2021

The Relationship Between Technology Adoption Determinants and the Intention to Use Software-Defined Networking

Wendell Russ
Walden University

Walden University

College of Management and Technology

This is to certify that the doctoral study by

Wendell Russ

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

Review Committee
Dr. Donald Carpenter, Committee Chairperson, Information Technology Faculty
Dr. Jodine Burchell, Committee Member, Information Technology Faculty
Dr. Gail Miles, University Reviewer, Information Technology Faculty

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

Walden University
2021

Abstract

The Relationship Between Technology Adoption Determinants and the Intention

to Use Software-Defined Networking

by

Wendell Russ

MA, Webster University, 1993

BS, Park University, 1992

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Information Technology

Walden University

April 2021

Abstract

The advent of distributed cloud computing and the exponential growth and demands of the internet of things and big data have strained traditional network technologies' capabilities and have given rise to software-defined networking's (SDN's) revolutionary approach. Some information technology (IT) cloud services leaders who do not intend to adopt SDN technology may be unable to meet increasing performance and flexibility demands and may risk financial loss compared to those who adopt SDN technology. Grounded in the unified theory of acceptance and use of technology (UTAUT), the purpose of this quantitative correlational study was to examine the relationship between IT cloud system integrators' perceptions of performance expectancy, effort expectancy, social influence, facilitating conditions, and their intention to use SDN technology. The participants (n = 167) were cloud system integrators who were at least 18 years old with a minimum of three months' experience and used SDN technology in the United States. Data were collected using the UTAUT authors' validated survey instrument. The multiple regression findings were significant, $F(4, 162) = 40.44$, $p < .001$, $R^2 = .50$. In the final model, social influence (ß = .236, t = 2.662, $p < .01$) and facilitating conditions (ß = .327, t = 5.018, $p < .001$) were statistically significant; performance expectancy and effort expectancy were not statistically significant. A recommendation is for IT managers to champion SDN adoption by ensuring the availability of support resources and promoting its use in the organization's goals. The implications for positive social change include the potential to enhance cloud security, quality of experience, and improved reliability, strengthening safety control systems.

The Relationship Between Technology Adoption Determinants and the Intention to Use Software-Defined Networking

by

Wendell Russ

MA, Webster University, 1993

BS, Park University, 1992

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Information Technology

Walden University

April 2021

Acknowledgements

I first thank Anita, my wonderful wife, for her incredible support and for always ensuring that my environment was studious. I thank my superb committee: Dr. Carpenter, whom I consider the "wise navigator," along with Dr. Burchell and Dr. Miles, whose recommendations also helped to improve the quality of my paper.

This achievement represents an accomplishment to be shared by my parents and siblings, whose shoulders I have stood on, and other family members. I also extend my gratitude to JD and Kevin for creating a work environment that promotes higher learning. But this exhilarating journey was also enduring. So, for giving me the energy, inspiration, and skills, I thank our great Lord and Savior Jesus Christ.

Table of Contents

List of Tables

List of Figures

Section 1. Foundation of the Study

Today's conventional network industry is manually intensive, costly, and plagued by inflexibility. To transform to the next-generation software-defined networking (SDN) technology, which could lead to substantial cost reductions through automation, greater processing capacity, and fine-grained service orchestration through programmability, it is paramount that industry leaders and system developers understand and adjust to the intricacies of its adoption. The results of this study may help to promote broader adoption and integration of SDN technology.

Background

The SDN concept originated in 2004 by the Internet Engineering Task Force as a revolutionary architectural model which, in contrast to the traditional model, separates the control plane from the data plane and consolidates the control plane onto a centralized controller, enabling globally aware network management and flow control capabilities (Mijumbi et al., 2016). In 2012, Nicira Networks proposed likely the first SDN solutions at Stanford University based on open standards and network virtualization, representing a potentially game-changing opportunity in rethinking how enterprise networks are managed and deliver services (Singh & Jha, 2017). Although SDN technology stands to achieve significant performance and efficiency gains, its integration into traditional networking environments faces significant challenges (Anan et al., 2016).

Potential SDN integration and implementation challenges include: (a) interoperability with the existing infrastructure and legacy networks, (b) the lack of standardized management and control interfaces to facilitate an ecosystem of open-source technologies across multiple vendors, (c) defining of new service delivery and capacity-sharing guarantees, and (d) standardizing best practices for SDN security (Cox et al., 2017). SDN also represents a paradigm shift, prompting new challenges that may include developing multidisciplinary support teams that foster the cross-utilization of skills and establishing standard practice application program interfaces (Cox et al., 2017). Such challenges have affected the adoption of SDN (Amin et al., 2018). In this study, I aimed to understand the relationship between cloud system integrators' perceptions of the determinants to use SDN technology and their adoption of the technology.

Problem Statement

The advent of distributed cloud computing and the exponential growth and demands of the internet of things (IoT) and big data have strained the capabilities of traditional network technologies and have given rise to the SDN revolutionary approach, although it is still in its infancy (Tomovic et al., 2017). SDN's programmability enables the dynamic orchestration of complex and diverse traffic demands while also supporting the automation of network functions, which may reduce the total cost of ownership by 40% over 5 years (Muciaccia & Passaro, 2017). The general IT problem is that despite SDN's potential for extraordinary benefits, IT cloud system integrators' perceptions may affect its adoption. The specific IT problem is that some IT cloud services decision-makers in the United States lack information about the requisite knowledge regarding the relationship between IT cloud system integrators' perceptions of performance expectancy, effort expectancy, social influence, facilitating conditions, and their intention to use SDN technology.

Purpose Statement

The purpose of this quantitative correlational study was to examine the relationship between IT cloud system integrators' perceptions of performance expectancy, effort expectancy, social influence, facilitating conditions, and the intention of IT cloud system integrators to use SDN technology. My dependent variable was IT cloud system integrators' intention to adopt SDN technology, while my independent variables were IT cloud system integrators' perceptions of performance expectancy, effort expectancy, social influence, and facilitating conditions. The target population for this study was IT cloud system integrators at cloud service providers in the United States. In this study, I sought to stimulate dialogue and raise awareness about potential social benefits of SDN technology, such as providing greater automation and network intelligence capabilities for data orchestration of smart cities that may result in enhanced quality of experience (QoE) for users and improved network security that may result in fewer service interruptions for users.

Nature of the Study

Of the three main approaches to scholarly research, I applied the quantitative methodology in this study. The quantitative methodology can be used to apply numerical and statistical analysis to measure and empirically investigate how attitudes and perceptions influence a phenomenon in scientific research (Allouch et al., 2019). I chose the quantitative method to investigate the relationship between the dependent and independent variables using statistical analysis. In contrast, the qualitative researcher seeks to understand the "how" and "why" of human behavioral characteristics, as well as the context of the phenomenon and the social realities (Mohajan, 2018). I did not choose the qualitative method because in this study I did not examine behavioral characteristics, environmental context, nor social reality attributes. The mixed-methods approach involves the integration of both quantitative and qualitative, using diverse data collections to derive a more comprehensive understanding of the research problem than either the quantitative or qualitative method alone (Long & Rodgers, 2017). I did not choose the mixed methodology because this study did not include the qualitative method, a central component of mixed-methods research.

Of the three major quantitative research designs, I chose correlational. The correlational design enables the researcher to analyze the relationship between the dependent and independent variables statistically and numerically and to test the hypotheses (Appelbaum et al., 2018). Because I performed statistical analysis on the relationship between the intention of IT cloud system integrators to adopt SDN technology and their perceptions of performance expectancy, effort expectancy, social influence, and facilitating conditions, the correlational design was appropriate for this study. The experimental design is a controlled study used to determine causal effects, consisting of one or more treatments or interventions (Zyphur & Pierides, 2017). The experimental design was not appropriate because in this study I did not seek to determine the causation of a phenomenon, nor did the study involve a treatment or an intervention. Lastly, the descriptive design involves observing and describing the behavior of a subject or phenomenon, and although nonexperimental, it does not test the hypothesis (Solheim et al., 2017). The descriptive design was not fitting because this study involved assessing the relation between the dependent and independent variables and testing the hypotheses.

Research Question and Hypotheses

RQ: What is the relationship between IT cloud system integrators' perceptions of performance expectancy, effort expectancy, social influence, facilitating conditions, and the intention of IT cloud system integrators to use SDN technology?

H_0: There is no significant relationship between IT cloud system integrators' perceptions of performance expectancy, effort expectancy, social influence, facilitating conditions, and the intention of IT cloud system integrators to use SDN technology.

H_a: There is a significant relationship between IT cloud system integrators' perceptions of performance expectancy, effort expectancy, social influence, facilitating conditions, and the intention of IT cloud system integrators to use SDN technology.

Theoretical Framework

The theoretical framework for this study was derived from the unified theory of acceptance and use of technology (UTAUT) by Venkatesh et al. (2003) in which they identified the following central determinants that explain user intentions to use a technology and subsequent usage of the technology: performance expectancy, effort expectancy, social influence, and facilitating conditions. Whereas performance expectancy reflects the degree in which an individual perceives that using the technology will benefit the individual's job performance, effort expectancy indicates the perceived degree of ease associated with using the technology. UTAUT, which evolved from eight previous models of theorizing individual acceptance and usage of technology, assesses facilitating conditions to determine whether an organizational and technical infrastructure exists to support the technology for the user, while social influence reflects the degree in which the user perceives how others expect them to use the technology (Venkatesh et al., 2003).

This research paper leveraged a recent study in which Lawrence (2018) applied the UTAUT model to examine the relationships between determinants, including technological, institutional, and demographic, that affect the acceptance of the “bring your own device” policy at public high schools in the Cayman Islands. Similarly, in this study I assessed factors that influence the intention to adopt SDN technology at cloud service providers in the United States. UTAUT was ideal for this study to understand the factors that influence the intention to adopt the paradigm-changing SDN technology. In this study, I adopted the core constructs of Venkatesh et al.’s (2003) empirically-validated UTAUT instrument.

Operational Definitions

Control plane: The SDN control plane is a logically centralized network operating system that performs unified management and configuration of connected network devices compared to traditional technology where each network node contains an independently managed control plane. The SDN control plane resides on the controller making decisions about traffic forwarding and preferences, comprising a single unit or multiple distributed units (Liu et al., 2019).

Data plane: The data plane performs traffic forwarding using instructions from the controller by means of the southbound interfaces. The data plane consists of network hardware devices, such as switches and routers, that forward packets towards the destination (Azka et al., 2017).

Mininet emulation: Mininet emulation provides an open-source virtual platform for SDN and OpenFlow protocol developers to prototype and model SDN topologies and configurations and evaluate performance capabilities, such as network response time, fault recovery, and scalability, without investing in SDN hardware and software (Yan & Dong, 2017).

Network function virtualization: The concept of network function virtualization provides a software-based virtual abstraction of physical network devices and network device functions, enabling on-demand scale-up and scale-down capabilities across distributed network hardware resources and promoting more efficient utilization and sharing of hardware resources (Rotsos et al., 2017).

Northbound interface: The northbound interface represents an abstraction element of service integration and orchestration between the controller and the application and service and components (Reisslein & Maier, 2019).

OpenFlow protocol: The OpenFlow protocol provides communication specifications and standards between the SDN controller and network devices, enabling the controller to push flow and security configurations to the network devices, which facilitates status updates and flow statistics from the network devices to the controller (Singh & Jha, 2017).

Quality of Experience (QoE): QoE refers to the quality of network service delivery, particularly for interactive voice and video mediums, from the customer's perspective (Baktir et al., 2017).

Southbound interface: The southbound interface represents an abstraction component for which the controller sends data forwarding instructions from the controller to network hardware devices, such as routers and switches, that perform traffic forwarding functions (Saraswat et al., 2019).

System integrator: The system integrator plans and executes the adaptation and incorporation of new system technologies for an organization. The system integrator implements architectural innovations that extend across hardware and software boundaries, ensuring system interoperability and infrastructure modularity while considering the organization's business objectives and resources. In addition to defining system interfaces and interactions, the system integrator may also assist in determining the adoption of technology paths and the resources needed (Coronado Mondragon & Coronado Mondragon, 2018).

Assumptions, Limitations, and Delimitations

Assumptions

According to Hathcoat and Meixner (2017), scientific research assumptions are beliefs, understandings, and predispositions that inform and guide research inquiries. In this study, I explored how the determinants of technology adoption affect SDN adoption for service providers. I assumed that participants provided accurate responses to survey questions. The clarity of survey questions promotes accuracy (Silva et al., 2018). I assumed that the survey results reflected the population. In scientific research, generalization refers to drawing broad inferences from the research findings and conclusions that reflect the population at large. The larger the sample, the more likely participants' representation reflect the beliefs, attitudes, and trends of the entire population (Martinez-Mesa et al., 2016). In addition, I assumed that the results were transferable and representative of other service and network providers with exposure to SDN technology.

Limitations

A limitation in research methods involves an imposed restriction due to potential weaknesses in the study that is outside of the researcher's control to address (Velte & Stawinoga, 2017). Due to the apparent scarcity of theoretical models and scientifically validated instruments for back-end infrastructure technologies such as SDN and cloud computing, as most focus on end-user technologies, a possibility exists that my related survey questions may introduce bias. In addition, my research suggests that there may be limited operational deployments of SDN technology to date, which may impact data collection opportunities.

Delimitations

The definition of delimitation in research methodologies involves factors or characteristics that contribute to or that result in boundary or scope limitations for the study, and that is typically within the researcher's control (Nagasaka, 2016). Although knowledge about SDN technology may exist in a broader population, this study's focus was limited to SDN system integrators with at least 3 months' experience working with the technology in the United States.

Significance of the Study

Contribution to Information Technology Practice

Although still in its early stages of development, SDN is transforming the IT networking field. In contrast to traditional networks in which the data, control, and application plane are typically vendor-proprietary closed technology, SDN's open technology enables programmability for each of the abstraction layers, thereby greatly enhancing customizability for user preferences. For example, an SDN-enabled smart grid communications network, with its runtime context-awareness and vulnerability response capabilities, provides advanced security protection against distributed denial of service (DDoS) attacks compared to traditional technology (Maziku et al., 2019). In addition, the results of this study may help in advancing options for addressing the rapidly growing IoT network and multidomain cloud computing scalability challenges, while also driving down operating expenses through increased automation (Wibowo et al., 2017).

Implications for Social Change

There are also social benefits associated with SDN integration. The results of this study may raise awareness about SDN researchers' future goals, including greater network automation and enhanced network security through machine learning (ML; Sultana et al., 2018). Smart healthcare systems, based on edge-cognitive-computing, can use SDN technology to monitor and analyze patient health status and to improve efficiency by dynamically optimizing real-time data flow resource allocations (M. Chen et al., 2018). In addition, the findings in this study may help advance the automation of repetitive human tasks through cognitive-inspired computing, a concept sought by academia and industry in which a machine learns, reasons, and dynamically interacts with humans and the surrounding environment (Cui et al., 2019).

Review of the Professional and Academic Literature

Overview

An essential component of scientific research involves a thorough literature review. In this literature review, I analyzed and synthesized my research problem through the lens of prior contributors who provided critical analysis to aspects of the problem and identified possible knowledge gaps. Baker (2016) provided additional illumination by defining the literature review as a systematic method for evaluating the central issues and context of the research problem and the integration of findings across studies. Also, the literature review provides insight into potential knowledge gaps and areas that require further investigation (Baker, 2016).

In analyzing the application of the applied IT problem, I begin by explaining the purpose of my study, followed by critical analysis and synthesis of literature pertaining to the theoretical framework. I investigated and analyzed the UTAUT framework, its composition, testing population and central findings, supporting theories, contrasting theories, and criticisms of the UTAUT model. I provided critical analysis and synthesis of my independent variables, dependent variables, and moderators adopted from the UTAUT model. I discussed the measurement of my variables. I analyzed UTAUT studies that were similar to mine, distinguishing key similarities and differences. I provided a comprehensive and critical analysis and synthesis of SDN literature, including its architectural framework, use cases, and critical challenges of SDN technology.

With respect to strategies in searching for literature resources, my primary keywords were *software-defined* and *SDN*. Secondarily, I often added other technology keywords in conjunction, such as *OpenFlow, 5G, IoT,* and *machine learning,* as well as additional keywords that help in exploring limitation characteristics, such as *security, standards,* and *challenges.* I typically began searches from Walden University Library's general search engine, Google Scholar, or directly from databases, such as the ACM Digital Library, IEEE Xplore Digital Library, ProQuest Central, Sage Journals, or ScienceDirect. My literature review contains 101 references, 98.0% peer-reviewed. With 300 total references, 88.7% meet the 5-year criteria, and 97.7% are peer-reviewed.

Application to the Applied IT Problem

The purpose of this quantitative correlational study was to examine the relationship between cloud system integrators' perceptions of performance expectancy, effort expectancy, social influence, facilitating conditions, and the intention of IT cloud system integrators to adopt SDN technology. Although SDN technology presents potentially game-changing and transformational benefits that may significantly improve flow orchestration and automation, recent studies indicate that early adoption has been generally tepid (Anan et al., 2016). In this study, I conducted statistical and regression analysis testing to empirically investigate SDN adoption at cloud service organizations. Equipping IT developers and managers with such critical data may help to advance the adoption of SDN's next-generation approach to networking.

Critical Analysis and Synthesis of Theoretical Framework

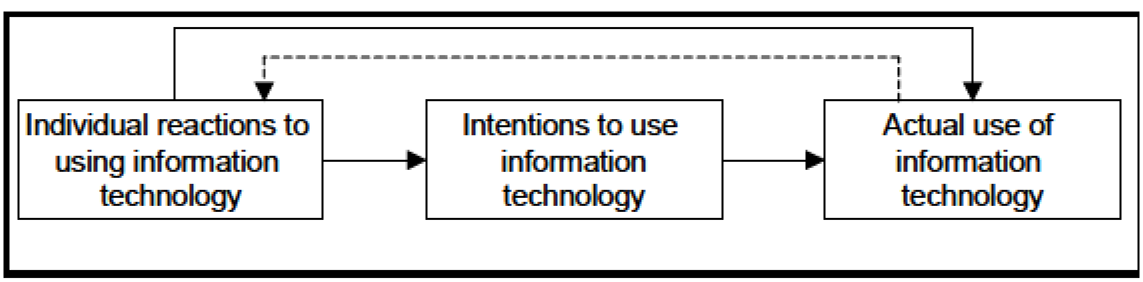
In the theoretical framework section of this study, I addressed and critically analyzed many aspects of the UTAUT model. I began by discussing UTAUT's foundational underpinnings and critical constructs, followed by its central findings and purpose. I critically analyzed each of UTAUT’s foundational models, most of which present similar approaches to analyzing and predicting technology usage and fall under the supporting theories category. I examined several studies that provide criticism about the UTAUT model. I provided critical analysis and synthesis of the independent and dependent variables, and the moderators, followed by a discussion on measurements for the variables. I concluded this section by critically analyzing UTAUT studies that are similar to mine.

Composition

The UTAUT model consists of four central determinants that reflect user perceptions and intention to use IT-based on eight previous models, and up to four moderators of key relationships. Seminal authors Venkatesh et al. (2003) described the UTAUT determinants, which are also the independent variables, as follows: (a) “performance expectancy,” which refers to the degree to which an individual believes that the technology system will enhance their job through productivity gains; (b) “effort expectancy,” which refers to the degree of ease of use of the system; (c) “social influence,” which indicates the degree to which an individual perceives that it is important that others believe that he or she should use the system; and (d) “facilitating conditions,” which refers to the degree to which an individual perceives that an organizational and technical infrastructure exists that supports the use of the system. In constructing UTAUT, seminal authors Venkatesh et al. (2003) extracted components from the other prominent technology acceptance models that existed at the time of their research. The models included the theory of reasoned action (TRA), the technology acceptance model (TAM), the motivational model (MM), the theory of planned behavior (TPB), the combined TAM and TPB (C-TAM-TPB), the model of personal computer utilization (MPCU), innovation diffusion theory (IDT), and the social cognitive theory (SCT; Venkatesh et al., 2003). According to Venkatesh et al. (2003), the central dependent variable for UTAUT is behavioral intention, a critical predictor of technology usage. Figure 1 illustrates the underlying concepts of the technology acceptance models, depicting the circular chain of events of how individual reactions towards using technology influence their intention to use the technology on subsequent occasions, which then affects their actual use of the technology.

Figure 1

Fundamental Concepts of User Acceptance Models



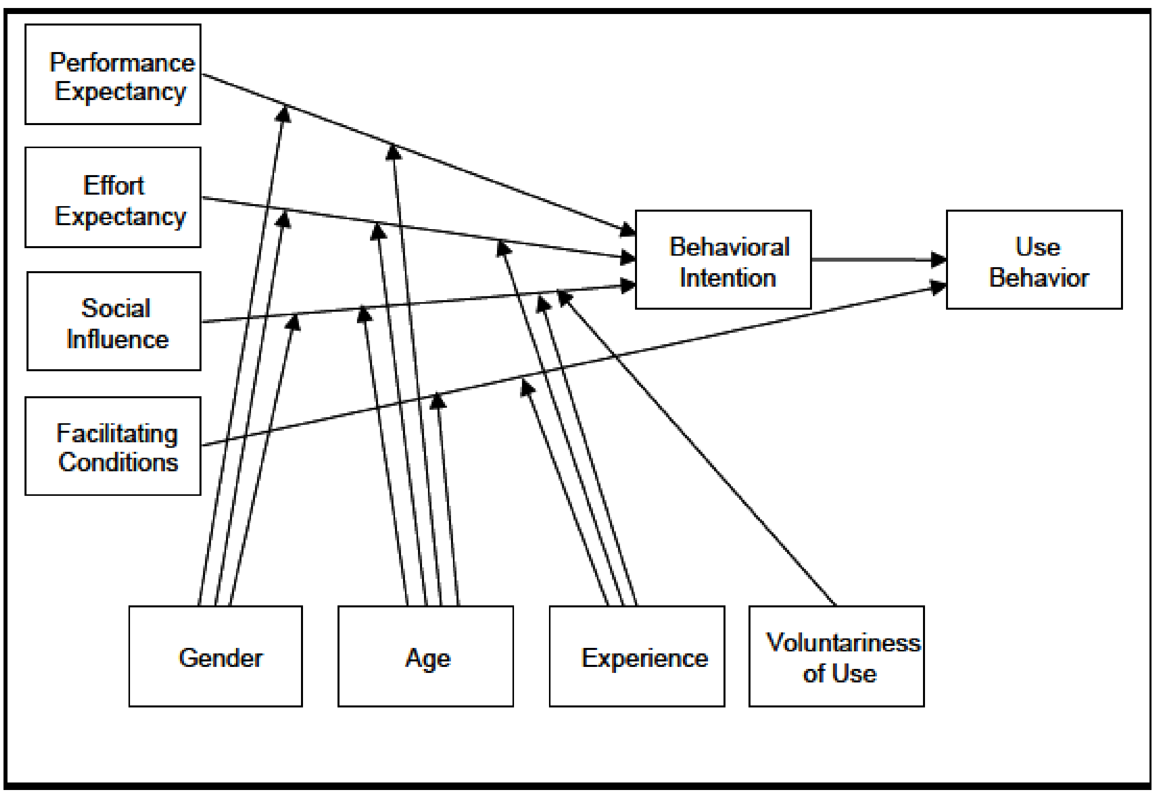
Note: Reprinted from "User Acceptance of Information Technology: Toward a unified view," by V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, 2003, MIS

Quarterly, 27(3), p. 427 (https://doi.org/10.2307/30036540). Copyright 2003 by MIS Quarterly. Reprinted with permission (see Appendix B).

The UTAUT model also specifies moderating factors that influence behavioral intention and use behavior as shown in Figure 2. According to Venkatesh et al. (2003), the UTAUT moderators of experience, voluntariness, gender, and age account for dynamic influences, such as organizational context, user experiences, and user demographical behaviors.

Figure 2

Unified Theory of Acceptance and Use of Technology Research Model Depicting the Relationships Between the Determinants and the Moderators



Note: Reprinted from "User Acceptance of Information Technology: Toward a Unified View," by V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, 2003, MIS Quarterly, 27(3), p. 447 (https://doi.org/10.2307/30036540). Copyright 2003 by MIS Quarterly. Reprinted with permission (see Appendix B).

The moderators of experience, gender, age, and voluntariness influence the UTAUT determinants to shape user perceptions, behavioral intentions, and use of technology innovations. According to Venkatesh et al. (2003), gender and age, for instance, are moderators for performance expectancy, while gender, age, and experience moderate the influence of effort expectancy. Concerning moderating influences for social influence, gender, age, experience, and voluntariness are significant factors, and the moderating influences for facilitating conditions are age and experience (Venkatesh et al., 2003).

Population and Central Findings

Many researchers have found the UTAUT model to be a good predictor of behavioral intentions. After assessing similarities and differences across the eight previous technology acceptance models, Venkatesh et al. (2003) conducted empirical testing over 6 months to include within-subjects longitudinal validation, using data acquired from questionnaire results from four organizations (N = 215). The UTAUT model accounted for 70% of the variance in usage intention, substantially higher than the previous models. They proceeded by empirically validating UTAUT using the original data and cross-validating with data from two additional organizations (n = 133) where the results consistently indicated significantly better results than the previous models. Central

UTAUT findings by Venkatesh et al. (2003) suggested the following: (a) the strength of performance expectancy is frequently a determinant of intention, and tends to vary with gender and age, with greater significance for men and younger workers; (b) effect of effort expectancy is also moderated by gender and age, with increased significance for women and older workers, while decreasing in significance with experience; (c) the four moderators tend to influence social influence in a nonsignificant way, similar to analyzing the same data without moderators; and (d) facilitating conditions indicated significance only in conjunction with age and experience, affecting older and experienced workers.

The UTAUT founders conducted extensive validity and reliability assessments. Venkatesh et al. (2003) applied the partial least square (PLS) test, which models the composites and factors that depict the relationship between the X and Y variables. Venkatesh et al. (2003) also evaluated convergent validity, discriminant validity, and reliability for each of the foundational models and UTAUT. Their results were highly consistent with previous findings, with all internal consistency reliabilities rated at .70 or higher. They used Chow's test of the beta differences ($p < .50$) to determine that UTAUT effort expectancy was more significant with limited exposure to the technology, that the effect decreased with increased experience, and that social influence was more significant with limited experience with the technology. Applying Chow's test of the beta differences ($p < .50$) to predict UTAUT usage behavior, Venkatesh et al. (2003) also found that behavioral intentions and facilitating conditions were significant, with facilitating conditions being more important to older workers. In addition, Puspitasari et al. (2019) tested their UTAUT measurement scale's reliability using Cronbach's alpha test, which indicated consistency and stability for the determinants of performance expectancy, effort expectancy, social influence, facilitating conditions, and behavior intention (Cronbach alpha > 0.60). To test the relationship between the hypotheses and the variables, the researchers applied the Spearman rank correlation test, used to measure the relationship between ranked variables (Puspitasari et al., 2019).

Purpose of Unified Theory of Acceptance and Use of Technology

UTAUT offers researchers a unified framework with which to understand the perception of users concerning the acceptance and use of IT and IT innovations. Venkatesh et al. (2003) observed that due to its rapid growth and expansion over the past several decades, IT expenditures typically consume up to 50% of capital investments. However, productivity gains depend upon user acceptance and usage of the IT products. With several existing theoretical models of origins ranging from IT to psychology and sociology, Venkatesh et al. (2003) sought to develop a unified framework that improves existing theories of understanding user perceptions towards the acceptance and use of IT and IT innovations. Venkatesh et al. (2003) also sought to understand the drivers of acceptance for the development of IT solutions. UTAUT accounted for 70% of the variance (adjusted R^2) in usage intention, reflecting a substantial improvement over the original eight models (Venkatesh et al., 2003).

Supporting Theories

Supporting theories are technology acceptance models that apply similar determinants as UTAUT for analyzing behavioral intent and predicting technology acceptance. Supporting theories include TRA, TAM, MM, TPB, C-TAM-TRA, and MPCU.

Theory of Reasoned Action. TRA describes the relationship between attitudes and behaviors that influence human behaviors across a wide variety of domains. Seminal authors Fishbein and Ajzen (1975) provided a systematic conceptual framework of the human attitude based on social psychology and distinguishing the differences among beliefs, attitudes, intentions, and behavior, concepts previously often and improperly used interchangeably. Buabeng-Andoh (2018) depicted TRA as a general theory for predicting and explaining human behavior across a wide spectrum of domains. Similarly, Shachak et al. (2019) described TRA as the origin of the social psychology view that focuses on the individual adopter and assumes direct causal influence of intention on the actual behavior of individuals. Beliefs, according to Fishbein and Ajzen (1975), represent information that an individual knows about an object, linking the object to some attribute about the object and formulating the individual’s attitude through the internal evaluation of their knowledge about the object, action, or event. Attitudes are learned behaviors about an individual’s principal beliefs and reveal a general predisposition or an inclination towards an object, action, or event that is consistently favorable or consistently unfavorably towards the object (Fishbein & Ajzen, 1975).

While attitudes reveal the amount of affection towards an object, action, or event, they also provide broad indicators of an individual’s intentions (Fishbein & Ajzen, 1975). Behavioral intention refers to the subjective probability that an individual will perform a certain behavior. Dwivedi et al. (2017), who underscored TRA’s social psychology origin, also observed that attitude directly affects behavioral intention, and attitude also affects subjective norms. Fishbein and Ajzen (1975) suggested that behavioral intention, which is a measurable characteristic, is the main predictor of actions and behaviors of individuals, and that the strength of an intention increases or decreases the likelihood of performance. In addition to TRA's central constructs of beliefs and attitude, Fishbein and Ajzen (1975) also included subjective norm, which refers to a person's discernment of whether they should perform a behavior or not based on their perceived expectation of others that are important to them and their motivation to comply with those expectations. In their research on the factors that influence mobile banking acceptance for Islamic banks in Pakistan, authors Raza et al. (2019) pointed out that a previous study on Pakistani credit card adoption indicated that subjective norm positively and significantly affected behavioral intention of individuals. A similar TRA study that investigated Islamic banking adoption in Indonesia likewise found that subjective norms significantly affected customer intentions (Raza et al., 2019). According to Fishbein and Ajzen (1975), subjective norms sometimes referred to as normative beliefs, form from either a referent informing the individual how they should react or the individual may observe an event that informs them about the referent's expectations. While some normative beliefs may involve an inference process, others may consist of syllogistic reasoning, which involves deductive reasoning based on an individual's derived premises that lead to their choice of actions or behaviors. (Fishbein & Ajzen, 1975).

Therefore, the consequences of performing a given act may please or displease reference individuals or groups, resulting in either reward or punishment. Behavioral intention reflects the summation of a person's attitude and their normative beliefs. Attempts to influence behavior, according to Fishbein and Ajzen (1975), must be directed at one or more of the individual's beliefs. Albashrawi and Motiwalla (2020), who explored subjective self-reported and objective computer-generated log data in mobile banking, described how researchers applied the TRA model to measure the objective use of a web-based patient-physician collaboration application by analyzing the number of emails sent. Fishbein and Ajzen (1975) defined reliability as the degree to which a measurement is free of variable errors, such as the individual's mood or testing environment, and which yields the same results on different occasions. Validity, on the other hand, refers to the degree to which an instrument depicts the true score as intended to be measured, such as belief, attitude, and intention (Fishbein & Ajzen, 1975). Buabeng-Andoh (2018) summarized TRA as an extensively applied theory which explains the determinants of consciously intended behaviors and suggests that an individual's behavioral intention, influenced by their attitude and subjective norm, determines their specific behavior. I did not select the TRA model because it lacks the needed constructs and, therefore, capability for a comprehensive assessment of critical technology adoption and usage factors. TRA also does not evaluate performance expectancy or facilitating conditions, and it does not consider gender or age moderators.

Technology Acceptance Model. TAM seeks to predict IT acceptance and utilization in the workplace. Upon highlighting apparent widespread resistance towards new technology systems in the workplace, seminal authors Davis et al. (1989) endeavored to develop a theoretical framework that explains why when they founded

TAM. They designed the TAM model to explain the determinants of technology acceptance and end-user behavioral intention across a broad range of technologies and populations. Davis et al. (1989) argued that understanding behavioral intention is central to predicting computer usage behaviors. A derivative of TRA, TAM, according to Buabeng-Andoh (2018), incorporates the constructs of perceived usefulness, perceived ease of use, and attitude. However, TAM places greater emphasis on behavioral intention towards the acceptance of new technologies (Buabeng-Andoh, 2018). Davis et al. (1989) promoted the concepts of perceived usefulness and perceived ease of use as central determinants for assessing the degree to which a person believes that a computer system will enhance their job performance. Venkatesh et al. (2003) observed that unlike TRA, however, TAM excludes the attitude construct. TAM2 extended the original TAM model with the addition of the subjective norm predictor for mandatory settings (Venkatesh et al. (2003).

Although the capabilities of computer systems improve each decade exponentially, end-users are often unwilling to harness their full potential. Researchers Davis et al. (1989) observed that it is a major challenge for computer system developers is to predict user exploitation behaviors, and to then design appropriate functional and interface characteristics that foster user acceptability and utilization. Albashrawi and Motiwalla (2020) noted that a previous study applied TAM to measure the use of a web-based courseware learning system. They assessed the system's use both objectively from the number of pages visited and subjectively from the frequency and duration of use (Albashrawi & Motiwalla, 2020). According to Davis et al. (1989), some studies about workers' behavior toward technology-based systems suggests that internal beliefs and attitudes are often influenced by external factors such as the following: (a) the system's technical design characteristics, (b) user insight in the development of the system, (c) the type of system development process applied, and (d) the nature of the integration and implementation process. However, due in part to a wide variety of measures employed to explain beliefs, attitudes, and satisfaction, often lacking theoretical and psychometric justification, such findings have encountered mixed reviews (Davis et al., 1989). TAM, therefore, according to Davis et al. (1989), seeks to provide a basis for tracking the extent to which external factors influence internal beliefs, attitudes, and intentions by modeling the relationships among variables.

Whereas TRA explains very general human behavioral intentions, TAM is specific to computer usage behavior. According to Davis et al. (1989), TAM applies TRA's theoretical basis for denoting causal linkage between perceived usefulness and perceived ease of use, and attitudes, intentions, and adoption behaviors. Lemay et al. (2018) applied TAM in their study to determine the perceptions of nursing students at a Northeastern college concerning simulation-based learning, which attempts to create a virtual learning environment that replicates a clinical setting to enhance students' knowledge, skills, and preparedness to respond to real-world situations. Their research in which they extended the TAM model to include self-efficacy and fidelity, revealed that most TAM beliefs are dependent upon enabling conditions, such as the readiness of technology to improve performance, and that fidelity influences perceived usefulness, rather than facilitating conditions (Lemay et al., 2018). Perceived usefulness, according to Davis et al. (1989), refers to user's perception that using a particular computer application will boost their job performance in an organizational context, while perceived ease of use refers to the degree to which the user believes that the target system is effortless to use. They further asserted that self-efficacy refers to an individual's belief and feeling of competence that they can attain prescribed performance objectives, and instrumentality refers to the ability of an individual to focus objectively, fostering easier decision-making (Davis et al., 1989). Lemay et al. (2018) reasoned that because individuals expect much more when motivated, that motivational belief may modulate performance expectancy. However, in the context of simulation-based learning, there was no apparent relationship between self-efficacy and perceived usefulness (Lemay et al., 2018). Even so, Davis et al. (1989) discovered in a longitudinal study to understand users' (n = 107) behavioral intentions towards a specific technology system that perceived usefulness strongly influenced intention-use correlations, while perceived ease of use had a weaker, but still significant effect which subsided over time.

On the other hand, according to Davis et al. (1989), attitudes only partially mediated the effects of beliefs on intentions, and subjective norms did not affect intentions. TAM provides a framework for modeling computer acceptance and rejection behaviors, enabling researchers to predict future system adoption behaviors based on brief system interactions. Davis et al. (1989) concluded with a synopsis suggesting that although the user-friendliness of a computer system is important, its perceived usefulness has a significantly greater impact on end-users. However, despite the broad acceptance and use of the TAM model, Buabeng-Andoh (2018) expressed concerns that considerable shortcomings exist. He argued that among TAM deficiencies are the following: its lack of extensive external validity research and its lack of emphasis on essential measures and system characteristics that can affect the perceived usability of the technology (Buabeng-Andoh, 2018). I did not select the TAM model because it lacks the needed constructs and, therefore, capability for extensive testing of technology adoption and usage factors in that it does not address facilitating conditions, and it does not consider age as a moderator.

Motivational Model. MM explores behavioral intentions toward technology from the perspective of an individual's emotional stimulation and determination. Seminal authors Davis et al. (1992) suggested that intrinsic and extrinsic motivation based on psychology concepts are critical factors that affect the adoption of new technologies in the workplace. Venkatesh et al. (2003) described MM as a theory founded in a significant body of research based on the motivational theory, which explains behavior, extended to the information systems domain, and in particular new technology adoption and use. According to Davis et al. (1992), intrinsic motivation refers to one's desire to perform an activity because they find it interesting, enjoyable, or engaging, with no apparent reinforcement involved. Extrinsic motivation, in contrast, refers to one's desire to perform an activity to achieve a valued outcome, reward, or to accomplish a goal, and to achieve the reinforcement of a valued outcome (Davis et al., 1992). Gan and Balakrishnan (2018), who applied TAM and four other technology acceptance models to research the adoption of mobile alternatives for higher education in Malaysia, suggested that extrinsic motivation in technology studies relates to the constructs of perceived usefulness, performance expectancy, or social influence, and intrinsic motivation in technology research relates to perceived enjoyment, satisfaction, or playfulness constructs.

Davis et al. (1992) expounded, asserting that their study revealed that perceived enjoyment, which refers to the extent to which an individual perceives that performing a particular computer activity is pleasurable or gratifying, and which reflects operationalized intrinsic motivation, significantly and positively influenced technology acceptance and technology use in the workplace. Extrinsic motivation, which reflects operationalized perceived usefulness, also strongly and positively influenced technology acceptance and usage (Davis et al., 1992). According to Gan and Balakrishnan (2018), intrinsic motivational factors, such as effort expectancy, attitude, and anxiety, were more significant in predicting intentions than extrinsic motivational factors, such as performance expectancy, social influence, and facilitating conditions. While with extrinsic motivation, the individual expects external rewards for performing a set of tasks, with intrinsic motivation, the individual's drive is that they enjoy performing the tasks (Gan & Balakrishnan, 2018). Davis et al. (1992) also suggested that voluntary usage is an important driver of perceived usefulness, which refers to an individual’s expectation that using a computer system will enhance their job performance, and is a key determinant of computer adoption in the workplace.

The MM model delineates the determinants perceived ease of use and perceived output function as antecedents that precede behaviors. Davis et al. (1992) described perceived ease of use, which refers to the expected degree of effort that an individual will need to exert to perform a computer activity, is an antecedent of usefulness and enjoyment. Perceived output quality refers to the degree of yield that an individual expects from the computer's output, and is also an antecedent of usefulness and enjoyment (Davis et al., 1992). In their findings, Gan and Balakrishnan (2018) discovered that enjoyment was a strong predictor of mobile technology instructional tools adoption, particularly among younger students that tend to be motivated by instant gratification activities. Davis et al. (1992) also concluded that computer programs that users find enjoyable and useful reflect in their behavioral intentions, thus leading to increased acceptance and usage. I did not select MM because of its scope limitations for assessing technology adoption and usage, since it does not evaluate social influence or facilitating conditions, and it does not consider experience, gender, age, or voluntariness moderators.

