228. https://doi.org/10.1097/dcc.0000000000000186

Mishra, P., Pandey, C. M., Singh, U., Gupta, A., Sahu, C., & Keshri, A. (2019). Descriptive statistics and normality tests for statistical data. *Annals of Cardiac Anaesthesia*, *22*(1), 67. https://doi.org/10.4103/aca.aca_157_18

Mishra, P., Singh, U., Pandey, C. M., Mishra, P., & Pandey, G. (2019). Application of student’s t-test, analysis of variance, and covariance. *Annals of Cardiac*

Anaesthesia, *22*(4), 407–411. https://doi.org/10.4103/aca.aca_94_19

Mitchell, C. M. (2020). *Effects of intimate partner violence on academic motivation among emerging adult women* (27736103) [Doctoral dissertation, Walden University]. ProQuest Dissertations and Theses Global.

Mkinga, M., & Mandari, H. (2020). Evaluating students information system success using DeLone and McLean's model: Student's perspective. *Journal of International Technology & Information Management*, *29*(2), 24–42. http://www.iima.org/

Modi, C., & Acha, K. (2017). Virtualization layer security challenges and intrusion detection/prevention systems in cloud computing: A comprehensive review. *Journal of Supercomputing*, *73*(3), 1192–1234. https://doi.org/10.1007/s11227-016-1805-9

Moeyaert, M. (2019). Quantitative synthesis of research evidence: Multilevel meta-analysis. *Behavioral Disorders*, *44*(4), 241–256. https://doi.org/10.1177/0198742918806926

Mohammed, F., Ibrahim, O., & Ithnin, N. (2016). Factors influencing cloud computing adoption for e-government implementation in developing countries: Instrument development. *Journal of Systems and Information Technology*, *18*(3), 297–327. https://doi.org/10.1108/jsit-01-2016-0001

Mohd Salleh, M. I., Zakaria, N., & Abdullah, R. (2016). The influence of system quality characteristics on health care providers' performance: Empirical evidence from Malaysia. *Journal of Infection and Public Health*, *9*(6), 698–707.

https://doi.org/10.1016/j.jiph.2016.09.002

Mohn, C. N. (1990). A manager's interpretation of cross tabulation survey data. *American Journal of Business*, *5*(2), 49–55. https://doi.org/10.1108/19355181199000012

Mojarro Aliaño, Á., Duarte Hueros, A. M., Guzmán Franco, M. D., & Aguaded, I. (2019). Mobile learning in university contexts based on the unified theory of acceptance and use of technology (UTAUT). *Journal of New Approaches in Educational Research*, *8*(1), 7–17. https://doi.org/10.7821/naer.2019.1.317

Mondal, S., & Mondal, H. (2017). Value of r2 in statistical analysis by pearson correlation coefficient. *Journal of Clinical and Diagnostic Research*, *11*(11), CL01. https://doi.org/10.7860/jcdr/2017/29763.10812

Monika, R., & Gaol, F. L. (2017). Measuring the success of e-cargo implementation at one of Indonesian airlines using DeLone and McLean model. *IOP Conference Series: Materials Science and Engineering*, *215*(1), 1–12. https://doi.org/10.1088/1757-899x/215/1/012037

Moreno-Vozmediano, R., Montero, R. S., Huedo, E., & Llorente, I. M. (2019). Efficient resource provisioning for elastic cloud services based on machine learning techniques. *Journal of Cloud Computing: Advances, Systems and Applications*, *8*(1), 1–18. https://doi.org/10.1186/s13677-019-0128-9

Morselli, D., Le Goff, J.-M., & Gauthier, J.-A. (2019). Self-administered event history calendars: A possibility for surveys?. *Contemporary Social Science*, *14*(3/4), 423–446. https://doi.org/10.1080/21582041.2017.1418528

Motschman, C. A., Gass, J. C., Wray, J. M., Germeroth, L. J., Schlienz, N. J., Munoz, D. A., Moore, F. E., Rhodes, J. D., Hawk, L. W., & Tiffany, S. T. (2016). Selection criteria limit generalizability of smoking pharmacotherapy studies differentially across clinical trials and laboratory studies: A systematic review on varenicline. *Drug and Alcohol Dependence*, *169*, 180–189. https://doi.org/10.1016/j.drugalcdep.2016.10.018

Mouradian, C., Naboulsi, D., Yangui, S., Glitho, R. H., Morrow, M. J., & Polakos, P. A. (2018). A comprehensive survey on fog computing: State-of-the-art and research challenges. *IEEE Communications Surveys & Tutorials*, *21*(1), 416–464. https://doi.org/10.1109/COMST.2017.2771153

Mtebe, J. S., & Raphael, C. (2018). Key factors in learners' satisfaction with the e-learning system at the University of Dar es Salaam, Tanzania. *Australasian Journal of Educational Technology*, *34*(4), 107–122. https://doi.org/10.14742/ajet.2993

Mukred, M., Yusof, Z. M., Mokhtar, U. A., & Fauzi, F. (2019). Taxonomic framework for factors influencing ERMS adoption in organisations of higher professional education. *Journal of Information Science*, *45*(2), 139–155. https://doi.org/10.1177/0165551518783133

Munafò, M. (2016). S.29.03 - Low statistical power of studies in cognitive neuroscience and the role of incentive structures. *European Neuropsychopharmacology*, *26*(S2), S151. https://doi.org/10.1016/s0924-977x(16)30965-8

Murray, J., Elms, J., & Curran, M. (2019). Examining empathy and responsiveness in a high-service context. *International Journal of Retail & Distribution Management*, *47*(12), 1364–1378. https://doi.org/10.1108/ijrdm-01-2019-0016

Murshed, F., & Zhang, Y. (2016). Thinking orientation and preference for research methodology. *Journal of Consumer Marketing*, *33*(6), 437–446. https://doi.org/10.1108/jcm-01-2016-1694

Murvin, K. (2019). *The correlation between manager work-life balance and employee engagement* (13862791) [Doctoral dissertation, Walden University]. ProQuest Dissertations & Theses Global.

Nagelkerke, E., Oberski, D. L., & Vermunt, J. K. (2016). Goodness-of-fit of multilevel latent class models for categorical data. *Sociological Methodology*, *46*, 252–282. https://doi.org/10.1177/0081175015581379

Nagy, S. (2017). The impact of country of origin in mobile phone choice of generation y and z. *Journal of Management and Training for Industries*, *4*(2), 16–29. https://doi.org/10.12792/jmti.4.2.16

Naicker, V., & Van Der Merwe, D. B. (2018). Managers' perception of mobile technology adoption in the life insurance industry. *Information Technology & People*, *31*(2), 507–526. https://doi.org/10.1108/itp-09-2016-0212

Neethling, A., Ferreira, J., Bekker, A., & Naderi, M. (2020). Skew generalized normal innovations for the ar(p) process endorsing asymmetry. *Symmetry*, *12*(8), 1253–1253. https://doi.org/10.3390/sym12081253

Negahban, A., Kim, D. J., & Kim, C. (2016). Unleashing the power of mCRM: Investigating antecedents of mobile CRM values from managers' viewpoint.

International Journal of Human-Computer Interaction, *32*(10), 747–764. https://doi.org/10.1080/10447318.2016.1189653

Nemeslaki, A., Aranyossy, M., & Sasvári, P. (2016). Could on-line voting boost desire to vote? - Technology acceptance perceptions of young Hungarian citizens. *Government Information Quarterly*, *33*(4), 705–714. https://doi.org/10.1016/j.giq.2016.11.003

Newman, I., & Houchins, D. E. (2018). Conceptualizing mixed methods questions in special education research. *Journal of Intercultural Communication*, *25*(2), 23–33.

Newman, M., & Robey, D. (1992). A social process model of user-analyst relationships. *MIS Quarterly*, *16*(2), 249–266. https://doi.org/10.2307/249578

Nezarat, A., & Shams, Y. (2017). A game theoretic-based distributed detection method for VM-to-hypervisor attacks in cloud environment. *Journal of Supercomputing*, *73*(10), 4407–4427. https://doi.org/10.1007/s11227-017-2025-7

Nguyen, T., Henderson, D., Stewart, D., Hlyva, O., Punthakee, Z., & Gorter, J. W. (2016). You never transition alone! Exploring the experiences of youth with chronic health conditions, parents and healthcare providers on self-management. *Child: Care, Health and Development*, *42*(4), 464–472. https://doi.org/10.1111/cch.12334

Nield, S. (2019). The mismeasure of culture: Self-report questionnaires and positivist analysis in intercultural communication research. *Journal of Intercultural Communication*, (50), 1–14.

Nielsen, E. E., Nørskov, A. K., Lange, T., Thabane, L., Wetterslev, J., Beyersmann, J., de Uña-Álvarez, J., Torri, V., Billot, L., Putter, H., Winkel, P., Gluud, C., & Jakobsen, J. C. (2019). Assessing assumptions for statistical analyses in randomised clinical trials. *BMJ Evidence-Based Medicine*, *24*(5), 185–189. https://doi.org/10.1136/bmjebm-2019-111174

Nieuwenhuis, L. J., Ehrenhard, M. L., & Prause, L. (2018). The shift to cloud computing: The impact of disruptive technology on the enterprise software business ecosystem. *Technological Forecasting and Social Change*, *129*, 308–313. https://doi.org/10.1016/j.techfore.2017.09.037

Nikpeyma, N., Maroufizadeh, S., & Esmaeili, M. (2020). The importance of reporting the effect size in quantitative studies. *Nursing Practice Today*, *8*(1), 4–6. https://doi.org/10.18502/npt.v8i1.4486

Nimon, K., Conley, D., Bontrager, M., Keiffer, G. L., & Hammack-Brown, B. (2019). Descriptive statistics from published research: A readily available alternative to raw data to assess analytic reproducibility and robustness. *Advances in Developing Human Resources*, *21*(4), 421–437. https://doi.org/10.1177/1523422319869853

Norris, J. M., Plonsky, L., Ross, S. J., & Schoonen, R. (2015). Guidelines for reporting quantitative methods and results in primary research. *Language Learning*, *65*, 470–476. https://doi.org/10.1111/lang.12104

Novalendo, F., Syarief, R., & Suroso, A. I. (2018). Measurement of success in the integrated prescribing information system at Ananda Bekasi Hospital. *Indonesian*

Journal of Business and Entrepreneurship, *4*(3), 282–290. https://doi.org/10.17358/ijbe.4.3.282

Nugroho, Y., & Prasetyo, A. (2018). Assessing information systems success: A respecification of the DeLone and McLean model to integrating the perceived quality. *Problems and Perspectives in Management*, *16*(1), 348–360. https://doi.org/10.21511/ppm.16(1).2018.34

Nusantara, P. D., Gayatri, N. A., & Suhartana, M. (2018). Combining two models of successful information system measurement. *Telkomnika*, *16*(4), 1793–1800. https://doi.org/10.12928/telkomnika.v16i4.7737

Nwagwu, W., & Ibeku, S. (2016). Understanding the innovativeness of information technology products and service providers in an IT cluster in Nigeria. *South African Journal of Libraries & Information Science*, *82*(1), 36–52. https://doi.org/10.7553/82-1-1598

Odwazny, L. M., & Berkman, B. E. (2017). The "reasonable person" standard for research informed consent. *American Journal of Bioethics*, *17*(7), 49–51. https://doi.org/10.1080/15265161.2017.1328540

O'Keefe, D. J. (2011). The asymmetry of predictive and descriptive capabilities in quantitative communication research: Implications for hypothesis development and testing. *Communication Methods & Measures*, *5*(2), 113–125. https://doi.org/10.1080/19312458.2011.568375

Oleson, J. J., Brown, G. D., & McCreery, R. (2019). Essential statistical concepts for research in speech, language, and hearing sciences. *Journal of Speech, Language,* *and Hearing Research*, *62*(3), 489–497. https://doi.org/10.1044/2018_jslhr-s-astm-18-0239

Olufemi, A. (2019). Considerations for the adoption of cloud-based big data analytics in small business enterprises. *Electronic Journal of Information Systems Evaluation*, *21*(2), 63–79.

Onel, A., & Firat Durdukoca, S. (2019). Identifying the predictive power of biological literacy and attitudes toward biology in academic achievement in high school students. *International Online Journal of Educational Sciences*, *11*(2), 214–228. https://doi.org/10.15345/iojes.2019.02.014

Onen, D. (2016). Appropriate conceptualisation: The foundation of any solid quantitative research. *Electronic Journal of Business Research Methods*, *14*(1), 28–38.

Ophoff, J., & Miller, S. (2019). Business priorities driving BYOD adoption: A case study of a South African financial services organization. *Issues in Informing Science and Information Technology*, *16*, 165–196. https://doi.org/10.28945/4303

Oredo, J., Njihia, J., & Iraki, X. N. (2019). Adoption of cloud computing by firms in Kenya: The role of institutional pressures. *African Journal of Information Systems*, *11*(3), 133–156.

Osborne, J. W. (2010). Data cleaning basics: Best practices in dealing with extreme scores. *Newborn and Infant Nursing Reviews*, *10*(1), 37–43. https://doi.org/10.1053/j.nainr.2009.12.009

Osei-Kyei, R., & Chan, A. P. (2019). Model for predicting the success of public-private partnership infrastructure projects in developing countries: A case of Ghana.

