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Influential Determinants of Internet of Things Adoption in the U.S. Manufacturing Sector

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Abstract

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MS, Walden University, 2017

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Doctoral Study Submitted in Partial Fulfillment

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Abstract

Manufacturers have been hesitant to adopt Internet of things (IoT) due to a lack of understanding about the innovate characteristics, technology, organizational and environmental factors related to IoT adoption and how their organizations can apply IoT correctly. This quantitative, correlational study used a combination of diffusion of innovation theory and technology–organization–environment framework as the foundation to examine if a relationship exists between relative advantage, complexity, compatibility, technology readiness, top management support, firm size, competitive pressure, and regulatory support and IT leaders' intent to adopt IoT in U.S. manufacturing organizations. A sample of 168 information technology (IT) leaders from the U.S. manufacturing sectors was used. Multiple regression analysis indicated significant relationships between the intent to adopt IoT by IT leaders of manufacturing organizations and only 3 of the 8 independent variables: technology readiness, top management support, and competitive pressure. The model was able to predict approximately 44% of the variation of IT leaders' intent to adopt IoT. The results of this study might help IT leaders in the U.S. manufacturing sectors understand the factors that influence IoT adoption. The findings from this study might contribute to positive social change by contributing to economic growth that results from increased efficiency gained from the adoption of IoT in key business areas.

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Dedication

I dedicate this work to my friends, colleagues, and family who provided unceasing support throughout this journey. Completion of this study is proof that an individual can achieve anything if they work hard at it. Do not let failures slow you down; they are signs that help you reach your goals.

"Let me tell you the secret that has led me to my goals: my strength lies solely in my tenacity."

-- Louis Pasteur

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Section 1: Foundation of the Study

In today's highly competitive market environment, business agility, flexibility, innovation, competitive advantage, lowering upfront cost, and economic gains increases are essential to business profitability and long-term survival. Internet of things (IoT) has the potential to increase value and efficiencies across many sectors via the vast network of smart things (Hsu & Lin, 2016a; Voas, 2016). Because IoT is a new information technology (IT) paradigm, factors such as technological, organization individualistic, environmental context, and others could influence the likelihood of adoption. Researchers described many reasons for the delay in the adoption of IoT, citing reasons such as lack of understanding of IoT characteristics and its value in various business sectors (Hwang, Kim, & Rho, 2016; Hsu & Lin, 2016a). It is necessary to understand better the relationship between those factors, and how organizations perceptions before deciding to adopt IoT solutions. The purpose of the study was to investigate factors that influence IoT adoption. In this chapter, I present the background, purpose statement, research question, definitions, theoretical frameworks, and the significance of the study.

Background of the Problem

Organizations typically seek to adopt innovative technologies that bolster efficiencies and business profitability while lowering upfront cost to ensure long-term survival. Organizations that fail to innovate are less agile, flexible, and competitive fail to survive (Rosas, Brito, Palma, & Barata, 2017; Taneja, Pryor, & Hayek, 2016).

IoT is an innovative technology that has the potential to increase an organization's value while improving operational efficiencies (Hsu & Lin, 2016a; Voas, 2016). Much of the growth of IoT is expected to occur in the manufacturing sector (Farooq, Waseem, Khairi, & Mazhar, 2015). According to Ives, Palese, and Rodriguez (2016), only 37% of U.S. organizations have IoT initiatives, and only 10% have successfully integrated IoT systems.

IoT is a critical enabler to spur growth within the manufacturing sector. However, manufacturers have been hesitant to adopt IoT due to a lack of understanding about the factors related to IoT adoption and how their organization can apply IoT correctly (Hwang et al., 2016; Oliveira, Thomas, & Espadanal, 2014). Few researchers have addressed IoT adoption at the organization level (Hsu, & Lin, 2016b; Hwang et al., 2016; Singh, Gaur, & Ramakrishnan, 2017; Tu, 2018; Yang, Lee, & Zo, 2017a). Even fewer researchers have utilized a combination of diffusion of innovation (DOI) and technology-organization-environment framework (TOE) to conduct studies within the manufacturing sector (Alkhalil, Sahandi, & John, 2017; Shaltoni, 2017; Wang & Wang, 2016). Through the literature review, I identified a gap that can be characterized as a lack of research evaluating the factors influencing IoT adoption in the manufacturing sector. My goal for this study was to determine the relationship between corporate IT leaderships' perceptions and their intent to adopt IoT within manufacturing organizations in the United States.

Problem Statement

Manufacturers have been hesitant to adopt IoT due to a lack of understanding about the factors related to IoT adoption and how their organization can apply IoT correctly (Hwang et al., 2016; Oliveira et al., 2014). Thirty-seven percent of U.S.

organizations have IoT initiatives; yet, only 10% have successfully integrated IoT systems (Ives et al., 2016). The general IT problem is that some manufacturing organizations lack the requisite knowledge of the determinants that influence IoT adoption. The specific IT problem is that some IT decision-makers (potentially CIO, directors, CISO, senior IT Managers) often lack the requisite knowledge of the relationship between corporate IT leadership's perception of determinants: relative advantage, complexity, compatibility, technology readiness, top management support, firm size, competitive pressure, regulatory support, and intent to adopt IoT in manufacturing organizations.

Purpose Statement

The purpose of this quantitative, correlational study was to examine the relationship between the independent variables, which were corporate IT leadership's perceptions of (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support, and the dependent variable, which was intent to adopt IoT in U.S manufacturing organizations. I measured firm size using a nominal scale and relative advantage, complexity, compatibility, technology readiness, top management support, competitive pressure, and regulatory support using a validated research instrument developed by Oliveira et al. (2014) who used a 5-point Likert scale ranging from *strongly disagree* to *strongly agree*. The population for the study was IT leaders with decision-making authority working for manufacturing organizations in the United States. Organizations adopting IoT gain efficiencies, thereby creating cost savings of goods and services offered to consumers. The findings from this study might contribute to positive social change by contributing to economic growth that results from increased efficiency gained from the adoption of IoT in key business areas.

Nature of the Study

For this study, I chose a quantitative methodology rooted in the positivist philosophy. Quantitative researchers use descriptive and inferential statistical analyses to describe the characteristics of a population under study and to generalize to other similar situations, provide explanations of predictions, and explain causal relationships (Haegele & Hodge, 2015). I chose a quantitative method to statistically analyze numerical data collected from Likert-scale responses to the survey questions and to make inferences to manufacturing organizations considering the adoption of IoT. Conversely, qualitative scholars focus on the why and how and the experience of a phenomenon when a more in-depth analysis of attitudes, motivations, and behaviors is needed, and numerical representation is inadequate (Abildgaard, Saksvik, & Nielsen, 2016). Because I used measurable, numerical data to identify correlations between dependent and independent variables, I did not choose a qualitative method for this study.

Mixed-methods scholars combine the attributes of both qualitative and quantitative analysis to develop completeness (Ingham-Broomfield, 2016). Because mixed-method studies include qualitative methods, which fall, outside of the scope of this study, mixed-methods approaches are not appropriate for the study. A quantitative research method is most appropriate because the primary purpose was to examine relationships between the IT corporate leadership's perceptions of the independent variables and intention to adopt IoT and test hypotheses.