Theory of Planned Behavior. TPB associates one's beliefs with their behavioral intentions. Seminal author Ajzen (1991) extended the scope of TRA's constructs of attitudes and subjective norms by incorporating the concept of perceived behavioral control, which reflects the extent to which an individual perceives the performance of a particular behavior as easy or difficult. Venkatesh et al. (2003) described TPB as a model that extends TRA by analyzing the perceived ease or difficulty of performing a behavior in a new construct called perceived behavioral control. TPB has shown to be useful in analyzing and understanding individual acceptance and usage of many different technologies (Venkatesh et al., 2003). Cheng (2019) offered a slightly different comparison, observing that while TPB tends to provide practical assessments on technology adoption and use, TAM's strength involves its adeptness for analyzing the intention to use technology. In an illustration of its versatility, researchers Lim and Suki

(2020) applied the TPB model in a study to investigate the factors that influence consumers' perceived behavioral control when purchasing affordable housing units in Malaysia. According to Ajzen (1991), whether an individual engages in a behavior or activity depends on their behavioral control, representing the amount of control they can exert over the behavior or activity, and their willingness to engage in the behavior or activity.

A central tenet of TPB involves an individual's intention to perform a given behavior, rather than the actual performance of the behavior. According to Ajzen (1991), TPB holds that behavioral intent is the integration of attitude towards the behavior, subjective norms, and perceived behavioral control. It follows, according to the author, that as an individual's attitude towards a particular behavior and subjective norms becomes more favorable, and as perceived behavioral control increases, so do the likelihood that the individual will perform the behavior in question (Ajzen, 1991). Teo et al. (2016) applied TAM in a study to understand Singapore's primary and secondary school teachers (*n* = 592) intention to use technology in teaching and learning environments. They discovered that attitude towards computer usage had the most significant positive impact on technology usage intention, followed by perceived behavioral control (Teo et al., 2016).

On the other hand, intentions also tend to reflect the motivational factors that influence behavior. According to Ajzen (1991), intentions provide indicators of how much effort an individual is willing to exert to perform the behavior. Therefore, the likelihood of behavioral performance increases as the intention to engage in the behavior increases (Ajzen, 1991). Teo et al. (2016) found that subjective norms negatively affected intention, while the inclusion of antecedent variables of perceived usefulness, perceived ease of use, and technical support strengthened TPB's assessment and explanation of intention. Ajzen (1991) asserted that perceived behavioral control, combined with behavioral intent, also provides a method for predicting behavioral achievement. However, he cautioned that limitations exist for perceived behavioral control for situations in which changes occurred in the requirement, introducing unfamiliar elements or changes in the availability of expected resources. Under such conditions, perceived behavioral control may not increase the accuracy of behavioral predictions (Ajzen, 1991). Teo et al. (2016) concluded that TPB could provide insight to educators and researchers about individual beliefs toward new technology. I did not select the TPB model because it lacks the needed constructs and, therefore, capability for extensive testing of technology adoption and usage in that it does not address performance expectancy.

Combined Technology Acceptance Model and the Theory of Planned Behavior. TAM was augmented to form the combined TAM and TPB (C-TAM-TPB) hybrid model. Seminal authors Taylor and Todd (1995) expanded the TAM model of perceived usefulness to also account for TPB's framework of how attitude influences behavior, subjective norm, and perceived behavioral control. According to Taylor and Todd (1995), they sought to determine the following: (a) whether technology models, such as TAM, can predict the behavior of inexperienced users and (b) whether technology usage determinants are the same for experienced and inexperienced users. Liang et al. (2019) applied the C-TAM-TPB model to investigate the psychological aspects of the intention to use technology-based shared parking in Taipei City, Taiwan. They sought to understand behavioral intention from the perspective of the demander, who is the customer who uses the shared parking system, the supplier, who rents spaces in the shared parking system, and the dual-user, who uses the spared parking and rents parking spaces (Liang et al., 2019). On the other hand, Taylor and Todd (1995) observed that while TAM enables the prediction of technology acceptance and facilitates design enhancements for inexperienced users before the system's deployment, it does not consider the social and control factors exhibited by experienced users. However, because most of the empirical testing using earlier models involved systems already deployed or systems already familiar to the end-users, a gap existed in understanding the behavioral intent of inexperienced users, and in determining whether the determinants for technology usage is the same for experienced and inexperienced users (Taylor & Todd, 1995). Liang et al. (2019) demonstrated a use case of the combined model by applying TAM elements to analyze the factors that influence the adoption of the shared parking mobile applications and TPB elements to explore the human aspects of the technology's adoption.

According to Taylor and Todd (1995), some previous technology acceptance models suggested that experience was a significant behavioral intent factor. To obtain additional insight, the researchers applied the C-TAM-TPB model, an experiment involving experienced (n = 430) and inexperienced (n = 356) business school students, and using a computing resource center (Taylor & Todd, 1995). Researchers Yang and Chung-Ho (2017) applied the C-TAM-TPB model to assess how learners adapt and respond to technology-based teaching through massive open online courses. Their findings revealed the following: (a) attitude exerted the greatest influence on the behavioral intention of learners, (b) the perceived behavioral control, subjective norm, and attitude of learners positively affected behavioral intention, and (c) behavioral intention positively influenced the actual behavior of learners (Yang & Chung-Ho, 2017). The testing objectives of Taylor and Todd (1995) were to compare the two groups statistically and to better understand the behavioral intent of inexperienced users compared to experienced users. The findings indicated that the C-TAM-TPB model accounted for 21% of the variance in behavior and 43% of the variance in behavioral intent for experienced users (Taylor & Todd, 1995). In comparison, the model account accounted for 17% of the variance in behavior and 60% of the variance in behavioral intent for inexperienced users (Taylor & Todd, 1995). According to Taylor and Todd (1995), their findings suggest that C-TAM-TPB predicts subsequent usage behavior for inexperienced system users, as well as for experienced system users. Liang et al. (2019) concluded that combining TAM and TPB provides a unified approach for investigating the adoption of new technologies for experienced and inexperienced users. I did not select the C-TAM-TPB model because it lacks the needed constructs and, therefore, can test critical technology adoption and usage factors. C-TAM-TPB does not consider gender, age, or voluntariness moderators.

Model of Personal Computer Utilization. The model of personal computer utilization (MPCU) seeks to predict the usage behaviors of personal computer users. Founders Thompson et al. (1991) designed MPCU to help researchers understand the factors that influence personal computer usage and the extent of computer adoption when use is optional. Venkatesh et al. (2003) described the MPCU model as having derived primarily from the theory of human behavior, and as a competing model to TRA and TPB that focuses more narrowly on predicting personal computer usage. Thompson et al. (1991) based the MPCU model in part on the theory of attitudes and behavior. They adopted from the theory of attitudes and behavior the following as determinants that influence a knowledgeable worker's personal computer utilization in an optional use setting: (a) the individual's affection towards using personal computers, (b) social factors in the workplace, (c) the individual's perceived consequences for computer usages, and (d) the environment's facilitating conditions in support of computer usage (Thompson et al., 1991). According to Venkatesh et al. (2003), the formulation of UTAUT's framework included the following constructs adopted from MPCU: job fit for UTAUT performance expectancy, complexity to UTAUT effort expectancy, social factors for UTAUT social influence, and facilitating conditions to UTAUT facilitating conditions. Moreover, Thompson et al. (1991) outlined three dimensions of perceived consequences, namely complexity and job fit, which have near-term effects, and long-term consequences of use.

Thompson et al. (1991) noted that affection, in the context of personal computer usage, refers to a positive feeling of elation or joy, or a negative feeling of disgust or displeasure about a particular task, while social factors refer to an individual's internalization to act in an appropriate way to the reference group's subjective cultural norms which consists of expected behavioral roles and perceived values. On the other hand, Gunasinghe et al. (2019) cautioned that MPCU assesses actual behavior, rather than the behavioral intention to use a computer system. According to Thompson et al. (1991), an individual's perceived consequences involve the extent to which they decide to base their choice of behavior on their expectation of a reward for performing the act or action. Based on the premise that a behavior cannot occur if the environmental conditions are prohibitive, facilitating conditions involve environmental circumstances and surroundings that reduce potential obstacles that promote and influence system utilization (Thompson et al., 1991). Nägle and Schmidt (2012) concurred after conducting a UTAUT study about the determinants of computer usage for older adults (*n* = 52) from ages 50–90, leveraging MPCU's facilitating conditions, which refers to eliminating barriers to use and ensuring that assistance to the user is available upon request. Their findings indicated that facilitating conditions were more salient for older adults (Nägle & Schmidt, 2012).

Thompson et al. (1991) observed that complexity refers to the degree to which an individual perceives that a particular innovation is relatively difficult to understand and use. Unlike the other factors of perceived consequences, complexity has a negative relationship to utilization. Still, according to Dwivedi et al. (2017) suggested that the attitude of an individual contemplating using a computer system influences the extent to which they utilize the computer system. Job fit refers to the extent to which an individual believes that a computer system will enhance job productivity and performance in the near term, thereby reducing the time to complete tasks or obtain better information for decision-making. On the other hand, according to Thompson et al. (1991), long-term consequences of use involve outcomes that benefit an individual's future goals, such as increasing opportunities for more meaningful work and increasing opportunities to change jobs. In their criticism of MPCU, Gunasinghe et al. (2019) asserted that although MPCU evaluates the computer usage factors of long-term consequences, job fit, complexity, social factors, and facilitating conditions, the MPCU model does not consider the effect of habit on computer utilization.

Nevertheless, as a result of their MPCU data modeling, Thompson et al. (1991) argued that organizational initiatives tailored to educating workers about the expected benefits of using a system might positively influence its utilization. User training also reduces perceived complexity, thereby reducing perceived barriers to use. When an organization promotes a system's benefits using a highly regarded champion, it strengthens the social factors for system adoption (Thompson et al., 1991). I did not select the MPCU model because it lacks the needed constructs and, therefore, capability for critical testing of technology adoption and usage factors. The MPCU model does not consider the moderators of age, gender, or voluntariness.

Contrasting Theories

Contrasting theories are technology acceptance models that apply fundamentally different approaches than UTAUT for predicting technology acceptance. Contrasting theories include IDT, SCT, and diffusion of innovations (DOI).

Innovation Diffusion Theory. The IDT theory focuses on measuring and understanding the perceptions of potential technology adopters. Venkatesh et al. (2003) described IDT as an individual technology acceptance model grounded in sociology and a variety of prior innovation studies. Seminal authors Moore and Benbasat (1991) developed IDT to address what they perceived as the lack of theoretical foundations, along with mixed and inconclusive research outcomes in the previous innovation models concerning technology adoption. They sought to solidify research for measuring and understanding the determinants that affect technology acceptance by potential adopters (Moore & Benbasat, 1991). IDT, according to Moore and Benbasat (1991), adopted the following subset of constructs that affect the rate of diffusion of an innovation from the theory of innovation: (a) relative advantage, which refers to the degree to which an individual perceives that an innovation is a better solution than its predecessor; (b) compatibility, which refers to the extent to which a potential adopter perceives that an innovation is consistent with their values, needs, and past experiences; (c) complexity, which refers to the degree to which a potential adopter perceives that an innovation is difficult to use; (d) observability and communicability, relabeled as results demonstrability, which refers to the extent to which an innovation can be measured, observed, and communicated to others; and (e) triability, which refers to the degree to which experiments can be conducted on an innovation. Mutahar et al. (2017) applied IDT and TAM in their study (*n* = 482) to understand mobile banks' acceptance in Yemen and the moderating effect of income. Their findings indicated that compatibility, observability, and triability function as antecedents to TAM's perceived ease of use and perceived usefulness, which in turn affects the intention to use mobile banking services. Moore and Benbasat (1991) also added the following two constructs to IDT, which they considered critical to understanding the adoption of an innovation: (a) image, which refers to the degree to which an individual perceives that an innovation bolsters their social system image and (b) voluntariness of use, which refers to the extent to which a potential adopter perceives that the using innovation is of their own free will, and is free of corporate mandates or policies that discourage usage. The findings by Mutahar et al. (2017) also suggested that mobile banking's compatibility with existing services is paramount for acceptances, and mobile banking simulations increase the intention to use the system. Both high- and low-income groups reflected a strong positive influence between perceived usefulness and intention to use mobile banking services (Mutahar et al., 2017). Moore and Benbasat (1991) argued that in contrast to previous diffusion models, which suggest that an innovation diffuses because of potential adopters' perception about the innovation itself, the IDT model emphasizes the prospective adopters' perception and behavioral intention towards using an innovation.

Researchers conducted extensive testing of the IDT instrument to ensure validity and reliability. Moore and Benbasat (1991) performed comprehensive testing of IDT, beginning with scale creation in Stage 1, where they focused on ensuring content validity by categorizing instrument items based on their perceived characterization of innovation and by certifying that measures represent all facets of the constructs. Stage 2 consisted of scale development, which involved construct validity to ensure that the scales measure what they purport to measure, and the use of judges to perform various sorting procedures to identify ambiguous items (Moore & Benbasat, 1991). Before testing their mobile banking hypotheses, Mutahar et al. (2017) conducted convergent validity testing by examining the factor loading, ensuring that items converge on a common point (a minimum of .50), composite reliability using Cronbach's alpha test (a minimum of .70), and average variance extracted (AVE) indicating that latent variables have high convergent validity (> .50). Stage 3 instrument testing, according to Moore and Benbasat (1991), involved two pilot tests to ensure the reliability of the instrument and a final field test, which consisted of 800 questionnaires distributed to seven companies in industries that included utilities, government departments, resource-based companies, and a natural grains pool. Moore and Benbasat (1991) observed that the results of the foundation IDT research suggest that relative advantage, the ability to demonstrate results, and visibility are the best predictors of adoption. Shiau et al. (2018) applied IDT and TAM to investigate the factors that influence acceptance of a geographical information system application called OpenStreetMap to Taiwanese graduate and undergraduate science, technology, engineering, and math students (*n* = 145). Their results indicated that ease of use, observability, and compatibility significantly and positively impacted students' perceived usefulness and their intention of continued use of the application (Shiau et al., 2018). On the other hand, according to Moore and Benbasat (1991), triability and image are weak predictors of technology adoption, while an individual's perception of using an innovation affects their decision to adopt or reject the innovation. IDT triability, while less significant in an organizational context, is a significant determinant of adoption for individuals that may consider adopting an innovation at their own risk (Moore & Benbasat, 1991). Shiau et al. (2018) agreed, finding that triability had no direct effect on perceived attitudes. I did not select the IDT model because it lacks the constructs and capability for critical testing of technology adoption and usage factors. The IDT model does not consider the moderators of age or gender.

Social Cognitive Theory. The SCT model holds that individuals' belief in their self-sufficiency of using a computer system affects their usage of the computer system. Seminal authors Compeau and Higgins (1995) investigated the effect of how individuals perceive their competency and abilities to use a computer system and how their perceptions affect their usage of the computer system. Dwivedi et al. (2017) described SCT as a model based on the study of human behavior and extended to incorporate behavior that affects computer utilization. Middleton et al. (2019) observed that SCT is a derivative of the social learning and imitation theory based on social motivation, which suggests that various drivers, cues, responses, and rewards spur individual learning. Thus, learning and the acquisition of knowledge are social processes and primary focuses of SCT (Middleton et al., 2019). The SCT behavioral model, according to Compeau and Higgins (1995), suggests that a triadic reciprocal relationship exists between the individual, their behavior, and their environment in the following manner: (a) environmental influences such as social pressures are reciprocally determined, (b) environmental factors affect behavior of a given situation, and behavior, in turn, affects environmental factors, and (c) cognitive and social factors affect behavior.

Consequently, individuals choose the environments from which they exist, and those environments influence the behavior of individuals (Compeau & Higgins, 1995). According to Compeau and Higgins (1995), cognitive factors on individual behavior suggest that outcome expectations and self-sufficiency are major cognitive forces that guide behavior. Outcome expectations provide a precursor to usage patterns and exert influence over the reaction of individuals to computing technology, such that satisfaction from favorable consequences links to the behavior itself, spurring increased affection for the behavior (Compeau & Higgins, 1995). Middleton et al. (2019) leveraged the SCT model as an interdisciplinary approach in the study of information science, behaviors associated with information use, and how workplace learning can enhance work innovation behavior in organizations.

The SCT model also consists of dimensions of self-efficacy, as well as affect and anxiety, which may influence behavior. According to Compeau and Higgins (1995), self-efficacy does not refer to the individual's actual skills. In contrast, self-efficacy refers to an individual's judgments concerning their abilities to organize and execute courses of action required to achieve particular performances or objectives. Venkatesh et al. (2003), on the other hand, found that self-efficacy and anxiety were not direct determinants of behavioral intention and therefore did not these factors as core constructs in the UTAUT model. On the other hand, Compeau and Higgins (1995) observed that self-efficacy refers to an individual's perception of their ability to use computers to accomplish a task, such as data formatting and data analysis. Middleton et al. (2019) elaborated, arguing that self-efficacy is especially relevant for learning and skills development, to include the application and effectiveness of skills. In addition, Compeau and Higgins (1995) stressed that there are three distinct, but interrelated, dimensions of self-efficacy, which consist of the following: (a) magnitude, which refers to the level of capability expected and the degree of task difficulty one believes that they can accomplish; (b) strength refers to an individual's degree of conviction or confidence about their judgment in their ability to accomplish a task; and (c) generalizability, which refers to the extent to which an individual perceives self-efficacy only in certain situations and circumstances, thereby limiting their perception of self-efficacy to a particular activity domain.

Affect refers to an individual's liking or preference for a particular behavior, which can exert a strong influence over their actions towards the behavior. According to Compeau and Higgins (1995), the SCT research results indicated that computer self-sufficiency exerted significant influence on individual’s anticipation of the outcomes of using computer systems, their emotional reaction towards computers, such as anxiety or affection, and their actual computer system use. Self-efficacy is a critical individual trait that moderates organizational influence for an individual's decision to use computer systems (Compeau & Higgins, 1995). In their SCT-based qualitative study on the adoption of wearable activity trackers for young adults (n = 57), Gowin et al. (2019) remarked that most participants stated that wearing activity trackers increased their confidence in meeting their health goals, revealing self-efficacy. Many participants described the wearable activity trackers as their assistant and even trainer, providing feedback and positive reinforcement concerning their goals (Gowin et al., 2019).

Similarly, Compeau and Higgins (1995) observed that encouragement of other workgroup members and the use of computers by others positively influenced and individual’s outcome expectation and self-efficacy. Still, Middleton et al. (2019) argued that despite SCT's significant use in information science research, opportunities exist for further development in the following areas: (a) the relationship between information behaviors and innovation processes, (b) knowledge management, and (c) workplace information and innovation literacy. Compeau and Higgins (1995) observed that anxiety, in the context of computer efficacy, reflects emotions of apprehensiveness and fear regarding computer usage, and negatively influences the use of computers. I did not select the SCT model because it lacks the needed constructs and, therefore, capability for the comprehensive and critical testing of technology adoption and usage factors. The SCT model does not evaluate facilitating conditions, and it does not consider experience, gender, age, or voluntariness moderators.

Diffusion of Innovations. The DOI model focuses on understanding the factors that influence the spread of ideas about technology. According to seminal author Rogers (2003), the DOI theory seeks to explain how that over time, an idea or innovation gains momentum and spreads through a population or social system. Through this diffusion process, people that make up the social system tend to adopt an idea, behavior, or product (Rogers, 2003). Keller et al. (2018) applied the DOI model to investigate car-sharers' intention (n = 711) to adopt an integrated multimodal mobility platform to optimize transportation options and sharing for specific routes. They sought to determine the diffusion rate and adopter characteristics of integrated multimodal mobility platforms, a little-known innovation aimed at reducing highway congestion and greenhouse gas emissions of vehicles (Keller et al., 2018). Rogers (2003) described the diffusion process as a two-way communication process in which participants obtain a mutual understanding through the convergence of shared information. He proceeded to establish the following adopter categories: (a) innovators, who tend to be the risk-takers who willingly try a new idea requiring little appeal or persuasion from others; (b) early adopters, who tend to represent the opinion leaders who are comfortable with leading change initiatives and who only require information sheets to begin promoting the new idea; (c) early majority, who typically are not leaders and tend to require evidence of an innovation's effectiveness before adopting it; (d) late majority, who are typically reluctant to change, and will only try an innovation after its acceptance by the majority; and (e) laggards, who tend to represent traditionalist who are typically skeptical of change and innovations, and who may require social pressure from other groups and appeals that address their fears before adopting a new idea (Rogers, 2003). Zhang (2018) applied the DOI model, extended with consumption analysis, to examine the impact of frugal information communication technologies on internet diffusion. However, the researchers argued that although the DOI explained general diffusion patterns, it did not differentiate between device sophistication, such as high-end phones versus low-end phones, which may diffuse differently due to societal variances (Zhang, 2018).

There are several factors that affect the rate of adoption for an innovation. According to Rogers (2003), the following determinants affect the degree of adoption for an innovation: (a) relative advantage, which refers to the perception and the degree to which an innovation is better than its predecessor; (b) compatibility, which refers to the perception and the degree to which an innovation supports existing needs; (c) complexity, which refers to the perception and the degree to which users find the innovation difficult to understand and use; (d) trialability, which refers to the perception and the degree to which an innovation allows for experimentation; and (e) observability, which refers to the perception and the degree to which an innovation is visible to potential adopters. In their findings, Keller et al. (2018) discovered that although most participants were not previously aware of integrated multimodal mobility and showed general interest, they showed no apparent intention to adopt the platform. Their study indicated that the strongest factors affecting the intention of potential users to adopt integrated multimodal mobility platforms were perceived advantage and personal compatibility, while less salient predictors were innovativeness, observability of use, and perceived technology security (Keller et al., 2018). Zhang (2018) concluded that frugal innovations, such as smartphones, have different diffusion patterns, and diffuse at a much faster rate than high-end innovations, resulting in reducing the digital divide between developing countries and developed countries. In addition, Rogers (2003) also asserted that other critical variables that determine the relative speed of adoption for an innovation are: the type and effectiveness of the decisions made concerning the innovation, the effectiveness of communication channels in diffusing the innovation at each stage of the decision process, the nature of the social system, and the degree of effort and effectiveness by the innovation's change agent. I did not select the DOI model because it lacks the needed constructs and, therefore, capability for critical testing technology adoption and usage determinants.

Critical Analysis and Synthesis of the Independent Variables and Moderators

Independent variables are the components in research that can be manipulated to influence or affect outcomes. As stated in my purpose statement, my independent variables are cloud system integrators' perceptions of the UTAUT constructs of performance expectancy, effort expectancy, social influences, and facilitating conditions. I did not apply the UTAUT moderators of age, gender, experience, and voluntariness of use, which are independent variables that affect the direction and strength of the relationship between the independent and dependent variables.

Performance Expectancy. The UTAUT construct of performance expectancy is the independent variable related to the expected effect of technology on job performance. According to Venkatesh et al. (2003), the UTAUT model defines performance expectancy as the degree to which an individual perceives that the new system will improve their job performance. They adopted elements from the following constructs in previous models to form UTAUT's performance expectancy construct: "perceived usefulness" from TAM/TAM2 and C-TAM-TPB, "extrinsic motivation" from MM, job fit from MPCU, "relative advantage" from IDT, and "outcome expectancy" from SCT. Key themes from previous models to form UTAUT's performance expectancy construct include: (a) using the system will make my job easier and more efficient, (b) using the system will increase my productivity, enabling me to accomplish more tasks at a faster rate, (c) my coworkers will perceive me as more competent, and (d) using the system will increase my chances for a promotion or reward (Venkatesh et al., 2003). Similarly, Thongsri et al. (2018), who investigated the determinants that influence mobile learning in developing countries, described performance expectancy as the level in which an individual perceives that using the system will help them achieve a goal. According to Venkatesh et al. (2003), their research findings indicated that performance expectancy is a significant determinant of behavioral intent in voluntary and mandatory use settings, and is also the strongest predictor of behavioral intention towards new technology. Age and gender tend to moderate the effect of performance expectancy on behavioral intent to use technology, with men more task-oriented than women. Younger workers place greater emphasis on extrinsic rewards (Venkatesh et al., 2003). Concerning performance expectancy, my study poses the following hypotheses:

$H1_0$: There is no significant relationship between cloud system integrators' perception of performance expectancy and the intention of IT cloud system integrators to use SDN technology.

$H1_a$: There is a significant relationship between cloud system integrators' perception of performance expectancy and the intention of IT cloud system integrators to use SDN technology.

Effort Expectancy. The UTAUT construct of effort expectancy is the independent variable related to how the expected effort required to use technology affects its adoption. Effort expectancy, according to Venkatesh et al. (2003), is the UTAUT construct, which refers to the level of effort for which an individual perceives the that they will need to exert to use the new system. They adopted elements from the following constructs in previous models to form the effort expectancy construct in the UTAUT model: "perceived ease of use" from TAM/TAM2, "complexity" from MPCU, and "ease of use" from IDT. Central components from previous models to form UTAUT's effort expectancy construct include: (a) learning to operate the system will be easy for me, and it will be easy for me to get the system to perform the tasks needed; (b) my interaction with the system will be clear, understandable, and flexible; and (c) using the system is excessively complicated, requiring too much time to make it worth the effort (Venkatesh et al., 2003). Likewise, Chiwara et al. (2017), who applied the UTAUT model to research internet usage for final-year students at the University of Fort Hare located in the Eastern Cape province in South Africa, described effort expectancy as the extent to which an individual considers the use of a technology innovation to be relatively effortless, requiring minimal effort on their part. The research findings by Venkatesh et al. (2003) suggested that effort expectancy is a significant determinant of behavioral intent, in both voluntary and mandatory use settings. However, effort expectancy tends to be more prominent during the early stages of a new behavior as the individual works through process entanglements and becomes nonsignificant after the initial training period in both voluntary and mandatory contexts. Women, which tend to gain knowledge cognitively through experiences and senses to a greater degree than men, also exhibit greater effort expectancy than men. Their research and previous research models suggested that increased age and limited experience tend to make the processing of complex stimuli more difficult. Venkatesh et al. (2003) summarized that the impact of effort expectancy on behavioral intent to use technology is more pronounced for older women with limited experience. With respect to effort expectancy, my study poses the following hypotheses:

> $H2_0$: There is no significant relationship between cloud system integrators' perception of effort expectancy and the intention of IT cloud system integrators to use SDN technology.
>
> $H2_a$: There is a significant relationship between cloud system integrators' perception of effort expectancy and the intention of IT cloud system integrators to use SDN technology.

Social Influence. The UTAUT construct of social influence is the independent variable related to how perceived social expectations affect technology adoption. Venkatesh et al. (2003) described the UTAUT construct of social influence as the degree to which an individual perceives the expectation of others important to them toward using the new system. They adopted components from the following constructs in previous models to form UTAUT's social influence construct: “subjective norms” from TAM/TAM2, TPB, C-TAM-TPB, “social factors” from MPCU, and “image” from IDT. Key themes from previous models to form UTAUT's social influence construct include: (a) my perception is that people who influence my behavior expect me to use the system, (b) my perception is that the proportion of my coworkers use the system, (c) my perception is that senior management, my supervisor, and my organization provide support for me to use of the system, and (d) my perception is that people in my organization who use the system are more prestigious and of higher stature than others that do not (Venkatesh et al., 2003). Maity et al. (2019), who sought to explain normative behavior in IT use, agreed, observing that the perceptions of an individual are in part socially constructed by the attitudes and behaviors of others in their social environment who are important to them. Venkatesh et al. (2003) argued that for each of the underlying social influence constructs, there exists an implicit and explicit notion that the way in which others perceive an individual's use of technology influences their behavior. While none of the underlying social influence constructs are significant in a voluntary use environment, each is significant in the early stages of an individual's experience with a new system when mandated, and becoming nonsignificant after continued usage. Women tend to be more sensitive to the opinion of others and are therefore more important with respect to the impact of social influence on technology usage. Concerning the effect of age, older workers tend to have greater affiliation needs and are also more likely to place increased salience for technology usage on social influence, which declines with experience (Venkatesh et al., 2003). With respect to social influence, my study poses the following hypotheses:

$H3_0$: There is no significant relationship between cloud system integrators' perception of social influence and the intention of IT cloud system integrators to use SDN technology.

$H3_a$: There is a significant relationship between cloud system integrators' perception of social influence and the intention of IT cloud system integrators to use SDN technology.

Facilitating Conditions. The UTAUT construct of facilitating conditions is the independent variable related to how environmental settings affect technology adoption. Facilitating conditions, according to Venkatesh et al. (2003), is the UTAUT construct, which refers to the extent to which an individual perceives that the organizational and technical infrastructure support use of the new system. They adopted elements from the following constructs in previous models designed to identify and remove use barriers to form UTAUT's facilitating conditions construct: "perceived behavioral control" from TPB and C-TAM-TPB, "compatibility" from IDT, and "facilitating conditions" from MPCU (Venkatesh et al., 2003). Similarly, Rahi et al. (2019), who applied the UTAUT model in their study about the adoption of internet banking, described facilitating conditions as the extent to which an individual perceives the need for an organizational and technical infrastructure to use the technology system. Central components from previous models to form UTAUT's facilitating conditions construct include: (a) the organization provided me with the needed resources to use the system, (b) I possess the appropriate guidance and knowledge to use and control the system, (c) the system is incompatible with other systems that I use, (d) assistance to use the system is available to me upon request, and (e) using the system fits my style and work habits (Venkatesh et al., 2003). They discovered that when both performance expectancy and effort expectancy constructs exist, facilitating conditions are nonsignificant. As a direct antecedent of usage, the effect of facilitating conditions tends to increase with experience, which reduces usage impediments. Older workers tend to place greater emphasis on requesting and receiving assistance. Therefore, facilitating conditions tend to significantly affect technology usage when moderated by experience and age (Venkatesh et al., 2003). Regarding facilitating conditions, my study poses the following hypotheses:

$H4_0$: There is no significant relationship between IT cloud system integrators' perception of facilitating conditions and the intention of IT cloud system integrators to use SDN technology.

$H4_a$: There is a significant relationship between IT cloud system integrators' perception of facilitating conditions and the intention of IT cloud system integrators to use SDN technology.

Moderators. The UTAUT moderators for the behavioral intention to use technology are gender, age, experience, and voluntariness of use. Research indicated that gender affects many aspects of individuals' intention to use technology. Venkatesh et al. (2003) leveraged the following previous technology acceptance models to derive at UTAUT's perspective of how gender influences technology acceptance and usage: TAM/TAM2 and TPB. The TAM model developers added gender as a moderator after empirical evidence indicated that perceived usefulness was more important for men, while perceived ease of use was more notable for women. The effect of subjective norm was more notable for women in the early stages of their technology system experience. Concerning TPB, attitude was more pronounced for men, while subjective norm and perceived behavioral control were more paramount for women in the early stages of their technology system experience (Venkatesh et al., 2003). Armed with research indicating that potential users often reject new mobile health applications, despite significant investments and high expectations, researchers Nunes et al. (2019) conducted a study based on UTAUT to investigate the determinants and moderators of this phenomenon. They examined the moderating roles of smartphone experience, age, and gender between behavioral intention to use mobile health applications and the technology acceptance determinants of performance expectancy, effort expectancy, social influence, and facilitating conditions. While performance expectancy was not moderated by gender, effort expectancy was more notable for older men. Social influence was more prominent among older women, and the influence of facilitating conditions was stronger for younger men (Nunes et al., 2019). Concerning the research findings by Venkatesh et al. (2003) regarding age, they leveraged TPB's age moderator to form UTAUT's posture of how age influences technology acceptance and usage. The TPB model suggested that perceived behavioral control was more noticeable for older workers, and attitude was more pronounced for younger workers. They also found that subjective norm was more salient for older women (Venkatesh et al., 2003).

The UTAUT model applies experience as a moderator of technology usage. Venkatesh et al. (2003) applied the following previous technology acceptance models to form UTAUT's posture of how experience influences technology acceptance and usage: TRA, TAM/TAM2, TPB, C-TAM-TPB, MPCU, and IDT. Concerning TRA, while attitude tends to be more important with increasing experience, subjective norm tends to become less significant with increasing experience. Empirical evidence from TAM/TAM2 suggests that ease of use becomes nonsignificant as experience increases. TPB studies indicate that subjective norm becomes less important with increased experience. Nunes et al. (2019) found that experience tends to influence each of the determinants for the intention to use mobile health applications. Effort expectancy was a predictor of mobile health application usage for a user with little or no experience with the application in under evaluation, and less experienced users are more likely to be influenced by others, while also placing more value upon technical and external assistance (Nunes et al., 2019).

On the other hand, C-TAM-TPB studies suggest that perceived usefulness, attitude toward behavior, and perceived behavioral control were each more noticeable with increasing experience, while subjective norm became less apparent as experience increased (Venkatesh et al., 2003). MPCU researchers found that complexity, affect toward use, facilitating conditions, and social factors were each stronger with less experience, while concern about long-term consequences became more important as experience levels increased. IDT researchers assessed the differences between adoption, which reflects little or no experience, and usage, which reflects increased experience. Venkatesh et al. (2003) discovered that significant predictors for adoption included relative advantage, ease of use, results demonstrability, visibility, and trialability, while only relative advantage and image were significant for usage. The UTAUT model also applies voluntariness of use as a moderator of technology usage. Nunes et al. (2019) did not consider voluntariness of use in their study on behavioral intent for mobile health applications, since the context of their testing environment was voluntary in nature. However, Venkatesh et al. (2003) used the following previous technology acceptance models to form UTAUT's stance of how voluntariness of use influences technology acceptance and usage: TRA, TAM2, TPB, and IDT. Concerning TRA, researchers discovered that when users perceived that system use is less voluntary, subjective norm tends to be more salient. Similarly, for TAM2, only mandatory system usage settings for users with limited experience indicated salience. Likewise, with the TPB model, subjective norm indicated more saliency when users perceived a less voluntary system usage setting. Although not tested as a moderator for IDT, research indicated that voluntariness directly affects intention (Venkatesh et al., 2003). Overall, the research model presented by Nunes et al. (2019), with the moderators included, explained 74% of the variance in the behavioral intention to use mobile health applications.

Critical Analysis and Synthesis of the Dependent Variables

Dependent variables are the outcome components in research that rely upon the influence of the independent variables. As stated in my purpose statement, my dependent variable is the behavioral intention of IT cloud system integrators to adopt SDN technology, and the usage behavior of IT cloud system integrators toward SDN technology, adopted from the UTAUT model.

Behavioral Intention

One of the UTAUT model's dependent variables is behavioral intention. Venkatesh et al. (2003) described behavioral intention as an individual's attitude, internal motivation, and subjective probability to use a technology system. They observed that the following determinants directly affect an individual's behavioral intention: performance expectancy, effort expectancy, and social influence. The determinants for behavioral intention may influence or persuade an individual's attitude toward using a new system positively or negatively and moderated by experience, age, gender, and voluntariness of use. Mikalef et al. (2016), who explored the cognitive factors that influence behavioral intent and the adoption of video-based learning for online education, described behavioral intention as the extent to which an individual formulates a conscious plan to perform or not to perform a specified future behavior. The UTAUT model enables the estimation the behavioral intent of potential system users in the following ways: (a) capturing and analyzing the user's intention to use the system over the coming *n* months, (b) capturing and analyzing the user's prediction that they intend to use the system over the coming *n* months, and (c) capturing and analyzing the user's plan that they intend to use the system over the coming *n* months (Venkatesh et al., 2003). They found that the UTAUT model accounted for 70% of the variance in usage intention (Venkatesh et al., 2003).

Usage Behavior

The other dependent variable of the UTAUT model is usage behavior. According to Venkatesh et al. (2003), usage behavior reflects an individual's actual usage pattern for a technology system, and results from the determinants intent and facilitating conditions. Applying the UTAUT framework, the researchers found that each moderator of experience, age, gender, and voluntariness of use is significant in determining usage behavior, thereby providing a more comprehensive picture than predecessor models concerning the dynamic nature of individuals' persuasions towards technology usage. In their study on social media adoption in employee recruitment in Central and Eastern Europe, researchers Ouirdi et al. (2016) agreed, observing that facilitating conditions provide an indicator of usage behavior. Moreover, their findings indicated that social media-related facilitating conditions and behavioral intent positively influenced recruiter’s usage behavior, with the effect being stronger for older workers with technology experience (Ouirdi et al., 2016). According to Venkatesh et al. (2003), studies indicate that usage behavior is a critical component for understanding both the short- and long-term implications of technology implementations and outcomes, such as productivity and job satisfaction.

Measurement of Variables

This study was quantitative and correlational, requiring statistical measurements of the relationship between the dependent and independent variables. I performed data collection using Likert-scale surveys based on the UTAUT model and constructs to record the participants' perceptions, attitudes, and opinions numerically for statistical analysis purposes. Ivanov et al. (2018) described the Likert-scale survey as an instrument for measuring respondents’ attitudes and beliefs by the extent of their agreement or disagreement to survey questions. They applied a problem-based learning approach to investigate the extent to which students’ understanding of discrete mathematics would improve by administering Likert-scale questionnaires focused on the subject matter, followed by related exploratory deliberations (Ivanov et al., 2018). Renshaw (2018) expounded when gauging the psychometrics of a revised version of a college student subjective well-being questionnaire for undergraduate students (*N* = 981) at a large university in the Southern United States, and applying a 7-point Likert-scale instrument for enhanced scoring administration and interpretability. Among Renshaw’s (2018) objectives were to evaluate the following quality measures: (a) structural validity, which relates to the extent to which the scores of the instrument reflect the dimensionality of the construct under test and (b) convergent validity, which assesses the degree to which constructs that are expected to be related are related. Each of the measurement items were adopted from previous studies to ensure content validity. Renshaw (2018) applied the following descriptions to the numerical values: 1 = strongly disagree, 2 = disagree, 3 = slightly disagree, 4 = neutral, 5 = slightly agree, 6 = agree, and 7 = strongly agree (Renshaw, 2018). Content validity, on the other hand, according to Shrotryia and Dhanda (2019), refers to the extent to which the test items represent the domain being measured. Content validity also involves leveraging subject matter experts when assessing the degree to which instrument elements are relevant and representative of the construct under evaluation (Shrotryia & Dhanda, 2019). To this end, I used the previously validated UTAUT instrument, and the Likert 7-point scale, which allows for the granularity of measurements, along with the directional and degree descriptions denoted above. I ensured content validity by referencing previously validated studies and consulting with SDN or similar technology subject matter experts when approved to do so in a corroborative effort that includes: (a) gleaming measurement data from previous similar surveys and studies, if available, (b) ensuring appropriateness of questions through job task and item analysis, (c) guarding against internal validity threats related to procedures and participants by applying best practices, to include defining the survey items and parameters in advance, and (d) by guarding against external validity threats by avoiding the generalization of the outcomes beyond the domain, group, and settings being studies.

Similar Studies

In this section, I reviewed some of the previous UTAUT studies that have similarities to my study and also significant differences. In my study, I investigated the adoption of SDN technology at cloud service organizations in the United States.

In Pakistan, Rahi et al. (2019) applied the UTAUT model to explore how technology and the electronic service factors of web design, customer service, reliability, and assurance may boost confidence and adoption of internet banking, as policy makers looked for ways to increase internet banking acceptance among commercial banking clientele. They selected the integrated unified UTAUT model because it reinforces the significance and predictability of results (Rahi et al., 2019). Concerning data collection and findings, the researchers surveyed metropolitan commercial bank customers (N = 650) in Pakistan. Using structural equation modeling for data analysis, Rahi et al. (2019) found that predictors accounted for approximately 80% of the variance in behavior intent of users to adopt internet banking. In contrast, my study involved investigating SDN adoption at cloud service organizations in the United States by measuring the relationship between cloud system integrators' perceptions of performance expectancy, effort expectancy, social influence, and facilitating conditions, and the intention of cloud system integrators to use SDN technology. Although both studies apply the UTAUT model for understanding behavioral intentions to use new technology, my study's purpose, population, and technology domain are vastly different.