Architectural Engineering and Design Management, *15*(3), 213–232. https://doi.org/10.1080/17452007.2018.1545632

Ottenbacher, K. J. (1989). Statistical conclusion validity of early intervention research with handicapped children. *Exceptional Children*, *55*(6), 534–540. https://doi.org/10.1177/001440298905500607

Ou, C. X., Davison, R. M., & Huang, V. Q. (2016). The social networking application success model: An empirical study of Facebook and Twitter. *International Journal of Knowledge Content Development & Technology*, *6*(1), 5–39. https://doi.org/10.5865/ijkct.2016.6.1.005

Padron-Hidalgo, J. A., Perez-Suay, A., Nar, F., Laparra, V., & Camps-Valls, G. (2020). Efficient kernel cook's distance for remote sensing anomalous change detection. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *13*, 5480–5488. https://doi.org/10.1109/jstars.2020.3020913

Pahl, C., Brogi, A., Soldani, J., & Jamshidi, P. (2019). Cloud container technologies: A state-of-the-art review. *IEEE Transactions on Cloud Computing*, *7*(3), 677–692. https://doi.org/10.1109/TCC.2017.2702586

Pampaka, M., Hutcheson, G., & Williams, J. (2016). Handling missing data: Analysis of a challenging data set using multiple imputation. *International Journal of Research & Method in Education*, *39*(1), 19–37. https://doi.org/10.1080/1743727x.2014.979146

Pantano, E., & Vannucci, V. (2019). Who is innovating? An exploratory research of digital technologies diffusion in retail industry. *Journal of Retailing and*

Consumer Services, *49*, 297–304. https://doi.org/10.1016/j.jretconser.2019.01.019

Park, H., & Choi, S. O. (2019). Digital innovation adoption and its economic impact focused on path analysis at national level. *Journal of Open Innovation: Technology, Market, and Complexity*, *5*(3), 56. https://doi.org/10.3390/joitmc5030056

Paterson, T. A., Harms, P. D., Steel, P., & Crede, M. (2016). An assessment of the magnitude of effect sizes: Evidence from 30 years of meta-analysis in management. *Journal of Leadership & Organizational Studies*, *23*(1), 66–81. https://doi.org/10.1177/1548051815614321

Pattison, S., Gutwill, J., Auster, R., & Cannady, M. (2019). Experimental and quasi-experimental designs in visitor studies: A critical reflection on three projects. *Visitor Studies*, *22*(1), 43–66. https://doi.org/10.1080/10645578.2019.1605235

Pawirosumarto, S. (2017). The determination on the use of e-learning systems in private universities in Jakarta. *Eurasia: Economics & Business*, *1*(1), 35–44. https://doi.org/10.18551/econeurasia.2017-01.05

Pecáková, I. (2016). Pitfalls of quantitative surveys online. *Acta Oeconomica Pragensia*, *24*(6), 3–15. https://doi.org/10.18267/j.aop.560

Pegoraro, L. G., Gvozd, R., Haddad, M. D., Vannuchi, M. T., Silva, L. G., & Rossaneis, M. A. (2018). Validation of instrument to assess software of patients' risk classification. *Revista Brasileira de Enfermagem*, *71*(3), 975–982. https://doi.org/10.1590/0034-7167-2017-0053

Perdices, M. (2018). Null hypothesis significance testing,p-values, effects sizes and confidence intervals. *Brain Impairment*, *19*(1), 70–80. https://doi.org/10.1017/brimp.2017.28

Persada, S. F., Miraja, B. A., & Nadlifatin, R. (2019). Understanding the generation z behavior on d-learning: A unified theory of acceptance and use of technology (UTAUT) approach. *International Journal of Emerging Technologies in Learning (iJET)*, *14*(5), 20–33. https://doi.org/10.3991/ijet.v14i05.9993

Perugini, M., Gallucci, M., & Costantini, G. (2018). A practical primer to power analysis for simple experimental designs. *International Review of Social Psychology*, *31*(1), 1–23. https://doi.org/10.5334/irsp.181

Peskun, P. H. (2020). Two-tailed p-values and coherent measures of evidence. *American Statistician*, *74*(1), 80–86. https://doi.org/10.1080/00031305.2018.1475304

Peterson, J. S. (2019). Presenting a qualitative study: A reviewer's perspective. *Gifted Child Quarterly*, *63*(3), 147–158. https://doi.org/10.1177/0016986219844789

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. https://doi.org/10.1057/ejis.2008.15

Petursdottir, A. I., & Carr, J. E. (2018). Applying the taxonomy of validity threats from mainstream research design to single-case experiments in applied behavior analysis. *Behavior Analysis in Practice*, *11*(3), 228–240. https://doi.org/10.1007/s40617-018-00294-6

Phillips, G. W., & Jiang, T. (2016). Measurement error and equating error in power analysis. *Practical Assessment, Research & Evaluation*, *21*(9), 1–12.

Piccioli, M. (2019). Educational research and mixed methods. Research designs, application perspectives, and food for thought. *Studi Sulla Formazione*, *22*(2), 423–438. https://doi.org/10.13128/ssf-10815

Pickett, S. D. (2018). *Work commitment, intrinsic motivation, and academic achievement in online adult learners* (10979661) [Doctoral dissertation, Walden University]. ProQuest Dissertations and Theses Global.

Plaushin, M. F. (2019). *Survey of U.S. undergraduate self-reported opioid diversion and heroin use, motives, sources, and collective efficacy as mediating factors* (13806364) [Doctoral dissertation, Walden University]. ProQuest Dissertations & Theses Global.

Politi, L., Codish, S., Sagy, I., & Fink, L. (2017). Balancing volume and duration of information consumption by physicians: The case of health information exchange in critical care. *Journal of Biomedical Informatics*, *71*, 1–15. https://doi.org/10.1016/j.jbi.2017.05.007

Prasad, K. (2019). Know some vital statistics: What is p value?. *Neurology India*, *67*(4), 1086. https://doi.org/10.4103/0028-3886.266277

Preiksaitis, M. K. (2016). *Servant leaders' use of high performance work practices and corporate social performance* (10182916) [Doctoral dissertation, Walden University]. ProQuest Dissertations & Theses Global.

Qasem, Y. A., Abdullah, R., Jusoh, Y. Y., Atan, R., & Asadi, S. (2019). Cloud computing adoption in higher education institutions: A systematic review. *IEEE Access*, *7*, 63722–63744. https://doi.org/10.1109/access.2019.2916234

Qasem, Y. M., Abdullah, R., Yaha, Y., & Atana, R. (2020). Continuance use of cloud computing in higher education institutions: A conceptual model. *Applied Sciences*, *10*(19), 6628. https://doi.org/10.3390/app10196628

Qiu, Y., Liu, L., & Lai, X. (2019). An online test for goodness-of-fit in logistic regression model. *IEEE Access*, *7*, 107179–107187. https://doi.org/10.1109/access.2019.2927035

Quessy, J.-F., Rivest, L.-P., & Toupin, M.-H. (2018). Goodness-of-fit tests for the family of multivariate chi-square copulas. *Computational Statistics & Data Analysis*, *140*, 21–40. https://doi.org/10.1016/j.csda.2019.04.008

Rahi, S., & Abd.Ghani, M. (2019). Integration of DeLone and McLean and self-determination theory in internet banking continuance intention context. *International Journal of Accounting & Information Management*, *27*(3), 512–528. https://doi.org/10.1108/ijaim-07-2018-0077

Rahi, S., Mansour, M. M., Alghizzawi, M., & Alnaser, F. M. (2019). Integration of UTAUT model in internet banking adoption context: The mediating role of performance expectancy and effort expectancy. *Journal of Research in Interactive Marketing*, *13*(3), 411–435. https://doi.org/10.1108/jrim-02-2018-0032

Rahi, S. B., Bisui, S., & Misra, S. C. (2017). Identifying critical challenges in the adoption of cloud-based services. *International Journal of Communication Systems*, *30*(12), 1–14. https://doi.org/10.1002/dac.3261

Rakotoasimbola, E., & Blili, S. (2019). Measures of fit impacts: Application to the causal model of consumer involvement. *International Journal of Market Research*, *61*(1), 77–92. https://doi.org/10.1177/1470785318796950

Ramachandran, M. (2016). Software security requirements management as an emerging cloud computing service. *International Journal of Information Management*, *36*(4), 580–590. https://doi.org/10.1016/j.ijinfomgt.2016.03.008

Ramírez-Correa, P. E., Rondán-Cataluña, F. J., & Arenas-Gaitán, J. (2018). Student information system satisfaction in higher education: The role of visual aesthetics. *Kybernetes*, *47*(8), 1604–1622. https://doi.org/10.1108/k-08-2017-0297

Ramírez-Correa, P. E., Rondan-Cataluña, F. J., Arenas-Gaitán, J., & Alfaro-Perez, J. L. (2017). Moderating effect of learning styles on a learning management system's success. *Telematics and Informatics*, *34*(1), 272–286. https://doi.org/10.1016/j.tele.2016.04.006

Rankupalli, B., & Tandon, R. (2010). Practicing evidence-based psychiatry: 1. applying a study's findings: The threats to validity approach. *Asian Journal of Psychiatry*, *3*(1), 35–40. https://doi.org/10.1016/j.ajp.2010.01.002

Rasinski, K. A., Willis, G. B., Baldwin, A. K., Wenchi Yeh, A. K., & Lee, L. (1999). Methods of data collection, perceptions of risks and losses, and motivation to give truthful answers to sensitive survey questions. *Applied Cognitive Psychology*, *13*(5), 465–484. https://doi.org/10.1002/(SICI)1099-0720(199910)13:53.0.CO;2-Y

Raut, R. D., Gardas, B. B., Jha, M. K., & Priyadarshinee, P. (2017). Examining the critical success factors of cloud computing adoption in the MSMEs by using ISM model. *Journal of High Technology Management Research*, *28*(2), 125–141.

https://doi.org/10.1016/j.hitech.2017.10.004

Raykov, T., & Marcoulides, G. A. (2016). Scale reliability evaluation under multiple assumption violations. *Structural Equation Modeling: A Multidisciplinary Journal*, *23*(2), 302-313. https://doi.org/10.1080/10705511.2014.938597

Reavis, D. (2019). Teaching case creating a request for proposal for software for a non-profit organization. *Journal of Information Systems Education*, *30*(2), 106–110. http://www.jise.appstate.edu

Regenwetter, M., & Cavagnaro, D. R. (2019). Tutorial on removing the shackles of regression analysis: How to stay true to your theory of binary response probabilities. *Psychological Methods*, *24*(2), 135–152. https://doi.org/10.1037/met0000196

Regmi, P. R., Waithaka, E., Paudyal, A., Simkhada, P., & van Teijlingen, E. (2016). Guide to the design and application of online questionnaire surveys. *Nepal Journal of Epidemiology*, *6*, 640–644.

Reiss, D., & Wyatt, R. J. (1975). Family and biologic variables in the same etiologic studies of schizophrenia: A proposal. *Schizophrenia Bulletin*, *1*(14), 64–81. https://doi.org/10.1093/schbul/1.14.64

Ren, J., Zhang, D., He, S., Zhang, Y., & Li, T. (2020). A survey on end-edge-cloud orchestrated network computing paradigms: Transparent computing, mobile edge computing, fog computing, and cloudlet. *ACM Computing Surveys*, *52*(6), 1–36. https://doi.org/10.1145/3362031

Rezazade Mehrizi, M. H., Rodon Modol, J., & Nezhad, M. Z. (2019). Intensifying to cease: Unpacking the process of information systems discontinuance. *MIS Quarterly*, *43*(1), 141–165. https://doi.org/10.25300/misq/2019/13717

Rice, S., Winter, S. R., Doherty, S., & Milner, M. (2017). Advantages and disadvantages of using internet-based survey methods in aviation-related research. *Journal of Aviation Technology and Engineering*, *7*(1), 58–65. https://doi.org/10.7771/2159-6670.1160

Ripper, L., Ciaravino, S., Jones, K., Jaime, M. C., & Miller, E. (2017). Use of a respondent-generated personal code for matching anonymous adolescent surveys in longitudinal studies. *Journal of Adolescent Health*, *60*(6), 751–753. https://doi.org/10.1016/j.jadohealth.2017.01.003

Roberts, N., Campbell, D. E., & Vijayasarathy, L. R. (2016). Using information systems to sense opportunities for innovation: Integrating postadoptive use behaviors with the dynamic managerial capability perspective. *Journal of Management Information Systems*, *33*(1), 45–69. https://doi.org/10.1080/07421222.2016.1172452

Robertson, R. E., Tran, F. W., Lewark, L. N., & Epstein, R. (2018). Estimates of non-heterosexual prevalence: The roles of anonymity and privacy in survey methodology. *Archives of Sexual Behavior*, *47*(4), 1069–1084. https://doi.org/10.1007/s10508-017-1044-z

Rodgers, J. L. (2019). Degrees of freedom at the start of the second 100 years: A pedagogical treatise. *Advances in Methods and Practices in Psychological Science*, *2*(4), 396–405. https://doi.org/10.1177/2515245919882050

Roman, M. (2017). *Relationships between women's glass ceiling beliefs, career advancement satisfaction, and quit intention* (10286666) [Doctoral dissertation, Walden University]. ProQuest Dissertations & Theses Global.

Roster, C. A., Lucianetti, L., & Albaum, G. (2015). Exploring slider vs. categorical response formats in web-based surveys. *Journal of Research Practice*, *11*(1), 1–19.

Rouibah, K., Qurban, H., Al-Qirim, N., & Tarhini, A. (2018). Understanding mobile government success in an ARAB country: Findings from a qualitative study. *Issues in Information Systems*, *19*(2), 185–198.

Rouse, S. V. (2016). Of teacups and t tests: Best practices in contemporary null hypothesis significance testing. *Psi Chi Journal of Psychological Research*, *21*(2), 127–133. https://doi.org/10.24839/2164-8204.jn21.2.127

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.

Sabi, H. M., Uzoka, F.-M. E., & Mlay, S. V. (2018). Staff perception toward cloud computing adoption at universities in a developing country. *Education and Information Technologies*, *23*(5), 1825–1848. https://doi.org/10.1007/s10639-018-9692-8

Saghaeiannejad-Isfahani, S., & Salimian-Rizi, N. (2020). Assessment of success of financial information system in educational, health, and medical centers affiliated to Isfahan university of medical sciences. *Journal of Education and Health*

Promotion, *9*(1), 128. https://doi.org/10.4103/jehp.jehp_675_19

Sakshaug, J. W., Vicari, B., & Couper, M. P. (2018). Paper, e-mail, or both? effects of contact mode on participation in a web survey of establishments. *Social Science Computer Review*, *37*(6), 750–765. https://doi.org/10.1177/0894439318805160

Sakshaug, J. W., Wiśniowski, A., Ruiz, D., & Blom, A. G. (2019). Supplementing small probability samples with nonprobability samples: A Bayesian approach. *Journal of Official Statistics*, *35*(3), 653–681. https://doi.org/10.2478/jos-2019-0027

Salam, M., & Farooq, M. S. (2020). Does sociability quality of web-based collaborative learning information system influence students' satisfaction and system usage? *International Journal of Educational Technology in Higher Education*, *17*(1), 1–39. https://doi.org/10.1186/s41239-020-00189-z

Sánchez-Oliva, D., Morin, A. J., Teixeira, P. J., Carraça, E. V., Palmeira, A. L., & Silva, M. N. (2017). A bifactor exploratory structural equation modeling representation of the structure of the basic psychological needs at work scale. *Journal of Vocational Behavior*, *98*, 173–187. https://doi.org/10.1016/j.jvb.2016.12.001

Saptono, A. (2017). Development instruments through confirmatory factor analysis (CFA) in appropriate intensity assessment. *Dinamika Pendidikan*, *12*(1), 13–19. https://doi.org/10.15294/dp.v12i1.10578

Säre, E., Tulviste, T., & Luik, P. (2017). The function of questions in developing a preschooler's verbal reasoning skills during philosophical group discussions. *Early Child Development and Care*, *189*(4), 555–568. https://doi.org/10.1080/03004430.2017.1331221

Schliep, M. E., Alonzo, C. N., & Morris, M. A. (2017). Beyond RCTs: Innovations in research design and methods to advance implementation science. *Evidence-Based Communication Assessment and Intervention*, *11*(3/4), 82–98. https://doi.org/10.1080/17489539.2017.1394807

Schmidt, A. F., & Finan, C. (2018). Linear regression and the normality assumption. *Journal of Clinical Epidemiology*, *98*, 146–151. https://doi.org/10.1016/j.jclinepi.2017.12.006

Schniederjans, D. G., & Hales, D. N. (2016). Cloud computing and its impact on economic and environmental performance: A transaction cost economics perspective. *Decision Support Systems*, *86*, 73–82. https://doi.org/10.1016/j.dss.2016.03.009

Schoenbach, K., Saeed, M., & Wood, R. (2018). Audience responses to online video in Mena: New favorite genres or just more of the same as on television?. *International Communication Gazette*, *80*(8), 697–713. https://doi.org/10.1177/1748048518759196

Schrepp, M. (2020). On the usage of cronbach's alpha to measure reliability of UX scales. *Journal of Usability Studies*, *15*(4), 247–258.