I chose a correlation design for the study. Researchers employ correlation designs to examine the relationship between two or more variables (Becker et al., 2016). I chose a correlation design because one of the primary aims of this study was to describe the distribution of a set of predictor variables (relative advantage, complexity, compatibility, technology readiness, top management support, firm size, competitive pressure, and regulatory support) and a dependent variable (intent to adopt IoT). Alternative designs such as quasi-experimental and experimental designs are appropriate when the researcher seeks to assess causal effects (Adamos & Nathanail, 2016). The purpose of this study was not to seek cause and effect; the experimental and quasi-experimental designs were not appropriate for this study. In this study, because the primary purpose was to examine the relationship between the IT corporate leadership' perceptions of independent variables and the intention to adopt IoT, a quantitative correlation design was chosen.

Research Question

What is the relationship between corporate IT leadership's perceptions of (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and intent to adopt IoT?

Hypotheses

Null Hypothesis ($H_0 1$): There is no statistically significant relationship between corporate IT leadership's perceptions of (a) relative advantage, (b) complexity, (c) compatibility (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and intent to adopt IoT.

Alternative Hypothesis (H_a1): There is a statistically significant relationship between corporate IT leadership's perceptions of (a) relative advantage, (b) complexity, (c) compatibility (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and intent to adopt IoT.

Theoretical Framework

The theoretical framework for this study includes a combination of the TOE framework as created by DePietro, Wiarda, and Fleischer in 1990 and the DOI as created by Rogers in 1962. The TOE framework embodies three aspects that influence technology adoption and innovation within the organization: (a) the technology that describes an organization's deployed technology and technical practices, (b) the organization that describes the characterizes of an organization like its size, and (c) the environment that describes the opportunities and limitations for technology adoption and innovation (Martins, Oliveira, & Thomas, 2106). Although proponents of TOE define organizational characteristics, the DOI theory includes five factors that influence innovation adoption: (a) relative advantage that describes possible improvement that may occur due to innovation, (b) compatibility that describes the degree of fit with the existing organization's needs, (c) complexity that describes the level of difficulty to assimilate the innovation, (d) trialability that describes the ease of which an innovation can be experimented with, and (e) observability that describes how visible the innovation is to others. Trialability and observability are often excluded from innovation studies because they are not solely related to the innovation diffusion process (Low, Chen, & Wu, 2011; Martins et al., 2106; Oliveira et al., 2014). In quantitative studies, the theoretical framework, or in qualitative studies, the conceptual framework, illustrates which ideas from the literature ground the research being conducted. Understanding the determinants of IoT is fundamental as organizations consider the adoption of IoT for business process transformation or to facilitate rapid application development. The integration of DOI and TOE frameworks formed the lens shaping the design of this study. Specifically, the combination of DOI and TOE frameworks are chosen to facilitate an understanding of the determinants of IoT adoption in the manufacturing industry.

Definition of Terms

Internet of things (IoT): A framework that is based on the availability of heterogeneous devices, objects, and interconnection solutions that provides a shared information base on a global scale to support the design of applications involving both people and representations of objects (Atzori, Iera, & Morabito, 2017).

Assumptions, Limitations, and Delimitations

Assumptions

Assumptions are a researcher’s beliefs that are believed to be true but are unjustifiable (Grant, 2014). Researchers should be cognizant of how an assumption can shape their research design, conduct, and interpretation of their study (Cunliffe, 2010). The assumptions are as follows:

- Participants voluntarily took part.

- Participants were knowledgeable about technology adoption and IoT and were able to give relevant answers.
- No participant submitted the survey more than once.
- IT leaders survey for this study had decision-making authority or were capable of influencing adoption decisions.

Limitations

Limitations are potential deficiencies in a study and are often independent of the research design; thus, they are outside the control of the researcher (Horga, Kaur, & Peterson, 2014). The limitations are as follows:

- Participants were unable to seek clarification, which could lead to misinterpretation of the survey questions from respondents. As a mitigating measure, I included detailed instructions at the beginning of the survey.
- A convenience sample of IT leadership with decision-making authority in manufacturing organization via Qualtrics targeted pool. Participants in this study were likely not to be representative of other IT leaders.
- The survey instrument uses closed-ended questions which do not allow participants to give additional insight.
- The DOI-TOE model excluded other factors which could influence IoT adoption.
- Results were limited by the statistical analysis results based on the independent and dependent variables.

- Because a correlation research design was chosen, and the study limited to the manufacturing sector, generalizability to a greater population is not possible.

Delimitations

Delimitations describe the scope and constraints of the study (Macheridis & Paulsson, 2017). The delimitations are as follows:

- This study scope was geographically limited to the United States.

Significance of the Study

Contribution to Information Technology Practice

Understanding the determinants of IoT is fundamental as organizations consider the adoption of IoT for business process transformation or to facilitate rapid application development to support business verticals, such as agriculture, healthcare, and manufacturing. This study is significant to IT practice in that it may give a practical model for understanding the determinants influencing the adoption of IoT technologies. This study is significant to researchers looking to combine more than one theoretical perspective to understand IT adoption involving disruptive technologies (Ebersold & Glass, 2015).

Implications for Social Change

This study has the potential for positive social change by contributing to economic growth that results from increased efficiency gained from the adoption of IoT in key business areas. Presumably, the efficiencies gained may create cost saving in manufacturing processes, thereby resulting in cost savings of goods and services offered to consumers. As profits increase, socially responsible organizations will provide increased wages and benefits to their employees, thus contributing to increased consumer spending powers.

A Review of the Professional and Academic Literature

Organizations do not always adopt innovative technology, such as the IoT, right away. The number of connected IoT devices is expected to grow to approximately 25 billion by 2020, with much of this growth occurring in the manufacturing sector (Farooq et al., 2015). As of 2016, 37% of U.S. organizations have IoT initiatives, and yet only 10% have successfully integrated IoT systems (Ives et al., 2016).

In this quantitative, correlation study, I examined the relationship between corporate IT leaderships' perceptions and their intent to adopt IoT within manufacturing organizations in the United States. In the literature review, I explain the purpose of the study, the hypotheses, present the DOI and TOE frameworks, and discuss alternative technology adoption theories of the technology acceptance model (TAM) and unified theory of acceptance and use of technology (UTAUT).

IT adoption has been studied extensively. Many theories have been developed to describe the adoption behaviors concerning the individual or an organization or enterprise level (Oliveira et al., 2014). In this study, I described two significant innovation theories: Rogers (2003) DOI and DePietro et al. (1990) TOE. I used current publications to critically examine the extent to which the determinants discussed in this study influence the adoption of IoT technologies.