In Botswana, researchers Tladi and Nleya (2017) leveraged the UTAUT model to investigate the extent to which quality factors influenced technology-based online elearning at Botswana College of Distance and Open Learning. Elearning has revolutionized higher education practices, lending to innovative pedagogical approaches at colleges and universities globally in recent years. However, elearning solutions from developed countries often encounter challenges that affect the quality in Botswana, which like many developing countries, often face technology hurdles with interactive teaching tools and communication accessibility, as well as cultural and geographical challenges, such as historical or political, that may impact the quality of elearning (Tladi & Nleya, 2017). Concerning data collection and findings, the researchers surveyed elearning students at Botswana College of Distance and Open Learning tertiary institutes (N = 66) in Botswana. Using Pearson's correlational data analysis model, Tladi and Nleya (2017) found a high correlation (.882) between quality factors and elearning implementations, suggesting that quality factors positively influenced elearning. On the other hand, my study involved investigating SDN adoption at cloud service organizations in the United States by measuring the relationship between cloud system integrators' perceptions of performance expectancy, effort expectancy, social influence, and facilitating conditions, and the intention of cloud system integrators to use SDN technology. Although both studies leverage the UTAUT framework for understanding behavioral intentions to use new technology, my study's purpose, population, and technology domain are significantly different.

Researchers Puspitasari et al. (2019) applied the UTAUT in their quest to determine the variables that influence the use and adoption of an integrated licensing service information system for Samarinda City Investments located in the Republic of Indonesia. For data collection, they used a combination of distributed questionnaires and interviews (N = 77) to the staff at Samarinda City Investments that used the integrated licensing service information system. Their main finding was that performance expectancy, which consisted of the utilization of perception, increasing effectiveness and productivity, and ease of getting information greatly and negatively influenced the system's acceptance and utilization, with only 11% of respondents indicating that the system processed license permits faster and more efficiently (Puspitasari et al., 2019). On the contrary, my study involved investigating SDN adoption at cloud service organizations in the United States by measuring the relationship between cloud system integrators' perceptions of performance expectancy, effort expectancy, social influence, and facilitating conditions, and the intention of cloud system integrators to use SDN technology. Despite how both studies employ the UTAUT model for understanding intentions to use new technology, my study's purpose, population, and technology domain are vastly different.

Comprehensive Critical Analysis and Synthesis of the Literature on Software-Defined Networking

In this section, I critically analyzed and synthesized recent SDN literature. I began by describing SDN's architectural framework, which includes its abstraction interfaces, its data, control, and application planes, and its use of the OpenFlow protocol. I explored SDN use cases in which different industries look to exploit its benefits, as well as key challenges that SDN early adopters face.

Architectural Framework of SDN

SDN architecture incorporates certain innovative design features in its pursuit to overcome conventional network architecture limitations. Singh and Jha (2017) identified the following defining characteristics of SDN: (a) the data plane is decoupled from the control plane, (b) the control plane functions in a unified manner in which a single program controls the data plane elements, (c) the controller or orchestrator maintains global control and view of data plane network elements (NEs), and (d) network function virtualization (NFV), which improves efficiency and elasticity. The goal of SDN is to provide a centralized and open platform that enables the programmability of data flow characteristics, thereby promoting user-controlled management of network traffic behaviors (Singh & Jha, 2017). Xie et al. (2019) agreed, emphasizing the decoupled nature of the control plane and the data plane, and how the application layer views the underlying network infrastructure as an abstraction of service delivery resources. In addition, its centralized control, programmability, global view, and software-based data-driven traffic analysis foster an ideal environment for increased automation through ML and cognitive techniques (Xie et al., 2019).

SDN improves performance and efficiency. Abbasi et al. (2016) asserted that due to the design limitations of traditional networks, which require manual and independent configuration of each network device, inherent challenges exist for network operators performing network management and optimization tasks. Maintaining traditional network infrastructure often involves using multiple control applications and tools such as command-line interfaces and scripting tools, which can become convoluted and error-prone, to implement network policies. In addition, innovation can be cumbersome due to proprietary vendor operating systems, prohibiting modification by customers (Abbasi et al., 2016). Singh and Jha (2017) contended that increasing network traffic demands, estimated in 2019 to be two zettabytes per year and 168 exabytes per month, challenge the scalability and processing capabilities of conventional networks, accelerated by emerging technologies such as IoT, ultra-high-definition video-on-demand, distributed cloud computing, and big data. Xie et al. (2019) also observed that rapid mobile and wireless innovations supporting various transmission protocols increase the complexity and heterogeneousness of the network, requiring greater intelligence for peak efficiency and effective management.

Abstraction Interfaces. SDN architecture leverages software abstractions, which provide an object-level representation of complex operations, hiding underlying complexities and details. Alenezi et al. (2019) described the SDN abstraction concept as the service abstraction layer, which integrates component services with application functions, concealing the underlying protocol negotiation complexities. According to Singh and Jha (2017), SDN abstraction interfaces define the logical interconnectivity between system functions and components, with the controller positioned as the central reference point. They elaborated by describing the northbound interface as the logical functionality that extends services from the controller to the higher-level application layer. In contrast, the southbound interface extends services from the controller to lower-level components, such as network switches, virtual switches, and wireless access points (Singh & Jha, 2017). The eastbound interface provides logical interconnectivity between the SDN controller and non-SDN domains, such as conventional legacy networks. On the other hand, the westbound interface provides interconnectivity between distributed SDN controllers and between multiple OpenFlow-enabled domains (Baktir et al., 2017). The westbound interface also provides network state information for routing decisions between the SDN control planes in a multi-controller environment (Baktir et al., 2017).

Data, Control, and Application Planes. By decoupling the control and data planes, SDN takes a markedly different approach to how networks function compared to conventional networks. Abbasi et al. (2016) observed that while traditional network architecture consolidates the data and control planes onto the same device, SDN, in contrast, separates the data and control plane onto different devices. Whereas the control plane provides device intelligence, controlling data flow functions such as resource allocation and data forwarding and routing decisions, the data plane provides transport for user and data traffic as directed by the control plane (Abbasi et al., 2016). In describing the central structure of SDN architecture, Singh and Jha (2017) noted that the SDN control plane unifies operations onto a centralized controller or a distributed group of controllers, and uses OpenFlow protocol to govern data plane elements, while NEs, such as network switches comprise the data plane. Xie et al. (2019) concurred, noting that the SDN controller functions as a network operating system by maintaining configuration data, managing network resources, and directing network traffic. The SDN controller maintains detailed knowledge of the network in a closed-loop method, thereby enabling adaptive network traffic management and fostering dynamic provisioning (Singh & Jha, 2017). Table 1 lists several open-source SDN controllers, along with their programming languages and public license agreements.

Table 1

Common Open Source Software-Defined Networking Controller and License Agreements

Controller	Programming language	Remarks
Beacon	Java	BSD-licensed, multi-thread and event-based operations; originated at Stanford University
Floodlight	Java	Leverages OpenFlow vSwitch and Apache public license (APL); predecessor of Beacon
NOX	C++/Python	Uses general public license (GPL), and supports C++ and Python; originated at Stanford University
Maestro	Java	Originated at Rice University; uses lesser general public license (LGPL)
OpenDaylight	Java	Originated from the Linux foundation; uses eclipse public license (EPL)
POX	Python	Predecessor of NOX, and uses APL; originated at Stanford University

Note: Adapted from "A Survey on Software-Defined Networking: Architecture for Next Generation Network," by S. Singh and R. K. Jha, 2017, Journal of Network and Systems Management, 25(2), p. 24 (https://doi.org/10.1007/s10922-016-9393-9).

SDN architecture also incorporates an application layer for data management and data orchestration. Xie et al. (2019) described the SDN application plane as consisting of northbound interface business applications, network virtualization, cloud computing, security applications, network monitoring, and mobility management. Islam et al. (2018) expanded, observing that application layer abstractions, communicating through the northbound interface, direct controller operations.

OpenFlow Protocol. OpenFlow is a central SDN protocol used for directing operations and intercommunications. Singh and Jha (2017) observed that in 2011 the open networking foundation established the OpenFlow protocol as the standard application programming interface for directing data flow operations between the SDN control plane and the southbound NEs in the data plane. OpenFlow-compliant network switches behave as NEs that forward packets as instructed by the SDN controller (Singh & Jha, 2017). Three of the central messages generated by OpenFlow include the following: (a) switch feature, which describes the features and capabilities of NEs; (b) “FlowMod,” used by the controller to define flow instructions for the NEs; and (c) “PortStatus,” which provides port status updates and characteristics, such as operational status and available bandwidth (Singh & Jha, 2017). Xie et al. (2019) offered additional flow details, noting the when an SDN switch receives a packet in its data plane, it extracts the packet header and searches for a matching flow table entry. Upon discovering a matching entry, processing will proceed using the controller's instructions for the flow entry. If not found, the switch will send an OpenFlow “PacketIn” message and the packet header, to the controller. The controller will then respond with a FlowMod message, providing flow instructions to the switch’s flow table (Xie et al., 2019).

Network Function Virtualization. NFV decouples network hardware and software, enabling multiple network operations to function over the same hardware. According to Mijumbi et al. (2016), NFV reduces organizations’ networking operating costs by enabling multiple network functions to share the same hardware resources, thereby reducing the need to purchase a dedicated hardware device for each network function or task. NFV’s concept of decoupling network functions from the network hardware is also an important tenet and an enabling characteristic of SDN (Mijumbi et al., 2016).

Salman et al. (2018) also described NFV as a complimentary technology to SDN that allows different applications to leverage common network infrastructure similar in concept to cloud computing virtualization. NFV operates by designating network resources, as needed, for each network function or application, enabling greater hardware utilization efficiency and scalability (Salman et al., 2018). Kobo et al. (2017) pointed out that NFV provides added flexibility in mobile cloud computing solutions, such as the follow-me cloud concept, which ensures optimal data center (DC) connectivity and seamless service migration for mobile cloud users. In addition, Mijumbi et al. (2016) asserted that NFV improves networking agility by enabling much faster ramp-up or ramp-down of services, often without requiring hardware modification.

Use Cases

There is a growing number of SDN use cases. In this section, I explored SDN use cases that include: artificial intelligence (AI) and ML, cloud computing orchestration, smart grids technology, network traffic engineering, and SDN IoT use cases, such as sensors, mobile networks, and vehicular networks.

Machine Learning. The programmability features of SDN technology promote automation and efficiency. Leveraging its programmability characteristics, Zhao et al. (2019) proposed integrating SDN with AI and ML to achieve network intellectualization, which may result in significantly enhancing performance, management, and scalability, while reducing operating costs. SDN’s decoupled control and data planes, and its centralized control of network traffic and network policies promote efficiency in ML predictive analysis used for resource optimization, route provisioning, and in providing dynamic orchestration of massive data inputs. Niyaz et al. (2017) similarly highlighted the programmable aspects of SDN that lend to next-generation networking capabilities, such as advanced intrusion detection through deep learning (DL) technology. Researchers Sultana et al. (2018) also expressed optimism in these emerging technologies, stressing that SDN’s segregation of the control and forwarding plane and its direct programmability fosters a new paradigm of innovativeness, as they introduced an SDN-enabled network intrusion detection system that applies ML and DL methods to improve detection accuracy and lower false positives.

Cui et al. (2019) demonstrated additional advancements by applying cognitive-inspired computing using a support vector machine algorithm that only requires a small sample of training data to address prevalent cyber-attacks, such as DDoS attacks, in SDN’s centralized control architecture, and to enhance detection capabilities for both known and unknown occurrences. In SDN-based fifth-generation (5G) cellular networks, Caraguay et al. (2017) commented that AI and ML algorithms stochastically diagnose the root cause of problems, and derive countermeasures and alternatives using self-organized network management in virtualized and software-defined network sensors. Boutaba et al. (2018) asserted that in contrast to SDN, legacy network systems are not conducive to the integration of AI, ML, and cognitive learning due to their independent control plane and proprietary design that limit cognitive learning and automation capabilities.

SDN-based intrusion detection system (IDS) systems employ ML and DL techniques that improve the detection of cyber-attacks and vulnerabilities. Sultana et al. (2018) outlined the following ML approaches: (a) unsupervised in which algorithms learn from unlabeled input data with the goal of modeling data structure and distribution, such as a self-organizing mapping; (b) semi-supervised, which trains from a small amount of labeled data and a large amount unlabeled data, used to improve detection accuracy, such as for network intrusion detection systems; and (c) supervised in which algorithms predict unknown representations from labeled training data (Sultana et al., 2018).

Zhao et al. (2019) likewise described how unsupervised ML algorithms seek to learn intrinsic data properties, categorizing data from unlabeled sources, while semi-supervised algorithms perform reinforcement learning and perform classification from incomplete training data. Supervised ML models, according to Zhao et al. (2019), are used in functions such as speech and object recognition and spam detection, and apply labeled training data to predict the output. While supervised learning techniques focus on solving attack classification problems, unsupervised learning techniques are applied to detect previously unknown attacks (Sultana et al., 2018).

Cloud Orchestration. SDN is an enabler of cloud orchestration. Y.-J. Chen et al. (2017) expounded by describing a key SDN feature called service chaining in which virtual machines can dynamically connect to application services upon user requests, thereby creating enormous potential for cloud orchestration. To address increasing industry demands to integrate the control and management of geographically distributed DCs and heterogeneous cloud computing environments with network orchestration, Mayoral et al. (2017) evaluated the functions of end-to-end inter-DC connectivity and VM migration by comparing an SDN single controller architecture solution with multi-controller solution called application-based network operations (ABNO). The quest to ensure dynamic application-driven service requests is further complicated by traffic control service agreement requirements in multidomain cloud environments. Unlike SDN single controller architecture, the researchers observed that ABNO separates the control and orchestration layers, enabling the delegation of some control tasks, which allows for greater scalability (Mayoral et al., 2017). On the other hand, ABNO introduced orchestration overhead, which resulted in its slightly lower intra-DC performance than SC-Arch. Still, ABNO demonstrated significantly improved inter-DC performance and responsiveness, due to its elimination of SC-Arch setup delay and its immediate virtual link creation (Mayoral et al., 2017).

SDN leverages virtualization, which increases flexibility and reduces costs. Alenezi et al. (2019) emphasized how SDN-enabled cloud infrastructure exploits NFV, which transforms network tasks and operations by decoupling network hardware from software, empowering DCs to achieve greater dynamicity, efficiency, and scalability in supporting spiraling network demands. Interestingly, Bakhshi (2017) noted that while Google uses an SDN platform to achieve increased manageability and resiliency among some of its geographically dispersed DCs around the globe, Microsoft Azure employs an SDN-based load-balancer solution in some of its multitenant cloud services environments that provides high scalability.

Researchers Baktir et al. (2017) underscored how SDN technology benefits a new trend in cloud computing called edge computing, which reduces end-user latency by off-loading delay-sensitive applications from far-away DCs to local infrastructure. SDN edge computing improves data flow management and service orchestration through its programmable architecture (Baktir et al., 2017). Bakhshi (2017) summarized additional SDN-based cloud advantages which include: (a) its open platform collaboration within the network development community that encourages the development of improved solutions, such as in the areas of security, performance, and efficiency; (b) its adoption may result in lower operating expenditures and lower capital expenditures through resource virtualization and gained efficiencies; (c) intelligent resource provisioning that enhances DC automation; and (d) increased energy efficiency through more granular control of resource-sharing, thereby reducing underutilized systems.

Smart Grids and Energy-Efficiency. Smart grid technology increasingly leverages SDN. Researchers de Pozuelo et al. (2017) presented a smart grid software-defined utility concept as an alternative to traditional rigid and complex hardware-based systems that support heterogeneous power system infrastructure. SDN architecture promotes programmability, context-aware security, flexible resource management, and higher reliability of high-speed communications in its energy-efficiency integration of technologies such as IoT and wireless machine-to-machine communications (de Pozuelo et al., 2017). Rehmani et al. (2019) proposed an SDN-enabled smart grid communication system to address increasing electricity demands, reliability challenges with legacy electrical power grid systems, and interoperability issues with conventional proprietary smart grid communication systems. SDN's programmability allows for improvements in energy efficiency through granular traffic flow orchestration, achieving considerable strides towards the goal of achieving renewable energy resources by 2024, while also reducing interoperability challenges through its use of OpenFlow to achieve protocol independence (Rehmani et al., 2019).

Aydeger et al. (2019a) demonstrated that the programmability features and capabilities of SDN could add resiliency to critical power grid systems that use wired power line communications that are easily damaged, sometimes resulting in extended power outages during natural disasters such as earthquakes or floods and human-induced incidents. In the event of a substation communications failure, their proposed SDN-based smart grid system provides real-time detection and self-healing mechanisms through alternate wireless communications to restore substation connectivity and power production. Using Mininet emulation, the researchers illustrated how SDN-based teleprotection demonstrated reliable link recovery for generic object-oriented substation events messages and intelligent electronic devices (Aydeger et al., 2019a). Al-Musawi and Al-Khatib (2019), on the other hand, proposed an SDN-based solution that applies a heuristic algorithm to optimize power and energy consumption for energy-inefficient data DCs. They reduced energy consumption significantly by identifying and powering off inactive network devices using fine-grained monitoring, without compromising the quality of service (QoS) and QoE service agreements (Al-Musawi & Al-Khatib, 2019).

Traffic Engineering. SDN fosters elastic and fine-grained control of network traffic behaviors. Abbasi et al. (2016) proposed an SDN-based traffic engineering solution that exploits its programmability and its centralized flow management, overcoming rigid conventional processes that are also frequently overprovisioned. SDN’s separation of the control and data plane and its centralized controller interacts with applications resulting in granular control of network traffic through OpenFlow abstraction channels, while also simplifying flow management and promoting innovation (Abbasi et al., 2016).

According to Jia et al. (2018), SDN's adaptability and dynamicity lend to an innovative approach in developing low earth orbit satellite networks leveraging Dijkstra's computational efficiency and depth-first-search algorithms that can streamline network expansion and achieve more flexible network monitoring and management. In their proposed solution, the SDN controller resides at the ground station with a global view and processes network device instructions using the OpenFlow protocol to determine the best data path (Jia et al., 2018). In addition, researchers Go et al. (2019) proposed ways to leverage SDN technology for delivering high quality, low delay IP-based video surveillance (IPVS) traffic during bandwidth contention periods among IPVS camera streams using quality of QoE bitrate adjustments, which places a higher priority on human eye-sensitive video patterns. Their proposed SDN OpenFlow-based IPVS solution dynamically prioritizes data streams upon reception to make relevant objects identifiable over under-provisioned networks, minimizing packet loss, jitter, and latency for selected flows, while also optimizing throughput efficiency through dynamic rate adjustment mechanisms that reroute lower priority traffic as needed (Go et al., 2019).

SDN can also perform traffic engineering in multicast environments. Islam et al. (2018) argued that the advantages of centralized control, flow abstractions, and dynamic flow updating drives the adoption of SDN, to include for internet protocol multicast where one or more senders can transmit to zero or more receivers. In addition to using multicast routing algorithms to minimize resource consumption, SDN multicast solutions typically also employ one of the following approaches to achieve the desired flow distribution goals: (a) application-independent, based on whether distribution of receivers is dense or sparse; (b) application-aware, which may involve QoS-aware applications or rely on multicast protocols such as the reliable multicast transport protocol to facilitate data delivery; or (c) topology-aware algorithms that use techniques such as scalable video coding to control the quality of video to receivers (Islam et al., 2018).

Coronado et al. (2018) applied an SDN multicast solution called scalable multigroup SDN@Play, which uses intelligent centralized control and management, rather than the inefficient conventional method of integrating these functions into distributed access points to improve performance and reliability of concurrent 802.11 wireless multicast video streams, and to reduce radio channel utilization. Using the SDN model, the researchers demonstrated increased multicast streams with reduced channel utilization, without service degradation (Coronado et al., 2018). Similarly, Bukhari and Yoon (2018) demonstrated increased multicast distribution efficiency and flexibility using an SDN-based centralized approach, which reduced radio transmissions significantly in a heterogeneous wireless test environment. In addition, Park et al. (2019) proposed an SDN-based multicast enhancement for large-scale IoT implementations, which reduces transfer delays and establishes bidirectional multicast trees between the publishers and subscribers to increase flow capacity.

IoT. SDN simplifies management and strengthens controls for IoT environments. According to Tomovic et al. (2017), due to the exponential expansion of the internet in volume and service diversity, which pose a significant challenge for traditional network and a new approach that provides new scalability levels and real-time data delivery is paramount. They asserted that IoT architecture, which encompasses an array of new technologies such as sensors and actuators for monitoring and controlling environment-sensitive devices, autonomous vehicles, smart machines, and drones, benefits from SDN's capability to provide sophisticated traffic control and resource management (Tomovic et al., 2017).

Similarly, Salman et al. (2018) expressed concerns about the capabilities of conventional networks to meet the internet's increasing heterogeneity, management complexities, scalability demands, and security challenges, spurred by IoT. They promoted SDN as the ideal platform to meet these challenges through centralized management, which eliminates the need to independently manage IoT network devices, its inoperability, and its support of new applications to strengthen IoT security and privacy (Salman et al., 2018). Tomovic et al. (2017) focused on using SDN integrated with fog computing to provide centralized connectivity management of IoT devices, and to foster dynamic service orchestration for IoT environments, such as smart cities.

On the other hand, Salman et al. (2018) described how SDN, integrated with NFV and OpenFlow, overcomes identity fragmentation and silos of traditional solutions, thereby strengthening IoT security, including identity management, access control, and privacy. Kim et al. (2019a) also explored a software-defined security framework to harvest sensitive and private information from IoT devices. The developers proposed a user-defined SDN gateway solution, which improves security by (a) identifying NEs and their states, (b) providing base security functions, (c) and detecting and resolving security conflicts (Kim et al., 2019a).

Sensors. SDN enhances data collection efficiency and management elasticity for IoT sensors. Ndiaye et al. (2017) provided an example using SDN architecture to address inherent challenges of heterogeneity, application dependency, and resource constraints of traditional wireless sensor networks in supporting IoT sensors, such as sensor nodes actuators used in smart farming, and smart grids sensors, smart health sensors, and smart grid sensors. They conducted a series of tests that demonstrated that the centralized management approach of SDN-based wireless sensor networks provided improved elasticity while simplifying device, protocol, and application management (Ndiaye et al., 2017).

Anadiotis et al. (2019) introduced a concept called software-defined wireless sensors, which leverage NFV to enhance flexibility, expandability, and to increase energy efficiency for WSNs. One way in which the researchers demonstrated the effectiveness of software-defined wireless sensors was by using trusted platform modules and context-based rules to dynamically guarantee security compliance, to include validating that node firmware is tamper-free and confirming that node rules and services originated from an authorized source (Anadiotis et al., 2019). To enhance automation for emerging smart city technologies, such smart grids, micro-grids, and electric vehicles, Abujubbeh et al. (2019) proposed a software-defined wireless sensor networks solution that delivers robust and secure bi-directional communications between utilities and consumers by employing smart meters and sensory devices (Abujubbeh et al., 2019).

In a much different terrain, researcher Wang et al. (2019) leveraged SDN technology in underwater acoustic sensor networks used in exploring ocean realms, and traditionally plagued with versatility constraints and low signal quality due to signal overlapping in redundant deployment configurations. SDN’s programmability overcomes the rigidity constraints and limitations of legacy underwater acoustic sensor network systems, resulting in reduced deployment risks. Developers Puente Fernandez et al. (2018) promoted a concept called software-defined sensor networks, based on smart sensor nodes that monitor environmental conditions such as temperature, humidity, and sound, and which applies centralized control and NFV to optimize energy consumption, durability, scalability, and fault tolerance (Puente Fernandez et al., 2018). Younus et al. (2019) observed that WSN sensors are typically battery-powered, and therefore power optimization and energy efficiency are essential.

***Mobile and Radio*.** SDN empowers emerging mobile and radio technologies. To address inflexibility and capacity constraints of traditional cellular infrastructure, Tello-Oquendo et al. (2019) developed an innovative SDN-based solution that bolsters 5G capabilities to support IoT, projected to reach 20 billion connected devices and 110 exabytes by 2023. Using software-defined gateways that function as IoT controllers, the researchers demonstrated significant enhancements, such as improved heterogeneity and QoS for IoT devices, remote radio head coordination, and improved front-haul network capabilities that can support massive volumes of diverse IoT traffic based on SoftAir 5G system architecture (Tello-Oquendo et al., 2019).

To address 5G's continuous connectivity and ubiquity requirements, developers Contreras et al. (2016) presented an SDN-enabled 5G mobility management system that uses its global flow and device database that guarantees ubiquitous session continuity, a major challenge for traditional mobile technologies. Researchers Habiba and Hossain (2018) promoted wireless network virtualization based on SDN and NFV architecture, which fosters service deployment flexibility to enhance capacity and resource management for the emerging 5G cellular technology. Wireless network virtualization applies the auction theory business model, which maximizes revenues through multitenancy and resource optimization from on-demand service requests (Habiba & Hossain, 2018).

In contrast, Yao et al. (2019) opted to focus on an SDN-5G solution that overcomes traditional 5G architecture management and uniformity limitations and to improve security. While SDN's consolidated and unified control plane hosted from the controller provides a holistic network view and network control, its open interface and programmability characteristics foster heterogeneity. To strengthen security, the developers designed a security module between the control and data planes, which applies integrated cryptographic authentication and moving target defense algorithms as a countermeasure against DDoS attacks (Yao et al., 2019). In addition, on a futuristic front, developers Ateya et al. (2018) proposed a 5G SDN core and mobile edge computing architecture that uses a centralized controller with a global view and knowledge of the network to overcome the ultra-low end-to-end latency requirement for the Tactile Internet. Tactile Internet technology, considered by some analysts as the next IoT evolution, enables human-to-machine haptic interactions in which the human touch stimulates communications to control IoT devices in real-time, requiring high network availability and efficiency (Ateya et al., 2018).

Vehicle Networks. SDN technology promotes smart mobility. In their survey on SDN-enabled vehicle ad hoc networks (VANETs), Chahal et al. (2017) explored ways in which VANETs empower intelligent traffic systems with advancements in traffic control, collision avoidance, lane change assistance, and emergency hazard warnings. The developers proposed a programmable and open-source software-defined vehicular network solution that overcomes frequent disconnects of tightly coupled traditional vehicular architecture, and that addresses the increasing demand for greater flexibility, reliability, and adaptability in heterogeneous environments (Chahal et al., 2017).

SDN technology fosters innovation in data flow optimization and traffic management. According to Chahal et al. (2017), their SDN model enabled dynamic bandwidth management, QoS, and latency-based routing, and enhanced wireless integration, thereby achieving substantially improved optimization of sensitive data flows (Chahal et al., 2017). In a similar approach that additionally extends into the area of entertainment, Maio et al. (2016) presented a VANET smart mobility concept which leverages SDN’s programmable approach, improving resource and mobility management, strengthening vehicle safety, and providing new opportunities for vehicle infotainment. By applying efficient channel utilization through its spectrum management techniques that ensure low collision probability, SDN dynamically adapts to frequent topology changes among moving vehicles, roadside units, and roadside unit controllers. Especially in vehicle platoons that occur during peak hours traffic congestion causing close formations, where safety traditionally relies on attentive drivers that accurately perceive road and environmental conditions, SDN-based smart mobility through vehicle-to-vehicle technology can optimize inter-vehicle distances by assessing environmental and road conditions, and thereby enhance safety (Maio et al., 2016).

SDN technology enables improved VANET content delivery and innovative traffic management techniques. According to Maio et al. (2016), in addition to minimizing latency during topology changes, SDN also provides content caching, forwarding, and multiple content sources, which improves the quality of content delivery for VANET multimedia users. Bhatia et al. (2020) advanced VANET traffic analysis to a greater degree by applying an ML model, which incorporates predictive analysis for vehicular traffic behaviors, using clustering algorithms to predict traffic densities and to find congestion-sensitive points.

Mahmood et al. (2019) emphasized security, low-latency, and innovative sensing in their proposed software-defined heterogeneous vehicular networking architecture, which uses vehicle sensors to support intelligent transportation system applications, such as forward collision warning, hazard location alerts, and pedestrian collision mitigation, paving the way for next-generation autonomous vehicles. Table 2 provides a summary of SDN use cases, along with traditional technology limitations.

Table 2
SDN Use Cases, Application, and Traditional Technology Limitations

Use case	SDN application	Traditional technology limitations
Machine learning	Open interface and centralized management promote programmability and automation	Independent control planes and proprietary systems hinder automation and interoperability
Cloud orchestration	Virtualization and programmability promote dynamicity and fine-grained flow control	Rigidity and scalability limitations
Smart grids	Programmability promotes flexibility for heterogeneous power systems infrastructure	Interoperability and reliability challenges spun from inflexibility
Traffic engineering	Programmability and centralized control enable innovation and fine-grained control	Flow orchestration excessively complex and inefficient, resulting in manageability limitations
Internet of things	Fosters scalability and management through centralized architecture	Heterogeneity and scalability limitations

Note: The table above provides a high-level summary of the SDN use categories described in this paper, along with their applications and the limitations of traditional technologies. Adapted from a “A Survey of Machine Learning Techniques Applied to Software-Defined Networking (SDN): Research Issues and Challenges,” by J. Xie et al., 2019, IEEE Communications Surveys and Tutorials, 21(1), p. 394 (https://doi.org/10.1109/COMST.2018.2866942); b“SDN Orchestration Architectures and Their Integration with Cloud Computing Applications,” by A. Mayoral, R. Vilalta, R. Muñoz, R. Casellas, and R. Martínez, 2017, Optical Switching and Networking, 26, p. 3 (https://doi.org/10.1016/j.osn.2015.09.007); c“Prototyping a Software-Defined Utility,” by R. M. de Pozuelo, A. Zaballos, J. Navarro, and G. Corral, 2017, Energies, 10(6), p. 2 (https://doi.org/10.3390/en10060818); d“Traffic Engineering in Software-Defined Networks: A Survey,” by M. R. Abbasi, A. Guleria, and M. S. Devi, 2016, Journal of Telecommunications and Information Technology, (4), p. 2; e“IoT Survey: An SDN and Fog Computing Perspective,” by O. Salman, I. Elhajj, A. Chehab, and A. Kayssi, 2018, Computer Networks, 143, p. 221 (https://doi.org/10.1016/j.comnet.2018.07.020).

As a technology still in its infancy, SDN faces considerable challenges. In this section, I analyzed some of the major challenges that SDN faces, including security vulnerabilities, optimization in a multi-controller environment, and other challenges, such as scalability and interoperability with traditional technologies.

Challenges

Security vulnerabilities are among the main concerns of SDN architecture. Isong et al. (2017) described SDN security as an assurance of data confidentiality, integrity, and availability, supported by authentication and authorization of protected resources. Researchers Azka et al. (2017) provided additional insight, observing that although SDN technology can revolutionize networking capabilities, significant security challenges exist concerning its control, data, and application plane. Common threats to the control plane include packet-in attacks involving repeated corrupt packets between the switch and the controller, denial of service (DoS) attacks that exhaust system resources through flooding, packets corruption that distorts the controller's topology database, side-channel attacks that exploit cryptography residual leaks through extensive monitoring, and controller authentication exploits.

The data plane also faces attacks. According to Azka et al. (2017), common SDN data plane exploitations include DoS, man-at-the-end attacks from flow table poisoning, and side-channel attacks. Azka et al. (2017) added that common security threats to the application plane include the following: (a) threats to the trust model, which refers to the degree to which SDN applications are trusted and adhere to established security policies; (b) nested applications that can sometimes by-pass established access control measures; (c) applications that can alter the SDN controller database; (d) interoperability concerns with third-party applications; and (e) misuse through rogue applications. Benzekki et al. (2016) described SDN security as encompassing the physical protection of hardware and software components, as well as the protection of logical network components against threats and vulnerabilities, whether intentional or accidental. SDN also inherits vulnerabilities from integrated components, such as applications and NEs, in addition to new security vulnerabilities introduced through the centralized controller architecture that makes it a potential target for attackers (Benzekki et al., 2016).

New countermeasures have been developed to combat security threats. Rietz et al. (2018) argued that because attacks are often initiated through sources such as malware-infected email attachments, external media, contaminated wireless injections, and hardware with pre-installed malware, security measures that only monitor inbound internet traffic have limited effectiveness. They presented a comprehensive SDN security monitoring solution that applies the extensible authentication protocol, and which exploits SDN's centralized controller architecture, open standards OpenFlow protocol, and decision authority to fortify security monitoring capabilities and security protection of heterogeneous systems (Rietz et al., 2018). To mitigate against potentially incapacitating SDN DoS attacks, Dao et al. (2016) proposed an OpenFlow-based solution that applies a probabilistic history-based IP filtering algorithm to analyze controller traffic characteristics, followed by adaptive suspicious prevention policies to unknown traffic to cancel NE ingress DoS attacks. In addition, to address the lack of trust between the SDN controller and applications, Isong et al. (2017) presented a proactive trust establishment framework based on OpenFlow, which certifies that applications function securely in performing their intended purpose.

Although distributed SDN controllers can be beneficial, determining their optimal placement on the network can be challenging. According to Suh and Pack (2018), single SDN controller networks inherently exhibit the following limitations: (a) a single-point-of-failure, (b) network size and scope, and (c) as the network size increases, controller-to-switch latency also increases. Qiu et al. (2016) underscored the capacity constraints of single controller architectures, noting a throughput limit of approximately three million flows per second, which is inadequate for large-scale high-volume networks. Lu et al. (2019a) asserted that while distributed SDN controllers can improve network reliability by eliminating the single-point-of-failure of single controller architectures, and also enhance scalability for large-scale networks, deciding their placement can significantly affect performance, revealing a phenomenon known as the controller placement problem. They applied the criteria of latency, reliability, deployment costs, and multi-objective, which involves tradeoffs across performance metrics to assess optimization options for the number of controllers the location of the controllers on the network (Lu et al., 2019a). Suh and Pack (2018) addressed potential controller conflict in multi-controller environments, requiring a single designated master controller to govern workflow rules by devising a low-complexity master assignment algorithm that minimizes controller conflict and setup latency. Similarly, Lu et al. (2019b) explored common access conflicts for SDN multi-controller environments that can cause routing conflicts and flow contentions as the network expands in size and complexity. The developers proposed a multi-branch tree-based conflict detection mechanism for multi-controller environments, demonstrating better efficiency and accuracy than predecessor models (Lu et al., 2019b). In addition, to address an apparent lack of secure communications between distributed controllers in an inter-domain environment, Shang et al. (2018) presented a multi-granularity security architecture that applies two-factor authentication form a secure channel between distributed controllers.

There are also other challenges for SDN that hinders its broad adoption. Researchers Saraswat et al. (2019) identified the following challenges in which SDN technology lacks maturity, and that may affect the growth and development of SDN: (a) network design, which includes increased scalability to support increased loads and new applications, improved hardware and software fault tolerance, flexibility to adapt to future designs, and elasticity which involves dynamic adaptability to changing network loads; (b) network implementation, which entails SDN's integration with existing networks, resource management of flow entries and resource conflict resolution, management of virtualized resources, and resource conflict resolution; (c) network performance, which includes latency, efficiency, consistency, and traffic management; and (d) network verification, which involves testing to validate expected performance before going operational, debugging of faults, and security verification to protect from unauthorized access, misuse, modification, malfunction, destruction, and improper disclosure. Researchers da Costa Cordeiro et al. (2017) raised concerns that despite increased interest, vulnerabilities, to include performance, security, privacy, and trust, exist in programmable data planes. Concerning SDN vehicular network challenges, Mahmood et al. (2019) observed that future architectures for highly dynamic VANETs must process handovers more efficiently to ensure seamless, ubiquitous, and undifferentiated connectivity. Future solutions must also provide enhanced trust management for the communication of safety-critical messages among vehicles, along with improved privacy features, such as location protection privacy (Mahmood et al., 2019). Concerning SDN-IoT challenges, according to Al-Kahtani and Karim (2017), in addition, security challenges of authentication and authorization, data confidentiality, and threat detection, to the current SDN-IoT architecture does not adequately address real-time performance requirements, such as jitter, latency, packet loss, and throughput, of distributed IoT multi-networks. The lack of defined standards for northbound interface communications between the application and the controller leads to interoperability problems (Al-Kahtani & Karim, 2017). Developers Sultana et al. (2018) also asserted that in addition to security vulnerabilities, such as DDoS attacks and forged traffic flows, fundamental challenges exist in how to efficiently process high volume traffic using SDN ML-based intrusion detection systems.

Transition and Summary

In this study, I explored the adoption of SDN in IT cloud service organizations in the United States. I applied the quantitative correlational research methodology to examine the relationship between the IT cloud system integrators' perceptions of the adoption determinants of performance expectancy, effort expectancy, social influence, facilitating conditions, and the intention of the IT cloud system integrators to adopt SDN technology. SDN, which originated just over two decades ago, prescribes an open system architecture and a programmability approach to networking to address traditional networking technologies' limitations. However, challenges persist with SDN technology, affecting behavioral intentions, and stymying its broad adoption.

Section 1 provided critical analysis and synthesis of UTAUT, the theoretical framework for this study, and SDN technology. In founding UTAUT, Venkatesh et al. (2003) sought to provide a unified technology acceptance model by adopting its core determinants of performance expectancy, performance expectancy, social influence, and facilitating conditions from the following eight previous models: TRA, TAM, MM, TPB, C-TAM-TPB, MPCU, IDT, and SCT. UTAUT also incorporated the moderators of gender, age, and voluntariness, which shape user perceptions and, subsequently, behavioral intentions. Using these constructs, the UTAUT model accounted for a substantially greater amount of variance in technology usage intention than the previous models. Venkatesh et al. (2003) argued that although technology expenditures absorb an increasing portion of corporations' budgets, productivity gains depend on user acceptance and use of the technology.

Concerning my critical analysis and synthesis of SDN, Section 1 provided an overview and taxonomy of its architectural framework, use cases by innovators and early adopters, and common challenges facing emerging SDN initiatives. Central tenets of SDN technology include its centralized controller-based management, abstraction interfaces that define the logical interconnectivity between system functions and components, and its use of the OpenFlow protocol, which promotes the programmability of network functions and communication, and NFV, which enhances agility and efficiency. Some of the SDN use cases applied by innovators and early adopters include: (a) AI and ML integration to advance network automation, (b) cloud orchestration for advanced control and optimization of data flows, (c) smart grids that promote energy efficiency, (e) traffic engineering for tuning data flows for enhanced user experience, and (f) IoT network innovations for strengthening traffic controls and enhancing scalability for emerging platforms of mobile networks, wireless sensors, and vehicular networks. Nonetheless, as a technology is still in its infancy, SDN technology faces several significant challenges, with security vulnerabilities that may expose the architecture to cyber-attacks being among the most prevalent. Although single-controller environments inherently pose a single-point-of-failure vulnerability and can present scalability challenges, management control conflicts are commonplace in multi-controller environments.

In Section 2, I took a closer look at the preparation aspects of conducting this study, providing my explanations and projections of why, who, and how. After reiterating the purpose statement, I provided an assessment of the factors that may influence my role as the researcher. I described my sampling population, sampling method, and I justified my planned sampling size. I also explained my strategies for ensuring participant eligibility and for gaining access to them. In addition, I identified and justified my research method and design.

In Section 3, I presented the findings of this study. My analysis included a summary of the critical findings and my detailed analysis of the data in the context of the theoretical framework. I discussed how the results are relevant and applicable for improving professional IT practices. From my conclusions, I provided recommendations for follow-up actions, as well as considerations for disseminating the literature through venues such as conferences and academic journals. I also discussed ways to address the limitations of this study and provided recommendations for future studies. In addition, I discussed the social change implications of this study.

Section 2. The Project

Purpose Statement

The purpose of this quantitative correlational study was to examine the relationship between IT cloud system integrators' perceptions of performance expectancy, effort expectancy, social influence, facilitating conditions, and the intention of IT cloud system integrators to use SDN technology. My dependent variable was IT cloud system integrators' intention to adopt SDN technology, while my independent variables were IT cloud system integrators' perceptions of performance expectancy, effort expectancy, social influence, and facilitating conditions. The target population for this study was IT cloud system integrators at cloud service provider organizations in the United States. In this study, I sought to stimulate dialogue and raise awareness about SDN technology's potential social benefits, such as providing greater automation and network intelligence capabilities for data orchestration of smart cities that may result in enhanced QoE for users, and improved network security may result in fewer service interruptions for users.