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

Sebo, P., Maisonneuve, H., Cerutti, B., Fournier, J. P., Senn, N., & Haller, D. M. (2017). Rates, delays, and completeness of general practitioners' responses to a postal versus web-based survey: A randomized trial. *Journal of Medical Internet Research*, *19*(3), e83. https://doi.org/10.2196/jmir.6308

Seddon, P. B. (1997). A respecification and extension of the DeLone and McLean model of IS success. *Information Systems Research*, *8*(3), 240–253. https://doi.org/10.1287/isre.8.3.240

Seeram, E. (2019). An overview of correlational research. *Radiologic Technology*, *91*(2), 176–179.

Sehrawat, D., & Gill, N. S. (2018). Emerging trends and future computing technologies: A vision for smart environment. *International Journal of Advanced Research in Computer Science*, *9*(2), 839–842. https://doi.org/10.26483/ijarcs.v9i2.5838

Senyo, P. K., Addae, E., & Boateng, R. (2018). Cloud computing research: A review of research themes, frameworks, methods and future research directions. *International Journal of Information Management*, *38*(1), 128–139. https://doi.org/10.1016/j.ijinfomgt.2017.07.007

Serra, M., Psarra, S., & O'Brien, J. (2018). Social and physical characterization of urban contexts: Techniques and methods for quantification, classification and purposive sampling. *Urban Planning*, *3*(1), 58–74. https://doi.org/10.17645/up.v3i1.1269

Setia, M. S. (2016). Methodology series module 5: Sampling strategies. *Indian Journal of Dermatology*, *61*(5), 505–509. https://doi.org/10.4103/0019-5154.190118

Shafawi, S., & Hassan, B. (2018). User engagement with social media, implication on the library usage: A case of selected public and academic libraries in Malaysia. *Library Philosophy & Practice*, 1–31.

Shamala, P., Ahmad, R., Zolait, A., & Sedek, M. (2017). Integrating information quality dimensions into information security risk management (ISRM). *Journal of Information Security and Applications*, *36*, 1–10. https://doi.org/10.1016/j.jisa.2017.07.004

Shannon, C. E., & Weaver, W. (1949). *The mathematical theory of communications*. University of Illinois Press.

Sharma, D. H., Dhote, C. A., & Potey, M. M. (2016). Identity and access management as security-as-a-service from clouds. *Procedia Computer Science*, *79*, 170–174. https://doi.org/10.1016/j.procs.2016.03.117

Sharma, S. K., Al-Badi, A. H., Govindaluri, S. M., & Al-Kharusi, M. H. (2016). Predicting motivators of cloud computing adoption: A developing country perspective. *Computers in Human Behavior*, *62*, 61–69. https://doi.org/10.1016/j.chb.2016.03.073

Sharma, S. K., & Sharma, M. (2019). Examining the role of trust and quality dimensions in the actual usage of mobile banking services: An empirical investigation. *International Journal of Information Management*, *44*, 65–75. https://doi.org/10.1016/j.ijinfomgt.2018.09.013

Shee, H., Miah, S. J., Fairfield, L., & Pujawan, N. (2018). The impact of cloud-enabled process integration on supply chain performance and firm sustainability: The moderating role of top management. *Supply Chain Management: An International Journal*, *23*(6), 500–517. https://doi.org/10.1108/SCM-09-2017-0309

Sheldrick, R. C., Chung, P. J., & Jacobson, R. M. (2017). Math matters: How misinterpretation of odds ratios and risk ratios may influence conclusions. *Academic Pediatrics*, *17*(1), 1–3. https://doi.org/10.1016/j.acap.2016.10.008

Shim, M., & Jo, H. (2020). What quality factors matter in enhancing the perceived benefits of online health information sites? Application of the updated DeLone and McLean information systems success model. *International Journal of Medical Informatics*, *137*, 104093. https://doi.org/10.1016/j.ijmedinf.2020.104093

Siedlecki, S. L. (2018). Research intervention fidelity: Tips to improve internal validity of your intervention studies. *Clinical Nurse Specialist*, *32*(1), 12–14. https://doi.org/10.1097/nur.0000000000000342

Siedlecki, S. L. (2020). Understanding descriptive research designs and methods. *Clinical Nurse Specialist*, *34*(1), 8–12. https://doi.org/10.1097/nur.0000000000000493

Silva, D. F., Sena-Evangelista, K. C., Lyra, C. O., Pedrosa, L. F., Arrais, R. F., & Lima, S. C. (2019). Instruments for evaluation of motivations for weight loss in individuals with overweight and obesity: A systematic review and narrative synthesis. *Plos One*, *14*(7), 1–13. https://doi.org/10.1371/journal.pone.0220104

Sligh, D., & Owusu, T. D. (2014). Considerations for employing server virtualization technologies. *Issues in Information Systems*, *15*(1), 418–429.

Smith, M. G., Witte, M., Rocha, S., & Basner, M. (2019). Effectiveness of incentives and follow-up on increasing survey response rates and participation in field studies. *BMC Medical Research Methodology*, *19*(1), 1–13. https://doi.org/10.1186/s12874-019-0868-8

Soberón, A., & Stute, W. (2017). Assessing skewness, kurtosis and normality in linear mixed models. *Journal of Multivariate Analysis*, *161*, 123–140. https://doi.org/10.1016/j.jmva.2017.07.010

Sohaib, O., Naderpour, M., Hussain, W., & Martinez, L. (2019). Cloud computing model selection for e-commerce enterprises using a new 2-tuple fuzzy linguistic decision-making method. *Computers & Industrial Engineering*, *132*, 47–58. https://doi.org/10.1016/j.cie.2019.04.020

Sokip, S. (2019). Emotive behavior control to reduce intolerance and depression among secondary school students in Tulungagung Indonesia. *Journal of Social Studies Education Research*, *10*(4), 75–96.

Somula, R., & Sasikala, R. (2018). A survey on mobile cloud computing: mobile computing + cloud computing (MCC = MC + CC). *Scalable Computing: Practice & Experience*, *19*(4), 309–337. https://doi.org/10.12694/scpe.v19i4.1411

Sox, C. B., & Campbell, J. M. (2018). Virtually impossible? Assessing factors for technology acceptance within the meeting environment. *Event Management*, *22*(4), 655–670. https://doi.org/10.3727/152599518x15299559637608

Spanaki, K., Gürgüç, Z., Mulligan, C., & Lupu, E. (2019). Organizational cloud security and control: A proactive approach. *Information Technology & People*, *32*(3), 516–537. https://doi.org/10.1108/ITP-04-2017-0131

Stahl, N., Lampi, J., & King, J. R. (2019). Expanding approaches for research: Mixed methods. *Journal of Developmental Education*, *42*(2), 28–30.

Stanley, M., Roycroft, J., Amaya, A., Dever, J. A., & Srivastav, A. (2020). The effectiveness of incentives on completion rates, data quality, and nonresponse bias in a probability-based internet panel survey. *Field Methods*, *32*(2), 159–179. https://doi.org/10.1177/1525822X20901802

Steenkamp, S., & Nel, R. (2016). Cloud computing activities: Guidelines on the South African income tax classification. *Journal of Economic and Financial Sciences*, *9*(1), 228–243. https://doi.org/10.4102/jef.v9i1.39

Stefanovic, D., Marjanovic, U., Delić, M., Culibrk, D., & Lalic, B. (2016). Assessing the success of e-government systems: An employee perspective. *Information & Management*, *53*(6), 717–726. https://doi.org/10.1016/j.im.2016.02.007

Stegaroiu, C.-E. (2018). Integrating cloud technologies in the business environment. *Analele Universităţii Constantin Brâncuşi din Târgu Jiu: Seria Economie*, *1*, 157–162.

Stott, R. N., Stone, M., & Fae, J. (2016). Business models in the business-to-business and business-to-consumer worlds - what can each world learn from the other?. *Journal of Business & Industrial Marketing*, *31*(8), 943–954. https://doi.org/10.1108/jbim-10-2016-267

Strickland, O. L. (2005). Impact of unreliability of measurements on statistical conclusion validity. *Journal of Nursing Measurement*, *13*(2), 83–85. https://doi.org/10.1891/jnum.2005.13.2.83

Stuart, E. A., Ackerman, B., & Westreich, D. (2018). Generalizability of randomized trial results to target populations. *Research on Social Work Practice*, *28*(5), 532–537. https://doi.org/10.1177/1049731517720730

Stuart, E. A., & Rhodes, A. (2017). Generalizing treatment effect estimates from sample to population: A case study in the difficulties of finding sufficient data. *Evaluation Review*, *41*(4), 357–388. https://doi.org/10.1177/0193841x16660663

Subiyakto, A., Septiandani, D., Nurmiati, E., Durachman, Y., Kartiwi, M., & Ahlan, R. (2017). Managers perceptions toward the success of e-performance reporting system. *Telkomnika*, *15*(3), 1389–1396. https://doi.org/10.12928/telkomnika.v15i3.5133

Sudmanns, M. (2019). Investigating schema-free encoding of categorical data using prime numbers in a geospatial context. *ISPRS International Journal of Geo-Information*, *8*(10), 452–453. https://doi.org/10.3390/ijgi8100453

Sugumar, R., & Rajesh, A. (2019). Performance analysis and evaluation of multi-cloud systems. *I-Manager's Journal On Cloud Computing*, *6*(1), 36–42.

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. https://doi.org/10.1016/j.ijinfomgt.2017.04.010

Suter, W. N., & Suter, P. M. (2015). How research conclusions go wrong: A primer for home health clinicians. *Home Health Care Management & Practice*, *27*(4), 171–177. https://doi.org/10.1177/1084822315586557

Sutrick, K. (2017). Teaching what degrees of freedom are in statistics. *Business Education Innovation Journal*, *9*(2), 173–183.

Suyudi, M., Suyatno, Rahmatullah, A. S., & Rachmawati, Y. (2020). Investigating the influence of entrepreneurial leadership on students' entrepreneurial intentions:

Teacherpreneurship as a mediating variable. *European Journal of Educational Research*, *9*(4), 1605–1614. https://doi.org/10.12973/eu-jer.9.4.1605

Svorobej, S., Endo, P. T., Bendechache, M., Filelis-Papadopoulos, C., Giannoutakis, K. M., Gravvanis, G. A., Tzovaras, D., Byrne, J., & Lynn, T. (2019). Simulating Fog and Edge computing scenarios: An overview and research challenges. *Future Internet*, *11*(3), 1–15. https://doi.org/10.3390/fi11030055

Tabrizchi, H., & Kuchaki Rafsanjani, M. (2020). A survey on security challenges in cloud computing: Issues, threats, and solutions. *Journal of Supercomputing*, *76*(12), 9493–9532. https://doi.org/10.1007/s11227-020-03213-1

Taeb, A., & Chandrasekaran, V. (2018). Interpreting latent variables in factor models via convex optimization. *Mathematical Programming*, *167*(1), 129–154. https://doi.org/10.1007/s10107-017-1187-7

Tam, C., & Oliveira, T. (2016). Understanding the impact of m-banking on individual performance: DeLone & McLean and TTF perspective. *Computers in Human Behavior*, *61*, 233–244. https://doi.org/10.1016/j.chb.2016.03.016

Tam, C., & Oliveira, T. (2017). Understanding mobile banking individual performance: The DeLone & McLean model and the moderating effects of individual culture. *Internet Research*, *27*(3), 538–562. https://doi.org/10.1108/intr-05-2016-0117

Tan, A. H., Muskat, B., & Johns, R. (2019). The role of empathy in the service experience. *Journal of Service Theory and Practice*, *29*(2), 142–164. https://doi.org/10.1108/jstp-10-2018-0221

Tan, C. K., Ramayah, T., Teoh, A. P., & Cheah, J.-H. (2019). Factors influencing virtual team performance in Malaysia. *Kybernetes*, *48*(9), 2065–2092. https://doi.org/10.1108/k-01-2018-0031

Tao, Z., Xia, Q., Hao, Z., Li, C., Ma, L., Yi, S., & Li, Q. (2019). A survey of virtual machine management in Edge Computing. *IEEE Proceedings*, *107*(8), 1482–1499. https://doi.org/10.1109/JPROC.2019.2927919

Tarabasz, A., & Poddar, G. (2019). Factors influencing adoption of wearable devices in dubai. *Journal of Economics and Management*, *36*(2), 123–143. https://doi.org/10.22367/jem.2019.36.07

Tarhini, A., Tarhini, J., & Tarhini, A. (2019). Information technology adoption and implementation in higher education: Evidence from a case study in Lebanon. *International Journal of Educational Management*, *33*(7), 1466–1482. https://doi.org/10.1108/ijem-04-2018-0144

Taylor, J., & Spurlock, D., Jr. (2018). Statistical power in nursing education research. *Journal of Nursing Education*, *57*(5), 262–264. https://doi.org/10.3928/01484834-20180420-02

Tengstedt, M. Å., Fagerstrøm, A., & Mobekk, H. (2018). Health interventions and validity on social media: A literature review. *Procedia Computer Science*, *138*, 169–176. https://doi.org/10.1016/j.procs.2018.10.024

Theodore, B. R., & Gatchel, R. J. (2008). Management and interpretation of data obtained from clinical trials in pain management. *Pain Practice*, *8*(6), 461–472.

Thielsch, M. T., Meeßen, S. M., & Hertel, G. (2018). Trust and distrust in information systems at the workplace. *PeerJ*, *6*, e5483. https://doi.org/10.7717/peerj.5483

Thompson, C. G., Kim, R. S., Aloe, A. M., & Becker, B. J. (2017). Extracting the variance inflation factor and other multicollinearity diagnostics from typical regression results. *Basic & Applied Social Psychology*, *39*(2), 81–90. https://doi.org/10.1080/01973533.2016.1277529

Thongsri, N., Shen, L., & Bao, Y. (2019). Investigating factors affecting learner's perception toward online learning: Evidence from classstart application in Thailand. *Behaviour & Information Technology*, *38*(12), 1243–1258. https://doi.org/10.1080/0144929x.2019.1581259

Thorogood, A., & Knoppers, B. M. (2017). Can research ethics committees enable clinical trial data sharing?. *Ethics, Medicine and Public Health*, *3*(1), 56–63. https://doi.org/10.1016/j.jemep.2017.02.010

Tijmstra, J. (2018). Why checking model assumptions using null hypothesis significance tests does not suffice: A plea for plausibility. *Psychonomic Bulletin & Review*, *25*(2), 548–559. https://doi.org/10.3758/s13423-018-1447-4

Tilahun, B., & Fritz, F. (2015). Modeling antecedents of electronic medical record system implementation success in low-resource setting hospitals. *BMC Medical Informatics and Decision Making*, *15*(1), 1–9. https://doi.org/10.1186/s12911-015-0192-0

Tilly, R., Posegga, O., Fischbach, K., & Schoder, D. (2017). Towards a conceptualization of data and information quality in social information systems. *Business & Information Systems Engineering*, *59*(1), 3–21. https://doi.org/10.1007/s12599-016-0459-8

Tipton, E., & Olsen, R. B. (2018). A review of statistical methods for generalizing from evaluations of educational interventions. *Educational Researcher*, *47*(8), 516–524. https://doi.org/10.3102/0013189x18781522

Torre, D. M., & Picho, K. (2016). Threats to internal and external validity in health professions education research. *Academic Medicine*, *91*(12), e21. https://doi.org/10.1097/acm.0000000000001446

Trafimow, D. (2019). A taxonomy of model assumptions on which p is based and implications for added benefit in the sciences. *International Journal of Social Research Methodology*, *22*(6), 571–583. https://doi.org/10.1080/13645579.2019.1610592

Tripathi, S. (2017). Understanding the determinants affecting the continuance intention to use cloud computing. *Journal of International Technology & Information Management*, *26*(3), 124–152.