This literature review included peer-reviewed articles and other scholarly articles published between 2015 and 2018, published dissertations, and books. I used Walden University's online library databases to find primary sources of literature, including ACM Digital Library, Computers, and Applied Sciences Complete, IEEE Xplore Digital Library, Computing Database, ScienceDirect, ProQuest Central, Sage Journal, Academic Search Complete, and Google Scholar. I used the following keywords as a direct variable or in combination: *Internet of Things* or *IoT, technology adoption, technology diffusion, innovation adoption, innovation diffusion, manufacturing, diffusion of innovation* or *DOI, technology-organization-environmental framework* or *TOE, technology acceptance model* or *TAM*, and *unified theory of acceptance* and *use of technology* or *UTAUT*

For this study, I referenced 205 sources. Eighty-six percent of them were published within the last five years, and 92% were from peer-reviewed sources. One hundred of the references were included in the literature review, and 88% of those were from peer-review sources. The references included eight books and zero doctoral dissertations.

Theoretical Foundation

Many theories have been developed to describe the adoption behaviors concerning the individual or an organization (enterprise; Oliveira et al., 2014). Technology adoption models include theories such as the theory of planned behavior (TPB) by Ajsen (1985), TAM by Davis (1989), TOE framework by DePietro et al. (1990), DOI by Rogers (1962), and the UTAUT by Venkatesh, Morris, Davis, and Davis (2003). Scholars have used these theories and others to describe innovation adoption behaviors concerning both the individual and organizational (enterprise) level (Oliveira et al., 2014; Tu, 2018). More recently, several scholars (e.g., Agag, & El-Masry, 2016; Alkhalil et al., 2017; Kapoor, Dwivedi, & Williams, 2014; Shaltoni, 2017; Wang & Wang, 2016) have made efforts to extend these theories to gain a deeper understanding of the true nature of technology adoption.

My study reflects the growing need to use IoT to innovate within the manufacturing industry. Understanding the determinants of IoT is fundamental as organizations consider the adoption of IoT for business process transformation or to facilitate rapid application development to support business verticals, such as agriculture, healthcare, and manufacturing. In the following sections, my focus was to describe DOI, TOE, and the theorists' viewpoints on innovation characteristics using current publications and critically examine the extent to which determinants influence the adoption of IoT technologies.

Analysis of Supporting Theories

Diffusion of innovation theory. Developed by Rogers in 1962, researchers have extensively used DOI theory to study IT innovation at both the individual and organizational level (Tu, 2018). Rogers argued that the four main elements of DOI theory are innovation, communications channels, time, and social systems. Rogers's focus was on the factors that influenced innovation adoption itself and created the five stages in the innovation-decision process (Figure 1). These five stages describe the process through which an individual or organization passes when deciding to accept or reject an innovation (Rogers, 2003, p. 168-169). Utilizing the five-stage process allows individuals or organizations to understand the innovation-decision process better and thus to manage uncertainty better. Rogers claimed that five attributes of innovation, namely relative advantage, compatibility, complexity, trialability, and observability, could explain 49-87% innovation adoption. Each attribute and its subdimension affects adoption differently and is influenced by the adopter perception of importance (Rogers, 2003).

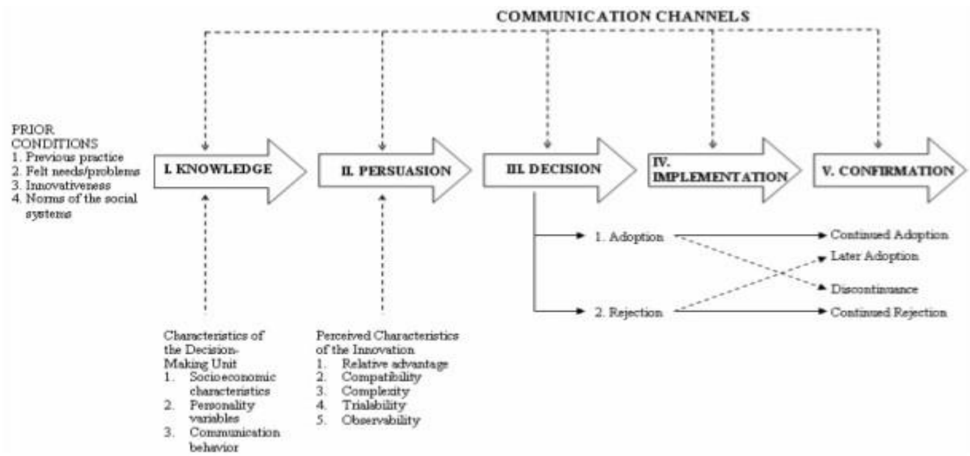

Figure 1. Diffusion of Innovation (DOI). A model of five stages in the innovation-decision process. Adopted from Diffusion of Innovations (p. 170), by E.M. Rogers, 2003 New York, NY: Free Press. Copyright 2003 by E. M. Rogers. Reprinted with permission.

Relative advantage describes the degree of the perceived superiority of innovative technology as compared to the existing solution (Rogers, 2003). Rogers (2003) explained there are other concepts embodied in this attribute such as prestige, increased efficiencies, convenience, and economic benefit. For example, the adoption of IoT technologies is expected to offer superior functionality, and increased efficiencies for both individuals and organizations (Balaji & Roy, 2016). Rogers claimed that relative advantage is the strongest predictor of an innovation adoption rate. Relative advantage is typically positively correlated with innovation adoption (Rogers, 2003; Sinha & Mukherjee, 2016).

Compatibility describes the degree to how well an innovation integrates with current practices or value systems (Rogers, 2003). The innovation adoption rate is proportional to the degree of compatibility; the greater the compatibility, the faster the adoption. Compatibility among sensors, networks, and application from different vendors are essential factors that influence the adoption of IoT (Haddud, DeSouza, Khare, & Lee, 2017). One issue highlighted in the literature is incompatibility issues such as failure to communicate between IoT devices that hamper IoT adoption (Stočes, Vaněk, Masner, & Pavlík, 2016). Compatibility is typically positively correlated with innovation adoption (Rogers, 2003; Sinha & Mukherjee, 2016).

Complexity describes the degree of difficulty to understand and use an innovation (Rogers, 2003). When users perceive innovation as complicated and challenging to use, its likelihood to be used and implemented is lower (Wang & Wang, 2016). For example, as the development of IoT devices matures and additional functionalities added, complexity will increase (Bi, 2017). The wide variety of IoT devices add a layer of complexity during product selection and planning (Zhong, Xu, & Wang, 2017). These complexities, in addition to a lack of skilled staff, to manage a multivendor environment, are detrimental to IoT adoption (Haddud et al., 2017). Complexity is typically negatively correlated with innovation adoption (Wang & Wang, 2016).

Trialability describes the degree to which an innovation may be tested within the adoption environment to understand how it works and assess its usefulness (Rogers, 2003). Trialability is typically positively correlated with innovation adoption (Pashaeypoor, Ashktorab, Rassouli, & Alavi-Majd, 2016; Rogers, 2003) because the technology that can be quickly tested or experimented on for a limited basis for free are more likely to be adopted faster (Chiyangwa & Alexander, 2016; Rogers, 2003). Organizations may conduct limited trials of innovative technologies to figure out their feasibility and distinguish reality from hype before presenting a business case to top-management (Hsu & Yeh, 2016; Shin & Jin Park, 2017). The more the innovation is tested, the better the adopter can access and dispel uncertainty.