Role of the Researcher

The researcher plays a vital role in establishing credibility and trustworthiness in data collection. Unlike qualitative studies in which the researcher is the primary data collection instrument, quantitative studies apply an instrument for data collection to capture participants' perceptions, beliefs, and behavioral intentions (Keisling & Sproles, 2020). Morgan (2018) asserted that in quantitative studies, the researcher generates evidence through a highly structured and closed-ended instruments, such as questionnaires, which increase objectivity while tending to minimize the researcher's personal influence in data collection. However, Morgan (2018) noted that the quantitative researcher decides subjectively what to study and how to conduct it. Suter and Cormier (2016) described bias as a conscious or subconscious deviation that clouds the researcher's objectivity or a systematic difference applied due to preference. Suter and Cormier (2016) recommended that the researcher implement measures to strengthen objectivity and provide transparency, such as (a) minimizing conscious or unconscious preferences through self-awareness and self-skepticism, (b) applying standard assessment frameworks and methods, (c) conducting consultation with subject matter experts during the planning phase to establish the premise and scope of the study, and (d) fostering an environment of openness through clarity of purpose and by disclosing potential conflicts of interest. In addition, Newcomer et al. (2019) emphasized that the researcher should seek to establish scientific integrity by demonstrating transparency and adhering to standard practices.

For transparency, as a network engineer with over 10 years of experience in conventional enterprise networking, I was interested in how the networking industry will address many of today's inefficiencies. For example, from my experience, within a network domain, many end-user nodes apply similar operating system applications and protocols, which are then independently configured on a per-node basis in a time-consuming and often highly proprietary process. I was particularly interested in understanding how adoption determinants affect the behavioral intentions and usage of the next-generation SDN technology, and whether its centralized, open architecture approach presents a viable alternative for some enterprise network use cases. I had no affiliation or relationships with representatives or participants in my targeted population. Therefore, I had no conflicts of interest in conducting a technology study involving cloud providers in the United States.

I also acquired approval to use the UTAUT founder's validated survey instrument (see Appendix C), and I used previously applied scales to ensure the validity of my data collection instrument. Boeren (2018) argued that using questions from previous studies and existing standardized scales increases validity and reliability. In addition, during data collection, I applied the Walden University Institutional Review Board's (IRB's) and *The Belmont Report's* guidelines to ensure adherence to procedural and ethical best practices for research and to communicate my research purpose and scope with clarity.

The Belmont Report (National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research, 1979) provides the research community with ethical guidelines and principles for conducting biomedical and behavioral studies on human subjects. *The Belmont Report* (National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research, 1979) outlines standards for human research based on the following ethical principles: (a) respect for persons, which refers to treating individuals with autonomy and extending protection to individuals with diminished autonomy; (b) beneficence, which refers to respecting the decisions of individuals and protecting their well-being; and (c) justice, which addresses fairness in the distribution of benefits to research recipients and mandates prevention of undue burdens on and the exploitation of research groups. I gained additional awareness about

The Belmont Report and its ethical research guidelines by completing the National Institute of Health's training course for researchers. Appendix A shows my certificate of completion. I was fully committed to upholding the tenets of *The Belmont Report.*

Participants

The participants for this study were cloud system integrators. System integrators are technology specialists who plan, design, implement, and support computer systems and networks for an organization and who may also assist in aligning technology requirements and resources with business objectives (Coronado Mondragon & Coronado Mondragon, 2018). The research question for this study was:

> RQ: What is the relationship between IT cloud system integrators’ perceptions of performance expectancy, effort expectancy, social influence, facilitating conditions, and the intention of IT cloud system integrators to use SDN technology?

Because the cloud system integrators who work at the cloud service provider organizations may possess considerable insight and knowledge about SDN technology usage, they may be ideally postured to characterize how adoption determinants affect behavioral intentions to use the technology. As businesses become more reliant upon technology and technology innovations, they become more dependent on integrators for technology decision-making. Hohpe et al. (2016) described the system integrators’ role as mostly technical in today’s evolving technology landscape, consisting of an array of functions, such as system design, development, and analytics, and with increasing participation in the business aspects of technology decision-making. According to

Farhangi and Konur (2018), the system of systems concept provides system integrators with a tool to manage objective functions and rapid changes in complex technology decision-making. Similarly, van Vliet and Tang (2016) explored how software integrators can leverage design decision processes to uncover the rationale of architecturally significant decisions and to mitigate cognitive bias.

Eligibility requirements in quantitative research consist of shared characteristics that individuals of the target population must possess to participate. To be eligible for this study, participants must have possessed at least 3 months' experience planning, devising, designing, implementing, or supporting SDN technology in the United States. System integrators with such experience were likely to possess valuable insight and perceptions about how the determinants of performance expectancy, effort expectancy, social influence, and facilitating conditions affect their use of SDN technology. Asiamah et al. (2017) stated that member eligibility within the target population delineates a group with certain common characteristics or attributes that satisfy the selection criteria outlined by the researcher. Authors van Dijk et al. (2017) stressed that eligibility criteria in quantitative and semiquantitative studies should be predefined. Also, as emphasized by Toledo-Fernández et al. (2016), eligibility screening is critical in obtaining accurate results. They underscored the importance of prescreening participants for eligibility to ensure the effectiveness of their cognitive functions before testing the effects of substance use disorder (Toledo-Fernández et al., 2016).

To ensure clarity and explicitness, and to establish an environment of trust and openness, my script for establishing communication with subject matter experts and participants included the following components: (a) the purpose of the study, (b) the sponsoring organization as Walden University, (c) eligibility requirements for participants, (d) that the study was voluntary and that a participant could withdraw at any time, (e) that the participants were anonymous, (f) the duration of the study and my process for administering the survey, (g) that there were no costs involved for participants, and (h) that there was no compensation provided to participants.

My target population consisted of cloud system integrators who use SDN technology. Cloud service providers and network providers are typically technology innovators, often located in high-tech areas near large population centers. For example, Zandiatashbar et al. (2019) observed that the high-tech areas of Northern California and Northern Texas tend to produce knowledge exchanges and innovation clustering in transit-accessible locations that form high-tech zones. Similarly, Asheim et al. (2017) explored innovation-inspired economic geography and how organizations and regions create knowledge bases in which collaboration with universities and research centers is commonplace. Likewise, in the manufacturing industry, Doussard et al. (2017) discovered that U.S. regions specialized in innovative manufacturing design also experienced regional job growth in manufacturing.

Also, as most of the organizations in my target population possess large capital expenditures and operating expenditures and span across multiple states, while several are multinational organizations, I suspected that sufficient sampling of SDN adoption would be available. Alenezi et al. (2019) projected substantial initial investment costs for providing cloud-based SDN and NFV infrastructure to support IoT devices, although energy costs would drop over time due to increased efficiency. Poularakis et al. (2019) also assessed from the service provider’s perspective the considerable costs and technical skills required to migrate from traditional networking to SDN. In another example, Anabi et al. (2019) described SDN-based 5G infrastructure as capable of providing enhanced mobile broadband connectivity with ultrareliable, low-latency communications. However, such innovations require sufficiently skilled staff to manage the following Four-C framework of emerging technology challenges: (a) computing, which refers to edge computing optimization; (b) cost, which refers leveraging virtualization to minimize cost; (c) complexity, which refers to the computational requirements to scale for massive 5G antennas systems; and (d) cross-layer, which refers to autonomy for each layer in the network stack (Anabi et al., 2019).

Concerning strategies for finding participants, I searched for participants using social media platforms, such as LinkedIn and also reached out to writers of technology journals, blogs, and periodicals. I also searched for participants by approaching professional technology organizations. After obtaining the prospective participants' contact information, I sent them an invitation to participate from my Walden University email account that outlined the purpose of my study and my ethical research commitment. Rattani and Johns (2017) observed that it is vital to establish purposeful communication during research study recruitment, which helps to build trust. In South Africa, authors Singh and Wassenaar (2016) stressed the importance of maintaining research ethics throughout the recruitment and collaboration process, to include obtaining informed consent before proceeding with collecting data. Vinkenburg (2017) argued that seeking diversity and heterogeneity in research subject representation tends to mitigate potential bias.

I also used SurveyMonkey's research survey panels, called Audience, in my data collection efforts. Audience sent my existing survey to a customized pool of survey panelists who met my study's criteria. Audience protects participants' privacy by prohibiting the collection of personal or sensitive information (SurveyMonkey, n.d.). According to Chandler et al. (2019), survey panels revolutionized data collection for social and behavioral scientists by eliminating the need and time required for researchers to recruit participants themselves, reducing the number of bad actors encountered, and also ridding the challenge of verifying participants' identify when payments are involved. Lowry et al. (2016) compared traditional data collection to online data panels. Their research suggested that the vast Amazon Mechanical Turk data panel provided substantially faster, higher quality, and higher impact results through its capability for a greater degree of screening for criteria such as demographics, geography, and language compared to traditional data collection methods (Lowry et al., 2016). Pedersen and Nielsen (2016) commented that even small compensation amounts to survey panel members tend to spur motivation and increase response rates and the quality of responses.

Research Method and Design

After choosing a research topic, the most critical step for the researcher is selecting the research methodology. The choice of a research methodology necessarily forges a fork-in-the-road decision path for major portions of one's study. Snyder (2019) argued that academic research involves building onto existing knowledge and that one's research purpose, as stated in their research question, should determine the research methodology, whether qualitative, quantitative, or mix-methods. Rutberg and Bouikidis (2018) summarized the fundamental differences in research methodologies. They described qualitative research as exploring an individual's lived experiences and examining the reasoning behind human behavior. Quantitative research, in contrast, involves applying statistical analysis techniques to objective measures such as tests or surveys, while the mixed-methods approach involves strategically combining qualitative and quantitative into one study to create a synergistic effect (Rutberg & Bouikidis, 2018).

After deciding on a research methodology, the next fork-in-the-road decision point involves determining the research design, which defines the type of inquiry and provides a general model for procedures. Rutberg and Bouikidis (2018) described the following types of quantitative research: (a) experimental, which typically involves a laboratory environment and randomized testing of control and experimental groups to determine causal effects; (b) quasi-experimental, which involves nonrandomized testing and may not include a control group to determine causal effects; and (c) nonexperimental, which may involve data collections from pretests and posttests, nonequivalent designs, or interrupted time series design for correlation and comparison analysis of an intervention (Rutberg & Bouikidis, 2018). Among the most prominent nonexperimental research design subcategories is a correlation, which, according to Seeram (2019), facilitates the evaluation of relationships among sampling variables, and provides an inference to the population at large. In this study, I explored the relationship between technology adoption determinants and the behavioral intention of cloud system integrators to use SDN technology to apply the quantitative methodology and the nonexperimental correlational research design.

Research Method

The quantitative methodology was appropriate for this study because it allowed for the production of descriptive and inferential statistics using structured research with minimal bias in addressing the research question. According to Taguchi (2018), the quantitative methodology enables the researcher to employ objective measures, such as surveys and tests, to produce descriptive and inferential statistics using numerical and statistical analysis. The quantitative approach also aligns with the postpositivist philosophy, preferring to use structured research practices to statistically analyze the problem and minimize personal bias (Lenzholzer & Brown, 2016). The researcher's philosophical worldview can also shape the research question. Lenzholzer and Brown (2016) observed that postpositivist researchers in landscape architecture and urban design tend to leverage the quantitative methodology to generate new knowledge in evaluating and testing microclimate design studies and architecture design guides. According to Teo and Yeo (2017), researchers who possess a postpositivist worldview typically apply quantitative methods to compare male and female gender groups' cognitive and affective differences. However, researchers sometimes differ somewhat in their perception about research methodology preferences for postpositivist. For instance, Gamlen and McIntyre (2018) stressed using quantitative measures to assess large-scale general data patterns of social actions.

I did not choose the qualitative method for this study because its purpose was to understand the relationships between the determinants of technology adoption and behavioral intent, rather than seeking to uncover human motivations and lived experiences of the technology's adoption. Constructivist tends to favor the qualitative research approach in which the researcher analyzes the underlying motivation, reasoning, and the "why" dynamics of human behaviors and social experiences to form scientific evidence (Rutberg & Bouikidis, 2018). They also observed that qualitative studies address the social aspects and context of a problem typically not well-understood, employing semi-structured data collection techniques, such as interviews, journal logs, and observations. Sometimes exploratory qualitative research precedes a more narrowly focused quantitative study (Rutberg & Bouikidis, 2018). Reflecting on the absence of a structured boilerplate for the constructivist qualitative researcher, Chandra and Shang (2017), proposed an open-source computer-assisted qualitative data analysis software tool which can enhance rigor, transparency, and validity of qualitative research. They demonstrated the capability to conduct netnography research to study the behavior of members of an online group using computer-mediated observational communications and computer-aided text analysis (Chandra & Shang, 2017). Peck and Mummery (2018) founded the concept of hermeneutics constructivism, aiming to improve the qualitative research approach by providing a deeper and more nuanced understanding of human experiences and placing greater emphasis on the role of language in individual experiences.

I did not choose the mixed-method for this study because its purpose was to understand the relationships between the determinants of technology adoption and the behavioral intent of cloud system integrators to use SDN technology. However, since the purpose of this study did not involve the qualitative component of contextually analyzing lived human and social experiences, the mixed-methods approach would also not be appropriate. The pragmatist researcher typically favors the mixed-methods research approach. Rutberg and Bouikidis (2018), scientists of second language developmental research, summarized the mixed-methods approach as a single study that employs both the quantitative and qualitative research methods from the collection and analysis of two discrete sets of data. The mixed-methods approach involves quantitative statistical measurements and underlying social and contextual details of the research question (Rutberg & Bouikidis, 2018). Taguchi (2018) argued that the mixed-method approach's effectiveness requires strategic alignment with the quantitative and qualitative components in a complementary manner and provides a purposeful and systematic approach to addressing the research question. Using two different philosophical and methodological research orientations, the mixed-methods approach can produce better and stronger inferences from the collected data (Taguchi, 2018). According to Hathcoat and Meixner (2017), pragmatism places high importance on the inquiry at hand and allots themselves a plurality of methods to address the research question. They asserted that pragmatism tends to apply all available resources in pursuit of the desired outcome, and is thereby philosophically attuned to the mixed-methods approach to research (Hathcoat & Meixner, 2017). Shannon-Baker (2016) suggested that pragmatism seeks to balance research objectivity and subjectivity, clarity in the research question, and transferability, which refers to the potential to apply knowledge gained to other settings.

Research Design

I chose the nonexperimental correlational research design to measure and describe the degree of association or relatedness between the variables and to make inferences about the population at large from sampling data. Seeram (2019) described the nonexperimental correlational design as a research process that enables the investigator to statistically examine the extent to which two or more variables may be related and to make predictions based on the discoveries. Scatter plot diagrams are useful in depicting correlations. The correlation coefficient ranges from +1 to -1, with a positive correlation reflecting the degree of similarity, a negative correlation reflecting the degree of dissimilarity, and a coefficient of 0 indicating the absence of a relationship (Seeram, 2019). Müller and Daller (2019) applied a correlational test to reveal significant correlations between the effectiveness of the English Test International English System test and a general English proficiency test for academic topics (0.509 and 0.381, respectively) and clinical topics (0.302 and 0.417, respectively) for international students applying for nursing registration purposes, although the cost of the general test was substantially lower. Also, researchers Fırat and Köksal (2017) used the nonexperimental correlational design to investigate the association between the use of online technologies, such as Web 2.0 utilities and biotechnology literacy. The results indicated that prospective science teachers' knowledge in biotechnology was insufficient and that factors such as increased time on the internet and the increased frequency of using Web

2.0 technology tools, such as wiki, blogs, social networks, and instant messaging, improved literacy (Fırat & Köksal, 2017).

I did not choose the experimental design because this study did not involve determining causation using an intervention of randomized testing of experimental and control groups in a laboratory environment. Obitube et al. (2020) applied the experimental design to assess the effectiveness of using an eclectic language learning method called total physical response (TPR) compared to the traditional audio-lingual method to learn the West African language Igbo as a second language. Using a control group of students (n = 50) and an experimental group of students (n = 50) and independent sample t-tests at .05 significance level, Obitube et al. (2020) determined that students using TPR generally outperformed the audio-lingual method in learning Igbo. Samii (2016) explored a quantitative experimental concept called causal empiricism, which emphasizes research design in pursuit of causal identification to establish that conditions exist to draw an unbiased conclusion from the data results. In addition, Samii (2016) commented that identifying conditions for causal effects might involve random assignment, conditional random assignment, and discontinuous assignment of the treatment variables to characterize specifically effected subpopulations. Mallick et al. (2017) surveyed the best practices for experimental designs to address the challenges related to determining disease causation in microbiome molecular epidemiology and in profiling human microbiome. In their search for a possible linkage between microbial data types and human health, they also sought computational and statistical methods that would efficiently integrate and analyze multivariant microbiome multi-omics data.

Microbial relates to the characteristics of microorganisms, and especially of disease-causing bacterium (Mallick et al., 2017).

I did not choose the quasi-experimental design because this study did not involve determining causation using an intervention and nonrandomized control and experimental groups, collected through pretests and posttests, nonequivalent designs, or interrupted time-series design. George et al. (2017) used the quantitative quasi-experimental design to compare a transformational clinical education model called dedicated education unit (DEU), which empowers the nurse and the nurse educator to share their expertise with the student to a greater degree, to the tradition clinical education (TCE) model. In a nonrandomized setting of baccalaureate program nursing students (N = 193) in which students were assigned to either the DEU or TCE group, the DEU students demonstrated significantly better pre-clinical and post-clinical self-efficacy scores than the TCE group.

In a similar study, Miller et al. (2018) conducted a quasi-experimental design assessment of baccalaureate nursing program students (N = 78) at two Midwestern universities using pretest and posttest measures to compare the scaffolded-based writing approach to the traditional writing method. The teacher first demonstrated the correct technique using the scaffolded-based approach, which was the intervention variable, and then repeated the process using the traditional writing method, which was the comparison variable. According to Miller et al. (2018), in evaluating pretest and posttest writing competency, although no significant difference existed on the Holistic scale (p = 0.024), the intervention group outperformed the comparison group on the Trait scale (p = 0.004).

Béné et al. (2020) applied the quasi-experimental design in Sahel, Niger, where concerns about recurrent droughts and other weather events often impede residents' ability in overcoming the next traumatic event, to evaluate the effects of a nonrandom resilience intervention initiative that targeted specific households, and that spanned over three years. The intended long-term impact of resilience intervention was to improve the well-being of individuals and communities plagued by environmental stressors and shock. The survey of control (*n* = 812) and treatment households (*n* = 686) indicated a significant effect on recipients' ability to recover from a shock event, but no significant difference in the overall well-being between the control and treatment households (Béné et al., 2020).

Population and Sampling

In the population and sampling phase of scientific research, the researcher identifies the phenomena's common characteristics of interest and determines the criteria and methods for collecting data. The population of a study consisted of a defined group from which the phenomena of interest may exist, and the researcher is interested in conducting data collection and analysis (Martinez-Mesa et al., 2016). Sampling involves using scientific techniques to select a representative portion of the population for data collection and analysis because it is typically impractical to collect and analyze data from the entire population of interest (Gamlen & McIntyre, 2018).

Population

The population for this study was cloud system integrators. According to Coronado Mondragon and Coronado Mondragon (2018), a system integrator plays an integral role in the adoption of new technology systems. The system integrator considers the organization's business objectives and other factors, such as available resources, and ensures interoperability and modularity of infrastructure components, extending across hardware and software boundaries (Coronado Mondragon & Coronado Mondragon, 2018).

The cloud component relates to service providers, as many cloud service providers have integrated SDN as a critical component of their infrastructure. According to Malik et al. (2017), with the proliferation of cloud-hosting platforms, such as infrastructure-as-a-service, platform-as-a-service, and software-as-a-service, a growing number of cloud service providers and DC hosting environments worldwide have integrated OpenStack's SDN network-as-a-service technology. Using a Microsoft Azure testbed, the researchers evaluated SDN performance, such as mean-time-between-failure, VM-spawning time, and VM launch failure rate, in a cloud-hosting environment (Malik et al., 2017). Mayoral et al. (2017) argued that SDN enables the efficient integration of cloud computing services and network management, control, and orchestration through programmability, which lends to greater adaption and precise handling of traffic demands. Researchers Yang et al. (2017) promoted an SDN-based cross stratum optimization solution for DCs upon observing challenges that conventional networks face in orchestrating large-scale and increasingly complex cloud services and DC requirements.

The increasing use of SDN and NFV technologies by service providers also makes them ideal for sampling for this study. Barakabitze et al. (2020) described a concept called softwarization, which enables service providers to leverage the programmability aspects SDN and NFV technology to construct service-tailored logical zones or slices to support unique QoS and QoE requirements, such as IoT, smartphone, and autonomous vehicle applications. According to Zhang et al. (2020), a growing number of service providers have integrated SDN and NFV to improve DC energy efficiency. The centralized management and programmability aspects of SDN, combined with the flexibility of NFV's virtual network functions, promote granular control of resources in a multidomain environment, and increased energy efficiency.

Conversely, Aydeger et al. (2019b) proposed a concept called moving target defense that applies SDN and NFV technology to thwart off network attacks in service provider environments, while also facilitating forensic investigations. In addition, Qafzezi et al. (2020) described SDN as an enabling technology from which system integrators and service providers and can integrate VANETs and intelligent transportation systems with cloud, fog, and edge computing to improve traffic safety, intercommunications, and responsiveness. The preceding examples suggest that system integrators in cloud and service provider environments would understand the intricacies of SDN integration. Thus, cloud system integrators would be an ideal population for querying about the determinants that affect SDN adoption, and thereby aligning with this study's research question, "What is the relationship between IT cloud system integrators' perceptions of performance expectancy, effort expectancy, social influence, facilitating conditions, and the intention of IT cloud system integrators to use SDN technology?"

Sampling

In this study, I applied nonprobabilistic purposive sampling. I based my sampling on my selective judgment in which my predefined criteria determine the eligibility of the participants of interest, rather than random selection. According to Hasani et al. (2019), the two general sampling method groups are nonprobabilistic and probabilistic. Nonprobabilistic sampling, also referred to as convenience sampling, involves a nonrandom engineered judgment in which some population units have a zero percent chance of selection, probabilistic sampling consists of random selection and each unit in the population has a non-zero percent chance of selection, and is therefore suited for generalization (Hasani et al., 2019).

Lu and Franklin (2018), who promoted a proxy selection protocol to overcome low response rates and to avoid contaminating the target population, asserted that one of the strengths of nonprobabilistic sampling is that it can be effective when conducting exploratory research, such as to determine whether an assumed problem exists. In addition, Sakshaug et al. (2019) observed that other advantages of the nonprobabilistic sampling method are that it is typically considerably less costly, less time-consuming, and more convenient than probability sampling. Hasani et al. (2019) commented that the nonprobabilistic sampling method provides only limited generalizability, and is therefore inferior to probability sampling. In addition, Lu and Franklin (2018) stated that because nonprobabilistic sampling involves subjective judgment, it is also subject to sampling bias.

Under the purposive subcategory of nonprobabilistic sampling, the participants are selected based on specific and subjective criteria. The criteria for the participants in this study consisted of the following: (a) participants must work in an SDN system integrator role and (b) participants must have at least three months’ experience working with SDN technology in the United States. Gheorghe et al. (2019) used nonprobabilistic purposive sampling to achieve the desired socio-demographics for their study on Romanian university students' intentions to adopt a pro-environmental behavior regarding single bottled-water usage. They defined participants' criteria as active student status, with a mean age of 20, and with Romanian nationality (Gheorghe et al., 2019). Serra et al. (2018) conducted nonprobabilistic purposive sampling to study the urban context of 77 state-sector secondary schools in Liverpool, England based on criteria derived from contextual characterization methods, such as local spatial associations and morphological descriptions, that allow for the selection of a specific combination of social and physical characteristics.

According to Serra et al. (2018), purposive sampling is advantageous in quantitative settings involving small populations, while it is also the most widely used nonprobabilistic method. Another advantage of purposive sampling is that it enables the selection of very specific cases, and thereby maximizing the probability of analyzing the phenomenon of interest (Serra et al., 2018). Similarly, Bhardwaj (2019) remarked that the selected participants in purposive sampling will be knowledgeable about the subject at hand, and will therefore likely provide more timely survey responses than other methods. Concerning the disadvantages of purposive sampling, Bhardwaj (2019) raised concerns about sampling bias, representativeness, and variability due to the subjective nature of the selection criteria. Another disadvantage of purposive sampling is that it lacks generalizability beyond the immediate sample.

Determining the appropriate sample size is a critical aspect of data collections. Cunningham and Gardner (2007) described the sample size as a function of the alpha level, beta level, and effect size. Chander (2017) argued that determining the sample size establishes the power and impact of the study. While an oversized sample could trigger ethical concerns, such as concerns about inflating the statistics to induce bias, causing undue exposure to participants, and consuming unnecessary time and resources and, an undersized sample may result in inconclusive findings and can negate the study's effectiveness (Chander, 2017). O'Neill et al. (2020) observed that as the sample size decreases, the item calibration, which enables the estimation of unanswered responses through the pooling items onto the same scale, also becomes less stable and less precise.

The confidence level of a sample reflects the expected percentage for which the entire population, if surveyed, would model the results of the sample. The confidence interval, on the other hand, indicates the margin of error in calculating the confidence level. Perdices (2018) remarked that the *p*-value reflects the probability of obtaining the results of the extreme value if the null hypothesis is true. Accordingly, a *p*-value of 0.05 indicates that if the null hypothesis were true, a sample result of this extreme would occur only 5% of the time (Perdices, 2018). However, the effect size reflects the extent to which the observed data differs from the posited null hypothesis, thereby indicating the intervention's degree of effectiveness (Perdices, 2018).

The researcher can adjust the alpha and beta threshold levels to guard against false-positives and false-negatives. According to Cunningham and Gardner (2007), the alpha level in statistical hypothesis testing reflects the minimum threshold for rejecting the null hypothesis. For instance, the typical minimum significance level of $p = 0.05$ indicates the probability of making a Type I (alpha) false-positive error of rejecting the null hypothesis when it is true (Cunningham & Gardner, 2007). They observed that although decreasing the significance level to $p = 0.01$ reduces Type I errors, the added granularity increases the risks of producing Type II (beta) false-negative errors, where a false null hypothesis is not rejected (Cunningham & Gardner, 2007).

Y.-J. Chen et al. (2017) argued that 0.05 is an acceptable significance level for decision-making in hypothesis testing, while 0.01 provides substantially greater accuracy when needed. According to Faul et al. (2009), G*Power allows for the calculation of any of the four parameters—alpha, beta, sample size, and effect size—derived as a function of the other three. The power of a test results from $1 – \beta$ (Faul et al., 2009). Cohen provided the following effect size scale, which has since been well-established in the scientific community for regression and other testing: 0.10 is small, 0.30 is medium, and 0.50 is large (Cohen, 1988, as cited in Correll et al., 2020).

G*Power is a statistical software package used to conduct an a priori sample size analysis (Faul et al., 2009). Using G*Power version 3.1.9.7 software, I performed a power analysis to determine this study's appropriate sample size, as illustrated in Figure D1. An a priori power analysis, assuming a medium effect size ($f = .15$), $\alpha = 0.05$, indicated a minimum sample size of 84 participants is required to achieve a power of

0.80. Increasing the sample size to 173 will increase power to 0.99. Therefore, I sought between 84 and 173 participants for this study, as depicted in Figure D1.

The use of a medium effect size (f = 0.15) is appropriate for this proposed study. The medium effect size was based on the analysis of three articles where objective web interactivity, the impact of conscientiousness on predicting college grades, and emotional stability as a predictor of leadership emergence were the outcome measurements. Yang and Shen (2018) applied a medium effect size (0.145) to measure objective web interactivity, compared to perceived web interactivity, which was more pronounced and reflected a large effect size (0.386). Noftle and Robins (2007) found that college students' conscientiousness indicated a medium effect size (0.26) impact on their grades, and was more significant than the factors of extraversion, agreeableness, neuroticism, and openness, each of which reflected small effect sizes. In addition, Ensari et al. (2011) discovered that emotional stability reflected a medium effect size (0.12) for predicting leadership emergence, while agreeableness indicated a small and negligible effect size (0.001), and creativity reflected a large effect size (0.36).

Ethical Research

Ethical research involves the professional code of conduct and behavior expected by researchers to ensure the protection of research subjects. I applied established ethical research standards and best practices to protect participants from harm and risks, while also safeguarding their confidentiality. According to Friesen et al. (2017), the Belmont Report sets forth ethical principles and guidelines for research involving human beings based on the following tenets: (a) respect for persons, which includes informed consent; (b) beneficence, which entails an obligation to protect participants from harm by minimizing risks while maximizing the benefits of research; and (c) justice, which refers to ethically balancing the potential benefits and burdens of research. Biros (2018) argued that ethical research requires balancing the society's need for scientific advancements and the protection of human subjects as outlined in the Belmont Report. Burr and Gibson (2018) maintained that the ethical review and informed consent processes strengthen the ethical application of scientific research, while also improving research repeatability and predictability.

Employing ethical research best practices, I first looked to establish transparency with prospective participants through an invitation to participate email. The bottom of the email contained a link to proceed to the online survey. The survey begins with an informed consent form, which must be agreed to proceed to the survey. Connors et al. (2019) stressed that the researcher's transparency in the informed consent process could boost the study's acceptance and increase data collection opportunities.

I applied intrinsic motivation tactics by explaining that the incentive for participation in this study involved the opportunity to assist in advancing the understanding of SDN technology, which could lead to advancements in data flow orchestration, network management, and in developing the automation of network and cloud services. Scholtz and Mlozo-Banda (2019), who investigated non-monetary incentives for participants of crowdsensing research, recommended the use of intrinsic motivational factors, such as participants' self-efficacy, interest, and enjoyment, when there are no monetary rewards associated with the study.

On my consent form, I stated that SurveyMonkey provided certain rewards or incentives for Audience survey panel participants and that additional incentive rewards were prohibited. Otherwise, there is no compensation or rewards for participants who complete this survey. According to Lowry et al. (2016), survey panels offer a nontraditional approach for data collection in which compensation to participants tends to promote more meaningful and honest responses than coerced uncompensated participants. Pedersen and Nielsen (2016) suggested that even low-cost incentives tend to improve participants' response rates. On the other hand, in an anonymous survey that explored volunteerability, Haski-Leventhal et al. (2018) found that among the strongest motivations for volunteering without monetary rewards were to exhibit positive societal behaviors.

I informed prospective participants that they had the right to decline or withdraw their participation at any time by simply notifying me of their decision. Ripley et al. (2018) reasoned that the informed consent process allows the potential participant to weigh the benefits of participating in a research study against the risks to make an informed choice. They described the ethical research code of conduct as consisting of the following components for which the researcher should inform participants: (a) the purpose and procedures involved, (b) their right to decline or withdraw, (c) the consequences for declining or withdrawing, (d) potential risks or discomfort, (e) incentives for participating, and (f) the researcher's contact information (Ripley et al., 2018).

I explained that candidates should possess at least three months' experience working in an SDN system integrator or system integrator role in the United States to be eligible to participate. According to Bowen et al. (2017), establishing eligibility criteria for members of the target population is often the key to improving the relevance to the research topic, the procedures used in the study, and the interpretation of the study's outcome.

I explained that this study, approved by Walden University's IRB oversight committee, employed strict confidentiality and privacy guidelines, maintaining anonymity for participants and their organizations. Willis et al. (2016) underscored how the IRB plays a critical role in reviewing and authorizing the researcher's data collection, dissemination, and storage procedures, and ensuring ethical compliance concerning participants' privacy and confidentiality.

This survey entails collecting participant's perceptions about non-sensitive and non-threatening technology adoption questions. I informed participants that the survey involved a questionnaire consisting of multiple-choice sections that range from "I completely agree" to "I completely disagree," and is expected to take 10–15 minutes to complete. Dam et al. (2018) applied a Likert scale survey to determine the extent to which factors, such as internal gratification, self-efficacy, and social motives influenced respondents' adoption intention and use of a mobile fitness app. From the results, the researchers established a linkage between the technology's adoption and usage and individual psychological factors and motivations (Dam et al., 2018). I included sample questions on my invitation to participate email. Knepp (2018) argued that inserting sample questions increase the respondent's interactiveness and reading of the consent form.

I informed participants that the survey tool was SurveyMonkey, which provides online efficiency and allows anonymous participant responses. The web-based SurveyMonkey data collection tool offers an anonymous survey option, which disassociates respondents' personally identifiable information, making the survey results anonymous (Eugene, 2012).

I established an informed consent form. Brehaut et al. (2009) stressed that informed consent documents should be readable, accurate, thorough, and easily accessible to the research ethics boards. I included onto the informed consent form my Walden University email address for participants' questions about the study and Walden University's Research Participant Advocate contact information for general inquiries. In Section 8.02(a) of the Ethical Principles of Psychologists and Code of Conduct, the American Psychological Association (2002) prescribed that the researcher includes on the informed consent form references that participants can contact for research questions or questions about participant's rights.

To ensure continued confidentiality protection for participants and organizations, I am storing the data collected in this study for five years in an encrypted and password-protected medium stored offline. After such time, I will destroy the medium. According to Goyal (2016), the Bitlocker disk encryption technology enables users to protect sensitive data by applying a trusted platform module authentication process and encrypting selected Microsoft Windows operating system drives. Walden University's IRB approval number for this research study is 12-02-20-0743529.

Instrumentation

I applied the UTAUT instrument developed and validated by Venkatesh et al. (2003). I obtained permission to use the UTAUT instrument in this study from the authors, shown in Appendix C. The UTAUT instrument assesses technology adoption by measuring the following core constructs: (a) performance expectancy, which refers to the degree to which an individual perceives that the system will help them achieve job performance gains; (b) effort expectancy, which refers to the degree to which an individual believes that the system is easy to use; (c) social influence, which refers to the degree to which an individual perceives that others important to them expect them to use the system; (d) facilitating conditions, which refers to the degree to which an individual believes that an organizational and technical infrastructure exists to support their use of the system; and (e) behavioral intention, which refers to an individual's aim to use the system within a certain period (Venkatesh et al., 2003).

Table E1 shows the questions for each of the constructs used for measuring the perceptions of the respondents. Venkatesh et al. (2003) described performance expectancy as the degree to which an individual perceives that the system will help them attain improved job performance. There are four instrument questions related to performance expectancy that ask the respondent to rate their perception of the system's degree of usefulness to their job performance, work tasks, productivity, and its usefulness towards increasing their chances for getting a pay raise. According to Venkatesh et al.

(2003), effort expectancy refers to the degree of ease associated with using the system. There are four effort expectancy questions, which focus on the user's interaction with the system, and ask the respondent to rate their perception about the clarity of their interaction with the system, the ease of using, operating, and becoming skillful using the system. Social influence refers to the extent to which the user perceives that others important to them think that they should use the system (Venkatesh et al., 2003). There are four social influence questions that ask the respondent to rate their perception of the expectations of important others for using the system, to include the opinion of important and influential people, and senior management and the organization in general.

Venkatesh et al. (2003) defined facilitating conditions as the degree to which the user perceives that the organizational and technical infrastructure accommodates their use of the system. There are four facilitating condition instrument questions, which ask the respondent rate their perception about the availability of resources and support for using the system, and assess the accessibility of resources and assistance to support their use of the system. According to Venkatesh et al. (2003), behavioral intention refers to the extent to which the user aims to use the system, given their formed perceptions. There are three behavioral intention instrument questions that ask respondents to rate their plan and intention to use the system within a period of time.

In this study, I applied the ordinal scale for each independent variable and the interval scale for the dependent variable. Ordinal data involves the ranking of items and relies on nonparametric statistical measurements that do not require normal distribution (Liddell & Kruschke, 2018). The choice of ordinal or interval for Likert scale data determines which data analysis options are available. According to Willits et al. (2016), statistical analysis of Likert scale ordinal data requires measurement by ranking, such as medians, ranges, rank correlations, and other nonparametric techniques. Chyung et al. (2017) asserted that ordinal data has rank-ordered characteristics with ratings that often reflecting good, neutral, and poor, and that researchers should use the median or mode to determine the central tendency for ordinal data, and category responses should be summarized in terms of frequencies or percentages. On the other hand, Sullivan and Artino (2013) argued that questions based on interval data, such as time, in a normal distribution, allow for the interval scale. Similarly, Norman (2010) suggested that numerically-based rating questions and mark grading of equal increments quality as interval selection can determine if data is interval or ordinal. Chyung et al. (2017) argued that interval refers to a variable used for measurements along an equidistance scale and that a defined mid-point of neutral allows for the interval categorization. I did not choose the nominal scale because nominal items are categorical and are not intrinsically ordered or arithmetically computable, which is insufficient for my data analysis requirements. I did not choose the ratio scale because, like the interval scale, the ratio scale is a continuous metrics-based variable, except that the value zero means the absence of an instance of a variable, which is inappropriate for my study.

The UTAUT model was appropriate for this study to explore the determinants that influence behavioral intentions for the adoption of SDN technology. According to Venkatesh et al. (2003), UTAUT consolidates, refines, and empirically validates the most effective components from eight previous technology adoption models. Venkatesh et al.

(2016) stated that the UTAUT model, which is well-established and used extensively in IT research, explained 77% of the variance in behavioral intention to use technology. Kaye et al. (2020) also observed that by incorporating other renowned theoretical models, UTAUT presents a very useful framework for assessing technology adoption.

I administered the instrument using the web-based SurveyMonkey tool. SurveyMonkey allows the user to email survey questions anonymously to participants (Eugene, 2012). Mahmud et al. (2018) used SurveyMonkey to create an anonymous survey to identify barriers to physician participation in clinical trials. Evans and Mathur (2018) described the increased use and acceptance of online surveys, including SurveyMonkey in marketing and the research community. Also, Tams et al. (2020) used an anonymous SurveyMonkey survey to explore the phenomenon of increased worker stress in the age of ubiquitous mobile technologies.

Concerning the meaning and calculation of the scores, this study applied the 7-point Likert scale selection choices for each instrument question. The scale levels have the following meaning: 1—strongly agree, 2—agree, 3—somewhat agree, 4—neither agree nor disagree 5—somewhat disagree, 6—disagree, and 7—strongly agree. The levels record the extent to which the respondent agrees or disagrees with the question. Liddell and Kruschke (2018) observed that Likert scale ordinal data typically reflects a discrete order of qualitative characteristics used to score the respondent's perception or opinion. The levels often range from strongly agree to strongly disagree, while the intervals between levels are not equal (Liddell & Kruschke, 2018).

Score calculations are determined by the treatment of the cumulative scores for each survey question and the type of coding applied. For the ordinal variables, which were the adoption determinants in this study, I used SPSS to calculate the central tendency and other statistical calculations based on the median average of the scores to each question. According to Willits et al. (2016), statistical analysis of Likert scale ordinal data requires measurement by ranking, such as medians, ranges, and rank correlations. Chyung et al. (2017) asserted that researchers should use the median or mode to determine the central tendency for ordinal data, and category responses should be summarized in terms of frequencies or percentages. Ordinal data involves the ranking of items and relies on nonparametric statistical measurements based on the median, which do not require normal distribution (Liddell & Kruschke, 2018). For the interval variable, which was the dependent variable in this study, I used SPSS to calculate the central tendency and other statistical calculations based on the mean average of the scores to each question and the standard deviations. Sullivan and Artino (2013) explained that interval data allow the use of mean for central tendency calculation and robust continuous-based parametric tests. Norman (2010) also noted that central tendency calculations for interval data are based on the mean average and allow for parametric tests.

Researchers have applied the UTAUT model to assess the determinants of technology adoption in a wide variety of applications. Madigan et al. (2017) used the UTAUT model to investigate the factors influencing users' [N = 315] acceptance of an automated road transportation system called CityMobil2 in Trikala, Greece, in search of alternative transportation solutions in European urban centers. Ye et al. (2020) applied the UTAUT model to analyze the factors that affect the adoption of mobility-as-a-service (MaaS), a technology that provides real-time linkage of travel preferences and service resources. They studied the MaaS adoption behaviors of travelers [*N* = 600] in Anting New Town, China, located near Shanghai (Ye et al., 2020). In addition, Hoque and Sorwar (2017) used a UTAUT-based framework to explore the factors influencing mobile health adoption by elderly populations in developing countries. They surveyed participants [*N* = 274] age 60 and older in Bangladesh, Bangladesh, where they discovered that technology anxiety and resistance to change were among the significant factors affecting behavioral intention (Hoque & Sorwar, 2017).