Tripathi, S. (2018). Moderating effects of age and experience on the factors influencing the actual usage of cloud computing. *Journal of International Technology & Information Management*, *27*(2), 121–158.

Trutschel, D., Palm, R., Holle, B., & Simon, M. (2017). Methodological approaches in analysing observational data: A practical example on how to address clustering and selection bias. *International Journal of Nursing Studies*, *76*, 36–44. https://doi.org/10.1016/j.ijnurstu.2017.06.017

Tsai, W.-L. (2021). Constructing assessment indicators for enterprises employing cloud IaaS. *Asia Pacific Management Review*, *26*(1), 23–29.

https://doi.org/10.1016/j.apmrv.2020.06.001

Tsao, M. (2019). Estimable group effects for strongly correlated variables in linear models. *Journal of Statistical Planning and Inference*, *198*, 29–42. https://doi.org/10.1016/j.jspi.2018.03.003

Tuan, A., Dalli, D., Gandolfo, A., & Gravina, A. (2019). Theories and methods in csrc research: A systematic literature review. *Corporate Communications: An International Journal*, *24*(2), 212–231. https://doi.org/10.1108/ccij-11-2017-0112

Tworek, K. (2018). Reliability of information systems in organization in the context of banking sector: Empirical study from Poland. *Cogent Business & Management*, *5*(1), 1–13. https://doi.org/10.1080/23311975.2018.1522752

Uanhoro, J. O., Wang, Y., & O'Connell, A. A. (2019). Problems with using odds ratios as effect sizes in binary logistic regression and alternative approaches. *Journal of Experimental Education*, 1–20. https://doi.org/10.1080/00220973.2019.1693328

Urquhart, R., Kendell, C., Folkes, A., Reiman, T., Grunfeld, E., & Porter, G. A. (2018). Making it happen: Middle managers' roles in innovation implementation in health care. *Worldviews on Evidence-Based Nursing*, *15*(6), 414–423. https://doi.org/10.1111/wvn.12324

U.S. Department of Health & Human Services. (1979, April 18). *The Belmont Report*. HHS.gov. https://www.hhs.gov/ohrp/regulations-and-policy/belmont-report/read-the-belmont-report/index.html

Vacek, J., Vonkova, H., & Gabrhelík, R. (2017). A successful strategy for linking anonymous data from students' and parents' questionnaires using self-generated identification codes. *Prevention Science*, *18*(4), 450–458. https://doi.org/10.1007/s11121-017-0772-6

Van Cauter, L., Verlet, D., Snoeck, M., & Crompvoets, J. (2017). The explanatory power of the DeLone & McLean model in the public sector: A mixed method test. *Information Polity*, *22*(1), 41–55. https://doi.org/10.3233/ip-170404

van Ginkel, J. R. (2020). Standardized regression coefficients and newly proposed estimators for r2 in multiply imputed data. *Psychometrika*, *85*(1), 185–205. https://doi.org/10.1007/s11336-020-09696-4

Vatanasakdakul, S., Aoun, C., & Chen, Y. (2017). Chasing success: An empirical model for IT governance frameworks adoption in Australia. *Science, Technology and Society*, *22*(2), 182–211. https://doi.org/10.1177/0971721817702278

Veazie, P., & Ye, Z. (2020). A simple goodness-of-fit test for continuous conditional distributions. *Ratio Mathematica*, *39*(0), 7–32. https://doi.org/10.23755/rm.v39i0.524

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. https://doi.org/10.1016/j.giq.2018.03.004

Vetter, T. R. (2017a). Descriptive statistics: Reporting the answers to the 5 basic questions of who, what, why, when, where, and a sixth, so what?. *Anesthesia & Analgesia*, *125*(5), 1797–1802. https://doi.org/10.1213/ane.0000000000002471

Vetter, T. R. (2017b). Fundamentals of research data and variables: The devil is in the details. *Anesthesia & Analgesia*, *125*(4), 1375–1380. https://doi.org/10.1213/ane.0000000000002370

Vitari, C. (2011). The success of expert recommending services and the part played by organizational context. *Knowledge Management Research & Practice*, *9*(2), 151–171. https://doi.org/10.1057/kmrp.2011.6

Vithayathil, J. (2018). Will cloud computing make the information technology (IT) department obsolete?. *Information Systems Journal*, *28*(4), 634–649. https://doi.org/10.1111/isj.12151

Von Eye, A., & Wiedermann, W. (2017). Testing event-based forms of causality. *Integrative Psychological and Behavioral Science*, *51*(2), 324–344. https://doi.org/10.1007/s12124-017-9378-6

Wadgave, U., Khairnar, M. R., & Wadgave, Y. (2018). Statistical issues in randomized controlled trials: An editorial. *Electronic physician*, *10*(10), 7293–7298. https://doi.org/10.19082/7293

Walton, T. K. (2019). *Relationship between technostress dimensions and employee productivity* (27544440) [Doctoral dissertation, Walden University]. ProQuest Dissertations & Theses Global.

Wang, S. L., & Lin, H. I. (2019). Integrating TTF and IDTto evaluate user intention of big data analytics in mobile cloud healthcare system. *Behaviour & Information Technology*, *38*(9), 974–985. https://doi.org/10.1080/0144929x.2019.1626486

Wang, Y.-S., Li, C.-R., Yeh, C.-H., Cheng, S.-T., Chiou, C.-C., Tang, Y.-C., & Tang, T.-I. (2016). A conceptual model for assessing blog-based learning system success in the context of business education. *International Journal of Management Education*, *14*(3), 379–387. https://doi.org/10.1016/j.ijme.2016.09.002

Wang, Y.-S., & Liao, Y.-W. (2008). Assessing egovernment systems success: A validation of the delone and mclean model of information systems success. *Government Information Quarterly*, *25*(4), 717–733. https://doi.org/10.1016/j.giq.2007.06.002

Wani, M., Raghavan, V., Abraham, D., & Kleist, V. (2017). Beyond utilitarian factors: User experience and travel company website successes. *Information Systems Frontiers*, *19*(4), 769–785. https://doi.org/10.1007/s10796-017-9747-1

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. https://doi.org/10.1080/09720510.2017.1338609

Welch, M. (2014). Exploring the impact of communication technologies on business air travel. *Journal of Organizational Culture, Communications and Conflict*, *18*(1), 187–214.

Werff, L. V., Fox, G., Masevic, I., Emeakaroha, V. C., Morrison, J. P., & Lynn, T. (2019). Building consumer trust in the cloud: An experimental analysis of the cloud trust label approach. *Journal of Cloud Computing: Advances, Systems and Applications*, *8*(1), 1–17. https://doi.org/10.1186/s13677-019-0129-8

Westreich, D., Edwards, J. K., Lesko, C. R., Cole, S. R., & Stuart, E. A. (2019). Target validity and the hierarchy of study designs. *American Journal of Epidemiology*, *188*(2), 438–443. https://doi.org/10.1093/aje/kwy228

White, P., & Gorard, S. (2017). Against inferential statistics: How and why current statistics teaching gets it wrong. *Statistics Education Research Journal*, *16*(1), 55–65.

Wibowo, A., & Sari, M. W. (2018). Measuring enterprise resource planning (ERP) systems effectiveness in Indonesia. *Telkomnika*, *16*(1), 343–351. https://doi.org/10.12928/telkomnika.v16i2.5895

Wibowo, M. I., Santoso, A. J., & Setyohadi, D. B. (2018). Factors affecting the successful implementation of e-government on network documentation and legal information website in Riau. *CommIT Journal*, *12*(1), 51–57. https://doi.org/10.21512/commit.v12i1.4361

Widiastuti, R., Haryono, B. S., & Said, A. (2019). Influence of system quality, information quality, service quality on user acceptance and satisfaction and its impact on net benefits (study of information system users lecturer performance load (BKD) in Malang State University). *HOLISTICA - Journal of Business and Public Administration*, *10*(3), 111–132. https://doi.org/10.2478/hjbpa-2019-0032

Wijayanto, H., & Haryono, T. (2018). Leadership style of transformational key user in the success of the implementation of enterprise resource planning in the universities in East Java, indonesia. *Journal of Innovation in Business and Economics*, *2*(1), 13–18. https://doi.org/10.22219/jibe.v2i01.5335

Williams, P. (2019). 'It all sounds very interesting, but we're just too busy!': Exploring why ‘gatekeepers’ decline access to potential research participants with learning disabilities. *European Journal of Special Needs Education*, *35*(1), 1–14. https://doi.org/10.1080/08856257.2019.1687563

Wooluru, Y., Swamy, D. R., & Nagesh, P. (2016). Process capability estimation for non-normally distributed data using robust methods - A comparative study. *International Journal for Quality Research*, *10*(2), 407–420. https://doi.org/10.18421/IJQR10.02-11

Xu, F., & Du, J. T. (2018). Factors influencing users’ satisfaction and loyalty to digital libraries in Chinese universities. *Computers in Human Behavior*, *83*, 64–72. https://doi.org/10.1016/j.chb.2018.01.029

Yadegaridehkordi, E., Nizam Bin Md Nasir, M. H., Fazmidar Binti Mohd Noor, N., Shuib, L., & Badie, N. (2018). Predicting the adoption of cloud-based technology using fuzzy analytic hierarchy process and structural equation modelling approaches. *Applied Soft Computing*, *66*, 77–89. https://doi.org/10.1016/j.asoc.2017.12.051

Yakubu, M. N., & Dasuki, S. I. (2018). Assessing elearning systems success in Nigeria: An application of the DeLone and McLean information systems success model. *Journal of Information Technology Education*, *17*, 182–202. https://doi.org/10.28945/4077

Yang, R., Carter, B. L., Gums, T. H., Gryzlak, B. M., Xu, Y., & Levy, B. T. (2017). Selection bias and subject refusal in a cluster-randomized controlled trial. *BMC Medical Research Methodology*, *17*(1), 94. https://doi.org/10.1186/s12874-017-

0368-7

Ye, L., & Yang, H. (2020). From digital divide to social inclusion: A tale of mobile platform empowerment in rural areas. *Sustainability*, *12*(6), 2424. https://doi.org/10.3390/su12062424

Yildiz, E., & Güngörmüş, Z. (2016). The validity and reliability study of the Turkish version of the evidence based practice evaluation competence questionnaire. *Nurse Education Today*, *45*, 91–95. https://doi.org/10.1016/j.nedt.2016.05.030

Yousefpour, A., Fung, C., Nguyen, T., Kadiyala, K., Jalali, F., Niakanlahiji, A., Kong, J., & Jue, J. P. (2019). All one needs to know about fog computing and related edge computing paradigms: A complete survey. *Journal of Systems Architecture*, *98*, 289–330. https://doi.org/10.1016/j.sysarc.2019.02.009

Yu, P., & Qian, S. (2018). Developing a theoretical model and questionnaire survey instrument to measure the success of electronic health records in residential aged care. *PLoS One*, *13*(1), e0190749. https://doi.org/10.1371/journal.pone.0190749

Yu, S., Alper, H. E., Nguyen, A.-M., Brackbill, R. M., Turner, L., Walker, D. J., Maslow, C. B., & Zweig, K. C. (2017). The effectiveness of a monetary incentive offer on survey response rates and response completeness in a longitudinal study. *BMC Medical Research Methodology*, *17*(1), 1–9. https://doi.org/10.1186/s12874-017-0353-1

Yuan, K.-H., & Chan, W. (2016). Measurement invariance via multigroup SEM: Issues and solutions with chi-square-difference tests. *Psychological Methods*, *21*(3), 405–426. https://doi.org/10.1037/met0000080

Zabukovšek, S. S., Bharadwaj, S. S., Bobek, S., & Strukelj, T. (2019). Technology acceptance model-based research on differences of enterprise resources planning systems use in India and the European Union. *Engineering Economics*, *30*(3), 326–338. https://doi.org/10.5755/j01.ee.30.3.21211

Zahle, J. (2018). Values and data collection in social research. *Philosophy of Science*, *85*(1), 144–163. https://doi.org/10.1086/694770

Zainol, Z., Fernandez, D., & Ahmad, H. (2017). Public sector accountants' opinion on impact of a new enterprise system. *Procedia Computer Science*, *124*, 247–254. https://doi.org/10.1016/j.procs.2017.12.153

Zaky, A., & Naufal, M. (2017). The analysis of electronic journal utilization in learning process: Technology acceptance model and information system success. *Jurnal Ilmu Sosial Mamangan*, *6*(2), 97. https://doi.org/10.22202/mamangan.2358

Zhang, J., Zhao, Y., & Wang, Y. (2016). A study on statistical methods used in six journals of library and information science. *Online Information Review*, *40*(3), 416–434. https://doi.org/10.1108/oir-07-2015-0247

Zhang, J.-T., Cheng, M.-Y., Wu, H.-T., & Zhou, B. (2019). A new test for functional one-way ANOVA with applications to ischemic heart screening. *Computational Statistics & Data Analysis*, *132*, 3–17. https://doi.org/10.1016/j.csda.2018.05.004

Zhang, M., Liu, Y., Yan, W., & Zhang, Y. (2016). Users' continuance intention of virtual learning community services: The moderating role of usage experience. *Interactive Learning Environments*, *25*(6), 685–703. https://doi.org/10.1080/10494820.2016.1172242

Zhang, S., Kwok, R. C.-W., Lowry, P. B., & Liu, Z. (2019). Does more accessibility lead to more disclosure? Exploring the influence of information accessibility on self-disclosure in online social networks. *Information Technology & People*, *32*(3), 754–780. https://doi.org/10.1108/itp-04-2017-0134

Zhao, C., & Yang, J. (2019). A robust skewed boxplot for detecting outliers in rainfall observations in real-time flood forecasting. *Advances in Meteorology*, *2019*, 1–7. https://doi.org/10.1155/2019/1795673

Zheng, J., Okamura, H., & Dohi, T. (2018). Component importance analysis of mobile cloud computing system in the presence of common-cause failures. *IEEE Access*, *6*, 18630–18642. https://doi.org/10.1109/ACCESS.2018.2822338

Zhou, R., Wang, X., Zhang, L., & Guo, H. (2017). Who tends to answer open-ended questions in an e-service survey? The contribution of closed-ended answers. *Behaviour & Information Technology*, *36*(12), 1274–1284. https://doi.org/10.1080/0144929x.2017.1381165

Zhu, M., Sari, A., & Lee, M. (2018). A systematic review of research methods and topics of the empirical MOOC literature (2014-2016). *Internet & Higher Education*, *37*, 31–39. https://doi.org/10.1016/j.iheduc.2018.01.002

Zimmermann, O. (2017). Architectural refactoring for the cloud: A decision-centric view on cloud migration. *Computing*, *99*(2), 129–145. https://doi.org/10.1007/s00607-016-0520-y

Zinbarg, R. E., Pinsof, W., Quirk, K., Kendall, A., Goldsmith, J., Hardy, N., He, Y., Sabey, A., & Latta, T. (2018). Testing the convergent and discriminant validity of the systemic therapy inventory of change initial scales. *Psychotherapy Research*, *28*(5), 734–749. https://doi.org/10.1080/10503307.2017.1325022

Žmuk, B. (2018). Impact of different questionnaire design characteristics on survey response rates: Evidence from Croatian business web survey. *Statistika: Statistics and Economy Journal*, *98*(1), 69–87.