Observability is typically positively correlated with innovation adoption (Rogers, 2003; Wang & Wang, 2016) and describes the level to which the results of an innovation are visible to the adopter and others (Alkhalil et al., 2017; Rogers, 2003). Visible results provide an opportunity to highlight innovation to stakeholders, specifically top-management. When the benefits of an innovation are easily demonstrable, it removes uncertainty and facilitates speedy adoption (McMullen, Griffiths, Leber, & Greenhalgh, 2015). While the organization may benefit from seeing other organizations that have successfully implemented IoT, individual experimentation with IoT may be difficult to observe due to limitations in emulating realistic production environments (Nysveen & Pedersen, 2014).

DOI theory has been modified by researchers and used to investigate technology adoption in organizations (Brancheau & Wetherbe, 1990; Hameed, Counsell, & Swift, 2012). Odoom, Anning-Dorson, and Acheampong (2017) used DOI theory to investigate the antecedents of social media adoption and performance benefits in small and medium-sized enterprises. Based on a review of the literature, Odoom et al. (2017) proposed a research model which evaluated three constructs; interactivity, cost-effectiveness, and compatibility, and their influence on social media usage and performance benefit. Findings from the study indicated that interactivity, cost-effectiveness, and compatibility positively influenced social media usage, which resulted in some performance benefits.

Osorio-Gallego, Londoño-Metaute, and López-Zapata (2016) extended the DOI theory by utilizing ten constructs to investigate what factors influence the adoption of information and communication technologies (ICT) in small to medium size enterprises in Columbia. The 10 constructs (relative advantage, observability, complexity, new business opportunities, effective client communication, business cost reduction, government incentives, unsuitable ICT for the business, lack of reliability in security, and ICT cost-benefit unbalance) chosen for analysis were derived from the literature and previous studies and according Osorio-Gallego et al. were best suited for the context of the study. Findings showed that a lack of confidence in ICT's security and privacy, a perception of ICT cost-benefit unbalance, had a negative impact on the adoption of ICTs, while relative advantage, observability, complexity, new business opportunities, effective client communication, business cost reduction and, government incentives all had a positive influence.

The DOI theoretical foundation has been used in many studies to explain technology adoption in organizations (Brancheau & Wetherbe, 1990; Hameed et al., 2012). Even so, DOI theory has received criticism in its application at the organizational level (Chau & Tam, 1997). For example, trialability and observability are often excluded from any innovation studies because they are not solely related to the innovation diffusion process (Martins et al., 2106). Lee and Cheung (2004) posited that DOI excluded factors influencing the organizational and environmental context. Fichman (2000) supported this claim by implying that DOI is focused on individual adoption. Hameed et al. (2012) asserted that DOI addresses preadoption and adoption decision stages; however, Brancheau and Wetherbe (1990) implied that DOI does not address the full implementation process of IT as it lacks logic for verifying use by the adopter. It also does not equally apply to all kinds of innovation adoption context (Fichman, 2000).

Rogers (2003) believed that an organizational decision to adopt or reject an innovation depends on receiver variables, social system variables, and perceived characteristics of innovation (relative advantage, compatibility, complexity, trialability, and observability). Rogers argued that these variables could explain 49–87% of innovation adoption at the individual or organization level. In this study, the adoption of innovation is not under the control of users but reside with the IT leadership of the organization. I investigated the adoption of IoT at the organization level. I adopted three attributes from Rogers's DOI theory for incorporation into the theoretical framework used in this study: relative advantage, compatibility, and complexity. I selected DOI as one of the foundational theories for this study due in part to its explanatory power of innovation adoption at the individual or organization level, relatedness to a variety of technological innovation and previous research that supports its' validity.

Technology-organization-environment framework. For organizational level analysis to be meaningful, the characteristics of the organization should be included as part of the research model (Hameed et al., 2012; Tornatzky & Fleischer, 1990). Developed by DePietro et al., in 1990, the TOE framework embodies three aspects that influence technology adoption and innovation within the organization, namely the organizational context, technological context, and the environmental context as shown in Figure 2 (Martins et al., 2016; Tornatzky & Fleischer, 1990).

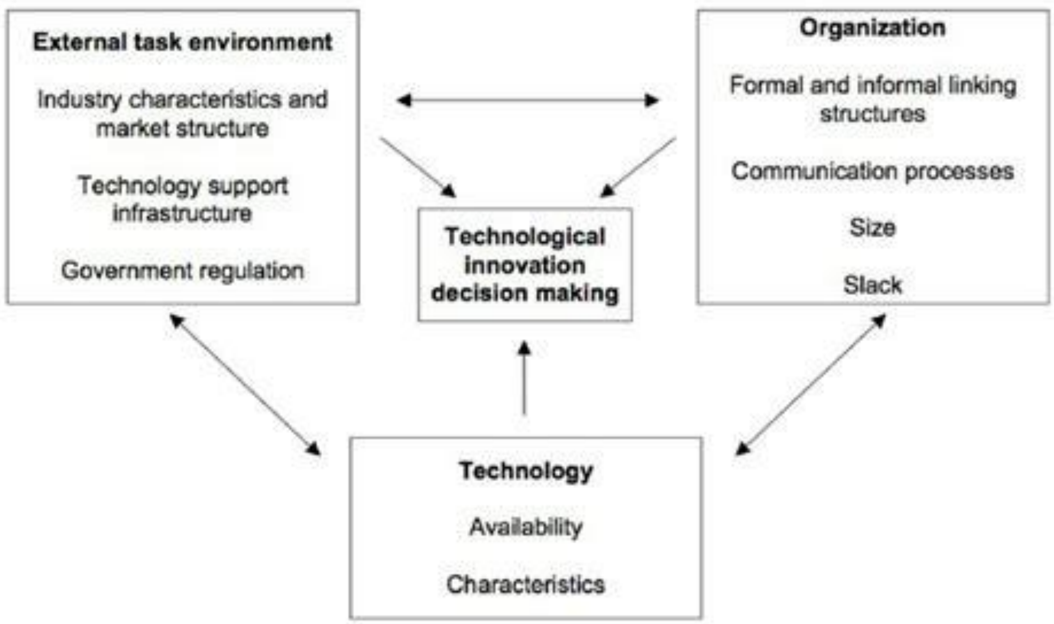

Figure 2. Technology-organization-environment (TOE) framework. Adopted from The Process of Technology Innovations (p. 153), by L. Tornatzky and M. Fleischer, 1990, Lexington, MA: Lexington Books. Copyright 1990 by Lexington Books. Reprinted with permission.

The organizational encompasses several descriptive measures (Figure 2). The organizational context refers to the characteristics of an organization such as its firm size, organizational structure, human resources, managerial structure and styles, and the internal resource availability (Hsu, Ray, & Li-Hsieh, 2014; Hsu & Yeh, 2016; Ji & Liang, 2016; Rahayu & Day, 2015; Tornatzky & Fleischer, 1990; Zhang & Xiao, 2017). According to Tornatzky and Fleischer (1990), the organization structure, business practices, and business mechanics influence the likelihood of adopting and implementing innovation. The organization, although being unique, has the potential to innovate. Tornatzky and Fleischer posited that internal and external communications no only communicate business instruction but also champion the generation of new ideas which could lead to innovation adoption. Although Tornatzky and Fleischer asserted that an organization's size and availability of resources have little empirical support in the literature, they acknowledged that an organization's availability of the correct resources influences innovation adoption. Tornatzky and Fleischer also suggested that top management leadership behaviors are fundamental to an organization's ability to adopt technology innovation.