Researchers have also applied the 7-point Likert scale in a broad range of use cases. Patil et al. (2020) applied the 7-point Likert scale to explore the determinants that influence adoption behaviors of a mobile payment system in India based on a modified framework of UTAUT. Bawack and Kala Kamdjoug (2018) used a UTAUT-based instrument with a 7-point Likert scale to measure the extent to which clinicians adopted a modern health information system in developing countries, including Cameroon, Africa. Similarly, Šumak and Šorgo (2016) applied the 7-point Likert scale to their UTAUT-based study to understand the factors that motivate primary, secondary, and university teachers in Slovenia to use interactive whiteboard technology.

The founders of the UTAUT model conducted and published the findings of their extensive testing to ensure its reliability. According to Braun et al. (2019), internal consistency reliability (ICR) assesses test items' effectiveness in measuring the same construct. Cronbach's coefficient alpha test can be used to check ICR, where alpha values of .70 to .95 are considered acceptable (Braun et al., 2019). Venkatesh et al. (2003) performed ICR assessments for each of UTAUT's constructs. They achieved ICR ratings greater than .70 for each of UTAUT's seven direct determinants of intention measured across three separate testing periods [$N = 215$]. The UTAUT model underwent substantial PLS testing. According to van Riel et al. (2017), PLS is a multivariant predictive technique that uses latent factors to explain a portion of the covariance between the independent and dependent, and then uses regression to predict the value of the dependent variable by decomposing the independent variable. Venkatesh et al. (2003) re-estimated the model after dropping reverse-coded items that indicated weak factor loading scores. They also applied the PLS modeling using the bootstrapping method to ensure the reliability and validity of the UTAUT instrument. According to Cronbach and Meehl (1955), reliability involves the quality and consistency of a measurement procedure in data collection and is a prerequisite to validity.

The developers of the UTAUT instrument also conducted and published the findings of their exhaustive validity testing. Venkatesh et al. (2003) confirmed the existence of convergent and divergent validity. Castilla-Earls and Fulcher-Rood (2018) described convergent validity as an assessment of whether a correlation exists between a measure and other measures of a similar construct. On the other hand, divergent validity evaluates whether a correlation does not exist with measures of a different construct (Castilla-Earls & Fulcher-Rood, 2018). Venkatesh et al. (2003) demonstrated that the average variance extracted values of the shared variance between the constructs and their measurement values were higher than the correlations across constructs. Content validity refers to the extent to which the elements within the measurement procedure are relevant and represent the construct that will be measured (Cronbach & Meehl, 1955). Ringle et al. (2020) also noted that measurement loadings represent standardized path weights associated with indicator variables and that the minimum recommended threshold for well-fitted loading is .70. According to Venkatesh et al. (2003), they achieved content validity by using only the loading items with values of .70 or higher, reflecting the most robust theoretical representation and fit of the constructs' underpinnings.

The UTAUT model assessments also established the existence of concurrent validity and criterion validity. Vencato et al. (2017) observed that cross-validation strengthens concurrent validity, assessing a new test's performance compared to an established test. Venkatesh et al. (2003) also performed cross-validation testing by first applying the original data from four organizations, followed by ingesting new data from two different organizations. In addition, the PLS regression test used in substantiating the UTAUT instrument assesses criterion validity in which the measure under assessment compares to established measures. Caronni et al. (2018) applied PLS regression to affirm criterion validity by demonstrating that instrument time up and go test tuning parameters are the best predictors of balance as measured by a clinical balancing scale.

Concerning data stewardship, researchers have an ethical obligation to maintain stewardship over research data and ensure its accessibility. The raw data for this study is being stored on an offline and password protected medium for five years, per Walden University IRB guidelines. I will make the raw data available upon request within the 5-

year period. Peng (2018) described data stewardship as the activities that lend to data usability, accessibility, and preservation. New mandates outlined in statues that include the US Information Quality Act and Office of Science and Technology Policy guidelines for open data, data sharing, and scientific integrity elevate the requirement for organizations to provide oversight of data stewardship for federally funded digital scientific data (Peng, 2018). To ensure the trustworthiness of scientific data, Peng et al. (2018), proposed a systematic and holistic enterprise framework to support new data stewardship directives imposed by US federal regulators. Leveraging the industry's best practices, the researchers constructed a quantitative evaluation process to assess how organizations manage data stewardship activities and compliance requirements (Peng et al., 2018). From a broader perspective, Boeckhout et al. (2018) discussed a new European Union framework for data stewardship called findability, accessibility, interoperability, and reusability (FAIR). Many European research policy-makers promote the guiding principles of FAIR as a cornerstone for research stewardship in life science (Boeckhout et al., 2018).

Concerning validity strategies, validity assesses the accuracy of a measure. Cronbach and Meehl (1955) described the following types of validity: (a) construct validity, referred to as an overarching concept for assessing the soundness of the measurement procedure of interest; (b) content validity, which refers to the extent to which elements within a measurement procedure are pertinent and characteristic of the construct to be measured; (c) concurrent validity, which is also a type of criterion validity and refers to leveraging an existing and established measurement procedure to create a new measurement procedure; and (d) predictive validity, which is a subcategory of criterion validity and assesses whether a measurement procedure can be used to make projection; and (Cronbach & Meehl, 1955). Castilla-Earls and Fulcher-Rood (2018) observed that convergent validity indicates consistency across two different measurement procedures. In contrast, divergent validity strengthens construct validity by demonstrating that the construct of interest is different from the contemplated constructs (Castilla-Earls & Fulcher-Rood, 2018).

Concerning reliability strategies, reliability assesses the consistency of a measure. In scientific research, reliability involves the extent to which the quality of the measurement procedure is stable and constant, indicating its repeatability (Mohajan, 2017). In light of that, threats to reliability are the factors that produce instability and unstableness to the measurement procedure. The uncertainty in the precision of the measurement procedure reflects its degree or amount of errors. Mohajan (2017) argued that one of the strategies for producing quality research involves minimizing the following errors that affect reliability: (a) Type I, which is a false-positive indicating statistical significance in a finding when it does not exist; (b) Type II, which is a false-negative that incorrectly indicates the absence of statistical significance when a discovery is significant; (c) Type III, which results in the rejection of the null hypothesis for an inappropriate reason; and Type IV, which results in the incorrect interpretation of a rightly rejected null hypothesis.

Validity strategies involve establishing that the measure achieves its intended outcome. According to Drew and Robert (2003), the researcher establishes construct validity by demonstrating a correlational pattern of the construct with other associated measures. Construct validity involves working through many procedures to assess validity, such as the threats to validity, appropriateness of the elements, confidence in the procedures, and whether the scores make accurate predictions (Morgado et al., 2017). Applying the predicted and obtained correlation effect size estimates can be applied to help in quantifying estimates for construct validity (Drew & Robert, 2003). Establishing sound operational definitions that ensure relevance and representativeness is a prerequisite for establishing content validity (Vencato et al., 2017). The study's purpose, the theoretical basis of the study, and the appropriateness of the elements should be considered. Multidimensional constructs, such as motivation, are complex and require thoughtful consideration to achieve appropriate context and content, and eliminate ambiguity (Vencato et al., 2017). Concerning strategies for concurrent validity, which assesses the correlation of a measurement procedure with a previously validated procedure, the researchers should ensure that the new procedure follows the established procedure within a short time period. Concurrent validity is ideal for providing fast data validation, such as processing personal attributes, but less suitable for more complex constructs, such as future performance assessments (Mohajan, 2017). Concerning predictive validity, strategies should consider the theoretical foundation from which the measurement procedure is based. The measurement procedure's theory indicates how the scores might predict the construct (Drost, 2011). Also, the new measurement procedure should be conducted for a longer period following the established procedure.

I made only the slightest modification to the UTAUT instrument. I assigned a value of 12 for the instrument's three behavioral intention questions that contain a placeholder and that end with the phrase, "in the next <n> months." Modification to a validated instrument can induce bias, threatening its validity. Jain et al. (2016) asserted that changes to a validated questionnaire could introduce bias and affect accuracy, requiring revalidation. Mohajan (2017) suggested that researcher bias can trigger instrumentation errors and invalid scores. In addition, Morgado et al. (2017) observed that shortcoming in the instrument development process can result in psychometric limitations and the lack of a robust demonstration of construct validity.

Data Collection Technique

Restating my research question, "What is the relationship between IT cloud system integrators' perceptions of performance expectancy, effort expectancy, social influence, facilitating conditions, and the intention of IT cloud system integrators to use SDN technology?" I used the survey technique, a self-reporting data collection instrument. Boeren (2018) described the quantitative survey as a method of collecting facts to analyze and quantify trends related to a phenomenon. She asserted that the survey instrument, which is typically a predetermined questionnaire, must provide clarity in content and context, minimizing ambiguity (Boeren, 2018). According to Schweitzer-Krah and Engartner (2019), the quantitative survey design enables the researcher to conduct explorative and empirical research of a representative sample group using a questionnaire to collect data, such as perceptions, behaviors, and trends, about a subject for statistical analysis. In addition, Kelley-Quon (2018) stipulated that the analytical survey design includes the following elements: (a) applies hypotheses to assess the relationships among the study's constructs, (b) applies a questionnaire and scale to collect data from respondents, (c) the survey questions must be crafted in an objective, and bias-free manner, (d) the survey questions should focus on capturing respondents' perceptions, behaviors, and trends of the phenomenon, (e) the data is self-reported by respondents, and (f) the data collected allows for numerical analysis.

To ensure efficiency for my data collection technique, I used the online survey delivery method, although the online also presents some disadvantages compared to conventional delivery methods. According to Lallukka et al. (2020), although participant response rates tended to be slightly lower, online health surveys are more cost-effective and less time-consuming than traditional mail-in surveys. Similarly, according to Kılınç and Fırat (2017), academicians using online surveys encountered lower return rates and decreased external validity than face-to-face surveys; however, online surveys facilitated faster data collection, more efficient processing, and were more effective in collecting sensitive data than the face-to-face method. Liu et al. (2017) explored acquiescent response style, which refers to the tendency to select "Yes" or agree responses, and extreme response style, which refers to the tendency to choose endpoint responses, in a comparison between a web-based and face-to-face survey approach. While web-based survey respondents were not constrained by time and indicated fewer anonymity concerns, face-to-face respondents reflected more acquiescent response styles and extreme response styles than their web counterparts (Liu et al., 2017). Also, Lux et al. (2017) conducted an online survey to determine preferred medications used by hospice care physicians for palliative sedation. Palliative sedation refers to medication that lowers patients' consciousness to reduce their awareness of an acute illness (Lux et al., 2017).

Concerning the advantages of the survey technique of data collection, Rutberg and Bouikidis (2018) observed that the survey questionnaire enables the researcher to control the study's constructs, research questions, and delivery environment. Keisling and Sproles (2020) noted that online surveys are considerably less costly than traditional data collection methods while also facilitating more efficient workflows. Sakshaug et al. (2019) noted that increasingly organizations choose nonprobabilistic sampling over probabilistic sampling because of its cost advantages. According to Morgan (2018), the closed-ended and predetermined nature of quantitative survey questions minimizes researcher bias. Serra et al. (2018) asserted that by applying participant qualification criteria, the purposive survey maximizes the chances of observing and analyzing the phenomenon of interest. Evans and Mathur (2018) described web-based surveys' programming logic as capable of forced-answer screening, requiring the respondent to confirm that they meet the study's eligibility criteria and that they agree with the study's informed consent posture. In addition, Ball (2019) commented that because online surveys do not require on-demand responses, they are more convenient and often preferred to respondents' interactive methods of data collection.

Concerning disadvantages of the survey method of data collection, Taguchi (2018) noted that closed-ended quantitative surveys are inflexible, lacking the capability to investigate the "how" and "what" questions about a phenomenon, and also lacking the ability to capture and characterize experiences, the context of the problem, or its social impact. Due to variances in participants' interpretation of questions, surveys tend to reflect lower validity than interactive collection methods where additional clarity can be provided (Taguchi, 2018). Morgado et al. (2017) argued that the self-reporting aspects of surveys tend to increase the chances of participant bias and social desirability bias. Social desirability bias means that participants tend to project a favorable image to others, and especially when using a multi-item scale. Also, according to Morgado et al. (2017), the cross-sectional methodology presents the following limitations: there is no capability to establish causal relationships, and measuring variables that change over time can be problematic.

This study's survey involves nonprobabilistic purposive sampling, and therefore has limitations for generalizability. Hasani et al. (2019) described nonprobabilistic sampling as convenience sampling, involving nonrandom sample selections. Purposive is a subcategory of nonprobabilistic sampling, where participants are selected based on specific and subjective criteria and are only generalizable to the immediately sampled population (Gheorghe et al., 2019). Evans and Mathur (2018) asserted that many people are reluctant to participate in online surveys due to concerns about data privacy and data security. In addition, Morgado et al. (2017) noted that web-based surveys are more prone to encountering nonresponse bias than traditional in-person or interview surveys. Nonresponse bias occurs when participants are demographically or attitudinally different than members of the population that did not respond to the survey (Morgado et al., 2017).

Data Analysis

My research question is: “What is the relationship between IT cloud system integrators’ perceptions of performance expectancy, effort expectancy, social influence, facilitating conditions, and the intention of IT cloud system integrators to use SDN technology?”

My hypotheses were:

H_0: There is no significant relationship between IT cloud system integrators’ perceptions of performance expectancy, effort expectancy, social influence, facilitating conditions, and the intention of IT cloud system integrators to use SDN technology.

H_1: There is a significant relationship between IT cloud system integrators’ perceptions of performance expectancy, effort expectancy, social influence, facilitating conditions, and the intention of IT cloud system integrators to use SDN technology.

The prerequisite for selecting the appropriate data analysis tests was first to examine the type of questions and the scale for each variable. Because this study’s independent variable (performance expectancy, effort expectancy, social influence, and facilitating conditions) questions ranked the extent of participant’s perception, I coded them as ordinal data because they capture respondents' perceptions and attitudes. Omilla (2019) stated that ordinal is appropriate for ranking attitude responses. According to Chyung et al. (2017), the ordinal scale allows for the rating of variable performance perceptions and attitudes, and the distance between categories is unknown. In addition, Wu and Leung (2017) described the ordinal data as order-preserving categorical data, but with no standard scale that indicates the difference between scores.

In contrast, because this study's dependent variable (behavioral intention) questions associated a factor of time (<n> months) into the scale, I coded behavioral intention as interval data. Sullivan and Artino (2013) argued that interval data allows for parametric tests, which are more robust and more accurate than ordinal-based nonparametric tests. They further maintained that the following use cases allow for the coding of Likert scale questions as interval data: (a) when normally distributed and (b) in cases where an interval factor, such as time, is weighted into the question. Norman (2010) argued that it is appropriate to treat Likert scale questions that consist of numerical values across many items as interval data, enabling the use of parametric tests that are more robust but require a normal distribution. According to Casper et al. (2020), constructing survey question scales with equal interval properties reduce measurement errors and improve the study's reliability, while also allowing for interval scale coding. In addition, Chyung et al. (2017) reasoned that odd-numbered Likert scales that treat the midpoint as neutral, neither agreeing nor disagreeing, can be coded as interval data.

Multiple Regression Analysis

Upon considering the research question for this study, which seeks to determine if a relationship exists between adoption variables and behavioral intention, along with the type of data collected and the associated scales, the most appropriate statistical test was the multiple regression test. Multiple regression analysis allows the researcher to use the value of two or more independent or predictor variables to predict the value of the dependent or outcome variable. Seminal authors Cohen et al. (2003) defined multiple regression analysis as a behavioral science statistical process ideal for testing hypotheses and predicting the relationship between the independent variables, called factors of interest, and the dependent variable referred to as the outcome variable. Multiple regression analysis seeks to account for all meaningful systematic variation in the dependent variable *Y* (Cohen et al., 2003). Young et al. (2020) described multiple linear regression as a statistical process the performs the following functions: (a) forecasts new values for the dependent variable, based on the independent variables and (b) determine the extent of variation of the dependent variable, given the independent variables. They applied the multiple linear regression analysis to forecast how the collective effect of predictor variables, including the institution's ranked size and stage of a standardized maturity scale, affects the maturity of user experience practice in academic libraries, which is the outcome variable. Olsen et al. (2020) employed multiple linear regression analysis to predict which factors influence students' performance on the Pharmacy Curriculum Outcomes Assessment. They observed that linear regression is an extension of Pearson's correlation, also known as Pearson's *r*, and that while correlation assesses whether two variables are associated, multiple regression analysis, reflected by the coefficient of determination "R^2" indicates the proportion of the variance in the dependent variable that is predictable from the independent variable (Olsen et al., 2020). In addition, Cohen et al. (2003) noted that although the dependent variable in multiple regression should be continuous (interval or ratio), the independent variables can be categorical (ordinal or nominal).

Other statistical tests were not appropriate for this study. The *t* tests were not suitable for this study because they provide group comparison analyses of categorical predictors between two groups, or between the same group at different intervals. This study involved the linear regression analysis of a single group in one instance. In comparing the sample mean of categorical predictors, the *t* test would not address whether a relationship exists between the independent and dependent variables, as stated in this study's research question. Guo and Yuan (2017) observed that while the two-sample *t* tests involve comparing two independent samples, the paired *t* test compares the mean of the same group at different times. The two-way ANOVA was also not appropriate for this study because it provides group comparison analyses of categorical predictors between two independent variables called factors. On the other hand, this study involved the linear regression analysis of a single group in one instance. Also, in comparing the mean difference of categorical predictors between groups and the degree of interaction between independent variables, the two-way ANOVA also would not address whether a relationship exists between the independent variables and the dependent variable of a single group, as stated in this study’s research question. Weissgerber et al. (2018) described the two-way ANOVA as variability assessments of two independent variables' interactions on the dependent variable of two or more independent groups.

Assumptions

There are several assumptions to consider for the multiple regression analysis tests. Statistical assumptions consist of data characteristics requirements for valid statistical analysis.

Variable Scales. The dependent variable should be continuous, using either the interval or ratio scale (Cohen et al., 2003). There should be two or more independent variables, either continuous or categorical (Cohen et al., 2003).

Homoscedasticity. The data should reflect homoscedasticity. Homoscedasticity refers to maintaining similar variances in the noise of the error term disturbances for the predictor variable along the regression line. The researcher can use scatterplot diagrams to evaluate homoscedasticity (Cohen et al., 2003).

Multicollinearity. The data should not indicate multicollinearity. Multicollinearity refers to predictors correlated with other predictors, such that a predictor variable produces one or more predictor variables. Correlation values of 0.8, 0.9, or higher between the predictor variables indicates the likely existence multicollinearity overlap (Kim, 2019).

Independence of Observation. The independence of observations should be maintained. The independence of observations means that the occurrence of one observation provides no information about the occurrence of another observation, and is thus independently assessed. The Durbin-Watson statistics test checks for the independence of observations (Dutcă et al., 2018).

Linearity. There should be a linear relationship between the dependent variable and each independent variable, and also the dependent variable and independent variables collectively. Scatterplot diagrams can assess linear relationships between variables (Cohen et al., 2003).

Normal Distribution. There should be no significant outliers, formed by excessively high or low data points that do not fit with the other data (Cohen et al., 2003). Also, residual errors should exhibit a normal distribution. The errors in prediction, also called residual errors, should model the Gaussian distribution bell curve. Most observations should cluster around the central peak and dissipate equally in both directions, moving away from the central point. A histogram with plotted residuals overlaid with a normal curve with the same mean and standard deviation, and the Q-Q plot, can assess the normality of residuals (Cohen et al., 2003).

Mitigating Assumption Violations

As needed, I applied existing statistical methods to mitigate the effects of violations of the following data characteristics: homoscedasticity, multicollinearity, independence of observation, linearity, and normal distribution. Although options exist for the variable scale's assumption, there are no mitigation for violations. Multiple linear regression model requires a continuous dependent variable, while the independent variable can be either categorical or continuous to perform valid statistical analysis (Cohen et al., 2003).

Homoscedasticity. Regarding violations of homoscedasticity, according to Cohen et al. (2003), mitigation treatment can be performed using weighted least squared regression, which minimizes disturbances using down-weights or transformation of the dependent variable.

Multicollinearity. Excessive multicollinearity violations increase the variance of the regression coefficients, making them unstable and difficult to interpret. Approaches for treating multicollinearity violations may involve: (a) revising the regression model, (b) collection of additional data, (c) ridge regression by inserting a constant to each independent variable, or (d) principal component regression, which refers to regressing the dependent variable on independent dimensions, rather than using the original set of predictor variables (Cohen et al., 2003).

Independence of Observation. Excessive violations of independence of observation can reflect a poorly fit model and can be checked using the Durbin-Watson statistical test (Cohen et al., 2003).

Linearity. Regarding treatments for linearity violations, according to Cohen et al. (2003), power transformations are effective in single-bend cases, while the Box-Cox and Box-Tidwell procedures can linearize more sophisticated violations.

Normal Distribution. Concerning outlier violations, mitigation actions may include the deletion of the anomalous data, the transformation of the data, or the recalibration of the regression model (Cohen et al., 2003). Cohen et al. (2003) stated that remedies for normality violations might include forming an initial linear relationship between *X* and *Y* when not correctly specified or specify a linear regression equation that conforms to a theoretically mathematical relationship.

Data Cleaning

The data cleaning process entails detecting and removing incomplete, invalid, duplicate entries, or improperly formatted. I leveraged the capabilities of the web-based SurveyMonkey tool to provide data cleaning. By enabling logic that requires respondents to answer each survey question before moving to the next question, my data collection process virtually eliminated the chances of receiving incomplete data. Disabling the option for multiple survey submissions ensured that the survey can be taken only once from the same device. The use of a drop-down menu selection scale ensured that responses are within a valid selection range. Evans and Mathur (2018) argued that online surveys provide significant advantages over previous data collection survey methods, such as preventing the omitting of questions through the forced-response option, controlling respondents' selections, and providing the researcher with greater control and flexibility over survey administration. Ball (2019) commented that the advent of the online survey promotes automation and processing efficiency, which reduces data entry errors and formatting complications, thus rending many aspects of data cleaning and data coding obsolete. Liu et al. (2017) also indicated that web-based Likert scale surveys produce higher quality data collection than traditional methods, thus reducing data collection discrepancies and data cleaning requirements. In addition, Eugene (2012) described how SurveyMonkey’s web page programming logic enables the researcher to design the survey for optimal data collection efficiency.

Data Screening

Data screening improves the quality and trustworthiness of data. I conducted data screening in the following ways: (a) by applying unobtrusive method, such explanatory data analysis for detecting low-quality data, which refers to monitoring participants’ response patterns for anomalies and (b) by applying the statistical TwoStep Cluster Analysis to assess similarities between two clusters in searching for outliers and Principal Component Analysis to screen for duplicates that would produce low-quality data.

Pryjmachuk and Richards (2007) described data cleaning as a necessary pre-analysis audit process for examining raw data to ensure data integrity and enable the researcher to become acquainted with the data. For data screening, they recommended that researchers consider exploratory data analysis methods such as scatterplots, boxplots, stem-and-leaf plots, and histograms to understand the general shape of the distribution and identify outliers and potential assumption violations (Pryjmachuk & Richards, 2007). DeSimone and Harms (2018) emphasized that low-quality data manifested in discrepancies such as self-reporting indicators, bogus items, response variability, and longstring, which refers to the marking of consecutive items the same way, can distort hypothesis testing and statistical results.

Missing Data

Missing data in research reduces the sample's representativeness and can distort inferences about the population. Since this study's questions are technology adoption-related derived from the UTAUT instrument and are not threatening or sensitive, I opted to require the respondent to answer each question. This process ensured that the returned survey do not have missing data. Some findings suggest that requiring respondents to answer each question may improve participation. Dolnicar (2018) found that forced answer surveys improved the reliability of results. Albaum et al. (2010) found no evidence that suggests that forced-answer surveys had lower completion rates. In addition, Tangmanee and Niruttinanon (2019) tested the following three forced answer categories: 100% forced-answer questions, 50% forced-answer questions, and 0% forced-answer questions. Their findings indicated that the participation rate improved as the percentage of forced-responses increased (Tangmanee & Niruttinanon, 2019).

There are three general categories for classifying missing data. According to Lang and Little (2018), missingness is generally classified into the following three categories: (a) missing at random (MAR), which can be predicted by the observed components of other data in the dataset, but not the missing components; (b) missing completely at random (MCAR), where missingness is independent of observed data and missing data; and (c) missing not at random (MNAR), where missingness is dependent upon unobserved component and is not predictable by observed components. Curley et al. (2019) observed that an MCAR case could occur if the respondent unintentionally omitted a survey question related to a variable. A MAR instance could arise if the respondent skipped a question about income, but completed questions about employment status, education level, and experience. On the other hand, an MNAR case could occur if the researcher sought to determine income level, but the respondent did not answer questions about employment status, education level, and experience (Curley et al., 2019).

One of the conventional methods for handling missing survey data is through deletion. According to Curley et al. (2019), the most popular missing data deletion method is listwise, where the researcher removes the entire response record if there is an omitted or incomplete survey item. Recent studies indicate that researchers in education and psychology employed listwise deletion in over 90% of the missing data cases (Curley et al., 2019). Although listwise may result in the loss of valuable data, it is easy to apply, and is ideal for MCAR and occasionally MAR. Shi et al. (2020) described the pairwise deletion method as a missing data handling process that applies all available cases in its polychoric correlation matrix to mitigate data loss. While pairwise can be an effective solution for MCAR, undue bias can occur when analyzing MAR cases (Shi et al., 2020).

Another method of handling missing data is substitution through imputation. Stavseth et al. (2019) concluded that some imputation methods are more effective for continuous data, while others are more effective for categorical data, considering the number of variables and the number of categories. Single imputation mean value replacement, according to Curley et al. (2019), is ideal for MCAR, but may distort the relationship between variables. Single imputation regression can be used for MCAR and MAR but misrepresents uncertainty of estimates. Curley et al. (2019) noted that the multiple imputation method, which produces multiple versions of the imputed data set, accounts for the uncertainty induced by data imputation and provides better missing data estimates for MCAR and MAR.

Data inconsistencies can also arise from other events. According to DeSimone and Harms (2018), the researcher should be watchful for potential content nonresponsivity, which refers to responses from participants who may have provided random answers to the survey without regard to the questions. Also, content-response faking, which refers to responses from participants who may have an ulterior motive for their responses besides the survey's intended purpose, can distort data analysis (DeSimone & Harms, 2018). Allen et al. (2016) applied Principal Component Analysis to screen for duplicate data, which they cautioned is especially a concern for data collection environments, such as surveys that involve self-reporting. According to Ortiz and

Bluyssen (2018), the TwoStep Cluster Analysis test allows for the analysis of dissimilarities of categorical and continuous variables simultaneously. After using a questionnaire to collecting data, they applied the TwoStep Cluster Analysis technique to distinguish between occupants' energy consumption patterns (Ortiz & Bluyssen, 2018).

Interpreting Inferential Statistics

Inferential statistics enable the researcher to make generalizations in describing the population of interest from a data sample. Since inferential statistics include a degree of uncertainty, I used the following statistical parameters to provide a scientific basis for explaining my findings' characteristics and values: confidence intervals, probability values, effect sizes, and odds ratios.

Calculating Confidence Intervals

I used observed sample data to compute the confidence intervals, which involved approximating upper limit and lower limit probability values to estimate uncertainty. Lee (2016) explained that a confidence interval computation reflects the magnitude of the effect, and uses the point estimate of the mean and the standard error of the mean. A 95% confidence interval of the sample mean indicates that in repeated tests from the same population, 95% of the results would match the population mean results. In a normal distribution, upper limit and lower limit probability values, which represent the degree of uncertainty on either side, indicate a value of 2.5% in this example (Lee, 2016). Stated succinctly, Hofmann and Meyer-Nieberg (2018) explained that the confidence interval suggests that if drawn indefinitely from random population samples, 95% would produce the same value, while 5%, representing the uncertainty probability value, would not.

Miller and Ulrich (2016) described the statistical confidence interval as a random probability interval facilitating the interpreting of the observed sample values and the predicted population values.

Calculating Effect Size

I used observed data from the sample to calculate the effect size, thus reflecting how the predictor variables affect the outcome variable using the commonly accepted reference scale of 0.10, 0.30, and 0.50 to indicate small, medium, or large effect size. Lee (2016) described the effect size as a standardized method for measuring the effect treatment's magnitude, expressed in terms of the mean difference between two groups. The effect size of 0.10 reflects a small effect, and 0.30 indicates a medium effect, while 0.50 suggests a large effect size (Lee., 2016). According to Hofmann and Meyer-Nieberg (2018), the effect size is the preferred method to characterize how sample results diverge from the expectations specified in the null hypothesis. Marshall and Jonker (2011) observed that the effect size provides more accuracy about the degree of an effect than the *P* value, which can be misleading for excessively large or small sample sizes. The effect size represents the amplitude effect of the hypothesized outcome (Marshall & Jonker, 2011).

I did not use odd ratios in this study, since odd ratios are experimental assessments comparing the outcomes of a treatment group and a controlled group. This study was nonexperimental, involving a single group. Hoppe et al. (2017) described odds ratios as a statistical method for comparing the outcome of a group given a treatment and a group's outcome without a treatment.

Statistical Software

I used the IBM SPSS Statistics Version 25 software in this study. Astivia and Zumbo (2019) explained how they used SPSS for analyzing Ordinary Least Squared Regression assumptions, including assessments for homoscedasticity variance. Awanto et al. (2020) used SPSS to perform regression analysis in their UTAUT study and survey to determine how technology determinants affect user intention and user behavior. Also, Bala (2016) noted the broad usage and impact of SPSS in social science research and experimentation, and its extensive applications for descriptive and inferential statistics.

Study Validity

Validity in scientific research weighs the state of assurance as to whether the research design and methods are sound and capable of producing accurate and plausible results. Statistical conclusion validity assesses whether one can reasonably conclude the existence or nonexistence of a statistical relationship between research variables. Seminal author Straub (1989) defined statistical conclusion validity as an examination of the mathematical relationship between variables and the likelihood that the assessment accurately portrays the true covariation. Factors such as sample size, reliability of measures, and statistical power are critical components to conclusion validity that, when insufficient or inappropriate, could lead to Type I (false positive) and Type II (false negative) errors (Straub, 1989). Mentzer and Flint (1997) argued that the attainment of statistical conclusion validity depends on the following factors: (a) the measurements must allow for sufficient precision, control, and sensitivity to draw a conclusion about the covariation, (b) the evidence must substantiate the existence of covariance, and (c) the strength of the evidence must establish assurance that a covariant relationship exists.

Statistical conclusion validity threats are the factors that could lead to incorrect conclusions concerning research findings. One of the threats to conclusion validity is an insufficiently low power rating (Straub, 1989). I looked to avoid the threat of low statistical power by using G*Power analysis to plan my study's intended power rating between .80 to .99. Straub (1989) described statistical power as the probability that the rejection of the null hypothesis was correct and considered findings with a power rating of less .80 as nonsignificant. Anderson and Maxwell (2017) observed that a standard benchmark for intended power is .80 to .90. In addition, Arend and Schäfer (2019) recommended that researchers target a power rating of .80 or higher to ensure statistical significance.

Another statistical conclusion validity threat is assumption violations. Drost (2011) stated that research assumption violations could lead to erroneous findings. Having identified the multiple regression assumptions and mitigative actions for violations, I was prepared to take steps, as needed, to ensure validity. For example, for homoscedasticity violations, I applied weight least squared regression using down-weights to transform the dependent variable or apply the Cox-Box transformation procedure. For normal distribution violations, I looked to achieve normality through data transformation of outliers or deletion of anomalous data. For violations of the independence of observation, I applied the Durbin-Watson statistical procedure to resolve spatial series and time-ordered discrepancies. According to Schmidt and Finan (2018), linear regression studies commonly apply transformation procedures to raw data to ensure normality conformance, thereby enabling an unbiased representation of estimated standard errors, confidence intervals, and *P* values. Celik and Erar (2017) observed that Cox-Box transformation is a common technique for correcting heteroscedasticity anomalies in multiple regression studies. In addition, Cohen et al. (2003) found that the mathematical transformation-based Durbin-Watson statistic procedure will resolve many ordered-time and spatial series independence of observation discrepancies.

Another statistical conclusion validity threat is low reliability of measure. Higgins and Straub (2006) asserted that low-reliability measurements might inflate the error variance and lead to Type II errors, suggesting no statistical difference between groups when a substantial difference exists. Straub (1989) stated that using a validated instrument is a critical aspect of statistical conclusion validity. I applied the validated UTAUT instrument in this study, which has undergone extensive reliability and validity testing and provided a framework for a reliable outcome. Venkatesh et al. (2003) empirically validated the UTAUT instrument, achieving ICR values of .70 or higher for the instrument's constructs. Taber (2018) observed that researchers commonly hold IRC thresholds of .70 or greater as acceptable in affective domain studies that use surveys to measure attributes, such as attitudes and motivation. Furthermore, according to Mohajan (2017), an ICR score of .70 or higher is the generally accepted standard for confirming that the instrument is reliable in measuring the constructs as intended.

Also, to facilitate the reliability of measure and to promote fine-grained measurement outcomes, in this study I applied the 7-point Likert scale selection options ranging from strongly agree to strongly disagree for each question. Boeren (2018) argued that using a standardized psychometric scale enables survey participants to express the extent of their agreement, disagreement, or neutrality with a survey question, and improves the interpretation and validation of the findings. Renshaw (2018) applied the 7-point Likert scale to capture behavioral characteristics in academic efficacy, academic satisfaction, school correctness, and collegiate gratitude of Southwestern United States college students. Also, according to Morgado et al. (2017), scales with many items tend to exhibit higher reliability than shorter scales, which can compromise the instrument's reliability.

External validity assesses how the researcher can make predictions about the broader population based on the sample findings. Reiss (2019) described external validity as an extrapolation process to determine what populations, settings, and variables the sample’s effect can be generalized. Reio (2016) explained that while experimental research establishes cause and effect relationships, nonexperimental research evaluates whether, through sampling, inferences about the population can be made. Nonexperimental research, which tends to be most useful during the early stages of research, focuses on determining whether linkage exists between the variables and to what extent, and does not involve manipulating the independent variables by the researcher (Reio, 2016). Reio (2016) cautioned that although nonexperimental designs, such as surveys, are useful for measuring and predicting how determinants affect perceptions, attitudes, and behaviors, experimental research is needed to demonstrate causation.

The reliability of the instrument is a critical aspect of generalizability. Higgins and Straub (2006) argued that the findings' relevance depends on the trustworthiness and validity of the measurement instrument used to generate knowledge. Moreover, instrumentation flaws threaten internal, as well as external validity (Higgins & Straub, 2006).

Using the empirically-validated UTAUT instrument in this study established one of the key pillars needed to generalize findings. Boeren (2018) underscored how the researcher enhances their research findings' reliability and validity by adopting a previously applied and validated instrument. To address the scarcity of reliable research about the potential benefits of students studying abroad, Streitwieser et al. (2019) developed and validated a survey instrument, which leverages psychometric best practices. In addition, Latif and Sajjad (2018) analyzed 43 corporate social responsibility survey instruments for psychometric validity due to stakeholders' perceptions of its elusiveness and vagueness among business organizations. Before selecting a preference, they evaluated each instrument's psychometric strength by conducting the following assessments: internal consistency and reliability, content validity, convergent validity, and discriminant validity (Latif & Sajjad, 2018).

The absence of assumption violations fosters generalizability. Higgins and Straub (2006) observed that when the researcher avoids assumption violations, it strengthens their case that the findings will be generalizable to the broader population. According to Rebar et al. (2019), inferences made about the population at large in linear regression studies are more meaningful and provide more precision when they are free of assumption violations, while unmet assumptions dilute generalization inferences at varying degrees depending on the extent of the violations. Also, Schmidt and Finan (2018) argued that adherence to the normality assumption in linear regressions promotes unbiased standard error estimates, although violations of normality in large samples are often not noticeable enough to affect the overall findings.

The sample size also affects the preciseness of generalizability. Show-Li and Shieh (2019) asserted that model adequacy, which includes sample size and statistical power computations, and validity justify a regression model's usefulness to make predictions about relationships between variables. In their multiple regression analysis studies, Show-Li and Shieh (2019) proposed a formula that applies random regression settings for calculating sample sizes and statistical power, improving the precision of confidence intervals and strengthening the statistical inferences of regression coefficients. Many research studies suggest that inappropriate sample sizes could lead to Type I or Type II errors. Vergouwe et al. (2005) noted that excessively small sample sizes could lead to Type II errors, indicating statistical insignificance when considerable differences exist, resulting in an incorrect generalization about the population. In extensive regression analysis testing of predictive accuracy models, Kirpich et al. (2018) found that excessive sample sizes tended to increase Type I errors, inversely influencing generalization effectiveness.

Transition and Summary

Section 2 provided details about the data collection and data analysis plans for this study. The researcher plays a central role in determining the data collection instrument and establishing the procedures and parameters. The Belmont Report provided the foundation for ethical research of human subjects based on respect for persons, beneficence, and justice. To ensure research transparency, I provided a synopsis of my background and interest in conducting a study on SDN technology adoption.

In this study, I applied the quantitative methodology and the nonexperimental research design. Regarding sampling, I applied nonprobabilistic sampling, which entailed nonrandom selection judgment in which some units of the population have a zero percent chance of selection. The sampling was also purposive, using subjection criteria to identify prospective participants. The sample size impacts the power of the study, with an undersized sample losing precision and an oversized sample potentially raising ethical concerns about statistics inflation. The confidence level reflects the expected percentages for the entire population, while the effect size stipulates the strength of the relation between two variables. Statistical power analysis enables the researcher to determine the smallest suitable sample size given a specified significance level. I used the G*Power statistical software package to estimate the desired sample size (84–173), based on a stated effect size, alpha (false-positive), and beta (false-negative) threshold levels.

In this study, I applied ethical research standards established in the Belmont Report and Walden University's IRB oversight to protect participants from harm and risks, while also safeguarding their confidentiality. I provided an informed consent form to each prospective participant that includes the following components: (a) background information, including the purpose of the study, (b) survey procedures and sample questions, (c) the voluntary nature of the study, (d) risks and benefits, (e) assurance of privacy and confidentiality, and (f) contact information for questions. Per IRB data stewardship guidelines, I will store this study's data for five years in an offline, encrypted, and password-protected medium, and I will destroy the data after this period.

Regarding instrumentation, I obtained permission to use the empirically-validated UTAUT instrument, as shown in Appendix C. The survey questions for the core constructs, which are performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention, are listed in Appendix E. In this study, I applied the well-vetted 7-point Likert scale, ranging from strongly agree to strongly disagree for each question. Venkatesh et al. (2003) performed extensive ICR assessments for each of UTAUT's constructs, achieving scores of greater than .70 for each as shown in Table 3. They also demonstrated convergent, divergent, concurrent, and criterion validity for the UTAUT instrument (Venkatesh et al., 2003).

Table 3

Unified Theory of Acceptance and Use of Technology Internal Consistency Reliability Summary (N = 215)

Variable	ICR T1	ICR T2	ICR T3
Performance expectancy	0.92	0.91	0.91
Effort expectancy	0.91	0.90	0.94
Social influence	0.88	0.94	0.92
Facilitating conditions	0.87	0.83	0.85
Behavioral intention	0.92	0.90	0.90

Note: (*N* = 215). Adapted from "User Acceptance of Information Technology: Toward a unified view," by V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, 2003, MIS Quarterly, 27(3), p. 458 (https://doi.org/10.2307/30036540).T1, T2, and T1 reflect the time intervals post-training, three months after training, and six months after training, respectively, from which the scores were captured. The variables represent the subset of UTAUT variables used in this study.