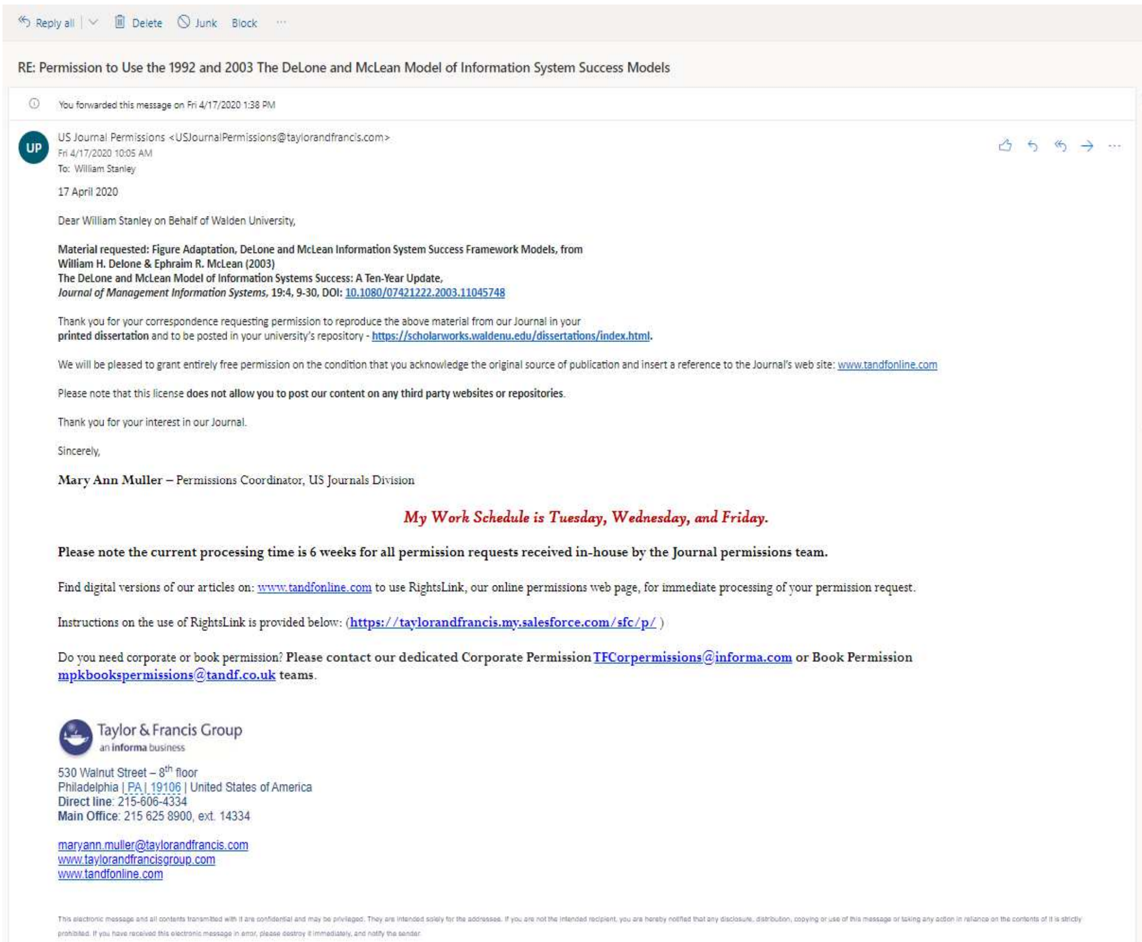
Zyphur, M. J., & Pierides, D. C. (2017). Is quantitative research ethical? tools for ethically practicing, evaluating, and using quantitative research. *Journal of Business Ethics*, *143*(1), 1–16. https://doi.org/10.1007/s10551-017-3549-8

Zyphur, M. J., & Pierides, D. C. (2019). Making quantitative research work: From positivist dogma to actual social scientific inquiry. *Journal of Business Ethics*. https://doi.org/10.1007/s10551-019-04189-6

Appendix A: Permission to Use DeLone and McLean Framework

Figure A1

Permission to Use the DeLone and McLean Framework from Publisher



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Note. The figure illustrates the permission to use the DeLeon and McLean Information System Success Model from the model's publisher in this study, Taylor and Francis Group.

Appendix B: Construct Measures Accompanying References

Table B1

Perception of Information Quality Construct Measures

Measures	**References**
Trustworthy	Kuo (2018)
	Jung and Jung (2019)
Accuracy	Rouibah, Qurban, Al-Qirim, and Tarhini (2018)
	Aldholay, Isaac, Abdullah, Abdulsalam, and Al-Shibami (2018)
	Veeramootoo, Nunkoo, and Dwivedi (2018)
Secure	Al-Azawei (2019)
	Daghouri, Mansouri, and Qbadou (2018)
	Fan, Gao, and Gao (2016)
Completeness	Tam and Oliveira (2016)
	Rahi and Abd.Ghani (2019)

Note. The table identifies the various references used within the literature review to define the measures for the construct perception of information quality.

Table B2

Perception of System Quality Construct Measures

Measures	References
Reliable	Cheng (2019)
	Thielsch, Meeßen, and Hertel (2018)
	French, Shim, Otondo, and Templeton (2018)
Ease of Use	Nusantara, Gayatri, and Suhartana (2018)
	Sharma and Sharma (2019)
Responsiveness	Jiang and Wu (2016)
(response time)	Al-Fraihat, Joy, Masa'deh, and Sinclair (2020)
Accessibility	Assegaff, Hendri, Sunoto, Yani, and Kisbiyanti (2017)
	Negahban, Kim, and Kim (2016)
	Chaw and Tang (2018)
Availability (high)	Thongsri, Shen, and Bao (2019)
	Ramírez-Correa, Rondan-Cataluña, Arenas-Gaitán, and Alfaro-Perez (2017)
	Rouibah, Qurban, Al-Qirim, and Tarhini (2018)

Note. The table identifies the various references used within the literature review to define the measures for the construct perception of system quality.

Table B3

Perception of Service Quality Construct Measures

Measures	**References**
Responsiveness	Aldholay, Isaac, Abdullah, and Ramayah (2018)
	Isaac, Aldholay, Abdullah, and Ramayah (2019)
Assurance	Arsyanur, Suroso, and Sukmawati (2019)
	Wani, Raghavan, Abraham, and Kleist (2017)
Empathy	Subiyakto, Septiandani, Nurmiati, Durachman, Kartiwi, and Ahlan (2017)
	Van Cauter, Verlet, Snoeck, and Crompvoets (2017)
Effective Solution	Gonzales, R., & Wareham, J. (2019)
	Alzahrani, Mahmud, Ramayah, Alfarraj, and Alalwan (2019)
Service Level	Lwoga and Sife (2018)
(Customer Service)	Cohen, Coleman, and Kangethe (2016)
Knowledgeable	Tam and Oliveira (2017)
(Experts)	Gay (2016)

Note. The table identifies the various references used within the literature review to define the measures for the construct perception of service quality.

Table B4

Perception of System Use Construct Measures

Measures	**References**
Frequency of Use	Isaac et al. (2017)
	Harr et al. (2019)
Duration of Use	Marjanovic et al. (2016)
	Al-Fraihat et al. (2020)
Continuance Use	Lin et al. (2018)
Intentions	Jiang and Wu (2016)
System Dependency	Agrifoglio et al. (2016)
	Lin et al. (2017)

Note. The table identifies the various references used within the literature review to define the measures for the construct perception of system use.

Table B5

Perception of User Satisfaction Construct Measures

Measures	**References**
Satisfied (Overall)	Yakubu and Dasuki (2018)
	Harr et al. (2019)
	Budiardjo et al. (2017)
Expectations	Stefanovic et al. (2016)
	Keikhosrokiani et al. (2018)
Adequacy	Aparicio et al. (2016)
	Cidral et al. (2018)
User Attitude	Kuo et al. (2018)
	Ramírez-Correa et al. (2017)

Note. The table identifies the various references used within the literature review to define the measures for the construct perception of user satisfaction.

Table B6

Net Benefits of Cloud Computing Services Construct Measures

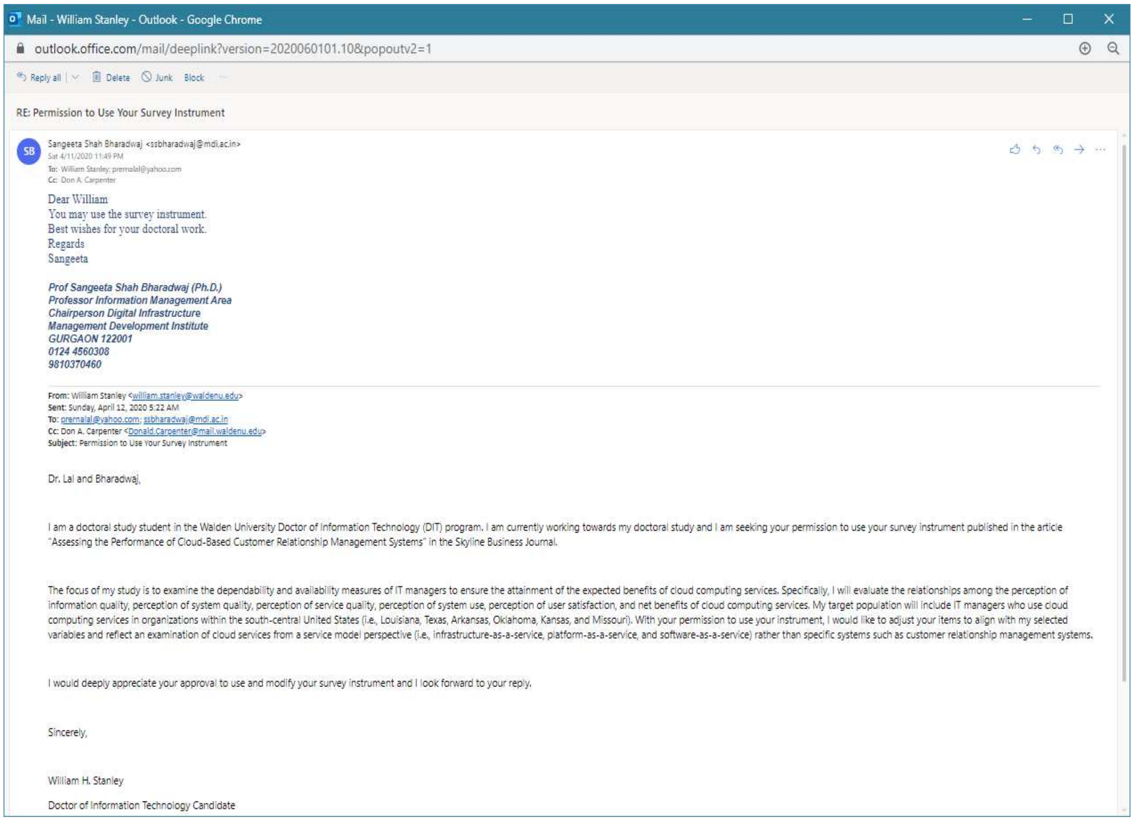
Measures	**References**
Improved Communication	Yu and Qian (2018) Jiang and Wu (2016)
Improved Customer Satisfaction	Wei et al. (2017) Subiyakto et al. (2017) Lal and Bharadwaj (2016)
Improved Productivity	Borena (2016) Monika and Gaol (2017)
Increasing Effectiveness	Arsyanur et al. (2019) Nusantara et al. (2018) Tilahun and Fritz (2015)
Improved Knowledge (or Understanding)	Marjanovic et al. (2016) Chiu et al. (2016)
Improved Decision Making	Fadhilah et al. (2015) Ghobakhloo and Tang (2015)

Note. The table identifies the various references used within the literature review to define the measures for the construct net benefits of cloud computing services.

Appendix C: Permission to Use Lal and Bharadwaj (2016) Survey Instrument

Figure C1

Permission to Use the Lal and Bharadwaj (2016) Survey Instrument



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Sangeeta Shah Bharadwaj <ssbharadwaj@mdi.ac.in>
Sat 4/11/2020 11:49 PM
To: William Stanley; premalal@yahoo.com
Cc: Don A. Carpenter

Dear William
You may use the survey instrument.
Best wishes for your doctoral work.
Regards
Sangeeta

Prof Sangeeta Shah Bharadwaj (Ph.D.)
Professor Information Management Area
Chairperson Digital Infrastructure
Management Development Institute
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From: William Stanley <william.stanley@waldenu.edu>
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Subject: Permission to Use Your Survey Instrument

Dr. Lal and Bharadwaj,

I am a doctoral study student in the Walden University Doctor of Information Technology (DIT) program. I am currently working towards my doctoral study and I am seeking your permission to use your survey instrument published in the article "Assessing the Performance of Cloud-Based Customer Relationship Management Systems" in the Skyline Business Journal.

The focus of my study is to examine the dependability and availability measures of IT managers to ensure the attainment of the expected benefits of cloud computing services. Specifically, I will evaluate the relationships among the perception of information quality, perception of system quality, perception of service quality, perception of system use, perception of user satisfaction, and net benefits of cloud computing services. My target population will include IT managers who use cloud computing services in organizations within the south-central United States (i.e., Louisiana, Texas, Arkansas, Oklahoma, Kansas, and Missouri). With your permission to use your instrument, I would like to adjust your items to align with my selected variables and reflect an examination of cloud services from a service model perspective (i.e., infrastructure-as-a-service, platform-as-a-service, and software-as-a-service) rather than specific systems such as customer relationship management systems.

I would deeply appreciate your approval to use and modify your survey instrument and I look forward to your reply.

Sincerely,

William H. Stanley

Doctor of Information Technology Candidate

Note. The figure illustrates the permission to use the Lal and Bharadwaj (2016) Survey Instrument from the publisher in this study.