The technology context relates to technology internal to an organization and external availability of technology and the organization current practices (Tornatzky & Fleischer, 1990). Tornatzky and Fleischer (1990) argued that the fit of the technology with the current technology is as important as the availability of the technology; due in part to the uniqueness of each organization technology implementation and the relevance of the technology. Similar to DOI theory, Tornatzky and Fleischer posited that compatibility and complexity of the technology related to the integration with the current environment influence innovation adoption.

The environmental context refers to the industry the organization conducts its business and external influences such as competitors, suppliers, and government agencies (Hsu et al., 2014; Tornatzky & Fleischer, 1990; Zhang & Xiao, 2017). According to Tornatzky and Fleischer (1990), the business segment, competition, and the organization's business strategy influence technology adoption. Tornatzky and Fleischer posited that the availability of a skilled labor force and access to related training and consultants positively influence the likelihood of adopting and implementing innovative technology; due in part to more possibilities and flexibility executing innovative strategies. One aspect that influences the external environment is government regulations, which, according to Tornatzky and Fleischer, can positively or negatively influence innovation adoption.

Unlike DOI theory, which primarily focuses is on technology context, TOE considers other contexts such as organizational and environmental; as these organization characteristics evolve can influence technology adoption (Rahayu & Day, 2015). The TOE framework has been used extensively in research on IT and IS adoption (Rahayu & Day, 2015; Zhang & Xiao, 2017)

Hossain, Quaddus, and Islam (2014) investigated the effect of 10 factors on four stages of RFID—initiation, adoption, routinization, and extension—in the Australia livestock industry. Hossain et al. found that the same factors have a different influence on each stage. Initiation was found to be dependent on perceived ease of use, external pressure, external support, and divisibility of RFID technology. Adoption is positively influenced by an organization’s resources, management attitudes, organizational pressures and uncertainties, and the external environment. RFID routinization was negatively affected by cost but positively impacted by interoperability, external support, and organizational self-efficacy. Finally, RFID extension was positively affected by factors such as interoperability, divisibility, external pressure, external support, and negatively affected by RFID cost and external uncertainty.

Rahayu and Day (2015) used the TOE to investigate factors that influence small and medium-sized enterprises (SMEs) in developing countries to adopt e-commerce. In their investigation, Rahayu and Day used a model based on 11 variables organized into four groups: technological factors, organizational factors, environmental factors, and individual factors. Results of the survey found that perceived benefits, technology readiness, owners' innovativeness, IT ability, and IT experience positively influence SMEs to adopt e-commerce.

Zhang and Xiao (2017) modified the TOE framework to investigate the key technological, organizational, and environmental factors that affect the assimilation of social media in local government agencies. Findings of the survey found that top management the strongest predictors of social media assimilation. Technology competency, perceived benefits, and citizen readiness also positively influence social media assimilation.

TOE is more advantageous than other adoption models due to the inclusion of technological, organizational, and environmental variables and lack of industry and firm size limitations (Gangwar, Date, & Raoot, 2014). However, TOE has its limitations. According to Gangwar et al. (2014), TOE is a taxonomy for characterizing variables, thus does not represent a well-developed theory. Awa and Ojiabo (2016) stated that TOE constructs apply to large organizations. The TOE framework should be bolstered by integrating with other models.

The TOE framework was developed to examine the organizational adoption of various IT/IS products and services (Tornatzky & Fleischer, 1990). In this study, I investigated the adoption of IoT at the organization level. I adopted five attributes related to the TOE framework: technology readiness, top management support, firm size, competitive pressure, and regulatory support. I chose TOE as one of the foundational theories for this study due in part to its explanatory power of organizational adoption of various IT/IS and previous research that supports its validity.

Analysis of Related Theories

During the literature review, many researchers used the TAM and UTAUT theories on investigating factors that influence IoT adoption. In the following paragraphs, I provide details on these two alternative theories.

Technology acceptance model. Davis (1989) developed the original TAM based on the theory of reasoned action (TRA). As shown in Figure 3, the TAM model uses two constructs perceived usefulness, and perceived ease-of-use, to determine individual user intention to use. Perceived usefulness is the degree to which an individual believes adopting a particular system will enhance their job performance, while perceived ease-of-use is the degree to which effort is lessened by adopting a system (Partala & Saari, 2015). TAM was developed to predict users' adoption of new technology.

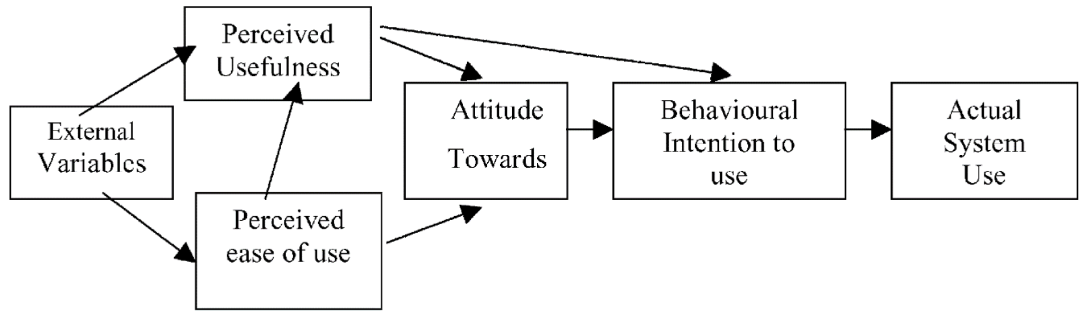

Figure 3. Technology acceptance model. It shows the interrelationship between adoption factors. Adapted from "Why do people use information technology? A critical review of the technology acceptance model," by Legris et al. (2003). Information & Management, 40(3), 191-204. Copyright 2003 by Elsevier. Reprinted with permission.

While TAM is a useful model and has been used in multiple studies (Alalwan, Dwivedi, Rana, & Williams, 2016; Dong, Chang, Wang, & Yan, 2017; Faqih, 2016; Kim & Shin, 2015; Mani & Chouk, 2016; Roy, Balaji, Quazi, & Quaddus, 2018; Singh et al., 2017), it has certain limitations. According to Legris, Ingham, and Collerette (2003), TAM only explains about 40% of system use and the results of the empirical analysis are not consistent or unambiguous. Bagozzi (2007) criticized TAM as being too simplistic to explain the decisions made across a wide range of technologies and contexts. Bagozzi and Legris et al. concluded that additional variables are needed to understand a user's decisions related to technology adoption. I did not select TAM as the theoretical framework for this study due to the limitations described above, and the fact that TAM focuses on individual adoption. This study was conducted within organizations; external factors besides perceived usefulness and perceived ease-of-use are influential to the IT leader's decision to adopt IoT. TAM was deemed not appropriate for this study.