For data collection technique, I used the web-based SurveyMonkey data collection application to collect the needed data to quantify the relationship between technology determinants and behavioral intention. The online survey technique provided efficiencies, such as more cost-efficient and requires less time, than traditional survey methods.

Concerning data analysis, I applied the ordinal scale for the independent variables and the interval scale for the dependent variable. I applied the ordinal scale to capture respondents' perceptions and attitudes for the following constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. The interval scale was be used for the behavioral intention construct, where the survey questions include the interval factor time, and enables the use of multiple regression statistical tests. The assumptions for multiple regression include the following: (a) dependent variable should be continuous and independent variables can be either continuous or categorical, (b) homoscedasticity, (c) avoidance of multicollinearity, (d) independence of observation, (e) linear relationship between the dependent variable and each independent variable, and (f) no significant outliers. Inferential statistics empower the researcher to make generalizations about the population of interest from a data sample. I used the IBM SPSS Statistics Version 25 software for data analysis.

Regarding data validity, statistical conclusion validity weighs whether one can reasonably conclude the existence or nonexistence of a statistical relationship between constructs. Statistical conclusion validity threats consist of the factors that could lead to incorrect conclusions, including a deficiently low power rating, assumption violations, and low reliability of measure. In this study, I looked to guard against low power ratings by using G*Power analysis to identify acceptable statistical boundaries beforehand. I used the validated UTAUT instrument, which has undergone extensive reliability and validity testing and provided a framework to produce a reliable outcome. By pre-identifying the assumptions for multiple regression, I mitigated against potential assumption discrepancies. External validity assesses whether the sample findings are generalizable to the broader population. Critical aspects of this study that fostered generalizability include: (a) the empirically-validated UTAUT instrument, (b) mitigation of assumption violations through transformation techniques, as needed, and (c) optimization of the sample size through pre-calculations that identify the suitable upper and lower boundaries.

Looking ahead, Section 3 explores the presentation of findings. I provided a deep-dive analysis on the following components: (a) statistical tests and the association of variables and hypotheses, (b) descriptive statistics, (c) statistical assumptions, (d) inferential statistics, (e) illustrative statistical tables and figures, (f) research question summaries, and (g) theoretical framework confirmation, disconfirmation, or knowledge extension. I analyzed potential applications of my findings and how my discoveries may be applied in improving professional IT practices. I also examined the potential implications for social change. I provided my considerations for disseminating the results and identified recommended areas for future research. In conclusion, I presented a synopsis of my DIT journey and concluding thoughts.

Section 3. Application for Professional Practice and Implications for Social Change

Introduction

The purpose of this quantitative correlational study was to examine the relationship between IT cloud system integrators' perceptions of performance expectancy, effort expectancy, social influence, facilitating conditions, and the intention of IT cloud system integrators to use SDN technology.

I used G*Power version 3.1.9.7 to calculate the desired sample size ranging from 84, with a power rating of .80, to 173, with a power rating of .99. My sample size of SDN cloud system integrators in this study was $N = 167$, achieving a power rating of .986 (98.6%). Participants were from SurveyMonkey's Audience survey panel and respondents to my solicitation postings. In this study, I applied a medium effect size ($f = 0.15$), which indicates the magnitude of the expected effect for which the predictor variables influence the outcome variable. An alpha level of .05 was also applied, representing the minimum false-positive threshold for rejecting a null hypothesis.

This analysis also yielded a confidence interval of .95, suggesting that repeated tests from the same population would produce the same results 95% of the time. The results indicated that while there was no significant relationship between performance expectancy and effort expectancy and the intention of SDN integrators to use SDN technology, both social influence and facilitating conditions revealed strong statistical significance.

Presentation of Findings

In my presentation of findings, I discussed the multiple regression assumptions for this study and the data characteristic requirements for valid statistical analysis. I presented descriptive statistics that summarize the dataset and its variables. I presented inferential statistics from which I drew conclusions from the sample data and generalize the population from which it was drawn. I also discussed the findings in the context of the theoretical framework. In addition, I provided answers to my research question.

Descriptive Statistics

This study consisted of 234 responses, with 67 being deleted during the data cleaning and data screening processes, leaving 167 responses for analysis. Because each question included forced-answer logic, there were no missing values. Of the 67 (29% of total) responses that were deleted, 30 (13% of total) were found to be outliers or had substantial inconsistencies and were removed. Gamo et al. (2019) observed that SPSS casewise diagnostics that reveal standard residuals of 3.0 or greater represent outliers and should be candidates for exclusion. Padron-Hidalgo et al. (2020) described Cook's distance as a technique to identify the extreme points or outliers in the independent variables. In addition, Józsa and Morgan (2017) recommended applying an iterative process to filter out highly inconsistent responses. I used SPSS' casewise diagnostics and Cook's distance to identify outliers, which were then removed.

Also, 37 (16% of total) of the responses were straight-line answers and were discarded. According to Kim et al. (2019b), survey straight-lined responses, where a participant's responses are identical or close to identical, deteriorate reliability and validity and reduce data quality. After data screening, I received 164 usable responses from SurveyMonkey's Audience and three of my survey solicitations, totaling 167 usable responses. For data normalization purposes, I also reverse-coded the responses to the negatively-connotated Survey Question 15 (facilitating conditions variable) because the other questions associated with facilitating conditions were positively-connotated. Józsa and Morgan (2017) observed that negatively oriented survey questions should be reverse-ordered if the other variable questions are positively oriented. Table 4 summarizes descriptive statistics for this study's multiple linear regression, including bootstrap 95% estimates.

Table 4

Means and Standard Deviations for Quantitative Variables

Variable	*M*	*SD*	Bootstrapped 95% CI (*M*)
Behavioral intention	5.6707	0.95549	[3.00, 7.00]
Performance expectancy	5.7829	0.80171	[3.25, 7.00]
Effort expectancy	5.6168	0.84436	[3.00, 7.00]
Social influence	5.3293	1.00079	[2.00, 7.00]
Facilitating conditions	5.1766	0.78354	[2.75, 7.00]

Note. (*n* = 167).

Tests of Assumptions

In this section, I tested the following multiple regression assumptions for this study initially addressed in Section 2: homoscedasticity, multicollinearity, independence of observation, linearity, and normal distribution. Flatt and Jacobs (2019) argued that researchers should always test assumptions because violations can lead to misleading and biased predictions that may not be duplicatable. My collected sample was resampled

1,000 times using bootstrap to combat potential assumption violations and to leverage the bootstrapped 95% confidence intervals where appropriate. Banjanovic and Osborne (2016) asserted that systematic bootstrapping creates robust empirical confidence intervals through its resampling process. My analysis and reasoning are below.

The multicollinearity assumption was examined. Multicollinearity increases the variance of regression coefficients, indicating that predictor variables are highly correlated with other predictor variables, and may suggest that one or more predictors are likely to spawn from other predictors (Kim, 2019). According to Kim (2019), correlation values of .8, .9, or higher between the predictor variables indicate the likely existence of multicollinearity overlap. The small to medium correlation coefficients shown in the bivariate correlation analysis of the predictor variables (Table 5) indicates the absence of multicollinearity violations. In addition, Salmeron et al. (2018) referred to a variance inflation factor (VIF) of 10 or greater as a likely indication of collinearity. Table 6 shows that each of my VIF predictor variable values is less than three, which indicates the absence of collinearity.

Table 5

Summary of Correlation Coefficients of Predictor Variables

Variable	PE	EE	SI	FC
PE	1.000	-0.410	-0.437	-0.122
EE	-0.410	1.000	-0.322	-0.136
SI	-0.437	-0.322	1.000	-0.166
FC	-0.122	-0.136	-0.166	1.000

Note: PE refs to performance expectancy, EE refs to effort expectancy, SI refers to social influence, and FC refs to facilitating conditions. N = 167.

The linearity assumption was assessed. Linearity indicates that the relationship between the predictor variables and the mean of the outcome variable is linear (Cohen et al., 2003). The P-P Plot (Figure 3) indicates close alignment between the plotted residuals and the model's standardized distribution line. Also, the scatterplot of standardized residuals (Figure 4) illustrates the relatively even and patternless dispersion of residual points centered on and around the X and Y axes over an imaginary rectangular plane. In addition, the scatterplot matrix shown in Figure F1 applies a line of best fit to demonstrate the strength of the linear relationships between the independent and dependent variables, each in this case with a positively-oriented slope coefficient.

The normality assumption was tested. Normal distribution indicates the absence of significant outliers in the error terms (Cohen et al., 2003). The scatterplot of standardized residuals (Figure 4) depicts a normal distribution with the data points being consistently close for the duration of the regression line, which means that the observed cumulative distribution function is close to the expected standardized residual. I also used a histogram (Figure 5) to illustrate the distribution's general shape, depicting a normal distribution by its bell-shaped symmetrical curves centered around the mean.

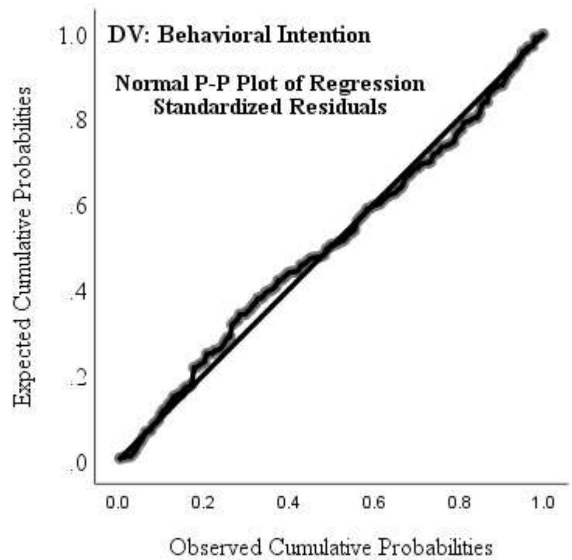
Table 6
Collinearity Statistics

Variable	Tolerance	VIF
Performance expectancy	0.367	2.721
Effort expectancy	0.410	2.436
Social influence	0.391	2.556
Facilitating conditions	0.728	1.375

Note: The Tolerance value is the reciprocal of the VIF.

Figure 3

Normal Probability Plot of the Regression Standardized Residuals

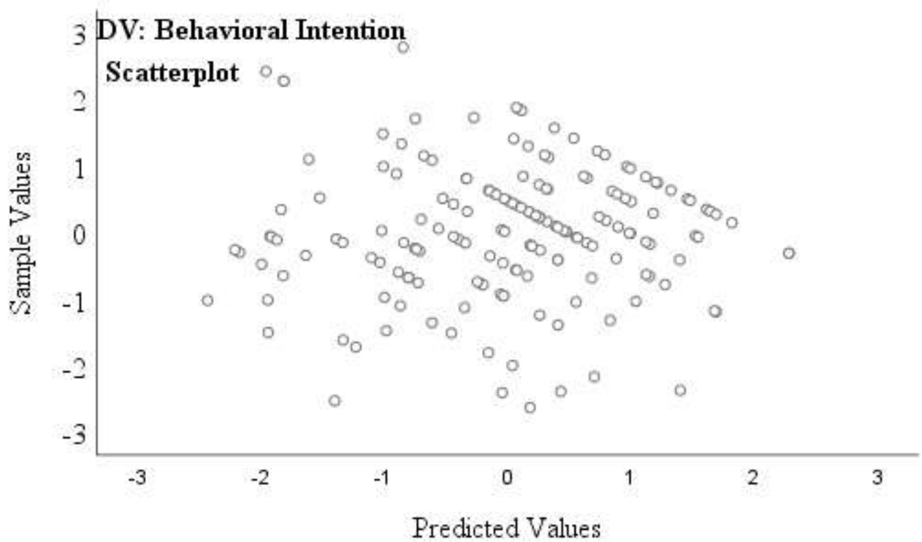


Homoscedasticity was verified. Homoscedasticity refers to a relationship in which the variances of the error terms are relatively equally distributed in values across the independent variables (Cohen et al., 2003). The scatterplot of standardized residuals (Figure 4) reflects homoscedasticity through its balanced distribution of residual data points, the absence of residual patterns, and with a balanced distribution of residual data points on either side of zero, as well as above and below zero for the *X* and *Y* axes, respectively.

The independence of observation assumption was confirmed. The independence of observations means that the occurrence of one observation provides no information about the occurrence of another observation and is therefore independently assessed (Dutcă et al., 2018). The scatterplot's (Figure 4) unstructured cloud of points randomly scattered around the centerline suggests independence within the collection sample. Also, Flatt and Jacobs (2019) stated that the optimal value is in the vicinity of 2.0 for Durbin-Watson test, which assesses the independence of observation, with a possible range of zero through four. The Durbin-Watson test registered a value of 2.019 for this study, which indicates strong independence, as shown in Table 7.

Figure 4

Scatterplot of Standardized Residuals



Inferential Statistics

The independent variables were performance expectancy, effort expectancy, social influence, and facilitating conditions. The dependent variable was the intention of cloud systems integrators to use SDN. The null hypothesis was that there is no significant relationship between IT cloud system integrators' perceptions of performance expectancy, effort expectancy, social influence, facilitating conditions, and IT cloud system integrators' intention to use SDN technology. The alternative hypothesis was that there is a significant relationship between IT cloud system integrators' perceptions of performance expectancy, effort expectancy, social influence, facilitating conditions, and

IT cloud system integrators' intention to use SDN technology. The efficacy of performance expectancy, effort expectancy, social influence, and facilitating conditions to predict IT cloud system integrators' intention to use SDN technology was analyzed using α = .05 (two-tailed).

Figure 5

Histogram Distribution of Sample Data

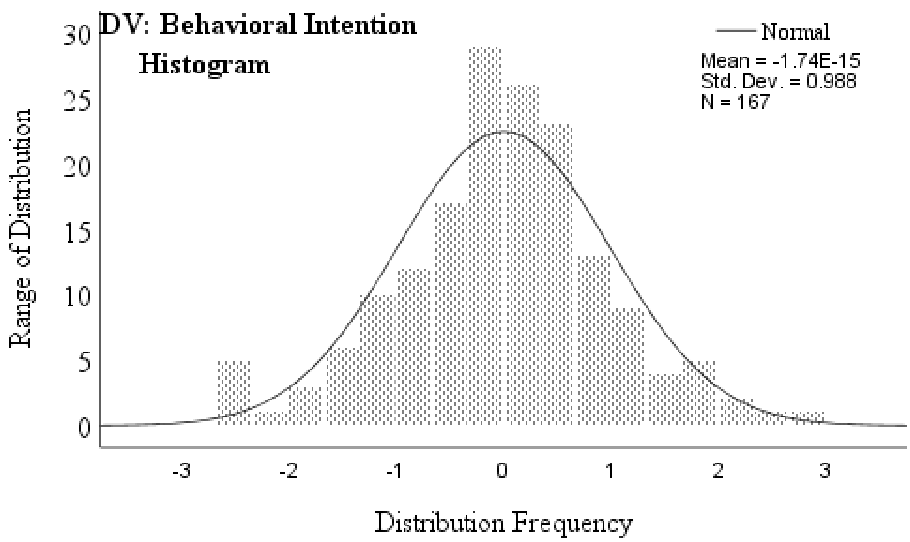


Table 7

Model Summary

Model	*R*	R^2	Sig. *F*	Durbin-Watson
SDN multiple regression	0.71	0.50	0.000	2.019

My analyses revealed no significant violations of the multiple regression assumptions of homoscedasticity, linearity, independence of observation, normality, or multicollinearity (see Tests of Assumptions). The model's summary indicated that the determinants significantly predicted the intention of cloud system integrators to use SDN technology, $F(4, 162) = 40.44$, $p < .001$, $R^2 = .50$. The resulting R^2 (.50) value suggests that 50% of variations in cloud system integrators' intention to use SDN technology is accounted for by the predictor variables' linear combination (performance expectancy, effort expectancy, social influence, and facilitating conditions) shown in Table 7. Also, the multiple correlation coefficient *R*-value of .71 reflects a strong linear relationship between the predicted scores and the actual scores and a good model fit.

In the final model, social influence ($t = 2.662$, $p < .01$) and facilitating conditions ($t = 5.018$, $p < .001$), were statistically significant, while performance expectancy and effort expectancy were not statistically significant. A summary of this study's concluding predictive equation was: Intention to Use SDN = 0.450 + 0.215(Performance Expectancy) + 0.127(Effort Expectancy) + 0.226(Social Influence) + 0.399(Facilitating Conditions). Positive slopes for performance expectancy, effort expectancy, social influence, and facilitating conditions indicate that the intention to use SDN increases as these determinants increases in value. Table 8 shows a summary of regression analysis of predictor variables. Appendix G shows my SPSS output.

The following is a summary of my analyses for determining the final model. According to Hoyt et al. (2006), multiple regression considers a set of predictor variables simultaneously to derive the best fit for predicting the variance in the outcome variable. Also drawn from multiple regression is the unique association of each predictor variable to the outcome variable with all other predictor variables controlled (Hoyt et al., 2006). Hoyt et al. (2006) referred to the following multiple regression statistics as critical for determining the model of best fit: (a) the model's variance prediction value R^2, (b) the model's multiple correlation value *R* between the predicted scores and the actual scores, and the model's significance value *p*.

Table 8

Summary of Regression Analysis for Predictor Variables

Variable	*B*	*SE B*	*β*	*t*	*Sig.*	Bootstrapped 95% CI (*M*)
PE	0.215	0.109	0.180	1.965	0.051	[-0.001, 0.430]
EE	0.127	0.098	0.112	1.291	0.198	[-0.067, 0.321]
SI	0.226	0.085	0.236	2.662	0.009	[0.058, 0.393]
FC	0.339	0.079	0.327	5.018	0.000	[0.242, 0.556]

Note: (*n* = 167). PE refs to performance expectancy, EE refs to effort expectancy, SI refers to social influence, and FC refs to facilitating conditions.

Table 9 shows a statistical summary of the following three regression models evaluated in this study: (Model 1) predictor variables performance expectancy, effort expectancy, social influence, and facilitating conditions (SPSS output Appendix G), (Model 2) predictor variables performance expectancy, social influence, and facilitating conditions (SPSS output Appendix H), and (Model 3) predictor variables effort expectancy, social influence, and facilitating conditions (SPSS output Appendix I). Model 1 produced the highest variance prediction value R^2 (0.500), followed by Model 2 (0.494), and Model 3 (0.488). Model 1 also achieved the highest multiple correlation value *R* (0.707), followed by Model 2 (0.703), and then Model 3 (0.698). With respect to the regression models' significance value *p,* each recorded an identical value of 0.000. Although each model indicates strong multiple regression representation, I selected Model 1 as the best fit for this study because of its slight statistical advantage in predicting the variance of SDN integrators' behavioral intention and a slightly more accurate correlation between the predicted and the actual scores. Also, the absence of collinearity between the empirically-tested UTAUT predictor variables (Table 5) suggests that Model 1 provided the best overall characterization of behavioral intention variance.

Table 9

Model of Best Fit Comparisons

Model	R^2	R	p
Model 1: Predictor variables PE, EE, SI, and FC	0.500	0.707	0.000
Model 2: Predictor variables PE, SI, and FC	0.494	0.703	0.000
Model 3: Predictor variables EE, SI, and FC	0.488	0.698	0.000

Note: (n = 167). PE refs to performance expectancy, EE refs to effort expectancy, SI refers to social influence, and FC refs to facilitating conditions. The outcome variable for each model is behavioral intention.

Theoretical Conversation on Findings

This study's findings indicated that the technology adoption determinants of social influence and facilitating conditions greatly influenced the behavioral intention of SDN cloud system integrators to adopt SDN technology, while performance expectancy and effort expectancy were not statistically significant. In this study, I also affirmed many of the UTAUT founder's results presented in the theoretical framework. Venkatesh et al. (2003) found that the UTAUT determinants were effective predictors of behavioral intention in a technology training scenario, accounting for 70% of the variance. Similarly, this study's determinants accounted for 50% of SDN cloud system integrators' intention to use SDN technology. Both studies provide empirical data suggesting that organizations could use the findings to enhance technology strategies.

The UTAUT theoretical framework is appropriate for this quantitative correlational technology adoption study. Venkatesh et al. (2003) developed UTAUT by integrating the most effective constructs of eight previous technology acceptance and technology innovation models. UTAUT focuses on factors that influence individuals' receptiveness to a new technology in the workplace. With these underpinnings, I explored the degree to which technology adoption determinants impacted SDN integrators. Because SDN is an infrastructure technology similar to cloud computing and virtualization where the use of the technology is not optional to the workforce, the organization-centric technology determinants were more prominent for SDN integrators. Accordingly, the predictor variables of social influence ($p < 0.01$) and facilitating conditions ($p < 0.001$) were greatly significant technology adoption factors, and the null hypotheses were rejected. On the other hand, the individual-oriented determinants of performance expectancy ($p < 0.051$) and effort expectancy ($p < 0.198$) were perceived as less relevant factors to SDN integrators in their adoption intentions and not statistically significant. The null hypotheses could not be rejected. SDN integrators deemed it more important that organizational leaders were advocates of the technology and that support resources were provided than to receive personal rewards, even if the technology was not always easy to use. Because SDN integrators viewed SDN technology adoption as essential to their jobs, their behavioral intention to use the technology was most influenced by their perception of the degree of organizational support and support resources provided.

This study's findings also further confirmed that the UTAUT model can be applied to improve technology adoption strategies across different industries, although often implemented differently. In this study, I used the UTAUT model to predict a 50% variance in SDN system integrators' intention to use SDN technology in environments where the use of SDN technology was not voluntary. This study indicated that facilitating conditions and social influence greatly influenced SDN integrators' adoption decisions, while the determinants of performance expectancy and effort expectancy were not statistically significant. In contrast, Tladi and Nleya (2017) applied the UTAUT model to assess quality factors' effectiveness in an alternative elearning education methodology. Upon evaluating elearning factors of students' perception of security, course materials, and instructors' qualifications, they found a high correlation (.882) between quality factors and elearning implementations for elearning at Botswana College of Distance and Open Learning (Tladi & Nleya, 2017).

A voluntary integrated licensing system study using the UTAUT model had substantially different findings than my research. Puspitasari et al. (2019) found that performance expectancy greatly influenced the acceptance of an integrated licensing service system for Samarinda City Investments in the Republic of Indonesia. Their results also revealed that the business expectation variables of social factors and facilitating conditions impacted low utilization of the system (Puspitasari et al., 2019).

Researchers in Germany applied an extended UTAUT model to analyze the organizations' adoption behaviors toward cloud services, where some findings were similar to my study. Moryson and Moeser (2016) discovered that social influence was a strong driver of attitudes towards using cloud services while facilitating conditions, and the external factor of attitudes towards use significantly influenced behavioral intent to use cloud services. After also factoring in performance expectancy, effort expectancy, and the external variables of perceived security and perceived trust, their extended UTAUT model accounted for 67% of the variance in the users' behavioral intention to use cloud services.

Application to Professional Practice

My study used the UTAUT framework to predict whether the technology determinants of performance expectancy, effort expectancy, facilitating conditions, and social influence variance could predict SDN adoption behaviors. My findings indicate that facilitating conditions and social influence were significant determinants in forecasting the acceptance and adoption of SDN technology in the workplace. Therefore, the application to professional practice consists of breaking down how each of these factors might be integrated into the work environment.

Social influence refers to the degree to which an individual perceives that it is important that others believe that they should use the system. The results of this study strongly suggest that social influence affects SDN integrators’ acceptance of SDN technology. As an infrastructure technology, SDN integration is typically a corporate management decision and a technology transformation goal for the organization, rather than an individual’s choice to use. In describing the adoption behaviors of cloud computing, an infrastructure technology similar to SDN, Loukis et al. (2017) concluded that organizational factors, such as management support and market competitiveness, and technology readiness are instrumental in its acceptance. Also, JosephNg (2018) observed that capital investments for infrastructure innovations tend to drive management’s expectations for technology adoption.

As such, SDN integrators feel compelled to adopt and support SDN technology because their organization's management expects them to implement the technology. SDN integrators are swayed by social influence and feel obliged to demonstrate SDN technology buy-in. Understanding the relevance of social influence, organizations planning to integrate SDN technology might consider promoting ways in which SDN technology could benefit the organization, and that could strengthen its competitiveness in the marketplace. To increase the workforce’s buy-in, managers might consider posting summaries of studies and surveys on the organization’s website that depict how tasks such as cloud orchestrations and node provisioning can be streamlined through SDN's automation capabilities and thereby strengthening the organization’s business posture.

Facilitating conditions are also highly relevant when assessing the application of this study’s findings to professional practice. Facilitating conditions refer to the extent to which an individual perceives that the organizational and technical infrastructure support use of the new system. The results of this study suggest that facilitating conditions strongly influence workers’ acceptance of SDN technology. Facilitating conditions indicate the system’s supportability to the workforce and compatibility with other systems used by workers. IT managers can positively influence perceptions about the system's availability by implementing a cohesive rollout strategy with senior leadership's endorsement. This study's findings suggest that managers must evaluate the new system’s compatibility through architectural assessments and reviews before procuring the system. In addition, SDN system architects can advance industry adoption by addressing and incorporating strategies that promote interoperability with existing systems.

The technology adoption determinants of performance expectancy and effort expectancy were not found to be significant determinants of SDN technology adoption. As a broadly encompassing infrastructure technology, when organizations implement SDN, its use and application become mandatory for SDN integrators. Due to the operational sustainment costs of running two parallel infrastructures, previous technologies are decommissioned soon after implementing SDN technology. Therefore, the influence of SDN's potential personal benefits was found to be less important than organizational factors.

Performance expectancy refers to the degree to which an individual perceives that the new system will improve their job performance. The findings in this study suggest that although SDN integrators welcomed the technology’s job performance enhancements, performance expectancy was not a statistically significant or pivotal determinant of SDN technology adoption. With SDN technology typically implemented as a broad infrastructure transformation initiative, SDN integrators feel that their jobs obligate them to adopt and support the technology, although they welcomed personal benefits received for using the technology. SDN integrators seemed to view adopting the technology as a requirement for their jobs, rather than expecting incentives for supporting SDN technology or personal productivity gains.

Effort expectancy refers to the level of effort for which an individual perceives that they will need to exert to use the new system. This study's findings indicated that effort expectancy was the lowest of the technology adoption determinants and was not a significant factor for SDN integrators in their decision as to whether to adopt the SDN technology. Regardless of the degree of difficulty required to support SDN technology, SDN integrators feel that their jobs require supporting the organization's SDN infrastructure, which inherently requires adopting the technology. SDN integrators' decisions regarding the adoption of SDN technology was not contingent upon the degree of effort required to use the technology.

Implications for Social Change

The potential for the new SDN technology paradigm to affect social change is enormous and can be transformational. SDN's centralized management and holistic view of the network domain can result in improved security for users. Through its enhanced visibility and bolstered centralized intelligence capabilities, SDN can foster the administration and implementation of global security policies that can be immediately applied and updated throughout the network domain. Such agility allows for superior protection against security vulnerabilities that can affect the confidentiality, integrity, or availability of users' data.

SDN technology deployments can improve the quality of cloud-based user services. SDN's capability for fine-grained traffic engineering, traffic prioritization and control, and multi-cloud integration and orchestration can improve the quality of end-user application experiences, such as high-definition streaming services and social media interactive application response times. SDN's integration with IoT sensors, mobile networks, and vehicular networks can improve reliability and safety for autonomous vehicles.

SDN's centralized management and holistic view of the network domain can greatly simplify network management and control and lead to substantially lower costs for system deployments and system upgrades. Low-touch to no-touch SDN-based branch office rollouts and upgrades can significantly reduce implementation time and costs. Through AI and ML integration, SDN's automation potential can result in reduced operating costs and smaller workforce requirements through automated instrumentation.

Recommendations for Action

This study's findings suggest that the facilitating conditions represent the strongest determinant of SDN technology adoption by the SDN integrator workforce. With this established knowledge, IT leaders and managers must ensure that the needed resources are available to SDN integrators to support the technology. IT managers must ensure that SDN technology awareness and user training are available and that SDN integrators complete recommended training courses. To advance SDN adoption, IT managers must ensure the availability of the needed utilities, tools, and documentation to support the technology's integration. SDN integrators also want to be assured that a specific person or group is available to assist with system difficulties and problems. Managers must also ensure that compatibility assessments with existing infrastructure are performed prior to making a purchase decision. Moreover, with this evidence, IT leaders and managers can champion SDN technology adoption by ensuring the availability of support resources and promoting its integration into the organization's goals and objectives. SDN developers can also advance industry adoption by addressing and incorporating strategies that promote interoperability with existing systems. In addition, SDN developers also have a major role in producing resources, such as SDN tools and utilities needed for support and sustainment, and developing SDN user training curricula and system documentation. SDN developers must also ensure interoperability with existing systems.

This study’s findings suggest that social influence is also a strong determinant of SDN adoption by the SDN integrator workforce. To advance SDN technology adoption, it is paramount that IT leaders and managers in the organization champion its use and their expectations of adoption by the workforce. IT leaders and managers can promote SDN technology acceptance by integrating SDN adoption expectations into the organization's short- and long-term strategic plans and incorporating SDN functions into job descriptions, work evaluations, and job postings. This study’s results suggest that the adoption determinant of facilitating conditions is a significant factor for the workforce towards adopting SDN technology. IT managers can cultivate positive perceptions about the system's availability by implementing a cohesive rollout strategy with managers and senior leadership's endorsement. IT managers can also take action to boost SDN adoption by posting summaries of studies on the organization's website that reflect how SDN can revolutionize network intelligence and provide game-changing advancements in data orchestration and automation.

With respect to disseminating my study's results, I will look to leverage social media platforms. Over recent months, I experienced the good fortunes of joining several cutting-edge technology groups, including SDN and next-generation networking, AI, ML, IoT, and data science groups, on LinkedIn comprised of industry professionals, some of who may have a vested interest in empirical research about SDN adoption behaviors. I will look to share a summary of my findings in LinkedIn's group conversation posts and the published works repository, some of which may lead to presentation opportunities. I will also seek presentation opportunities on BrightTALK, a virtual event-hosting forum that showcases future technologies. In addition, I will provide a summary of the results to any interested party upon request.

Recommendations for Further Research

The limitations identified in Section 2 provided opportunities for further research regarding SDN technology and its adoption in the marketplace. I identified the following limitations: (a) the scarcity of theoretical models for back-end infrastructure technologies and (b) limited operational deployments of SDN technology could impact data collection efforts. Perhaps the most significant limitation relates to how the majority of IT adoption theoretical frameworks address personal end-user computing technologies, such as mobile applications and wearable smart devices, versus back-end infrastructure technologies, such as cloud systems, virtualization, and software-defined technologies. Unlike end-user technologies, infrastructure technologies are typically not optional, and organizations often integrate back-end technologies into their enterprise architecture for business transformation purposes. Rad et al. (2018) observed that while most technology adoption models are individual-oriented, organizational-focused models remain sparse but increasing.

In addition, back-end infrastructure adoption behaviors tend to rely on the organization’s delivery capabilities. Technology infrastructure adoption determinants emphasize factors such as IT personnel competency, system interoperability, system resiliency, system security, system scalability, upgradeability, and return on investment. The advent of IT applications for business operations has boosted organizational-centric studies (Rad et al., 2018). To evaluate such factors, the population would likely need to include enterprise and corporate leaders and managers who have a broader view of the infrastructure, capabilities, and costs.

Although some types of SDN technology deployments are rapidly expanding in the marketplace, the current overall lack of bountiful operational implementations can present data collection challenges for researchers. For instance, I found it challenging to recruit SDN participants in SDN and related technology social network forums, many of which have tens of thousands of members. Also, perhaps reflecting a lack a breadth in prospective SDN participants, 29% of my survey panel responses were rejected due to extreme outliers or straight-line answers. However, there are indications of expanding SDN market share on the horizon, which will also increase the potential pool of participants for SDN studies. For example, Nadal et al. (2020) commented that market demands for open-source SDN-enhanced wavelength division multiplexing are rising as organizations become aware of potential efficiency gains through its programmability features and look to avoid vendor lock-in. Also, according to Medeiros et al. (2020), the exponential growth of the internet and the demand to support the hyper-scalability and flexibility of next-generation mobile networks have spurred increased investments in SDN and cloud-based software-defined radio access networks.

Reflections

In reflection, my background and training as an IT professional seem to have been well-suited for the DIT program, including my quantitative research study. The DIT program and my deep-dive research on SDN technology, along with my experience in contemporary networking technologies, may lead to potential opportunities in helping to bridge my organization to next-generation networking and cloud computing.

The DIT program and my study on SDN adoption behaviors may also lead to new opportunities to engage in discussions and challenges related to SDN technology. To find a venue to post my survey solicitations and to become more acquainted with the SDN community and industry players, I joined several related social media groups, including seven SDN, SD-WAN, and secure access service edge networking groups, two OpenFlow/OpenStack groups, and seven AI, ML, big data, and data science groups, many of which have thousands of members. In retrospect, although survey panel participants responded at a much faster rate than my solicitation posts, I value the experience and exposure gained by engaging with next-generation networkers.

Interestingly, SD-WAN has emerged as a dominant force in the marketplace since I began my SDN journey in 2018. A growing number of organizations look to leverage its automation capabilities, cost-cutting touchless deployments, and other advantages compared to traditional technologies.

Conclusion

This multiple regression study revealed that the adoption determinants of performance expectancy, effort expectancy, social influence, and facilitating conditions, collectively, explain 50% of the variance in cloud system integrators' intention to use SDN technology. With SDN being an infrastructure technology, there is strong empirical evidence that SDN integrators view its adoption as necessary to maintain their job position in the organization. As such, this study indicated that the most significant determinant of SDN adoption is facilitating conditions, which refers to having the resources needed, such as training and assistance, and utilities and tools to support using the system. Social influence, which refers to the degree to which an individual perceives that it is important that others believe that they should use the system, was also a strong determinant of SDN adoption. This study indicated that it is important to SDN integrators that IT leaders and managers exhibit buy-in, promoting the technology on all fronts.

Although SDN integrators showed preference towards effort expectancy, which refers to the level of effort for which an individual perceives that they will need to exert to use the new system, it was not found to be a pivotal factor in their intention to adopt the technology. Performance expectancy, which refers to the degree to which an individual perceives that the new system will improve their job performance, was also not found to be a significant determinant of SDN adoption. The findings in this study revealed that organizational factors are more important to SDN integrators than personal factors regarding their intention to adopt SDN technology.