Appendix D: Lal and Bharadwaj (2016) Instrument Construct and Measures

System Quality
SQ1: Cloud-based CRM systems are easy to adopt.
SQ2: Cloud-based CRM systems are available 24/7.
SQ3: Cloud-based CRM systems can be accessed from any location.
SQ4: Cloud-based CRM systems can be accessed from any device.
SQ5: Cloud-based CRM systems are reliable.

Service Quality
SERQ1: Cloud service provider is expert.
SERQ2: Cloud service provider provides 24/7 customer service.
SERQ3: Cloud service provider keeps updating the technology.
SERQ4: Cloud service provider keeps updating the functions and features of CRM system.
SERQ5: Cloud service provider promptly responses to customer queries.
SERQ6: Cloud service provider's reputation is very good.

Information Quality
IQ1: Cloud-based CRM systems can be customized according to our need.
IQ2: Cloud-based CRM systems provide security of data.
IQ3: Cloud-based CRM systems are easy to understand.
IQ4: Cloud-based CRM systems provide relevant information

Use of Cloud-based CRM
USE1: We are using cloud-based CRM systems to interact with the customers.
USE2: We are using cloud-based CRM systems for lead management.
USE3: We are using cloud-based CRM systems for managing sales force.
USE4: We are using cloud-based CRM systems for promoting our products/ services.

User Satisfaction
US1: We are satisfied with the Cloudbased CRM systems.
US2: Cloud-based CRM systems are of high quality.
US3: Cloud-based CRM systems have met our expectations.
US4: Cloud-based CRM systems enhances employees' performance.

Organizational Benefits
OB1: Cloud-based CRM systems have helped in the reduction of customer response time
OB2: Cloud-based CRM systems have helped in the improving the quality of customer service.
OB3: Cloud-based CRM systems have increased customer satisfaction
OB4: Cloud-based CRM systems have helped in the reduction of IT implementation cost.
OB5: Cloud-based CRM systems have helped in the reduction of IT maintenance cost.
OB6: Cloud-based CRM systems have helped us in increasing the market share.

Appendix E Study Survey Instrument

Table E1

Qualifying Questions 1–3

Question No.	Question	Value	Scale
1	Are you a manager with your organization's information technology department?	(1) Yes (2) No	Nominal
2	Are you a manager of information technology resources or services that reside in the cloud?	(1) Yes (2) No	Nominal
3	Has your company subscribed to a cloud computing service for no less than one (1) year?	(1) Yes (2) No	Nominal

Note. The table identifies the survey instrument's qualifying questions that will be presented to the participants to ensure that they meet the study's eligibility criteria.

Table E2

Demographic Questions 4–7

Question No.	Question	Value	Scale
4	What is your highest education level?	(1) Less than high school (2) High School/GED (3) Some College (4) Associates (5) Bachelor's degree (6) Graduate Degree	Nominal
5	What managerial role best describes your current job position?	(1) Front-line Manager (manage nonsupervisory workers and report to higher middle manager level) (2) Middle Manager (manage front-line managers and report to senior-level or department manager) (3) Senior Manager (department manager or executive, i.e., director or CIO)	Nominal
6	How long have you been in the current managerial position?	(1) Less than 1 year (2) at least 1 - but less than 3 years (3) at least 3 - but less than 5 years (4) 5 years and above	Nominal
7	What are your current years of experience with cloud computing service(s)?	(1) Less than 6 months (2) at least 6 months but less than 1 Year (3) at least 1 - but less than 2 years (4) at least 2 - but less than 5 years (5) 5 years and above	Nominal

Note. The table identifies the survey instrument's first four demographic questions, which capture the participant's level of education, managerial role, managerial position, and years of experiencing managing cloud computing services.

Table E3

Demographic Questions 8–10

Question No.	Question	Value	Scale
8	What is your organization's size (Number of employees)?	(1) less than 100 employees (2) between 100 and 500 employees (3) between 500 and 1000 employees (4) more than 1000 employees	Nominal
9	What is your organization's primary cloud computing service(s) model strategy?	(1) IaaS (2) SaaS (3) PaaS (4) Hybrid (5) Unknown	Nominal
10	What is your organization's primary cloud computing service(s) deployment model strategy?	(1) Public Cloud (2) Private Cloud (3) Community Cloud (4) Hybrid Cloud (5) Unknown	Nominal

Note. The table identifies the survey instrument's demographic questions 8–10, which captures the participant's organizational size, primary cloud computing service model strategy, and primary deployment model strategy.

Table E4

Demographic Question 11

Question No.	Question	Value	Scale
11	What is your organization's primary business or industry?	(1) Agriculture, Forestry, & Wildlife (2) Automotive, Sales, & Marketing (3) Cloud Service Provider & IT Services (4) Construction, Real Estate, & Housing (5) Education (6) Energy, Utilities, & Gas (7) Financial, Insurance, Banking, & Legal (8) Food & Hospitality (9) Government & Military (10) Health Care & Pharmaceutical (11) Non-profit (12) Other	Nominal

Note. The table identifies the survey instrument's demographic question 11, which captures the participant's organization's primary business or industry.

Table E5

Perception of Information Quality Questions 12–15

Question No.	Question	Value	Scale
12	The primary cloud-based service(s) information is trustworthy.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal
13	The primary cloud-based service(s) information is secure.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal
14	The primary cloud-based service(s) information is accurate.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal
15	The primary cloud-based service(s) information is complete (possess all desired data).	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal

Note. The table identifies the survey instrument's questions 12–15, which captures the participant's expression regarding how much they agree or disagree with the measures trustworthy, secure, accuracy, and completeness of the construct perception of information quality.

Table E6

Perception of System Quality Questions 16–20

Question No.	Question	Value	Scale
16	The primary cloud-based service(s) is easy to use.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal
17	The primary cloud-based service(s) is available 24/7.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal
18	The primary cloud-based service(s) is responsive to user requests.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal
19	The primary cloud-based service(s) can be accessed from any device.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal
20	The primary cloud-based service(s) is reliable.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal

Note. The table identifies the survey instrument’s questions 16–20, which captures the participant’s expression regarding how much they agree or disagree with the measures ease of use, availability, responsive, accessibility, and reliability of the construct perception of system quality.

Table E7

Perception of Service Quality Questions 21–26

Question No.	Question	Value	Scale
21	The primary cloud service(s) provider is knowledgeable (experts).	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal
22	The primary cloud service(s) provider provides an acceptable level of customer service.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal
23	The primary cloud service(s) provider demonstrates empathy during a service experience.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal
24	The primary cloud service(s) provider offers effective solutions.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal
25	The primary cloud service(s) provider promptly responses to customer queries.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal
26	The primary cloud service(s) provider demonstrates assurance toward satisfying support requirements.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal

Note. The table identifies the survey instrument's questions 21–26, which captures the participant's expression regarding how much they agree or disagree with the measures responsiveness, assurance, empathy, effective solution, service level, and knowledgeable of the construct perception of service quality.

Table E8

Perception of System Use Questions 27–30

Question No.	Question	Value	Scale
27	The frequency of use of the primary cloud-based service(s) is high.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal
28	The duration of use of the primary cloud-based service(s) is high.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal
29	The continuance use intentions of the primary cloud-base service(s) are high.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal
30	The system dependency of the primary cloud-base service(s) is high.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal

Note. The table identifies the survey instrument's questions 27–30, which captures the participant's expression regarding how much they agree or disagree with the measures frequency of use, duration of use, continuance use intentions, and system dependency of the construct system use.

Table E9

Perception of User Satisfaction 31–34

Question No.	Question	Value	Scale
31	The primary cloud-based service(s) meets our overall satisfaction.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal
32	The primary cloud-based service(s) are adequate in providing timely information.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal
33	The primary cloud-based service(s) meets our expectations.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal
34	The primary cloud-based service(s) improves user attitude.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal

Note. The table identifies the survey instrument's questions 31–34, which captures the participant's expression regarding how much they agree or disagree with the measures satisfaction, expectations, adequacy, and user attitude of the construct user satisfaction.

Table E10

Net Benefits of Cloud Computing Services Questions 35–37

Question No.	Question	Value	Scale
35	The primary cloud-based service(s) has helped to increase the department's effectiveness.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal
36	The primary cloud-based service(s) has helped improve the department's productivity.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal
37	The primary cloud-based service(s) has increased customer satisfaction.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal

Note. The table identifies the survey instrument's questions 35–37, which captures the participant's expression regarding how much they agree or disagree with the measures increasing effectiveness, improved productivity, and improved customer satisfaction of the construct net benefits of cloud computing services.

Table E11

Net Benefits of Cloud Computing Services Questions 38–40

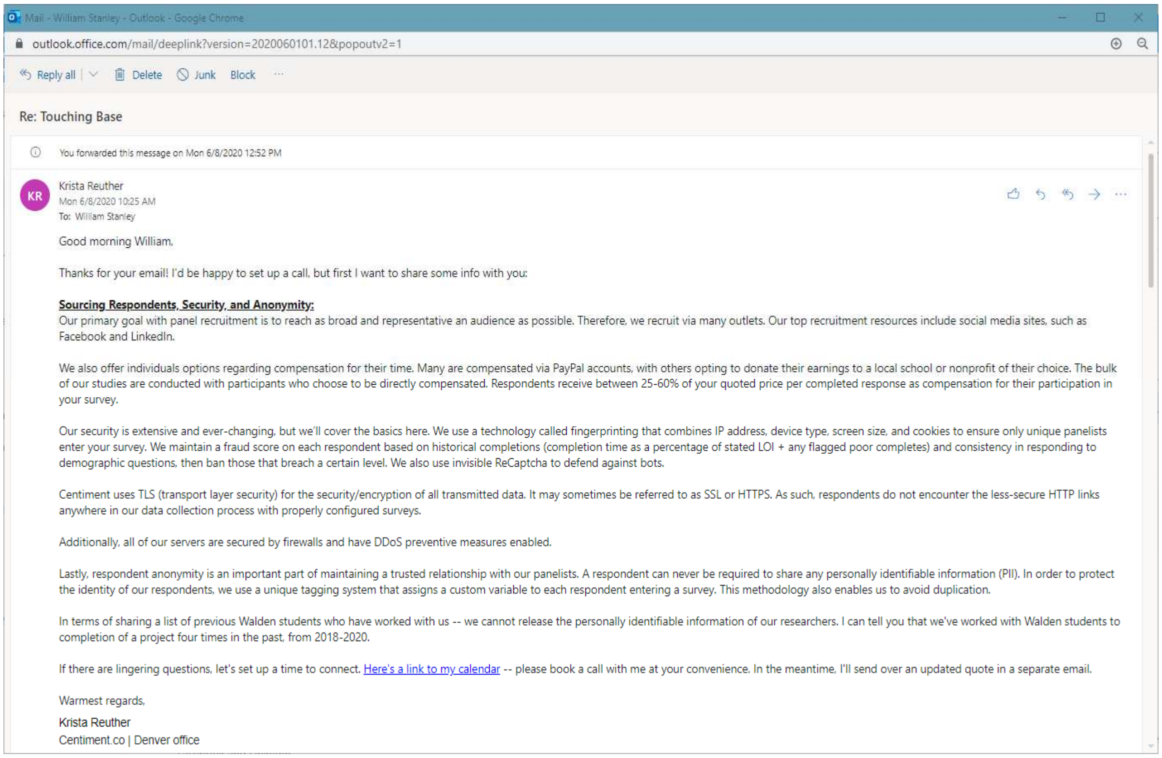
Question No.	Question	Value	Scale
38	The primary cloud-based service(s) has helped improve the department's communication.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal
39	The primary cloud-based service(s) has helped improve the department's knowledge creation process.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal
40	The primary cloud-based service(s) has helped improve the department's decision making.	(1) Strongly disagree (2) Disagree (3) Neither agree nor disagree (4) Agree (5) Strongly agree	Ordinal

Note. The table identifies the survey instrument's questions 38–40, which captures the participant's expression regarding how much they agree or disagree with the measures improved communication, improved knowledge, and improved decision making of the construct net benefits of cloud computing services.

Appendix F: Centiment's Security Components

Figure F1

Centiment's Security Components



Mail - William Stanley - Outlook - Google Chrome

outlook.office.com/mail/deeplink?version=2020060101.12&popoutv2=1

Reply all | Delete | Junk | Block

Re: Touching Base

You forwarded this message on Mon 6/8/2020 12:52 PM

KR Krista Reuther
Mon 6/8/2020 10:25 AM
To: William Stanley

Good morning William,

Thanks for your email! I'd be happy to set up a call, but first I want to share some info with you:

Sourcing Respondents, Security, and Anonymity:
Our primary goal with panel recruitment is to reach as broad and representative an audience as possible. Therefore, we recruit via many outlets. Our top recruitment resources include social media sites, such as Facebook and LinkedIn.

We also offer individuals options regarding compensation for their time. Many are compensated via PayPal accounts, with others opting to donate their earnings to a local school or nonprofit of their choice. The bulk of our studies are conducted with participants who choose to be directly compensated. Respondents receive between 25-60% of your quoted price per completed response as compensation for their participation in your survey.

Our security is extensive and ever-changing, but we'll cover the basics here. We use a technology called fingerprinting that combines IP address, device type, screen size, and cookies to ensure only unique panelists enter your survey. We maintain a fraud score on each respondent based on historical completions (completion time as a percentage of stated LOI + any flagged poor completes) and consistency in responding to demographic questions, then ban those that breach a certain level. We also use invisible ReCaptcha to defend against bots.

Centiment uses TLS (transport layer security) for the security/encryption of all transmitted data. It may sometimes be referred to as SSL or HTTPS. As such, respondents do not encounter the less-secure HTTP links anywhere in our data collection process with properly configured surveys.

Additionally, all of our servers are secured by firewalls and have DDoS preventive measures enabled.

Lastly, respondent anonymity is an important part of maintaining a trusted relationship with our panelists. A respondent can never be required to share any personally identifiable information (PII). In order to protect the identity of our respondents, we use a unique tagging system that assigns a custom variable to each respondent entering a survey. This methodology also enables us to avoid duplication.

In terms of sharing a list of previous Walden students who have worked with us -- we cannot release the personally identifiable information of our researchers. I can tell you that we've worked with Walden students to completion of a project four times in the past, from 2018-2020.