Unified theory of acceptance and use of technology. UTAUT, developed by Venkatesh et al. (2003), combined eight adoption theories, namely: TRA, TAM/TAM2, motivation model (MM), TPB, combined TAM and TPB (C-TAM-TPB), a model of PC utilization (MPCU), DOI, and social cognitive theory (SCT). As shown in Figure 4, UTAUT consists of four fundamental constructs, including performance expectancy, effort expectancy, social influence, and facilitating conditions, which are determinants of behavioral intent and use behavior (Venkatesh et al., 2003). Gender, age, experience, and voluntariness of use interact with the four fundamental constructs, thus influencing intention and behavior (Venkatesh et al., 2003). UTAUT has been used extensively in the literature (Canhoto & Arp, 2016; Leong, Ping, & Muthuveloo, 2017; Shin & Jin Park, 2017) and accounts for 70% of the variance in behavioral Intention to Use (BI) and about 50% in actual use (Venkatesh et al., 2003). Because of the combination of eight adoption theories, the model used 41 independent variables for predicting intention and eight independent variables for predicting behavior. The complexity of UTAUT makes it difficult to apply (Bagozzi, 2007). Due to this complexity, UTAUT was deemed not appropriate for this study.

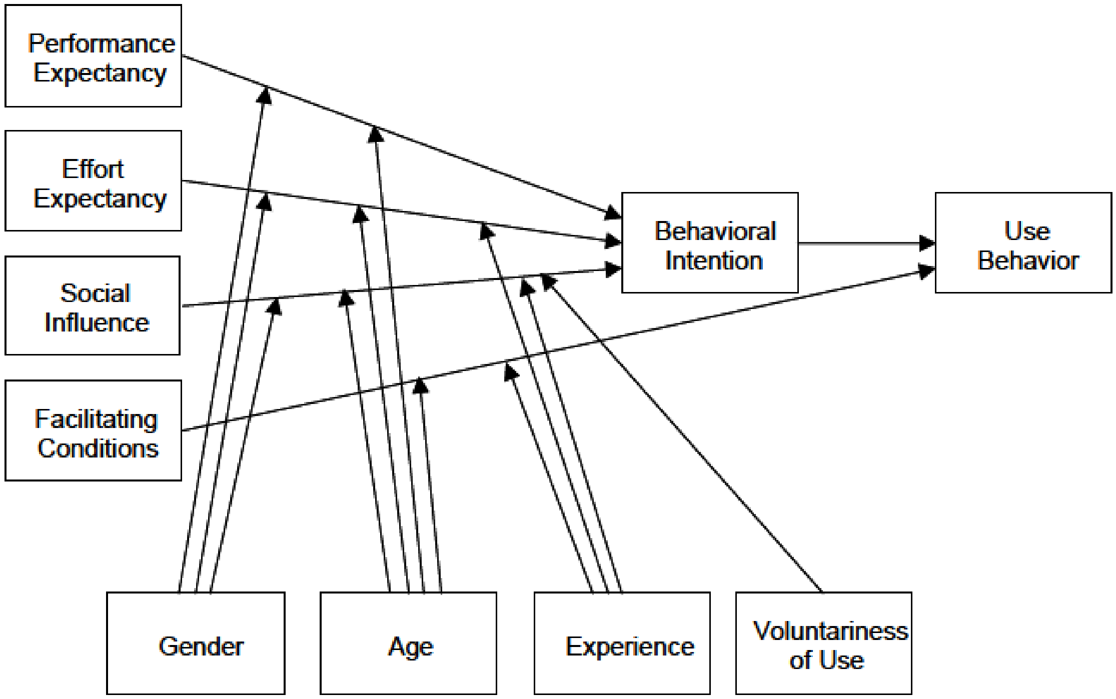

Figure 4. Unified theory of acceptance and use of technology. It shows the two-dimensional influence of behavioral intention. Adopted from “Users Acceptance of Information Technology: Towards a Unified View,” by V. Venkatesh, M.G. Morris, F.D Davis, and G.B. Davis, *MIS Quarterly*, *27(3)*, 425, pp. 425-478. Copyright 2016 by MISRC. Reprinted with permission.

Diffusion of Theory and Technology-Environment Framework.

In this study, I use a combination of DOI Theory and TOE framework, henceforth DOI-TOE theoretical framework. For this research, I was interested in how the technical context and organizational context influence IoT adopt. In this study I adopted three technical attributes from the DOI theory —relative advantage, compatibility, and complexity —, and five organizational attributes from the TOE framework— technology readiness, top management support, firm size, competitive pressure, and regulatory support — for incorporation into the integrative DOI-TOE theoretical framework used in this study. Some fundamental differences between DOI and TOE theories must be considered. Because of DOI's shortcomings, the TOE framework helps to provide a more comprehensive perspective for understanding IT adoption by including the technology, organization, and environmental contexts (Chau & Tam, 1997; Fichman, 2000; Lee & Cheung, 2004).

Similarly, TOE does not specify the role of individual characteristics (e.g., top management support), while DOI suggests their inclusion (Gangwar et al., 2014). Although there are shortcomings in both DOI and TOE, there is also an overlap which results in both theories complementing each other. According to Ji and Liang (2016), combining DOI and TOE allows researchers to identify factors from inside and outside an organization along with technological characteristics.

Researchers posited that combining multiple frameworks overcome the limitations inherent in each model while enhancing the understanding of innovation adoption by enhancing explanatory power (Alkhalil et al., 2017; Awa, Ojiabo, & Orokor, 2017; Cheng, 2015). Combining multiple frameworks enhance the understanding of innovation adoption, and TOE in suitable to integrate with DOI. Combining DOI and TOE will complement each other and provide a better understanding of innovation adoption (Alkhalil et al., 2017; Awa et al., 2017; Wang & Wang, 2016). Similar to other researchers, I combined, and abstracted ten key innovation adoption factors from then DOI theory and TOE framework to construct integrative DOI-TOE model. Figure 5. shows the theoretical model proposed for this study.