References

Abbasi, M. R., Guleria, A., & Devi, M. S. (2016). Traffic engineering in software-defined networks: A survey. *Journal of Telecommunications and Information Technology, 4*, 3–14. https://www.researchgate.net/publication/311970882_Traffic_Engineering_in_Software_Defined_Networks_A_Survey

Abujubbeh, M., Al-Turjman, F., & Fahrioglu, M. (2019). Software-defined wireless sensor networks in smart grids: An overview. *Sustainable Cities and Society, 51*, 1–18. https://doi.org/10.1016/j.scs.2019.101754

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Albashrawi, M., & Motiwalla, L. (2020). An integrative framework on mobile banking success. *Information Systems Management*, *37*(1), 16–32. https://doi.org/10.1080/10580530.2020.1696530

Albaum, G., Roster, C. A., Wiley, J., Rossiter, J., & Smith, S. M. (2010). Designing web surveys in marketing research: Does use of forced-answering affect completion rates? *Journal of Marketing Theory and Practice, 18*(3), 285–293. https://doi.org/10.2753/MTP1069-6679180306

Alenezi, M., Almustafa, K., & Meerja, K. A. (2019). Cloud-based SDN and NFV architectures for IoT infrastructure. *Egyptian Informatics Journal, 20*(1), 1–10. https://doi.org/10.1016/j.eij.2018.03.004

Al-Kahtani, M. S., & Karim, L. (2017). Architectures and security of software-defined networks for internet of things: State-of-the-art and challenges. *International Journal of Computer Engineering and Information Technology, 9*(6), 108–116. https://ict.senecacollege.ca/~lutful.karim/J10-1Vol9No6.pdf

Allen, P. J., Lourenco, A., & Roberts, L. D. (2016). Detecting duplication in students' research data: A method and illustration. *Ethics and Behavior*, *26*(4), 300–311. https://doi.org/10.1080/10508422.2015.1019070

Allouch, A., Koubâa, A., Khalgui, M., & Abbes, T. (2019). Qualitative and quantitative risk analysis and safety assessment of unmanned aerial vehicles missions over the internet. *IEEE Access*, *7*, 53392–53410. https://doi.org/10.1109/ACCESS.2019.2911980

Al-Musawi, R., & Al-Khatib, O. (2019). Optimized energy-aware resource allocation algorithm using software-defined network technology. *Journal of Telecommunications and Information Technology, 2*, 83–91. https://doi.org/10.26636/jtit.2019.129418

American Psychological Association. (2002). Ethical principles of psychologists and code of conduct. *American Psychologist*, *57*(12), 1060–1073. https://doi.org/10.1037/0003-066X.57.12.1060

Amin, R., Reisslein, M., & Shah, N. (2018). Hybrid SDN networks: A survey of existing approaches. *IEEE Communications Surveys and Tutorials, 20*(4), 3259–3306. https://doi.org/10.1109/COMST.2018.2837161

Anabi, H. K., Alsharif, M. H., Athirah, M. R., Abdullah, N. F., & Nordin, R. (2019). The four-C framework for high-capacity ultra-low latency in 5G networks: A review. *Energies*, *12*(18), 1–35. https://doi.org/10.3390/en12183449

Anadiotis, A.-C., Galluccio, L., Milardo, S., Morabito, G., & Palazzo, S. (2019). SD-WISE: A software-defined wireless sensor network. *Computer Networks*, *159*, 84–95. https://doi.org/10.1016/j.comnet.2019.04.029

Anan, M., Al-Fuqaha, A., Nasser, N., Mu, T.-Y., & Bustam, H. (2016). Empowering networking research and experimentation through software-defined networking. *Journal of Network and Computer Applications*, *70*, 140–155. https://doi.org/10.1016/j.jnca.2016.05.001

Anderson, S. F., & Maxwell, S. E. (2017). Addressing the “replication crisis”: using original studies to design replication studies with appropriate statistical power. *Multivariate Behavioral Research*, *52*(3), 305–324. https://doi.org/10.1080/00273171.2017.1289361

Appelbaum, M., Cooper, H., Kline, R. B., Mayo-Wilson, E., Nezu, A. M., & Rao, S. M. (2018). Journal article reporting standards for quantitative research in psychology: The APA Publications and Communications Board task force report. *American Psychologist*, *73*(1), 3–25. https://doi.org/10.1037/amp0000191

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

Asheim, B., Grillitsch, M., & Trippl, M. (2017). Introduction: Combinatorial knowledge bases, regional innovation, and development dynamics. *Economic Geography*, *93*(5), 429–435. https://doi.org/10.1080/00130095.2017.1380775

Asiamah, N., Mensah, H. K., & Oteng-Abayie, E. F. (2017). General, target, and accessible population: Demystifying the concepts for effective sampling. *Qualitative Report*, *22*(6), 1607–1622. https://nsuworks.nova.edu/tqr/vol22/iss6/9

Astivia, O. L. O., & Zumbo, B. D. (2019). Heteroskedasticity in multiple regression analysis: What it is, how to detect it, and how to solve it with applications in R and SPSS. *Practical Assessment, Research and Evaluation*, *24*(1), 1–16. https://doi.org/10.7275/q5xr-fr95

Ateya, A. A., Muthanna, A., Gudkova, I., Abuarqoub, A., Vybornova, A., & Koucheryavy, A. (2018). Development of intelligent core network for Tactile Internet and future smart systems. *Journal of Sensor and Actuator Networks*, *7*(1), 1–20. https://doi.org/10.3390/jsan7010001

Awanto, A. N., Ardianto, Y. T., & Prasetya, A. (2020). UTAUT model implementation on user behavior in use of information technology. *Jurnal Teknologi Dan Manajemen Informatika*, *6*(1), 53–59. https://doi.org/10.26905/jtmi.v6i1.4156

Aydeger, A., Saputro, N., & Akkaya, K. (2019a). A moving target defense and network forensics framework for ISP networks using SDN and NFV. *Future Generation Computer Systems*, *94*, 496–509. https://doi.org/10.1016/j.future.2018.11.045

Aydeger, A., Saputro, N., Akkaya, K., & Uluagac, S. (2019b). SDN-enabled recovery for smart grid teleprotection applications in post-disaster scenarios. *Journal of*

Network and Computer Applications, *138*, 39–50. https://doi.org/10.1016/j.jnca.2019.04.011

Azka, G., Revathi, S., & Geetha, A. (2017). A survey of applications and security issues in software-defined networking. *International Journal of Computer Network and Information Security*, *9*(3), 21–28. https://doi.org/10.5815/ijcnis.2017.03.03

Baker, J. D. (2016). The purpose, process, and methods of writing a literature review: Editorial the official voice of perioperative nursing the official voice of perioperative nursing. *AORN Journal*, *103*(3), 265–269. https://doi.org/10.1016/j.aorn.2016.01.016

Bakhshi, T. (2017). State-of-the-art and recent research advances in software-defined networking. *Wireless Communications and Mobile Computing*, *2017*, 1–35. https://doi.org/10.1155/2017/7191647

Baktir, A. C., Ozgovde, A., & Ersoy, C. (2017). How can edge computing benefit from software-defined networking: A survey, use cases, and future directions. *IEEE Communications Surveys and Tutorials*, *19*(4), 2359–2391. https://doi.org/10.1109/COMST.2017.2717482

Bala, J. (2016). Contribution of SPSS in social sciences research. *International Journal of Advanced Research in Computer Science*, *7*(6), 250–254. https://doi.org/10.26483/ijarcs.v7i6.2773

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

Banjanovic, E. S., & Osborne, J. W. (2016). Confidence intervals for effect sizes: Applying bootstrap resampling. *Practical Assessment, Research, and Evaluation*, *21*(5), 1–20. https://doi.org/10.7275/dz3r-8n08

Barakabitze, A. A., Ahmad, A., Mijumbi, R., & Hines, A. (2020). 5G network slicing using SDN and NFV: A survey of taxonomy, architectures, and future challenges. *Computer Networks*, *167*, 1–40. https://doi.org/10.1016/j.comnet.2019.106984

Bawack, R. E., & Kala Kamdjoug, J. R. (2018). Adequacy of UTAUT in clinician adoption of health information systems in developing countries: The case of Cameroon. *International Journal of Medical Informatics*, *109*, 15–22. https://doi.org/10.1016/j.ijmedinf.2017.10.016

Béné, C., Riba, A., & Wilson, D. (2020). Impacts of resilience interventions—Evidence from a quasi-experimental assessment in Niger. *International Journal of Disaster Risk Reduction*, *43*, 1–14. https://doi.org/10.1016/j.ijdrr.2019.101390

Benzekki, K., El Fergougui, A., & Elbelrhiti Elalaoui, A. (2016). Software-defined networking (SDN): A survey. *Security and Communication Networks*, *9*(18), 5803–5833. https://doi.org/10.1002/sec.1737

Bhardwaj, P. (2019). Types of sampling in research. *Journal of the Practice of Cardiovascular Sciences*, *5*(3), 157–163. https://doi.org/10.4103/jpcs.jpcs_62_19

Bhatia, J., Dave, R., Bhayani, H., Tanwar, S., & Nayyar, A. (2020). SDN-based real-time urban traffic analysis in VANET environment. *Computer Communications*, *149*, 162–175. https://doi.org/10.1016/j.comcom.2019.10.011

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

Boeckhout, M., Zielhuis, G. A., & Bredenoord, A. L. (2018). The FAIR guiding principles for data stewardship: fair enough? *European Journal of Human Genetics*, *26*(7), 931–936. https://doi.org/10.1038/s41431-018-0160-0

Boeren, E. (2018). The methodological underdog: A review of quantitative research in the key adult education journals. *Adult Education Quarterly*, *68*(1), 63–79. https://doi.org/10.1177/0741713617739347

Boutaba, R., Salahuddin, M. A., Limam, N., Ayoubi, S., Shahriar, N., Estrada-Solano, F., & Caicedo, O. M. (2018). A comprehensive survey on machine learning for networking: Evolution, applications, and research opportunities. *Journal of Internet Services and Applications*, *9*(1), 1–99. https://doi.org/10.1186/s13174-018-0087-2

Bowen, D., Hyams, T., Goodman, M., West, K., Harris, W. J., & Yu, J. (2017). Systematic review of quantitative measures of stakeholder engagement. *CTS: Clinical and Translational Science*, *10*(5), 314–336. https://doi.org/10.1111/cts.12474

Braun, T., Ehrenbrusthoff, K., Bahns, C., Happe, L., & Kopkow, C. (2019). Cross-cultural adaptation, internal consistency, test-retest reliability and feasibility of the German version of the evidence-based practice inventory. *BMC Health Services Research*, *19*(1), 1–17. https://doi.org/10.1186/s12913-019-4273-0

Brehaut, J. C., Saginur, R., & Elwyn, G. (2009). Informed consent documentation necessary but not sufficient. *Contemporary Clinical Trials*, *30*, 388–389. https://doi:10.1016/j.cct.2009.05.006

Buabeng-Andoh, C. (2018). Predicting students' intention to adopt mobile learning: A combination of theory of reasoned action and technology acceptance model. *Journal of Research in Innovative Teaching*, *11*(2), 178–191. https://doi.org/10.1108/JRIT-03-2017-0004

Bukhari, J., & Yoon, W. (2018). Multicasting in next-generation software-defined heterogeneous wireless networks. *IEEE Transactions on Broadcasting, Broadcasting*, *64*(4), 915–921. https://doi.org/10.1109/TBC.2018.283472

Burr, J., & Gibson, B. (2018). Informed consent in research ethics: An analysis from the perspective of Luhmann's social systems theory. *Social Theory and Health*, *16*(3), 241–255. https://doi.org/10.1057/s41285-017-0054-1

Caraguay, V., Leonardo, A., Villalba, G., & Javier, L. (2017). Monitoring and discovery for self-organized network management in virtualized and software-defined networks. *Sensors*, *17*(4), 1–31. https://doi.org/10.3390/s17040731

Caronni, A., Sterpi, I., Antoniotti, P., Aristidou, E., Nicolaci, F., Picardi, M., Pintavalle, G., Redaelli, V., Achille, G., Sciumè, L., & Corbo, M. (2018). Criterion validity of the instrumented timed up and go test: A partial least square regression study. *Gait and Posture*, *61*, 287–293. https://doi.org/10.1016/j.gaitpost.2018.01.015

Casper, W. C., Edwards, B. D., Wallace, J. C., Landis, R. S., & Fife, D. A. (2020). Selecting response anchors with equal intervals for summated rating scales.

Journal of Applied Psychology, *105*(4), 390–409. https://doi.org/10.1037/apl0000444

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

Celik, R., & Erar, A. (2017). An alternative method correcting BDR type of heteroscedasticity by the weighting re-estimated absolute residuals. *Communications in Statistics: Theory and Methods*, *46*(23), 11514–11538. https://doi.org/10.1080/03610926.2016.1271429

Chahal, M., Harit, S., Mishra, K. K., Sangaiah, A. K., & Zheng, Z. (2017). A survey on software-defined networking in vehicular ad hoc networks: Challenges, applications, and use cases. *Sustainable Cities and Society*, *35*, 830–840. https://doi.org/10.1016/j.scs.2017.07.007

Chander, G. N. (2017). Sample size estimation. *Indian Prosthodontic Society Journal*, *17*(3), 217–218. https://doi.org/10.4103/jips.jips_169_17

Chandler, J., Rosenzweig, C., Moss, A. J., Robinson, J., & Litman, L. (2019). Online panels in social science research: Expanding sampling methods beyond Mechanical Turk. *Behavior Research Methods*, *51*(5), 2022–2038. https://doi.org/10.3758/s13428-019-01273-7

Chandra, Y., & Shang, L. (2017). An RQDA-based constructivist methodology for qualitative research. *Qualitative Market Research*, *20*(1), 90–112. https://doi.org/10.1108/QMR-02-2016-0014

Chen, M., Li, W., Hao, Y., Qian, Y., & Humar, I. (2018). Edge the UTAUT model to examine factors affecting the acceptance of the bring your own device (BYOD) policy at public high schools in the Cayman Islands-based smart healthcare system. *Future Generation Computer Systems*, *86*, 403–411. https://doi.org/10.1016/j.future.2018.03.054

Chen, Y.-J., Wang, L.-C., Lin, F.-Y., & Lin, B.-S. P. (2017). Deterministic quality of service guarantee for dynamic service chaining in software-defined networking. *IEEE Transactions on Network and Service Management*, *14*(4), 991–1002. https://doi.org/10.1109/TNSM.2017.2758328

Cheng, E. W. L. (2019). Choosing between the theory of planned behavior (TPB) and the technology acceptance model (TAM). *Educational Technology Research and Development*, *67*(1), 21–37. https://doi.org/10.1007/s11423-018-9598-6

Chiwara, J. R., Chinyamurindi, W. T., & Mjoli, T. Q. (2017). Factors that influence the use of the internet for job-seeking purposes amongst a sample of final-year students in the Eastern Cape province of South Africa. *South African Journal of Human Resource Management*, *15*(1), 1–9. https://doi.org/10.4102/sajhrm.v15i0.790

Chyung, S. Y., Roberts, K., Swanson, I., & Hankinson, A. (2017). Evidence-based survey design: The use of a midpoint on the Likert scale. *Performance Improvement*, *56*(10), 15–23. https://doi.org/10.1002/pfi.21727

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

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences* (3rd ed.). Lawrence Erlbaum Associates. https://doi.org/10.4324/9780203774441

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly*, *19*(2), 189–211. https://doi.org/10.2307/249688

Connors, E. C., Krupnikov, Y., & Ryan, J. B. (2019). How transparency affects survey responses. *Public Opinion Quarterly*, *83*, 185–209. https://doi.org/10.1093/poq/nfz013

Contreras, L., Cominardi, L., Qian, H., & Bernardos, C. (2016). Software-defined mobility management: architecture proposal and future directions. *Mobile Networks and Applications*, *21*(2), 226–236. https://doi.org/10.1007/s11036-015-0663-7

Coronado, E., Riggio, R., Villalon, J., & Garrido, A. (2018). Efficient real-time content distribution for multiple multicast groups in SDN-based WLANs. *IEEE Transactions on Network and Service Management*, *15*(1), 430–443. https://doi.org/10.1109/TNSM.2017.2786660

Coronado Mondragon, A. E., & Coronado Mondragon, C. E. (2018). Managing complex, modular products: How technological uncertainty affects the role of systems integrators in the automotive supply chain. *International Journal of Production Research*, *56*(20), 6628–6643. https://doi.org/10.1080/00207543.2018.1424362

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

Cox, J. H., Chung, J., Donovan, S., Ivey, J., Clark, R. J., Riley, G., & Owen, H. L. (2017). Advancing software-defined networks: A survey. *IEEE Access, 5*, 25487–25526. https://doi.org/10.1109/ACCESS.2017.2762291

Cronbach, L. J., & Meehl, P. E. (1955). Construct validity in psychological tests. *Psychological Bulletin*, 52(*4)*, 281-302. https://doi.org/10.1037/h0040957

Cui, J., Wang, M., Luo, Y., & Zhong, H. (2019). DDoS detection and defense mechanism based on cognitive-inspired computing in SDN. *Future Generation Computer Systems*, *97*, 275–283. https://doi.org/10.1016/j.future.2019.02.037

Cunningham, J. B., & Gardner, E. (2007). Power, effect, and sample size using GPower: Practical issues for researchers and members of research ethics committees. *Evidence-Based Midwifery, 5*, 132–136. https://www.researchgate.net/publication/281570233_Power_effect_and_sample_size_using_GPower_Practical_issues_for_researchers_and_members_of_research_ethics_committees

Curley, C., Krause, R. M., Feiock, R., & Hawkins, C. V. (2019). Dealing with missing data: A comparative exploration of approaches using the Integrated City Sustainability Database. *Urban Affairs Review*, *55*(2), 591–615. https://doi.org/10.1177/1078087417726394

da Costa Cordeiro, W. L., Marques, J. A., & Gaspary, L. P. (2017). Data plane programmability beyond OpenFlow: Opportunities and challenges for network and service operations and management. *Journal of Network and Systems Management*, *25*(4), 784–818. https://doi.org/10.1007/s10922-017-9423-2

Dam, L., Roy, D., Atkin, D. J., & Rogers, D. (2018). Applying an integrative technology adoption paradigm to health app adoption and use. *Journal of Broadcasting and Electronic Media*, *62*(4), 654–672. https://doi.org/10.1080/08838151.2018.1519568

Dao, N., Kim, J., Park, M., & Cho, S. (2016). Adaptive suspicious prevention for defending DoS attacks in SDN-based convergent networks. *PLoS One*, *11*(8), 1–24. https://doi.org/10.1371/journal.pone.0160375

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 8*, 982–1003. https://doi.org/10.1287/mnsc.35.8.982

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. *Journal of Applied Social Psychology*, *22*(14), 1111–1132. https://doi.org/10.1111/j.1559-1816.1992.tb00945.x de Pozuelo, R. M., Zaballos, A., Navarro, J., & Corral, G. (2017). Prototyping a software-defined utility. *Energies, 10*(6), 1–25. https://doi.org/10.3390/en10060818

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

Dolnicar, S. (2018). A reflection on survey research in hospitality. *International Journal of Contemporary Hospitality Management*, *30*(11), 3412–3422. https://doi.org/10.1108/IJCHM-06-2017-0386

Doussard, M., Schrock, G., & Lester, T. W. (2017). Did U.S. regions with manufacturing design generate more production jobs in the 2000s? New evidence on innovation and regional development. *Urban Studies*, *54*(13), 3119–3137. https://doi.org/10.1177/0042098016663835

Drew, W., & Robert, R. (2003). Quantifying construct validity: Two simple measures. *Journal of Personality and Social Psychology*, *84*(3), 608–618. https://doi.org/10.1037/0022-3514.84.3.608

Drost, E. A. (2011). Validity and reliability in social science research. *Education Research and Perspectives*, *38*(1), 105–123.

Dutcă, I., Stăncioiu, P. T., Ioan, V. A., & Ioraș, F. (2018). Using clustered data to develop biomass allometric models: The consequences of ignoring the clustered data structure. *PLoS One*, *13*(8), 1–17. https://doi.org/10.1371/journal.pone.0200123

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2017). Re-examining the unified theory of acceptance and use of technology (UTAUT):

Towards a revised theoretical model. *Information Systems Frontiers*, *21*, 719–734. https://doi.org/10.1007/s10796-017-9774-y

Ensari, N., Riggio, R. E., Christian, J., & Carslaw, G. (2011). Who emerges as a leader? Meta-analyses of individual differences as predictors of leadership emergence. *Personality and Individual Differences*, *51*(4), 532–536. https://doi.org/10.1016/j.paid.2011.05.017

Eugene, W. (2012). How I use it: SurveyMonkey. *Occupational Medicine*, *62*(6), 477. https://doi.org/10.1093/occmed/kqs075

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

Farhangi, H., & Konur, D. (2018). System of systems architecting problems: Definitions, formulations, and analysis. *Procedia Computer Science*, *140*, 29–36. https://doi.org/10.1016/j.procs.2018.10.289

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*, 1149–1160. https://doi.org/10.3758/brm.41.4.1149

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2020). *G*Power* (Version 3.1.9.7) [Computer software]. Heinrich-Heine-Universität. https://www.psychologie.hhu.de/arbeitsgruppen/allgemeine-psychologie-und-arbeitspsychologie/gpower.html

Fırat, E. A., & Köksal, M. S. (2017). The relationship between use of Web 2.0 tools by prospective science teachers and their biotechnology literacy. *Computers in Human Behavior*, *70*, 44–50. https://doi.org/10.1016/j.chb.2016.12.067

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research reading*. Addison-Wesley

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

Friesen, P., Kearns, L., Redman, B., & Caplan, A. L. (2017). Rethinking the Belmont Report? *American Journal of Bioethics*, *17*(7), 15–21. https://doi.org/10.1080/15265161.2017.1329482

Gamlen, A., & McIntyre, C. (2018). Mixing methods to explain emigration policies: A postpositivist perspective. *Journal of Mixed Methods Research*, *12*(4), 374–393. https://doi.org/10.1177/1558689818782822

Gamo, B. R., Kim, D.-S., & Park, D.-B. (2019). Factors influencing community satisfaction in rural South Korea. *Journal of Rural and Community Development*, *14*(3), 109–125.

Gan, C. L., & Balakrishnan, V. (2018). Mobile technology in the classroom: What drives student-lecturer interactions? *International Journal of Human-Computer Interaction*, *34*(7), 666–679. https://doi.org/10.1080/10447318.2017.1380970

George, L. E., Locasto, L. W., Pyo, K. A., & W. Cline, T. (2017). Effect of the dedicated education unit on nursing student self-efficacy: A quasi-experimental research study. *Nurse Education in Practice*, *23*, 48–53. https://doi.org/10.1016/j.nepr.2017.02.007

Gheorghe, I. R., Purcărea, V. L., & Gheorghe, C. M. (2019). Pro-environmental behavior and bioeconomy: Reflections on single-bottled water consumption. *Amfiteatru Economic*, *21*(50), 105–120. https://doi.org/10.24818/EA/2019/50/105

Go, S. J. Y., Festin, C. A. M., & Tan, W. M. (2019). An SDN-based framework for improving the performance of under-provisioned IP video surveillance networks. *Journal of Network and Computer Applications*, *132*, 49–74. https://doi.org/10.1016/j.jnca.2019.01.026

Gowin, M., Wilkerson, A., Maness, S., Larson, D. J., Crowson, H. M., Smith, M., & Cheney, M. K. (2019). Wearable activity tracker use in young adults through the lens of social cognitive theory. *American Journal of Health Education*, *50*(1), 40–51. https://doi.org/10.1080/19325037.2018.1548314

Goyal, D. (2016). Survey on Bitlocker techniques. *International Journal of Advanced Research in Computer Science*, *7*(6), 255–257. https://doi.org/10.26483/ijarcs.v7i6.2774

Gunasinghe, A., Hamid, J. A., Khatibi, A., & Azam, S. M. F. (2019). Academicians' acceptance of online learning environments: A review of information system theories and models. *Global Journal of Computer Science and Technology, 19*(1), 30–39. https://doi.org/10.34257/GJCSTHVOL19IS1PG31

Guo, B., & Yuan, Y. (2017). A comparative review of methods for comparing means using partially paired data. *Statistical Methods in Medical Research*, *26*(3), 1323–1340. https://doi-org.org/10.1177/0962280215577111

Habiba, U., & Hossain, E. (2018). Auction mechanisms for virtualization in 5G cellular networks: Basics, trends, and open challenges. *IEEE Communications Surveys and Tutorials*, *20*(3), 2264–2293. https://doi.org/10.1109/COMST.2018.2811395

Hasani, M., Jahangiri, A., Sener, I. N., Munira, S., Owens, J. M., Appleyard, B., Ryan, S., Turner, S. M., & Ghanipoor Machiani, S. (2019). Identifying high-risk intersections for walking and bicycling using multiple data sources in the city of San Diego. *Journal of Advanced Transportation*, *2019*, 1–15. https://doi.org/10.1155/2019/9072358

Haski-Leventhal, D., Meijs, L. C. P. M., Lockstone-Binney, L., Holmes, K., & Oppenheimer, M. (2018). Measuring volunteerability and the capacity to volunteer among non-volunteers: Implications for social policy. *Social Policy and Administration*, *52*(5), 1139–1167. https://doi.org/10.1111/spol.12342

Hathcoat, J. D., & Meixner, C. (2017). Pragmatism, factor analysis, and the conditional incompatibility thesis in mixed methods research. *Journal of Mixed Methods Research*, *11*(4), 433–449. https://doi.org/10.1177/1558689815622114

Higgins, P. A., & Straub, A. J. (2006). Understanding the error of our ways: Mapping the concepts of validity and reliability. *Nursing Outlook*, *54*(1), 23–29. https://doi.org/10.1016/j.outlook.2004.12.004

Hofmann, M., & Meyer-Nieberg, S. (2018). Time to dispense with the p-value in OR? *Central European Journal of Operations Research, 26*(1), 193–214. https://doi.org/10.1007/s10100-017-0484-9

Hohpe, G., Ozkaya, I., Zdun, U., & Zimmermann, O. (2016). The software architect’s role in the digital age. *IEEE Software, 33*(6), 30–39. https://doi.org/10.1109/MS.2016.137

Hoppe, F. M., Hoppe, D. J., & Walter, S. D. (2017). Odds ratios deconstructed: A new way to understand and explain odds ratios as conditional risk ratios. *Journal of Clinical Epidemiology, 82*, 87–93. https://doi.org/10.1016/j.jclinepi.2016.08.007

Hoque, R., & Sorwar, G. (2017). Understanding factors influencing the adoption of mHealth by the elderly: An extension of the UTAUT model. *International Journal of Medical Informatics, 101*, 75–84. https://doi.org/10.1016/j.ijmedinf.2017.02.002

Hoyt, W. T., Leierer, S., & Millington, M. J. (2006). Analysis and interpretation of findings using multiple regression techniques. *Rehabilitation Counseling Bulletin, 49*(4), 223–233. https://doi.org/10.1177/00343552060490040401

Islam, S., Muslim, N., & Atwood, J. W. (2018). A survey on multicasting in software-defined networking. *IEEE Communications Surveys and Tutorials, 20*(1), 355–387. https://doi.org/10.1109/COMST.2017.2776213

Isong, B., Kgogo, T., & Lugayizi, F. (2017). Trust establishment in SDN: Controller and applications. *International Journal of Computer Network and Information Security, 9*(7), 20–28. https://doi.org/10.5815/ijcnis.2017.07.03

Ivanov, O. A., Ivanova, V. V., & Saltan, A. A. (2018). Likert-scale questionnaires as an educational tool in teaching discrete mathematics. *International Journal of Mathematical Education in Science and Technology*, *49*(7), 1110–1118. https://doi.org/10.1080/0020739X.2017.1423121

Jain, S., Dubey, S., & Jain, S. (2016). Designing and validation of questionnaire. *International Dental and Medical Journal of Advanced Research*, *2*(2016), 1–3. https://doi.org/10.15713/ins.idmjar.39

Jia, M., Zhu, S., Wang, L., Guo, Q., Wang, H., & Liu, Z. (2018). Routing algorithm with virtual topology toward to huge numbers of LEO mobile satellite network based on SDN. *Mobile Networks and Applications*, *23*(2), 285–300. https://doi.org/10.1007/s11036-017-0948-0

JosephNg, P. S. (2018). EaaS optimization: Available yet hidden information technology infrastructure inside a medium-size enterprise. *Technological Forecasting and Social Change*, *132*, 165–173. https://doi.org/10.1016/j.techfore.2018.01.030

Józsa, K., & Morgan, G. A. (2017). Reversed items in Likert scales: Filtering out invalid responders. *Journal of Psychological and Educational Research*, *25*(1), 7–25. https://www.researchgate.net/publication/317264817_Reversed_Items_in_Likert_Scales_Filtering_Out_Invalid_Responders

Kaye, S.-A., Lewis, I., Forward, S., & Delhomme, P. (2020). A priori acceptance of highly automated cars in Australia, France, and Sweden: A theoretically-informed investigation guided by the TPB and UTAUT. *Accident Analysis and Prevention*, *137*, 1–11. https://doi.org/10.1016/j.aap.2020.105441

Keisling, B. L., & Sproles, C. (2020). Building a sustainable collection review process: Managing qualitative and quantitative eresource data over time. *Serials Review*, *46*(1), 1–9. https://doi.org/10.1080/00987913.2020.1727400

Keller, A., Aguilar, A., & Hanss, D. (2018). Car sharers' interest in integrated multimodal mobility platforms: A diffusion of innovations perspective. *Sustainability*, *10*(12), 1–20. https://doi.org/10.3390/su10124689

Kelley-Quon, L. I. (2018). Surveys: Merging qualitative and quantitative research methods. *Seminars in Pediatric Surgery*, *27*(6), 361–366. https://doi.org/10.1053/j.sempedsurg.2018.10.007

Kılınç, H., & Fırat, M. (2017). Opinions of expert academicians on online data collection and voluntary participation in social sciences research. *Educational Sciences: Theory and Practice*, *17*(5), 1461–1486. https://doi.org/10.12738/estp.2017.5.0261

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, Y., Dykema, J., Stevenson, J., Black, P., & Moberg, D. P. (2019a). Straight-lining: Overview of measurement, comparison of indicators, and effects in mail–web mixed-mode surveys. *Social Science Computer Review*, *37*(2), 214–233. https://doi.org.org/10.1177/0894439317752406

Kim, Y., Nam, J., Park, T., Scott-Hayward, S., & Shin, S. (2019b). SODA: A software-defined security framework for IoT environments. *Computer Networks*, *163*, 1–12 https://doi.org/10.1016/j.comnet.2019.106889

Kirpich, A., Ainsworth, E. A., Wedow, J. M., Newman, J. R. B., Michailidis, G., & McIntyre, L. M. (2018). Variable selection in omics data: A practical evaluation of small sample sizes. *PLoS One*, *13*(6), 1–19. https://doi.org/10.1371/journal.pone.0197910

Knepp, M. M. (2018). Using questions to improve informed consent form reading behavior in students. *Ethics and Behavior*, *28*(7), 560–577. https://doi.org/10.1080/10508422.2017.1320665

Kobo, H. I., Abu-Mahfouz, A. M., & Hancke, G. P. (2017). A survey on software-defined wireless sensor networks: Challenges and design requirements. *IEEE Access*, *5*, 1872–1899. https://doi.org/10.1109/ACCESS.2017.2666200

Lallukka, T., Pietiläinen, O., Jäppinen, S., Laaksonen, M., Lahti, J., & Rahkonen, O. (2020). Factors associated with health survey response among young employees: A register-based study using online, mailed, and telephone interview data collection methods. *BMC Public Health*, *20*(1), 1–13. https://doi.org/10.1186/s12889-020-8241-8

Lang, K. M., & Little, T. D. (2018). Principled missing data treatments. *Prevention Science, 19*(3), 284–294. https://doi.org/10.1007/s11121-016-0644-5

Latif, K. F., & Sajjad, A. (2018). Measuring corporate social responsibility: A critical review of survey instruments. *Corporate Social Responsibility and Environmental Management*, *25*(6), 1174–1197. https://doi.org/10.1002/csr.1630

Lawrence, C. L. (2018). *Factors affecting the adoption of bring your own device by teachers in Caymanian* (Doctoral dissertation). Retrieved from ProQuest

Dissertations and Theses Full-Text database. (Publication No. 10813891) [Doctoral dissertation, Walden University]. ProQuest Dissertations and Theses Global.

Lee, D. K. (2016). Alternatives to *P* value: Confidence interval and effect size. *Korean Journal of Anesthesiology*, *69*(6), 555–562. https://doi.org/10.4097/kjae.2016.69.6.555

Lemay, D. J., Morin, M. M., Bazelais, P., & Doleck, T. (2018). Modeling students' perceptions of simulation-based learning using the technology acceptance model. *Clinical Simulation in Nursing*, *20*, 28–37. https://doi.org/10.1016/j.ecns.2018.04.004

Lenzholzer, S., & Brown, R. D. (2016). Postpositivist microclimatic urban design research: A review. *Landscape and Urban Planning*, *153*, 111–121. https://doi.org/10.1016/j.landurbplan.2016.05.008

Liang, J.-K., Eccarius, T., & Lu, C.-C. (2019). Investigating factors that affect the intention to use shared parking: A case study of Taipei City. *Transportation Research Part A: Policy and Practice*, *130*, 799–812. https://doi.org/10.1016/j.tra.2019.10.006

Liddell, T. M., & Kruschke, J. K. (2018). Analyzing ordinal data with metric models: What could possibly go wrong? *Journal of Experimental Social Psychology*, *79*, 328–348. https://doi.org/10.1016/j.jesp.2018.08.009

Lim, W. S., & Suki, N. M. (2020). Conceptual study of consumers' intention to purchase sustainable building in Malaysia. *International Journal of Psychosocial*

Rehabilitation, *24*(2), 1869–1879. https://doi.org/10.37200/IJPR/V24I2/PR200488

Liu, M., Conrad, F. G., & Lee, S. (2017). Comparing acquiescent and extreme response styles in face-to-face and web surveys. *Quality and Quantity*, *51*(2), 941–958. https://doi.org/10.1007/s11135-016-0320-7

Liu, Y., Zhao, B., Zhao, P., Fan, P., & Liu, H. (2019). A survey: Typical security issues of software-defined networking. *China Communications*, *16*(7), 13–31. https://doi.org/10.23919/JCC.2019.07.002

Long, H., & Rodgers, C. R. (2017). Re-conceptualize mixed methods research: Introducing a new conceptual framework. *Quality and Quantity*, *51*(6), 2813–2829. https://doi.org/10.1007/s11135-016-0447-6

Loukis, E., Arvanitis, S., & Kyriakou, N. (2017). An empirical investigation of the effects of firm characteristics on the propensity to adopt cloud computing. *Information Systems and eBusiness Management*, *15*(4), 963–988. https://doi.org/10.1007/s10257-017-0338-y

Lowry, P. B., D’Arcy, J., Hammer, B., & Moody, G. D. (2016). “Cargo Cult” science in traditional organization and information systems survey research: A case for using nontraditional methods of data collection, including Mechanical Turk and online panels. *Journal of Strategic Information Systems*, *25*(3), 232–240. https://doi.org/10.1016/j.jsis.2016.06.002

Lu, J., Zhang, Z., Hu, T., Yi, P., & Lan, J. (2019a). A survey of controller placement problem in software-defined networking. *IEEE Access, 7*, 24290–24307 https://doi.org/10.1109/ACCESS.2019.2893283

Lu, T., & Franklin, A. L. (2018). A protocol for identifying and sampling from proxy populations. *Social Science Quarterly*, *99*(4), 1535–1546. https://doi.org/10.1111/ssqu.12519

Lu, Y., Fu, Q., Xi, X., Chen, Z., Zou, E., & Fu, B. (2019b). A policy conflict detection mechanism for multi-controller software-defined networks. *International Journal of Distributed Sensor Networks, 15*(5), 1–12. https://doi.org/10.1177/1550147719844710

Lux, M. R., Protus, B. M., Kimbrel, J., & Grauer, P. (2017). A survey of hospice and palliative care physicians regarding palliative sedation practices. *American Journal of Hospice and Palliative Medicine*, *34*(3), 217–222. https://doi.org/10.1177/1049909115615128

Madigan, R., Louw, T., Wilbrink, M., Schieben, A., & Merat, N. (2017). What influences the decision to use automated public transport? Using UTAUT to understand public acceptance of automated road transport systems. *Transportation Research Part F: Traffic Psychology and Behaviour, 50*, 55–64. https://doi.org/10.1016/j.trf.2017.07.007

Mahmood, A., Zhang, W. E., & Sheng, Q. Z. (2019). Software-defined heterogeneous vehicular networking: The architectural design and open challenges. *Future Internet*, *11*(3), 1–17. https://doi.org/10.3390/fi11030070

Mahmud, A., Zalay, O., Springerq, A., Arts, K., & Eisenhauer, E. (2018). Barriers to participation in clinical trials: a physician survey. *Current Oncology*, *25*(2), 119–125. https://doi.org/10.3747/co.25.3857

Maio, A. D., Palattella, M. R., Soua, R., Lamorte, L., Vilajosana, X., Alonso-Zarate, J., & Engel, T. (2016). Enabling SDN in VANETs: What is the impact on security? *Sensors*, *16*(12), 1–24. https://doi.org/10.3390/s16122077

Maity, M., Bagchi, K., Shah, A., & Misr, A. (2019). Explaining normative behavior in information technology use. *Information Technology and People*, *32*(1), 94–117. https://doi.org/10.1108/ITP-11-2017-0384

Malik, A., Ahmed, J., Qadir, J., & Ilyas, M. U. (2017). A measurement study of open-source SDN layers in OpenStack under network perturbation. *Computer Communications*, *102*, 139–149. https://doi.org/10.1016/j.comcom.2016.12.014

Mallick, H., Ma, S., Eric, A., Franzosa, T. V., Morgan, X. C., & Huttenhower, C. (2017). Experimental design and quantitative analysis of microbial community multi-omics. *Genome Biology*, *18*(1), 1–16. https://doi.org/10.1186/s13059-017-1359-z

Marshall, G., & Jonker, L. (2011). An introduction to inferential statistics: A review and practical guide. *Radiography*, *17*(1), 1–6. https://doi.org/10.1016/j.radi.2009.12.006

Martinez-Mesa, J., Gonzalez-Chica, D. A., Duquia, R. P., Bonamigo, R. R., & Bastos, J. L. (2016). Sampling: how to select participants in my research study? *Anais Brasileiros de Dermatologia*, *91*(3), 326–330. https://doi.org/10.1590/abd1806-4841.20165254

Mayoral, A., Vilalta, R., Muñoz, R., Casellas, R., & Martínez, R. (2017). SDN orchestration architectures and their integration with cloud computing applications. *Optical Switching and Networking*, *26*, 2–13. https://doi.org/10.1016/j.osn.2015.09.007

Maziku, H., Shetty, S., & Nicol, D. M. (2019). Security risk assessment for SDN-enabled smart grids. *Computer Communications*, *133*, 1–11. https://doi.org/10.1016/j.comcom.2018.10.007

Medeiros, G. O., João, C. W. A. C., Cardoso, D. L., & Santos, A. D. F. (2020). An intelligent SDN framework based on QoE predictions for load balancing in C-RAN. *Wireless Communications and Mobile Computing*, *2020*, 1–15. http://doi.org/10.1155/2020/7065202

Mentzer, J. T., & Flint, D. J. (1997). Validity in logistics research. *Journal of Business Logistics*, *18*(1), 199–216.