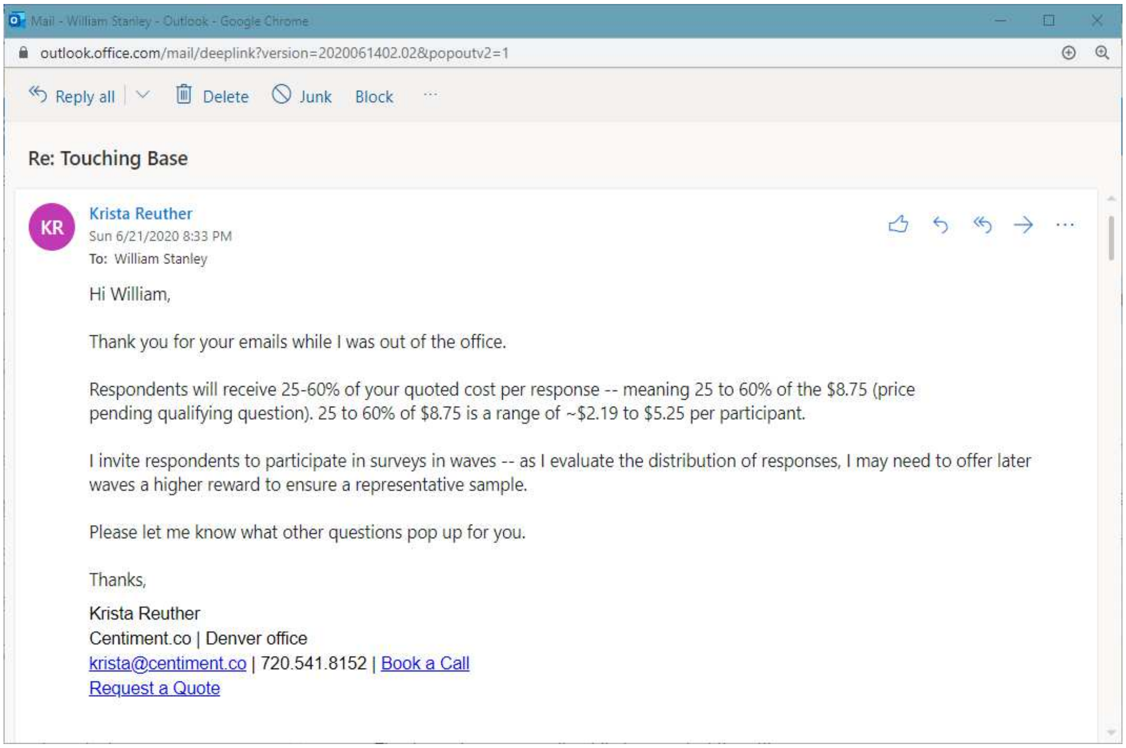
If there are lingering questions, let's set up a time to connect. Here's a link to my calendar -- please book a call with me at your convenience. In the meantime, I'll send over an updated quote in a separate email.

Warmest regards,
Krista Reuther
Centiment.co | Denver office

Note. The figure contains the personal correspondence from Centiment Project Manager Krista Reuther. It explains Centiment's security components as it relates to their sourcing of respondents, security methods, privacy, and anonymity.

Figure F2

Centimen's Incentive Cost Per Response



Mail - William Stanley - Outlook - Google Chrome

outlook.office.com/mail/deeplink?version=2020061402.02&popoutv2=1

Reply all | Delete | Junk | Block

Re: Touching Base

Krista Reuther
Sun 6/21/2020 8:33 PM
To: William Stanley

Hi William,

Thank you for your emails while I was out of the office.

Respondents will receive 25-60% of your quoted cost per response -- meaning 25 to 60% of the $8.75 (price pending qualifying question). 25 to 60% of $8.75 is a range of ~$2.19 to $5.25 per participant.

I invite respondents to participate in surveys in waves -- as I evaluate the distribution of responses, I may need to offer later waves a higher reward to ensure a representative sample.

Please let me know what other questions pop up for you.

Thanks,

Krista Reuther
Centiment.co | Denver office
krista@centiment.co | 720.541.8152 | Book a Call
Request a Quote

Note. The figure contains the personal correspondence from Centiment Project Manager Krista Reuther. It explains Centiment's methods for quantifying the sum of incentives provided to each respondent based on the contract rate.

Appendix G: Centiment Contract Quote

Figure G1

Centiment Contract Quote

QUOTE

centiment

Centiment LLC
Your data collection team:
derek@centiment.co 720.541.8257 | krista@centiment.co 720.541.8152 | kurt@centiment.co 720.541.8812

Company:	Walden University	Doc #:	Doc 4524
Name:	William Stanley	Date:	June 8, 2020
Email:	William.Stanley@Waldenu.edu	Tool:	SurveyMonkey
Phone:	504-289-4648		

Target audience	# Questions	Est Min to Complete	# Responses
Respondents in the IT department across all industries. Managers+, including executives. Department must use cloud computing and must have had cloud computing capabilities for at least one year in Louisiana, Texas, Arkansas, Oklahoma, Kansas, or Missouri.	37	10	138

Item	Price / Response	QTY	Subtotal
Survey Responses price pending qualifying question	$8.75	138	$1,207.50

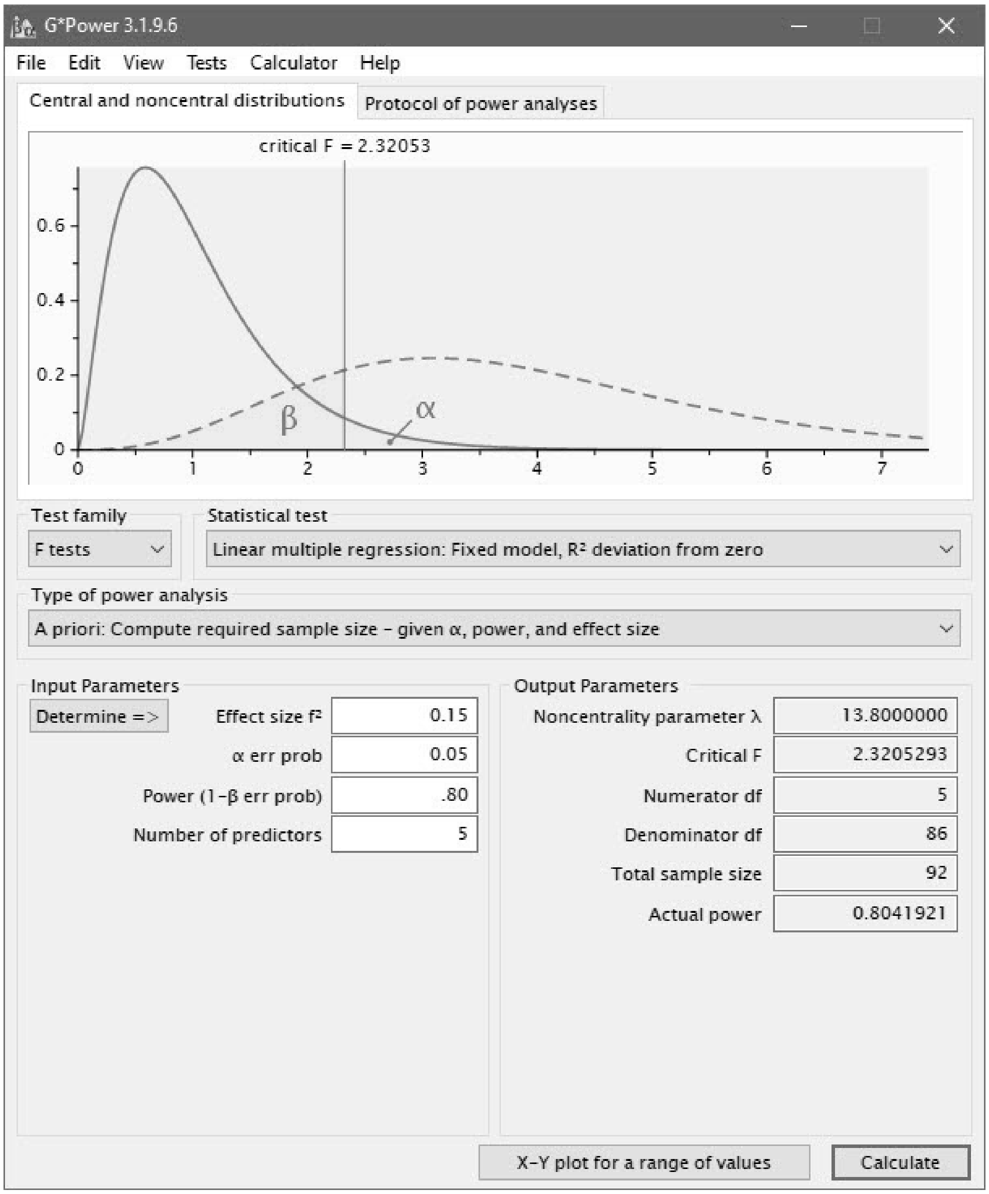
Total $1,207.50

Note. The figure illustrates Centiment's contract quote for their panel services, which is also used to calculate the participant incentives.

Appendix H: G*Power Analysis to Determine Sample Size

Figure H1

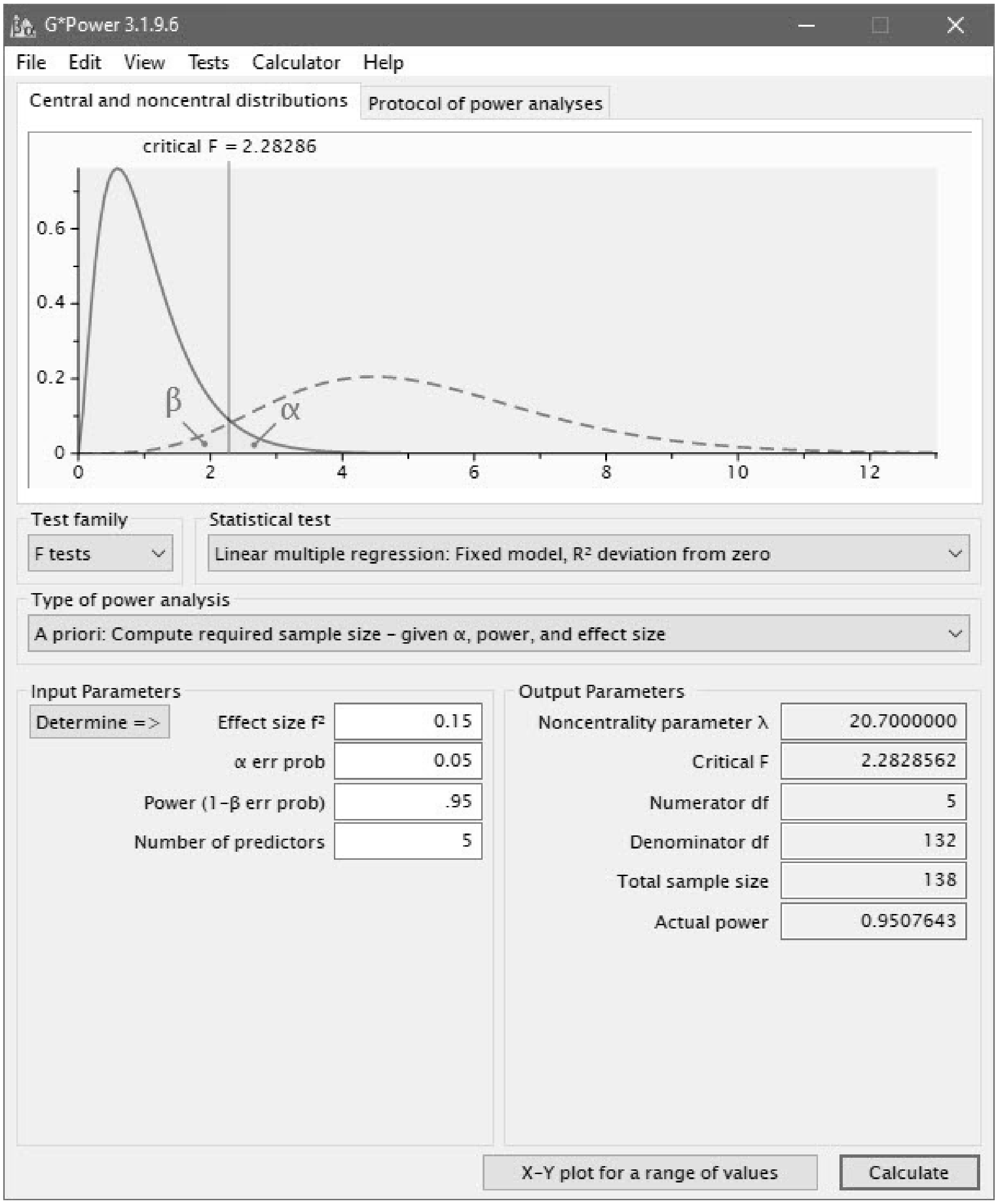
*G*Power Analysis to Determine the Minimal Sample Size*



Note. The figure illustrates the parameters used in G*Power to calculate the minimal sample size for using linear multiple regression with a fixed model.

Figure H2

*G*Power Analysis to Determine the Maximum Sample Size*



Note. The figure illustrates the parameters used in G*Power to calculate the maximum sample size for using multiple linear regression with a fixed model.

Appendix I: Invitation

My name is Student Name and I am a doctoral candidate student in the Doctor of Information Technology program at Walden University. I would like to invite you to participate in my research about the technical benefit returns of cloud computing services.

Background Information:

The purpose of this study is to investigate your perceived overall benefits of the cloud computing services from the perspective of its:

- information quality (i.e., trustworthy, accuracy, secure, and completeness)
- system quality (i.e., reliable, ease of use, responsiveness or response time, accessibility, and high availability)
- service quality of the service provider (i.e., responsiveness, assurance, empathy, effective solution, service level or customer service, and knowledge as experts)
- system use (i.e., frequency of use, duration of use, continuance use intentions, system dependency)
- user satisfaction (i.e., overall satisfaction, expectations, adequacy, user attitude)

Eligibility Requirements:

In order to participate in the study, you must meet the following criteria:

- You are manager with your organization's information technology department.
- You are a manager of information technology resources or services that reside in the cloud.
- Your company has subscribed to a cloud computing service for no less than one (1) year.

Benefits of Being in the Study:

The study's potential benefit includes helping to understand better how IT leaders perceive the rationale that drives organizations to migrate to cloud services. This examination of cloud success may also help IT and business leaders to strengthen their due diligence process as the findings may aid to support or repudiate some of the perceived benefits of cloud computing adoption.

Procedures:

I have provided the Survey Monkey link below. Also, If you agree to be in this study, you will be asked to:

- answer questions regarding demographic information about yourself and your organization

- answer questions regarding your current cloud computing services and your perception of the effectiveness of the system(s)
- the survey will include questions focused on the technical functionality of the system, and the level of customer service for the cloud service provider
- the survey will take about 20 minutes to complete

Voluntary Nature of the Study:

This study is voluntary. You are free to accept or turn down the invitation. No one at Walden University nor individuals within your organization will treat you differently if you decide not to be in the study. If you decide to be in the study now, you can still change your mind later. If you start the survey, you can always change your mind and stop at any time. Furthermore, it is recommended that you keep/print a copy of this consent form for your personal records.

Payment:

Centiment will offer their panel members monetary incentives to the individuals who participate and fully complete the survey questions. Otherwise, there is no reimbursement or cost for participating in this study.

Contacts and Questions:

If you have questions, you may contact the researcher via cell phone (xxx) xxx-xxxx and/or email address studnen.name@Waldenu.Edu. If you want to talk privately about your rights as a participant, you can call the Research Participant Advocate at my university at 612-312-1210.