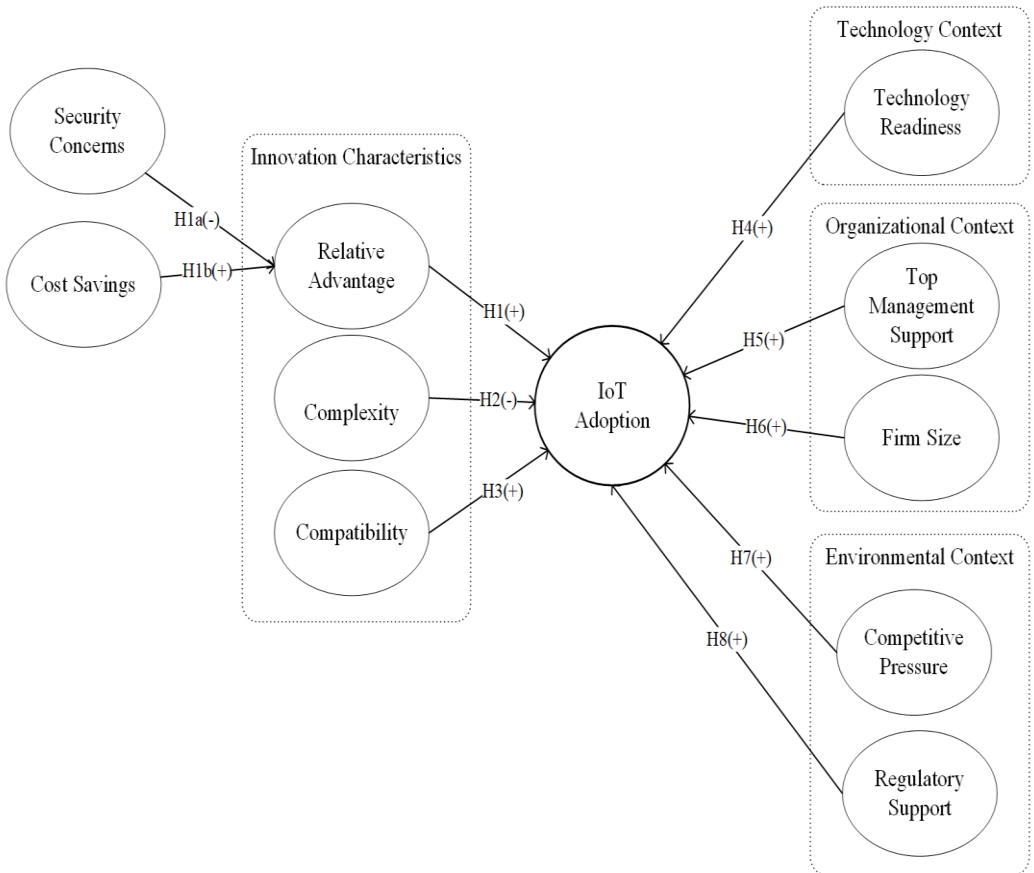

Figure 5. Integrative DOI-TOE model proposed for this study.

Critical Analysis and Synthesis of Independent Variables

As shown in Figure 5, the integrative DOI-TOE model consists of 10 constructs that were used to investigate an organization's intention to adopt IoT. These constructs are categorized as innovation characteristics, technology context, organizational context, an environmental context. These four constructs consist of 10 variables found in existing technology adoption models (Oliveira et al., 2014).

Innovation characteristics. In this study, five variables were used to describe the innovation characteristics construct: relative advantage, security, cost, complexity, and compatibility.

Relative advantage. Relative advantage describes the degree of the perceived superiority of innovative technology as compared to the existing solution (Rogers, 2003). Relative advantage positively influences IoT adoption (Balaji & Roy, 2016; Ma, Xu, Trigo, & Ramalho, 2017; Shin & Jin Park, 2017; Tu, 2018). Innovation that increases organization strategic effectiveness (e.g., increase efficiencies, production, or sales) and operational effectiveness (e.g., reducing cost) are more likely to be adopted (Oliveira et al., 2014; Rymaszewska, Helo, & Gunasekaran, 2017; Tu, 2018). In the analysis of the literature studies using the combination of DOI and TOE relative advantage was the most significant predictor or adoption (Alkhalil et al., 2017; Ji & Liang, 2016; Shaltoni, 2017; Wang & Wang, 2016). H1; Relative advantage will positively influence IoT adoption.

Security context. IoT is enabling the realization of innovative applications in multiple domains. However, due to its heterogeneous and wide-scale deployments (billions of devices), the lack of standardization, inventory control, constrained resources, and limited computational capabilities of IoT devices results in many new security and privacy issues (Attaran, 2017; De Cremer, Nguyen, & Simkin, 2016; Ge, Hong, Guttmann, & Kim, 2017; Hosek et al., 2017; Rymaszewska et al., 2017). Even with all the work being done to secure IoT devices, there are still many gaps, such as:

- Lack of secure low-cost security communication protocols (Cheng, Lu, Petzoldt, & Takagi, 2017; Junqing, Duong, Woods, & Marshall, 2017; Sciancalepore et al., 2016; Wang, Jiang, Li, & Lv, 2017a). Without these protocols and proper key-management, IoT communications will remain vulnerable.

- Lack IoT security analytics frameworks and methodologies (Ge et al., 2017; Mavropoulos, Mouratidis, Fish, Panaousis, & Kalloniatis, 2017; Mohsin, Anwar, Zaman, & Al-Shaer, 2017). The inability to assess the current expose will leave the organization open to theaters.
- Lack of IoT security automation (Mavropoulos et al., 2017). With the number or predicted IoT devices, automation would be the key to ensure the secure configuration of devices.
- Lack of workforce and training to address the now threats space for IoT (Saarikko, Westergren, & Blomquist, 2017).
- Lack of security standards, and lack of IoT laws and regulations (country and internationally; Ahlmeyer & Chircu, 2016). The lack of standards and low makes interoperability a nightmare, thus inhibiting the diffusion of IoT devices

IoT devices are facing many threats and attacks, thus protecting IoT while a challenging task is an important task. The lack of standards, mature security protocols implies organization may be reluctant to adopt IoT. H1a; Security and privacy concerns will negatively influence the relative advantage of IoT adoption.

Cost savings. IoT adoption creates an opportunity for organizations to achieve higher productivity, higher quality, and lower production costs via the automation of business processes (Balaji & Roy, 2016; Caputo, Marzi, & Pellegrini, 2016; Ferretti & Schiavone, 2016; Roy, Zalzala, & Kumar, 2016; Singh et al., 2017). A secondary effect of reduced production cost is a lower cost of consumer goods and services (Caputo et al., 2016; Roy et al., 2016). H1b; Cost savings will positively influence the relative advantage of IoT adoption.

Complexity. Complexity describes the degree of difficulty to understand and use an innovation (Rogers, 2003). In the context of this study, it refers to the degree of difficulty to which IoT adoption and integration is perceived. The wide variety of IoT devices add a layer of complexity during product selection and planning (Zhong et al., 2017). These complexities, in addition to the lack of skilled staff to manage a multivendor environment, are detrimental to IoT adoption (Haddud et al., 2017; Lin, Lee, & Lin, 2016; Wang & Wang, 2016). H2; Complexity will negatively influence IoT adoption.

Compatibility. Compatibility describes the degree to how well an innovation integrates with current practices or value systems (Rogers, 2003). The innovation adoption rate is proportional to the degree of compatibility; therefore, the higher the compatibility, the faster the adoption. Compatibility among sensors, networks, and application from different vendors are essential factors that influence the adoption of IoT (Haddud et al., 2017; Ng & Wakenshaw, 2017). H3; Compatibility will positively influence IoT adoption.

Technology context. In this study, technology readiness is used to describe the technology context construct.

Technology readiness. The technology context describes two facets of an organization, its organizational structure, and the availability of knowledgeable and skilled human resources (Tornatzky & Fleischer, 1990). The organization structure refers to the current technological infrastructure and its ability of the legacy system to easily integrate with IoT (Rosas et al., 2017; Tornatzky & Fleischer, 1990). Human resources refer to the knowledge, skill, and availability of personnel to implement and operate IoT technologies (Tornatzky & Fleischer, 1990). An organization that meets these two characteristics has a higher degree of technological readiness and thus is more likely to adopt IoT. Organizations with a higher degree of technological readiness and competency are in a better position for the adoption of IoT (Kiel, Arnold, & Voigt, 2017; Martins et al., 2016). H4; technological readiness will positively influence IoT adoption.