Middleton, L., Hall, H., & Raeside, R. (2019). Applications and applicability of social cognitive theory in information science research. *Journal of Librarianship and Information Science*, *51*(4), 927–937. https://doi.org/10.1177/0961000618769985

Mijumbi, R., Serrat, J., Gorricho, J., Bouten, N., De Turck, F., & Boutaba, R. (2016). Network function virtualization: State-of-the-art and research challenges. *IEEE Communications Surveys and Tutorials*, *18*(1), 236–262. https://doi.org/10.1109/COMST.2015.2477041

Mikalef, P., Pappas, I. O., & Giannakos, M. (2016). An integrative adoption model of video-based learning. (2016). *International Journal of Information and Learning Technology*, *33*(4), 219–235. https://doi.org/10.1108/IJILT-01-2016-0007

Miller, J., & Ulrich, R. (2016). Interpreting confidence intervals: A comment on Hoekstra, Morey, Rouder, and Wagenmakers (2014). *Psychonomic Bulletin and Review*, *23*(1), 124–130. https://doi.org/10.3758/s13423-015-0859-7

Miller, L. C., Russell, C. L., Cheng, A.-L., & Zembles, S. (2018). Testing the efficacy of a scaffolded writing intervention with online degree-completion nursing students: A quasi-experimental design. *Nurse Education in Practice*, *32*, 115–121. https://doi.org/10.1016/j.nepr.2018.06.011

Mohajan, H. K. (2017). Two criteria for good measurements in research: Validity and reliability. *Annals of Spiru Haret University Economic Series*, *17*(4), 59–82. https://doi.org/10.26458/1746

Mohajan, H. K. (2018). Qualitative research methodology in social sciences and related subjects. *Journal of Economic Development, Environment and People*, *7*(1), 23–48. https://doi.org/10.26458/jedep.v7i1.571

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research*, *2*(3), 192–222. https://doi.org/10.1287/isre.2.3.192

Morgado, F. F. R., Meireles, J. F. F., Neves, C. M., Amaral, A. C. S., & Ferreira, M. E. C. (2017). Scale development: Ten main limitations and recommendations to improve future research practices. *Psicologia: Reflexao e Critica*, *30*(3), 1–20. https://doi.org/10.1186/s41155-016-0057-1

Morgan, D. L. (2018). Living within blurry boundaries: The value of distinguishing between qualitative and quantitative research. *Journal of Mixed Methods Research*, *12*(3), 268–279. https://doi.org/10.1177/1558689816686433

Moryson, H., & Moeser, G. (2016). Consumer adoption of cloud computing services in Germany: Investigation of moderating effects by applying a UTAUT model. *International Journal of Marketing Studies*, *8*(1), 14–32. https://doi.org/10.5539/ijms.v8n1p14

Muciaccia, T., & Passaro, V. M. N. (2017). Future scenarios for software-defined metro and access networks and software-defined photonics. *Photonics*, *4*(1), 1–27. https://doi.org/10.3390/photonics4010001

Müller, A., & Daller, M. (2019). Predicting international students' clinical and academic grades using two language tests (IELTS and C-test): A correlational research study. *Nurse Education Today*, *72*, 6–11. https://doi.org/10.1016/j.nedt.2018.10.007

Mutahar, A., Norzaidi, M., Ramayah, T., Isaac, O., & Alrajawy, I. (2017). Integration of innovation diffusion theory (IDT) and technology acceptance model (TAM) to understand mobile banking acceptance in Yemen: The moderating effect of income. international journal of soft computing. *International Journal of Soft Computing*, *12*(3), 164–177. https://doi.org/10.36478/ijscomp.2017.164.177

Nadal, L., Svaluto Moreolo, M., Hernandez, J. A., Fabrega, J. M., Casellas, R., Munoz, R., Vilalta, R., Rodriguez, L., Vilchez, F. J., & Martinez, R. (2020). SDN-enabled S-BVT for disaggregated networks: Design, implementation and cost analysis. *Journal of Lightwave Technology, 38*(11), 3037–3043. https://doi.org/10.1109/JLT.2020.2969457

Nagasaka, N. (2016). Visualizing historical trends in global maritime boundary delimitations since the 1940s. *Marine Policy*, *71*, 29–37. https://doi.org/10.1016/j.marpol.2016.05.017

Nägle, S., & Schmidt, L. (2012). Computer acceptance of older adults. *Work*, *41*, 3541–3548. https://doi.org/10.3233/wor-2012-0633-3541

National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research. (1979). *The Belmont report: Ethical principles and guidelines for the protection of human subjects of research.* U.S. Department of Health and Human Services. https://www.hhs.gov/ohrp/regulations-and-policy/belmont-report/index.html

Ndiaye, M., Hancke, G. P., & Abu-Mahfouz, A. (2017). Software-defined networking for improved wireless sensor network management: A survey. *Sensors*, *17*(5), 1–32. https://doi.org/10.3390/s17051031

Newcomer, S. R., Xu, S., Kulldorff, M., Daley, M. F., Fireman, B., & Glanz, J. M. (2019). A primer on quantitative bias analysis with positive predictive values in research using electronic health data. *Journal of the American Medical*

Informatics Association: JAMIA, *26*(12), 1664–1674. https://doi.org/10.1093/jamia/ocz094

Niyaz, Q., Sun, W., & Javaid, A. Y. (2017). A deep learning-based DDoS detection system in software-defined networking (SDN). *EAI Endorsed Transactions on Security and Safety*, *4*(12), 1–12. https://doi.org/10.4108/eai.28-12-2017.153515

Noftle, E. E., & Robins, R. W. (2007). Personality predictors of academic outcomes: Big five correlates of GPA and SAT scores. *Journal of Personality and Social Psychology*, *93*(1), 116–130. https://doi.org/10.1037/0022-3514.93.1.116

Norman, G. (2010). Likert scales, levels of measurement, and the "laws" of statistics. *Advances in Health Sciences Education*, *15*(5), 625–632. https://doi.org/10.1007/s10459-010-9222-y

Nunes, A., Limpo, T., & Castro, S. L. (2019). Acceptance of mobile health applications: Examining key determinants and moderators. *Frontiers in Psychology*, *10*, 1–10. https://doi.org/10.3389/fpsyg.2019.02791

Obitube, K. F. O., Mbah, B. M., & Babarinde, O. (2020). The impact of audio-lingual and TPR methods in teaching Igbo to L2 learners. *Southern African Linguistics and Applied Language Studies*, *38*(1), 16–26. https://doi.org/10.2989/16073614.2019.1698304

Olsen, A. A., McLaughlin, J. E., & Harpe, S. E. (2020). Using multiple linear regression in pharmacy education scholarship. *Currents in Pharmacy Teaching and Learning*, *12*(10). 1258–1268. https://doi.org/10.1016/j.cptl.2020.05.017

Omilla, F. O. (2019). Muddles in pentatonic Likert-type scale: Accuracy cost in psychometric measurements for small enterprise development. *ILIRIA International Review*, *9*(1), 69–83. https://doi.org/10.21113/iir.v9i1.476

O'Neill, T. R., Gregg, J. L., & Peabody, M. R. (2020). Effect of sample size on common item equating using the dichotomous Rasch model. *Applied Measurement in Education*, *33*(1), 10–23. https://doi.org/10.1080/08957347.2019.1674309

Ortiz, M. A., & Bluyssen, P. M. (2018). Proof-of-concept of a questionnaire to understand occupants' comfort and energy behaviors: First results on home occupant archetypes. *Building and Environment*, *134*, 47–58. https://doi.org/10.1016/j.buildenv.2018.02.030

Ouirdi, M. E., Ouirdi, A. E., Segers, J., & Pais, I. (2016). Technology adoption in employee recruitment: The case of social media in Central and Eastern Europe. *Computers in Human Behavior*, *57*, 240–249. https://doi.org/10.1016/j.chb.2015.12.043

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

Park, J.-H., Kim, H.-S., & Kim, W.-T. (2018). DM-MQTT: An efficient MQTT based on SDN multicast for massive IoT communications. *Sensors*, *18*(9), 1–15. https://doi.org/10.3390/s18093071

Patil, P., Tamilmani, K., Rana, N. P., & Raghavan, V. (2020). Understanding consumer adoption of mobile payment in India: Extending Meta-UTAUT model with personal innovativeness, anxiety, trust, and grievance redressal. *International Journal of Information Management*, *54*, 1–16. https://doi.org/10.1016/j.ijinfomgt.2020.102144

Peck, B., & Mummery, J. (2018). Hermeneutic constructivism: An ontology for qualitative research. *Qualitative Health Research*, *28*(3), 389–407. https://doi.org/10.1177/1049732317706931

Pedersen, M. J., & Nielsen, C. V. (2016). Improving survey response rates in online panels: Effects of low-cost incentives and cost-free text appeal interventions. *Social Science Computer Review*, *34*(2), 229–243. https://doi.org/10.1177/0894439314563916

Peng, G. (2018). The state of assessing data stewardship maturity—an overview. *Data Science Journal*, *17*, 1–12. https://doi.org/10.5334/dsj-2018-007

Peng, G., Privette, J. L., Tilmes, C., Bristol, S., Maycock, T., Bates, J. J., Hausman, S., Brown, O., & Kearns, E. J. (2018). A conceptual enterprise framework for managing scientific data stewardship. *Data Science Journal*, *17*, 1–17. https://doi.org/10.5334/dsj-2018-015

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

Poularakis, K., Iosifidis, G., Smaragdakis, G., & Tassiulas, L. (2019). *Optimizing gradual SDN upgrades in ISP networks. IEEE/ACM Transactions on Networking, 27*(1), 288–301. https://doi.org/10.1109/TNET.2018.2890248

Pryjmachuk, S., & Richards, D. A. (2007). Look before you leap and don't put all your eggs in one basket: the need for caution and prudence in quantitative data analysis. *Journal of Research in Nursing*, *12*(1), 43–53. https://doi.org/10.1177/1744987106070260

Puente Fernandez, J. A., García Villalba, L. J., & Tai-Hoon, K. (2018). Software-defined networks in wireless sensor architectures. *Entropy*, *20*(4), 1–23. https://doi.org/10.3390/e20040225

Puspitasari, N., Firdaus, M. B., Haris, C. A., & Setyadi, H. J. (2019). An application of the UTAUT model for analysis of adoption of integrated license service information system. *Procedia Computer Science*, *161*, 57–65. https://doi.org/10.1016/j.procs.2019.11.099

Qafzezi, E., Bylykbashi, K., Ikeda, M., Matsuo, K., & Barolli, L. (2020). Coordination and management of cloud, fog, and edge resources in SDN-VANETs using fuzzy logic: A comparison study for two fuzzy-based systems. *Internet of Things*, *11*, 1–12. https://doi.org/10.1016/j.iot.2020.100169

Qiu, C., Zhao, C., Xu, F., & Yang, T. (2016). Sleeping mode of multi-controller in green software-defined networking. *EURASIP Journal on Wireless Communications and Networking*, *2016*(1), 1–9. https://doi.org/10.1186/s13638-016-0779-x

Rad, M. S., Nilashi, M., & Dahlan, H. M. (2018). Information technology adoption: A review of the literature and classification. *Universal Access in the Information Society*, *17*(2), 361–390. http://doi.org/10.1007/s10209-017-0534-z

Rahi, S., Mansour, M. M. O., 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

Rattani, A., & Johns, A. (2017). Collaborative partnerships and gatekeepers in online research recruitment. *American Journal of Bioethics*, *17*(3), 27–29. https://doi.org/10.1080/15265161.2016.1274800

Raza, S. A., Shah, N., & Ali, M. (2019). Acceptance of mobile banking in Islamic banks: Evidence from modified UTAUT model. *Journal of Islamic Marketing*, *10*(1), 357–376. https://doi.org/10.1108/JIMA-04-2017-0038

Rebar, A. L., Rhodes, R. E., & Gardner, B. (2019). How we are misinterpreting physical activity intention-behavior relations and what to do about it. *International Journal of Behavioral Nutrition and Physical Activity*, *16*, 1–13. https://doi.org/10.1186/s12966-019-0829-y

Rehmani, M. H., Davy, A., Jennings, B., & Assi, C. (2019). Software-defined network-based smart grid communication: A comprehensive survey. *IEEE Communications Surveys and Tutorials*, *21*(3), 2637–2670. https://doi.org/10.1109/COMST.2019.2908266

Reio, T. G., Jr. (2016). Nonexperimental research: strengths, weaknesses and issues of precision. *European Journal of Training and Development*, *40*(8/9), 676–690. https://doi.org/10.1108/EJTD-07-2015-0058

Reiss, J. (2019). Against external validity. *Synthese*, *196*(8), 3103–3121. https://doi.org/10.1007/s11229-018-1796-6

Reisslein, M., & Maier, G. (2019). Transport SDN at the dawn of the 5G era. *Optical Switching and Networking*, *33*, 34–40. https://doi.org/10.1016/j.osn.2019.02.001

Renshaw, T. L. (2018). Psychometrics of the revised college student subjective wellbeing questionnaire. *Canadian Journal of School Psychology*, *33*(2), 136–149. https://doi.org/10.1177/0829573516678704

Rietz, R., Cwalinski, R., König, H., & Brinner, A. (2018). An SDN-based approach to ward off LAN attacks. *Journal of Computer Networks and Communications*, *2018*, 1–12. https://doi.org/10.1155/2018/4127487

Ringle, C. M., Sarstedt, M., Mitchell, R., & Gudergan, S. P. (2020). Partial least squares structural equation modeling in HRM research. *International Journal of Human Resource Management*, *31*(12), 1617–1643. https://doi.org/10.1080/09585192.2017.1416655

Ripley, K. R., Hance, M. A., Kerr, S. A., Brewer, L. E., & Conlon, K. E. (2018). Uninformed consent? The effect of participant characteristics and delivery format on informed consent. *Ethics and Behavior*, *28*(7), 517–543. https://doi.org/10.1080/10508422.2018.1456926

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press

Rotsos, C., King, D., Farshad, A., Bird, J., Fawcett, L., Georgalas, N., Gunkel, M., Shiomoto, K., Wang, A., Mauthe, A., Race, N., & Hutchison, D. (2017). Network service orchestration standardization: A technology survey. *Computer Standards and Interfaces*, *54*(Part 4), 203–215. https://doi.org/10.1016/j.csi.2016.12.006

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.

Sakshaug, J. W., Wiśniowski, A., Ruiz, D. A. P., & 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

Salman, O., Elhajj, I., Chehab, A., & Kayssi, A. (2018). IoT survey: An SDN and fog computing perspective. *Computer Networks*, *143*, 221–246. https://doi.org/10.1016/j.comnet.2018.07.020

Salmeron, R., Garcia, C. B., & Garcia, J. (2018). Variance inflation factor and condition number in multiple linear regression. *Journal of Statistical Computation and Simulation*, *88*(12), 2365–2384. https://doi.org/10.1080/00949655.2018.1463376

Samii, C. (2016). Causal empiricism in quantitative research. *Journal of Politics*, *78*(3), 941–955. https://doi.org/10.1086/686690

Saraswat, S., Agarwal, V., Gupta, H. P., Mishra, R., Gupta, A., & Dutta, T. (2019). Challenges and solutions in software-defined networking: A survey. *Journal of*

Network and Computer Applications, *141*, 23–58 https://doi.org/10.1016/j.jnca.2019.04.020

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

Scholtz, B., & Mlozo-Banda, C. (2019). Applying theories for using non-monetary incentives for citizens to participate in crowdsensing projects. *South African Computer Journal*, *31*(2), 99–116. https://doi.org/10.18489/sacj.v31i2.787

Schweitzer-Krah, E., & Engartner, T. (2019). Students' perception of the pluralism debate in economics: Evidence from a quantitative survey among German universities. *International Review of Economics Education*, *30*, 1–12. https://doi.org/10.1016/j.iree.2018.07.003

Seeram, E. (2019). An overview of correlational research. *Radiologic Technology*, *91*(2), 176–179. http://www.radiologictechnology.org/content/91/2/176.extract

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

Shachak, A., Kuziemsky, C., & Petersen, C. (2019). Beyond TAM and UTAUT: Future directions for HIT implementation research. *Journal of Biomedical Informatics*, *100*(2019), 1–5. https://doi.org/10.1016/j.jbi.2019.103315

Shang, F., Li, Y., Fu, Q., Wang, W., Feng, J., & He, L. (2018). Distributed controllers multigranularity security communication mechanism for software-defined networking. *Computers and Electrical Engineering*, *66*, 388–406. https://doi.org/10.1016/j.compeleceng.2017.07.003

Shannon-Baker, P. (2016). Making paradigms meaningful in mixed methods research. *Journal of Mixed Methods Research*, *10*(4), 319–334. https://doi.org/10.1177/1558689815575861

Shi, D., Lee, T., Fairchild, A. J., & Maydeu-Olivares, A. (2020). Fitting ordinal factor analysis models with missing data: A comparison between pairwise deletion and multiple imputations. *Educational and Psychological Measurement*, *80*(1), 41–66. https://doi.org/10.1177/0013164419845039

Shiau, S. J. H., Huang, C.-Y., Yang, C.-L., & Juang, J.-N. (2018). A derivation of factors influencing the innovation diffusion of the OpenStreetMap in STEM education. *Sustainability*, *10*(10), 1–29. https://doi.org/10.3390/su10103447

Show-Li, J., & Shieh, G. (2019). Sample size calculations for model validation in linear regression analysis. *BMC Medical Research Methodology, 19*, 1–9 https://doi.org/10.1186/s12874-019-0697-9

Shrotryia, V. K., & Dhanda, U. (2019). Content validity of assessment instrument for employee engagement. *Sage Open*, *9*, 1–7. https://doi.org/10.1177/2158244018821751

Silva, H. P., Lehoux, P., & Hagemeister, N. (2018). Developing a tool to assess responsibility in health innovation: Results from an international Delphi study. *Health Policy and Technology*, *7*(4), 388–396. https://doi.org/10.1016/j.hlpt.2018.10.007

Singh, S., & Jha, R. K. (2017). A survey on software-defined networking: Architecture for next generation network. *Journal of Network and Systems Management, 25*(2), 321–374. https://doi.org/10.1007/s10922-016-9393-9

Singh, S., & Wassenaar, D. (2016). Contextualizing the role of the gatekeeper in social science research. *South African Journal of Bioethics and Law*, *9*(1), 42–46. https://doi.org/10.7196/SAJBL.2016.v9i1.465

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, *104*, 333–339, https://doi.org/10.1016/j.jbusres.2019.07.039

Solheim, E., Plathe, H. S., & Eide, H. (2017). Nursing students' evaluation of a new feedback and reflection tool for use in high-fidelity simulation—formative assessment of clinical skills: A descriptive quantitative research design. *Nurse Education in Practice*, *27*, 114–120. https://doi.org/10.1016/j.nepr.2017.08.021

Stavseth, M. R., Clausen, T., & Røislien, J. (2019). How handling missing data may impact conclusions: A comparison of six different imputation methods for categorical questionnaire data. *Sage Open Medicine, 7*, 1–12. https://doi.org/10.1177/2050312118822912

Straub, D. W. (1989). Validating instruments in MIS research. *MIS Quarterly*, *13*(2), 147–169. https://doi.org/10.2307/248922

Streitwieser, B., Bryant, F. B., Drane, D., & Light, G. (2019). Assessing student conceptions of international experience: Developing a validated survey instrument. *International Journal of Intercultural Relations*, *68*, 26–43. https://doi.org/10.1016/j.ijintrel.2018.10.004

Suh, D., & Pack, S. (2018). Low-complexity master controller assignment in distributed SDN controller environments. *IEEE Communications Letters*, *22*(3), 490–493. https://doi.org/10.1109/LCOMM.2017.2787590

Sullivan, G. M., & Artino, A. R., Jr. (2013). Analyzing and interpreting data from Likert-type scales. *Journal of Graduate Medical Education*, *5*(4), 541–542. https://doi.org/10.4300/JGME-5-4-18

Sultana, N., Chilamkurti, N., Peng, W., & Alhadad, R. (2018). Survey on SDN-based network intrusion detection system using machine learning approaches. *Peer-to-Peer Networking and Applications, 12*(2), 493–501. https://doi.org/10.1007/s12083-017-0630-0

Šumak, B., & Šorgo, A. (2016). The acceptance and use of interactive whiteboards among teachers: Differences in UTAUT determinants between pre- and post-adopters. *Computers in Human Behavior*, *64*, 602–620. https://doi.org/10.1016/j.chb.2016.07.037

SurveyMonkey. (n.d.). *SurveyMonkey Audience guidelines policies*. Retrieved December 18, 2020, from https://help.surveymonkey.com/articles/en_US/kb/SurveyMonkey-Audience-Guidelines-and-Policies

Suter, G. W., II, & Cormier, S. M. (2016). Bias in the development of health and ecological assessments and potential solutions. *Human and Ecological Risk Assessment*, *22*(1), 99–115. https://doi.org/10.1080/10807039.2015.1056062

Taber, K. S. (2018). The use of Cronbach's Alpha when developing and reporting research instruments in science education. *Research in Science Education*, *48*(6), 1273–1296. https://doi.org/10.1007/s11165-016-9602-2

Taguchi, N. (2018). Description and explanation of pragmatic development: Quantitative, qualitative, and mixed methods research. *System*, *75*, 23–32. https://doi.org/10.1016/j.system.2018.03.010

Tams, S., Ahuja, M., Thatcher, J., & Grover, V. (2020). Worker stress in the age of mobile technology: The combined effects of perceived interruption overload and worker control. *Journal of Strategic Information Systems*, *29*(1), 1–17. https://doi.org/10.1016/j.jsis.2020.101595

Tangmanee, C., & Niruttinanon, P. (2019). Web survey's completion rates: Effects of forced responses; question display styles; and subjects' attitude. *International Journal of Research in Business and Social Science, 8*(1), 20–29. https://doi.org/10.20525/ijrbs.v8i1.183

Taylor, S., & Todd, P. (1995). Assessing IT usage: The role of prior experience. *MIS Quarterly*, *19*(4), 561–570. https://doi.org/10.2307/249633

Tello-Oquendo, L., Lin, S.-C., Akyildiz, I. F., & Pla, V. (2019). Software-defined architecture for QoS-Aware IoT deployments in 5G systems. *Ad Hoc Networks, 93*, 1–11. https://doi.org/10.1016/j.adhoc.2019.101911

Teo, T., Zhou, M., & Noyes, J. (2016). Teachers and technology: Development of an extended theory of planned behavior. *Educational Technology Research and Development*, *64*(6), 1033–1052. https://doi.org/10.1007/s11423-016-9446-5

Teo, T. W., & Yeo, L. W. (2017). Gender studies of science and science education in Singapore. *Asian Women*, *33*(3), 1–21. https://doi.org/10.14431/aw.2017.09.33.3.1

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal computing: Toward a conceptual model of utilization. *MIS Quarterly*, *15*(1), 125–143. https://doi.org/10.2307/249443

Thongsri, N., Shen, L., Bao, Y., & Alharbi, I. M. (2018). Integrating UTAUT and UGT to explain behavioral intention to use m-learning: A developing country’s perspective. *Journal of Systems and Information Technology*, *20*(3), 278–297. https://doi.org/10.1108/JSIT-11-2017-0107

Tladi, L., & Nleya, P. (2017). The influence of quality on elearning implementation in Botswana tertiary institutions: The case for Botswana College of Distance and Open Learning. *African Educational Research Journal*, *5*(4), 240–245. https://eric.ed.gov/?id=EJ1214169

Toledo-Fernández, A., Villalobos-Gallegos, L., & Marín-Navarrete, R. (2016). Is the mini-mental state examination (MMSE) useful for eligibility screening of research participants with substance use disorder? *Revista Internacional de Investigación En Adicciones*, *2*(1), 39–44. https://doi.org/10.28931/riiad.2016.1.06

Tomovic, S., Yoshigoe, K., Maljevic, I., & Radusinovic, I. (2017). Software-defined fog network architecture for IoT. *Wireless Personal Communications, 92*(1), 181–196. https://doi.org/10.1007/s11277-016-3845-0

van Dijk, R., van Assen, M., Vliegenthart, R., de Bock, G. H., van der Harst, P., & Oudkerk, M. (2017). Diagnostic performance of semi-quantitative and quantitative stress CMR perfusion analysis: A meta-analysis. *Journal of Cardiovascular Magnetic Resonance, 19*(1), 1–16. https://doi.org/10.1186/s12968-017-0393-z

van Riel, A. C. R., Henseler, J., Kemény, I., & Sasovova, Z. (2017). Estimating hierarchical constructs using consistent partial least squares: The case of second-order composites of common factors. *Industrial Management and Data Systems, 117*(3), 459–477. https://doi.org/10.1108/IMDS-07-2016-0286

van Vliet, H., & Tang, A. (2016). Decision making in software architecture. *Journal of Systems and Software*, *117*, 638–644. https://doi.org/10.1016/j.jss.2016.01.017

Velte, P., & Stawinoga, M. (2017). Integrated reporting: The current state of empirical research, limitations, and future research implications. *Journal of Management Control*, *28*(3), 275–320. https://doi.org/10.1007/s00187-016-0235-4

Vencato, M. M., Karageorghis, C. I., Priest, D.-L., & Nevill, A. M. (2017). Concurrent validity and cross-validation of the Brunel Lifestyle Physical Activity Questionnaire. *Journal of Science and Medicine in Sport*, *20*(8), 766–770. https://doi.org/10.1016/j.jsams.2016.12.077

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

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

Vergouwe, Y., Steyerberg, E. W., Eijkemans, M. J. C., & Habbema, J. D. (2005). Substantial effective sample sizes were required for external validation studies of predictive logistic regression models. *Journal of Clinical Epidemiology, 58*(5), 475–83. https://doi.org/10.1016/j.jclinepi.2004.06.017

Vinkenburg, C. J. (2017). Engaging gatekeepers, optimizing decision making, and mitigating bias: Design specifications for systemic diversity interventions. *Journal of Applied Behavioral Science*, *53*(2), 212–234. https://doi.org/10.1177/0021886317703292

Wang, J., Kong, D., Chen, W., & Zhang, S. (2019). Advances in software-defined technologies for underwater acoustic sensor networks: A survey. *Journal of Sensors, 2019*, 1–13. https://doi.org/10.1155/2019/3470390

Weissgerber, T. L., Garcia-Valencia, O., Garovic, V. D., Milic, N. M., & Winham, S. J. (2018). Why we need to report more than 'data were analyzed by t-tests or ANOVA.' *ELife, 7*, 1–16. https://doi.org/10.7554/eLife.36163

Wibowo, F. X., Gregory, M. A., Ahmed, K., & Gomez, K. M. (2017). Review: Multi-domain software-defined networking: Research status and challenges. *Journal of*

Network and Computer Applications, *87,* 32–45. https://doi.org/10.1016/j.jnca.2017.03.004

Willis, J., Slade, S., & Prinsloo, P. (2016). Ethical oversight of student data in learning analytics: A typology derived from a cross-continental, cross-institutional perspective. *Educational Technology Research and Development*, *64*(5), 881–901. https://doi.org/10.1007/s11423-016-9463-4

Willits, F. K., Theodori, G. L., & Luloff, A. E. (2016). Another look at Likert scales. *Journal of Rural Social Sciences*, *31*(3), 126–139.

Wu, H., & Leung, S.-O. (2017). Can Likert scales be treated as interval scales? A simulation study. *Journal of Social Service Research*, *43*(4), 527–532. https://doi.org/10.1080/01488376.2017.1329775

Xie, J., Yu, F. R., Huang, T., Xie, R., Liu, J., Wang, C., & Liu, Y. (2019). A survey of machine learning techniques applied to software-defined networking (SDN): Research issues and challenges. *IEEE Communications Surveys and Tutorials, 21*(1), 393–430. https://doi.org/10.1109/COMST.2018.2866942

Yan, J., & Dong, J. (2017). A lightweight container-based virtual time system for software-defined network emulation. *Journal of Simulation, 11*(3), 253–266. https://doi.org/10.1057/s41273-016-0043-8

Yang, F., & Shen, F. (2018). Effects of web interactivity: A meta-analysis. *Communication Research*, *45*(5), 635–658. https://doi.org/10.1177/0093650217700748

Yang, H., & Chung-Ho, S. (2017). Learner behaviour in a MOOC practice-oriented course: In empirical study integrating TAM and TPB. *International Review of Research in Open and Distributed Learning, 18*(5), 35–62. https://doi.org/10.19173/irrodl.v18i5.2991

Yang, H., Zhang, J., Zhao, Y., Han, J., Lin, Y., & Lee, Y. (2017). Cross stratum optimization for software-defined multidomain and multi-layer optical transport networks deploying with data centers. *Optical Switching and Networking*, *26*, 14–24. https://doi.org/10.1016/j.osn.2015.10.006

Yao, J., Han, Z., Sohail, M., & Wang, L. (2019). A robust security architecture for SDN-based 5G networks. *Future Internet, 11*(4), 1–14. https://doi.org/10.3390/fi11040085

Ye, J., Zheng, J., & Yi, F. (2020). A study on users' willingness to accept mobility as a service based on UTAUT model. *Technological Forecasting and Social Change*, *157*, 1–9. https://doi.org/10.1016/j.techfore.2020.120066

Young, S. W. H., Chao, Z., & Chandler, A. (2020). User experience methods and maturity in academic libraries. *Information Technology and Libraries*, *39*(1), 1–31. https://doi.org/10.6017/ital.v39i1.11787

Younus, M. U., Saif, U. I., & Kim, S. W. (2019). Proposition and real-time implementation of an energy-aware routing protocol for a software-defined wireless sensor network. *Sensors*, *19*(12), 1–22. https://doi.org/10.3390/s19122739

Zandiatashbar, A., Hamidi, S., & Foster, N. (2019). High-tech business location, transportation accessibility, and implications for sustainability: Evaluating the differences between high-tech specializations using empirical evidence from U.S. booming regions. *Sustainable Cities and Society*, *50*, 1–12. https://doi.org/10.1016/j.scs.2019.101648

Zhang, C., Wang, X., Dong, A., Zhao, Y., He, Q., & Huang, M. (2020). Energy-efficient network service deployment across multiple SDN domains. *Computer Communications*, *151*, 449–462. https://doi.org/10.1016/j.comcom.2020.01.019

Zhang, X. (2018). Frugal innovation and the digital divide: Developing an extended model of the diffusion of innovations. *International Journal of Innovation Studies*, *2*(2), 53–64. https://doi.org/10.1016/j.ijis.2018.06.001

Zhao, Y., Li, Y., Zhang, X., Geng, G., Zhang, W., & Sun, Y. (2019). A survey of networking applications applying the software-defined networking concept based on machine learning. *IEEE Access*, *7*, 95397–95417. https://doi.org/10.1109/ACCESS.2019.2928564

Zyphur, M., & Pierides, D. (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

Appendix A: Researcher's National Institutes of Health Certificate

Certificate of Completion

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

Date of Completion: 07/15/2018

Certification Number: 2863471

NIH National Institutes of Health
Office of Extramural Research

Appendix B: Permission to Reprint From MISQ

MIS Quarterly
Carlson School of Management
University of Minnesota
Suite 4-339 CSOM
321 19th Avenue South
Minneapolis, MN 55455

October 8, 2019

Wendell Russ
9043 Rich Quail
San Antonio, TX 78251

Walden University
Doctorate of Information Technology

Permission to use material from
MIS Quarterly in Dissertation
Dissertation Title: *The Relationship Between SDN Acceptance and the Intention to adopt the Technology at South Texas Universities*

Permission is hereby granted to Wendell Russ to reprint the information outlined in detail below –UTAUT Model (and supporting material as necessary).

UTAUT Model
Title: *User Acceptance of Information Technology: Toward a Unified View*
Authors: Venkatesh, V., Morris, M.G., Davis, F.D., and Davis, G.B.
Publish Date: September 2003
Journal: MIS Quarterly
Content requesting permission for: UTAUT Model
Journal volume: 27
Issue: 3
Page: 447

Appendix C: Permission to Use Survey Instrument

Papers-Permissions/Download

site@vvenkatesh.com
Mon 12/2/2019 5:50 PM
To: Wendell Russ <wendell.russ@waldenu.edu>

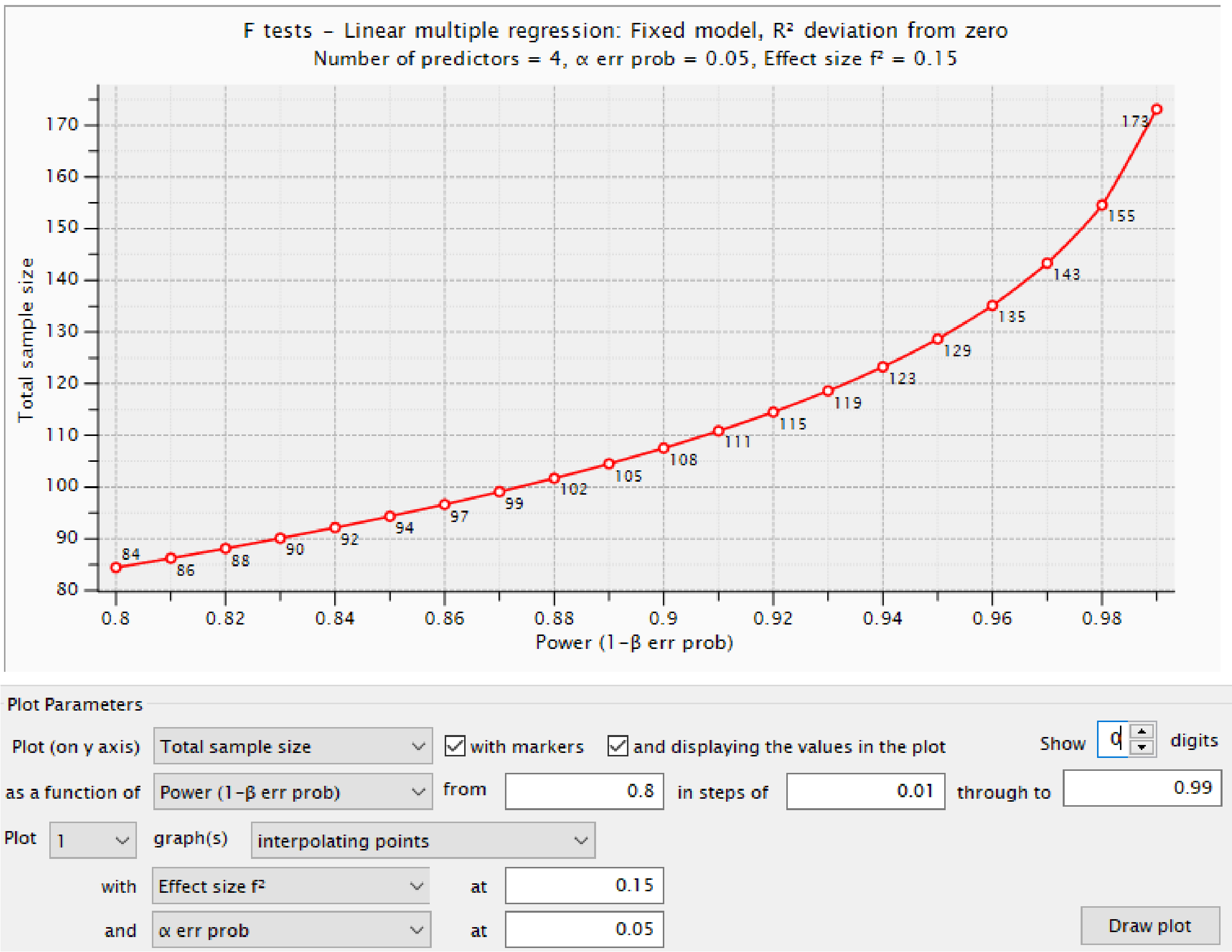
Thank you for your interest. Your permission to use content from the paper is granted. Please cite the work appropriately. Note that this permission does not exempt you from seeking the necessary permission from the copyright owner (typically, the publisher of the journal) for any reproduction of any materials contained in this paper.

Sincerely,
Viswanath Venkatesh
Distinguished Professor and George and Boyce Billingsley Chair in Information Systems
Email: vvenkatesh@vvenkatesh.us
Website: http://vvenkatesh.com

Appendix D: G*Power Graph

Figure D1

Power as a Function of Sample Size



Note: The G*Power graph above depicts the linear regression modeling of the relationship between the sample sizes and the power of the sample. As the sample size increases, so does the power of the sample, enabling the researcher to consider best practices and to establish an a priori range of desired samples as they prepare for data collection. Adapted from "*G*Power* (Version 3.1.9.7) [Computer Software]," by F. Faul, E. Erdfelder, A. Buchner, and A.-G. Lang, (2020), Published 2020 by Heinrich-Heine-Universität (https://www.psychologie.hhu.de/arbeitsgruppen/allgemeine-psychologie-und-arbeitspsychologie/gpower.html). In the public domain.

Appendix E: Unified Theory of Acceptance and Use of Technology Instrument

Table E1

Unified Theory of Acceptance and Use of Technology Instrument Constructs and Data

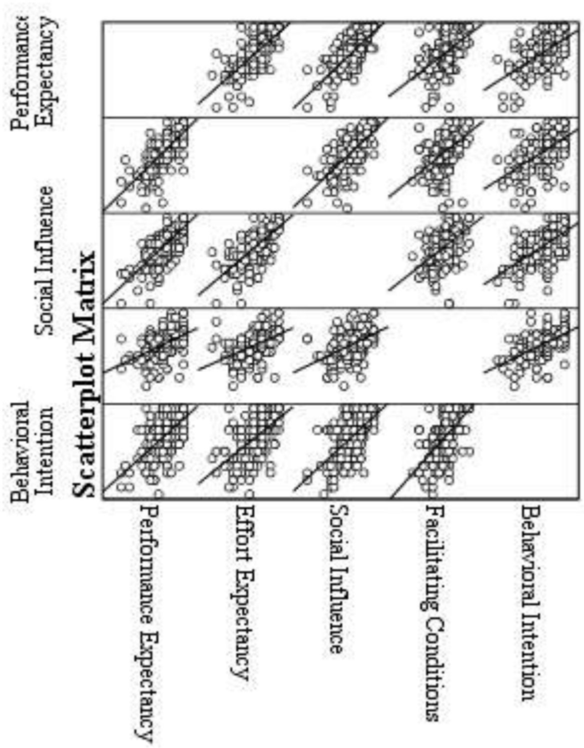
Construct	Instrument data
PE1	I would find the system useful in my job.
PE2	Using the system enables me to accomplish tasks more quickly.
PE3	Using the system increases my productivity.
PE4	If I use the system, I will increase my chances of getting a raise.
EE1	My interaction with the system would be clear and understandable.
EE2	It would be easy for me to become skillful at using the system.
EE3	I would find the system easy to use.
EE4	Learning to operate the system is easy for me.
SI1	People who influence my behavior think that I should use the system.
SI2	People who are important to me think that I should use the system.
SI3	The senior management of this business has been helpful in the use of the system.
SI4	In general, the organization has supported the use of the system.
FC1	I have the resources necessary to use the system.
FC2	I have the knowledge necessary to use the system.
FC3	The system is not compatible with other systems I use.
FC4	A specific person (or group) is available for assistance with system difficulties.
BI1	I intend to use the system in the next <n> months.
BI2	I predict I would use the system in the next <n> months.
BI3	I plan to use the system in the next <n> months.

Note: PE refers to performance expectancy, EE refers to effort expectancy, SI refers to social influence, FC refers to facilitating conditions, and BI refers to behavioral intention. Adopted from "User Acceptance of Information Technology: Toward a unified view," by V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, 2003, *MIS Quarterly*, *27*(3), p. 460 (https://doi.org/10.2307/30036540). Copyright 2003 by MIS Quarterly.

Appendix F: Scatterplot Matrix

Figure F1

Scatterplot Matrix of Independent and Dependent Variables



Appendix G: SPSS Output

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Performance Expectancy	167	3.25	7.00	5.7829	.80171	.643	-.563	.188	.473	.374
Effort Expectancy	167	3.00	7.00	5.6168	.84436	.713	-.630	.188	.233	.374
Social Influence	167	2.00	7.00	5.3293	1.00079	1.002	-.656	.188	.468	.374
Facilitating Conditions	167	2.75	7.00	5.1766	.78354	.614	-.386	.188	.520	.374
Behavioral Intention	167	3.00	7.00	5.6707	.95549	.913	-.511	.188	-.443	.374
Valid N (listwise)	167									

Descriptive Statistics

	Mean	Std. Deviation	N
Behavioral Intention	5.6707	.95549	167
Performance Expectancy	5.7829	.80171	167
Effort Expectancy	5.6168	.84436	167
Social Influence	5.3293	1.00079	167
Facilitating Conditions	5.1766	.78354	167

Correlations

		Behavioral Intention	Performance Expectancy	Effort Expectancy	Social Influence	Facilitating Conditions
Pearson Correlation	Behavioral Intention	1.000	.588	.558	.603	.576
	Performance Expectancy	.588	1.000	.723	.735	.469
	Effort Expectancy	.558	.723	1.000	.697	.463
	Social Influence	.603	.735	.697	1.000	.478
	Facilitating Conditions	.576	.469	.463	.478	1.000
Sig. (1-tailed)	Behavioral Intention	.	.000	.000	.000	.000
	Performance Expectancy	.000	.	.000	.000	.000
	Effort Expectancy	.000	.000	.	.000	.000

	Social Influence	.000	.000	.000	.	.000
	Facilitating Conditions	.000	.000	.000	.000	.
N	Behavioral Intention	167	167	167	167	167
	Performance Expectancy	167	167	167	167	167
	Effort Expectancy	167	167	167	167	167
	Social Influence	167	167	167	167	167
	Facilitating Conditions	167	167	167	167	167

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.707[a]	.500	.487	.68418	.500	40.440	4	162	.000	2.019

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

b. Dependent Variable: Behavioral Intention

Coefficients[a]

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95.0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	.450	.444		1.013	.312	-.427	1.327		
	Performance Expectancy	.215	.109	.180	1.965	.051	-.001	.430	.367	2.721
	Effort Expectancy	.127	.098	.112	1.291	.198	-.067	.321	.410	2.436
	Social Influence	.226	.085	.236	2.662	.009	.058	.393	.391	2.556
	Facilitating Conditions	.399	.079	.327	5.018	.000	.242	.556	.728	1.375

a. Dependent Variable: Behavioral Intention

ANOVA[a]

Model	Sum of Squares	df	Mean Square	F	Sig.

1	Regression	75.720	4	18.930	40.440	.000[b]
	Residual	75.833	162	.468		
	Total	151.553	166			

a. Dependent Variable: Behavioral Intention

b. Predictors: (Constant), Facilitating Conditions, Effort Expectancy, Social Influence, Performance Expectancy

Collinearity Diagnostics[a]

				Variance Proportions				
Model	Dimension	Eigenvalue	Condition Index	(Constant)	Performance Expectancy	Effort Expectancy	Social Influence	Facilitating Conditions
1	1	4.956	1.000	.00	.00	.00	.00	.00
	2	.019	16.144	.24	.01	.02	.29	.17
	3	.012	20.401	.33	.03	.04	.04	.81
	4	.007	25.804	.30	.01	.66	.50	.02
	5	.005	30.893	.13	.96	.28	.17	.00

a. Dependent Variable: Behavioral Intention

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	4.0283	7.2114	5.6707	.67539	167
Std. Predicted Value	-2.432	2.281	.000	1.000	167
Standard Error of Predicted Value	.056	.267	.112	.039	167
Adjusted Predicted Value	4.0879	7.2206	5.6708	.67586	167
Residual	-1.79390	1.90082	.00000	.67589	167
Std. Residual	-2.622	2.778	.000	.988	167
Stud. Residual	-2.655	2.841	.000	1.007	167
Deleted Residual	-1.83929	1.98700	-.00019	.70198	167
Stud. Deleted Residual	-2.706	2.905	.000	1.015	167
Mahal. Distance	.123	24.360	3.976	3.924	167
Cook's Distance	.000	.107	.008	.018	167
Centered Leverage Value	.001	.147	.024	.024	167

a. Dependent Variable: Behavioral Intention

Appendix H: SPSS Output for Model Without Effort Expectancy

Model Summary[b]

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.703[a]	.494	.485	.68558	.494	53.146	3	163	.000	2.035

a. Predictors: (Constant), Facilitating Conditions, Performance Expectancy, Social Influence

b. Dependent Variable: Behavioral Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	74.940	3	24.980	53.146	.000[b]
	Residual	76.613	163	.470		
	Total	151.553	166			

a. Dependent Variable: Behavioral Intention

b. Predictors: (Constant), Facilitating Conditions, Performance Expectancy, Social Influence

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.568	.436		1.304	.194	-.292	1.428		
	Performance Expectancy	.272	.100	.229	2.728	.007	.075	.470	.441	2.265
	Social Influence	.261	.080	.273	3.243	.001	.102	.420	.436	2.292
	Facilitating Conditions	.413	.079	.338	5.231	.000	.257	.568	.741	1.349

a. Dependent Variable: Behavioral Intention

Appendix I: SPSS Output for Model Without Performance Expectancy

Model Summary[b]

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.698[a]	.488	.478	.69016	.488	51.726	3	163	.000	2.009

a. Predictors: (Constant), Facilitating Conditions, Effort Expectancy, Social Influence

b. Dependent Variable: Behavioral Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	73.913	3	24.638	51.726	.000[b]
	Residual	77.639	163	.476		
	Total	151.553	166			

a. Dependent Variable: Behavioral Intention

b. Predictors: (Constant), Facilitating Conditions, Effort Expectancy, Social Influence

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.761	.419		1.817	.071	-.066	1.587		
	Effort Expectancy	.206	.090	.182	2.277	.024	.027	.384	.493	2.028
	Social Influence	.299	.077	.313	3.881	.000	.147	.451	.484	2.067
	Facilitating Conditions	.418	.080	.343	5.252	.000	.261	.575	.739	1.354

a. Dependent Variable: Behavioral Intention