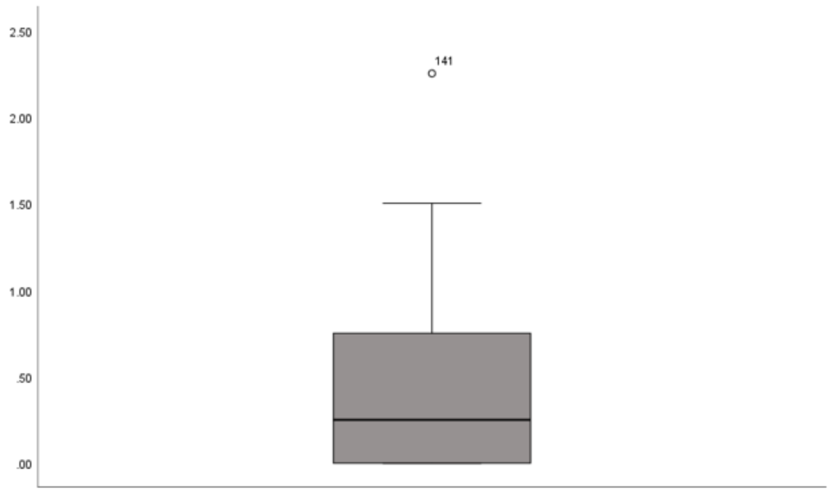
Link to Survey:

The link to the Survey Monkey study is as follows: <URL>

Appendix J: Outlier Boxplots

Figure J1

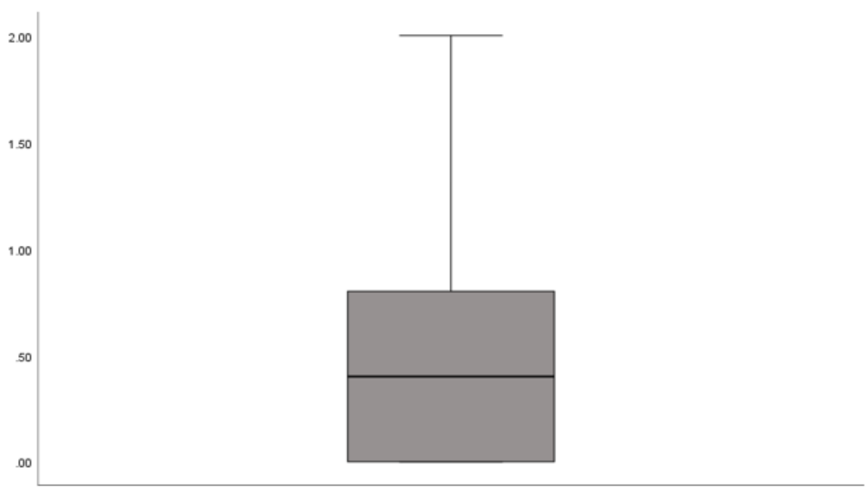
Outlier Boxplot of Perception of Information Quality



Note. The figure illustrates the outlier (case: 141) for the independent variable perception of information quality.

Figure J2

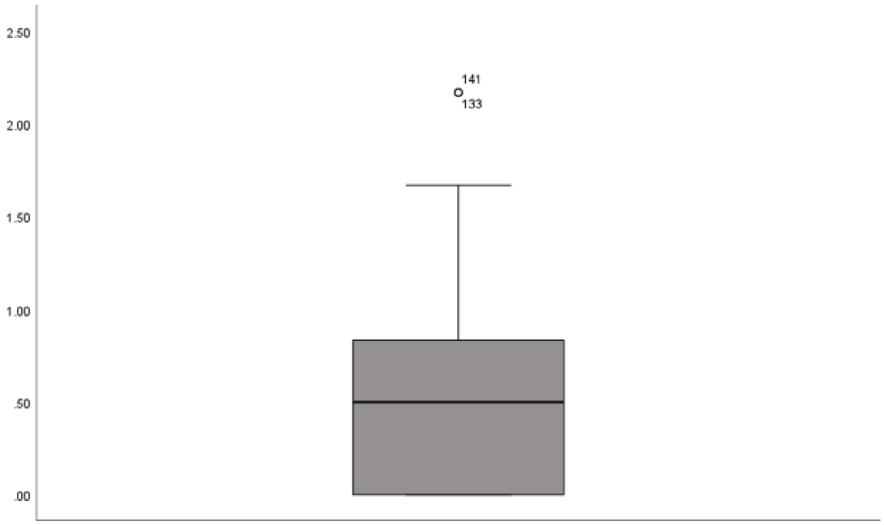
Outlier Boxplot of Perception of System Quality



Note. The figure illustrates that there were no outliers identified for the independent variable perception of system quality.

Figure J3

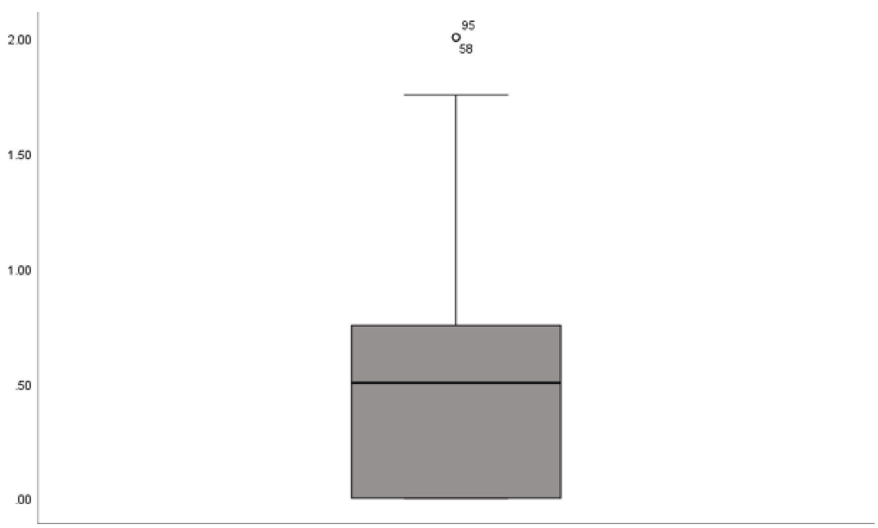
Outlier Boxplot of Perception of Service Quality



Note. The figure illustrates the outliers (case: 133, 141) for the independent variable perception of service quality.

Figure J4

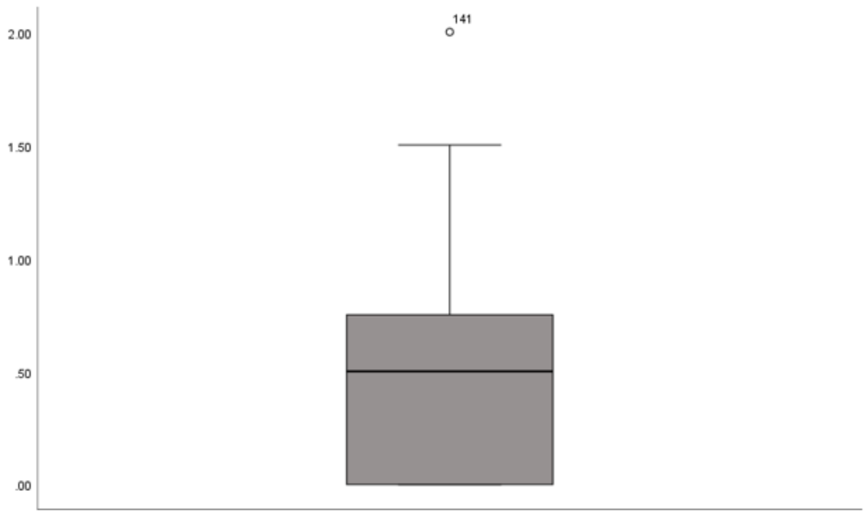
Outlier Boxplot of Perception of System Use



Note. The figure illustrates the outliers (case: 58, 95) for the independent variable perception of system use.

Figure J5

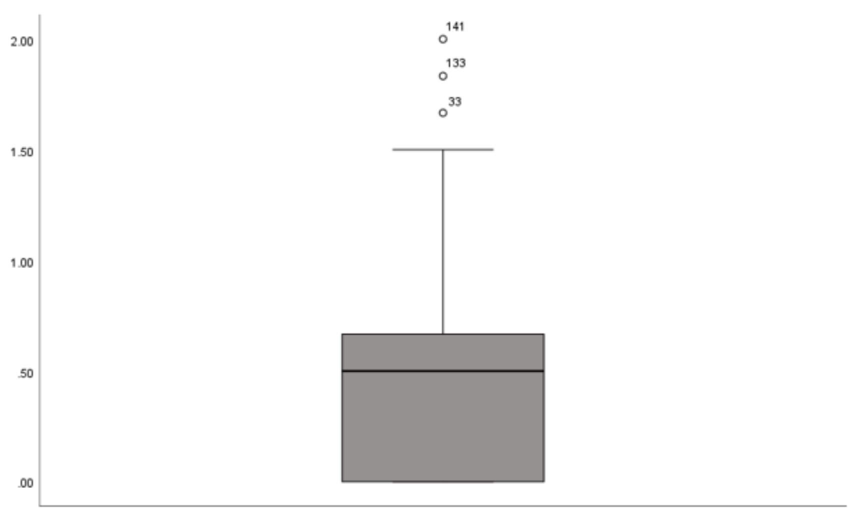
Outlier Boxplot of Perception of User Satisfaction



Note. The figure illustrates the outlier (case: 141) for the independent variable perception of user satisfaction.

Figure J6

Outlier Boxplot of Net Benefits of Cloud Computing Services



Note. The figure illustrates the outliers (case: 33, 133, 141) for the dependent variable net benefits of cloud computing services.

Appendix K: Goodness of Fit

Table K1

Test for Goodness-of-Fit for Perception of Information Quality Indicator Variables

Indicator Measure	NET1	NET2	NET3	NET4	NET5	NET6
INF1						
X^2	31.48	7.78	22.95	25.00	18.39	13.38
df	2	2	3	2	3	2
p	0.000	0.020	0.000	0.000	0.00	0.001
INF2						
X^2	20.21	14.83	32.44	47.37	15.82	32.96
df	4	4	6	4	6	4
p	0.000	0.005	0.000	0.000	0.015	0.000
INF3						
X^2	25.44	20.65	37.22	18.79	43.89	30.87
df	4	4	6	4	6	4
p	0.000	0.000	0.00	0.001	0.000	0.000
INF4						
X^2	35.02	31.47	29.19	23.53	96.12	30.41
df	6	6	9	6	9	6
p	0.00	0.000	0.001	0.001	0.000	0.000

Note. Total N = 137. The table provides the chi-square analysis values of the four indicator variables for the construct perception of information quality versus the five indicator variables of dependent construct net benefits of cloud computing services.

Table K2

Test for Goodness-of-Fit for Perception of System Quality Indicator Variables

Indicator Measure	NET1	NET2	NET3	NET4	NET5	NET6
SYS1						
X^2	42.31	46.46	33.79	22.26	87.62	24.39
df	6	6	9	6	9	6
p	0.000	0.000	0.000	0.001	0.000	0.000
SYS2						
X^2	26.47	23.71	40.36	58.81	93.37	15.41
df	6	6	9	6	9	6
p	0.000	0.001	0.000	0.000	0.000	0.017
SYS3						
X^2	11.84	18.74	26.06	14.96	26.93	32.36
df	4	4	6	4	6	4
p	0.019	0.001	0.000	.005	0.000	0.000
SYS4						
X^2	19.09	38.79	18.79	19.54	39.19	15.73
df	6	6	4	6	9	6
p	0.004	0.000	0.027	0.003	0.000	0.015
SYS5						
X^2	30.73	21.47	36.70	16.86	22.75	32.28
df	4	4	6	4	6	4
p	0.000	0.000	0.000	0.002	0.001	0.000

Note. Total N = 137. The table provides the chi-square analysis values of the five indicator variables for the construct perception of system quality versus the five indicator variables of dependent construct net benefits of cloud computing services.

Table K3

Test for Goodness-of-Fit for Perception of Service Quality Indicator Variables

Indicator Measure	NET1	NET2	NET3	NET4	NET5	NET6
SER1						
X^2	34.31	7.88	31.88	45.33	32.81	12.53
df	4	4	4	4	6	4
p	0.000	0.096	0.000	0.00	0.000	0.014
SER2						
X^2	36.88	27.62	32.67	20.67	42.54	17.39
df	4	4	6	4	6	4
p	0.000	0.000	0.000	0.000	0.000	0.002
SER3						
X^2	28.05	8.92	36.83	21.15	32.97	26.95
df	6	6	9	6	9	6
p	0.000	0.004	0.000	0.002	0.000	0.000
SER4						
X^2	43.49	24.02	20.51	35.31	55.88	16.85
df	6	6	9	6	9	6
p	0.00	0.001	0.015	0.000	0.000	0.010
SER5						
X^2	30.63	20.81	1.61	26.99	40.76	28.10
df	6	6	9	6	9	6
p	0.000	.002	0.000	0.000	0.000	0.000
SER6						
X^2	24.89	31.88	22.68	23.38	19.55	26.63
df	4	4	6	4	6	4
p	0.000	0.000	0.001	0.000	0.003	0.000

Note. Total $N = 137$. This table provides the chi-square analysis values of the six indicator variables for the construct perception of service quality versus the five indicator variables of dependent construct net benefits of cloud computing services.

Table K4

Test for Goodness-of-Fit for Perception of System Use Indicator Variables

Indicator Measure	NET1	NET2	NET3	NET4	NET5	NET6
USE1						
X^2	27.51	15.18	21.41	25.72	30.70	18.96
df	4	4	6	4	6	4
p	0.000	.004	0.002	0.000	0.000	0.001
USE2						
X^2	27.87	20.90	46.47	48.21	42.64	34.68
df	6	6	9	6	9	6
p	0.000	0.002	0.000	0.000	0.000	0.000
USE3						
X^2	40.71	26.65	20.53	28.74	84.01	31.11
df	6	6	9	6	9	6
p	0.000	0.000	0.015	0.000	0.000	0.000
USE4						
X^2	29.22	48.75	48.71	26.56	24.41	34.78
df	6	6	9	6	9	6
p	0.000	0.000	0.000	0.000	0.004	0.000

Note. Total $N = 137$. The table provides the chi-square analysis values of the four indicator variables for the construct perception of system use versus the five indicator variables of dependent construct net benefits of cloud computing services.

Table K5

Test for Goodness-of-Fit for Perception of User Satisfaction Indicator Variables

Indicator Measure	NET1	NET2	NET3	NET4	NET5	NET6
SAT1						
X^2	22.06	16.41	38.60	16.13	17.99	23.74
df	4	4	6	4	6	4
p	0.000	0.003	0.000	0.003	0.006	0.000
SAT2						
X^2	26.53	76.54	19.52	31.82	60.23	34.30
df	6	6	9	6	9	6
p	0.000	0.000	0.021	0.000	0.000	0.000
SAT3						
X^2	23.09	19.24	26.79	25.35	32.53	33.14
df	4	4	6	4	6	4
p	0.000	0.001	0.000	0.000	0.000	0.000
SAT4						
X^2	21.71	49.33	33.50	79.10	36.62	42.38
df	6	6	9	6	9	6
p	0.001	0.000	0.000	0.000	0.000	0.000

Note. Total $N = 137$. The table provides the chi-square analysis values of the four indicator variables for the construct perception of user satisfaction versus the five indicator variables of dependent construct net benefits of cloud computing services.