Organizational context. In this study, two variables describe the organization context construct, namely: top management support and firm size.

Top management support. Top management support plays a vital role in IoT adoption because it guides the allocation of resources, the integration of services, and the re-engineering of processes (Hsu & Yeh, 2016; Martins et al., 2016; Wang & Wang, 2016). Without the influence and support of top management, the organization is likely to resist the adoption of IoT (Wang & Wang, 2016). H5; top management support will positively influence IoT adoption.

Firm size. Large firms have an advantage over small ones because they have more resources and can take more significant risks associated with innovation adoption (Carcary, Doherty, Conway, & McLaughlin, 2014). Small firms, although more adaptable, do not have the resources or knowledge to readily adopt newer technologies (Carcary et al., 2014). The size of a firm is a determinant of IoT adoption. H6; firm size will positively influence IoT adoption.

Environmental context. In this study, two variables describe the organization context construct: competitive pressure and regulatory support.

Competitive pressure. Organizations adopt IoT as a strategy to improve competitiveness (Rosas et al., 2017). An organization that fails to innovate grows less competitive and fail to survive (Rosas et al., 2017; Taneja et al., 2016). The organization should remain agile and adaptable as possible, and a means to ensure continued competitiveness (Balaji & Roy, 2016; Ferretti & Schiavone, 2016; Rosas et al., 2017). An organization that remains agile and adaptable can more readily respond to competitive pressure (Mourtzis, Vlachou, & Milas, 2016). Competitive pressure from competitors and others in supporting industries often lead the organization to innovate (Hsu & Yeh, 2016). H7; Competitive pressure will positively influence IoT adoption.

Regulatory support. Government regulations can influence organizations in IoT adoption. However, IoT regulation is in its infancy (Ahlmeyer & Chircu, 2016; Atzori et al., 2017; Hosek et al., 2017). When a government requires businesses to comply with IoT-specific standards and protocols, firms will be more willing to adopt IoT technologies, as failure to comply can lead to severe consequences (Krotov, 2017; Ng & Wakenshaw, 2017). H8; Regulatory support will positively influence IoT adoption.

The ten variables discussed above informed the assumption for the hypotheses that explain the effect on a manufacturing organizations' decision to IoT adoption. The variables will be tested, and the findings presented in Section 3 of this study.

Critical Analysis and Synthesis of Dependent Variables

IoT adoption is the dependent variable in this study. The concept of IoT had existed since the early 1990s when Weiser envisioned that technologies would merge with the environment (Bojanova, Hurlburt, & Voas, 2014; Mavropoulos et al., 2017). In the last few years, IoT has become more integrated into our lives; this is made clear by all the connected things within the commercial and consumer spaces

IoT continues to grow. The proliferation of IoT devices has skyrocketed over the last few years (Del Giudice, 2016). There is enormous potential for organizations to capitalize on this rapid expansion of IoT devices by harnessing and utilizing data gathered from these “smart” devices (Akhtar, Khan, Tarba, & Jayawickrama, 2017; Attaran, 2017; Atzori et al., 2017; Bi, 2017; Caputo et al., 2016; Ferretti & Schiavone, 2016; Jang & Kim, 2017; Rymaszewska et al., 2017; Singh et al., 2017; Tan, Ng, & Low, 2017; Thomas, Costa, & Oliveira, 2015; Tu, 2018; Wan et al., 2018; Wang, Yang, Zhang, & Xu, 2017b; Zheng & Wu, 2017; Zhong et al., 2017); however, organizations need to consider the impact on their business strategy, infrastructure, and security posture (Ahlmeyer & Chircu, 2016; Kumar, Vealey, & Srivastava, 2016).

IoT adoption is affected by many factors such as relative advantage, compatibility, top management support, organizational readiness, competition, organizational size and external pressure, and cost. These factors typically have a positive influence on IoT adoption (Lin et al., 2016; Mangula, Van De Weerd, & Brinkkemper, 2017; Tu, 2018). However, organizations have been slow to adopt IoT (Ives et al., 2016). For the diffusion of IoT technologies and associated applications, limitations such as cost, privacy, and security issues and others need to be addressed so that potential of the IoT technology and their applications can be realized. Key factors need to be identified to enhance the probability of organizational IoT adoption.

Measurement of Variables

This quantitative correlation research study statistically analyzes numerical data collected from Likert-scale responses to the survey questions to identify a correlation between DOI and TOE variables. I used an instrument by Oliveira et al. (2014) that was previously tested to ensure reliability and validity. I used SPSS version 25 statistical analyze software for PC/Windows, to generate descriptive statistics, assess reliability and validity, and conduct a correlation analysis on the data. Finding will be presented in Section 3.

Relationship of this Study to Previous Research

The purpose of this quantitative, correlational study was to examine the relationship between the independent variables, which are corporate IT leadership's perceptions of (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and the dependent variable, which was intent to adopt IoT in manufacturing organizations. Several researchers dealt with IoT technology adoption at the individual level. TAM was the most common framework employed by researches investigation IoT adoption at the individual level (Dong et al., 2017; Faqih, 2016; Gao, Li, & Luo, 2015; Kim & Shin, 2015; Mani & Chouk, 2016; Roy et al., 2018). Canhoto and Arp (2016) used UTAUT while Mital, Chang, Choudhary, Papa, and Pani (2017) used the TOE framework. Hsu and Lin (2016a) and Roy et al. (2016) used network externalities and a model based on the United Nations Development Programme India's criteria for growth, respectively.

There were a few studies that were conducted at a societal level; mostly in the context of smart homes and cities (Kim, Park, & Choi, 2017; Leong et al., 2017; Yang et al., 2017a). Kim et al. (2017) used a combination of value-based adoption model and TAM to study the adoption of IoT smart home service. Leong et al. (2017) used the unified theory of acceptance and use of Technology 2 to assess the antecedents for the adoption of IoT in the context of smart cities in Malaysia. Yang et al. (2017a) used TBA to explain potential customers' behavioral intention to adopt and use smart home services.

Like this study, other researchers focused on studies at the organization level (Hsu & Lin, 2016b; Hwang et al., 2016; Singh et al., 2017; Tu, 2018). Hsu and Lin (2016b) used the value-based adoption model to examine the influences of benefits (perceived usefulness and perceived enjoyment) and sacrifices (perceived privacy risk and perceived fee) to evaluate the user's perceived value of an intention to use IoT services provided by Taiwanese IoTs service providers. Findings from the study showed that perceived usefulness and perceived enjoyment positively affect behavioral intention through perceived value. While perceived privacy negatively affects IoT adoption.

Hwang et al. (2016) investigated what the value configuration factors, including specific technology attributes and IoT business contexts that influence IoT diffusion were. Five value configuration patterns (id-based service model, multiple operation management, service-combined inventory management model, intelligent inventory transport model, and sensor-based multiple service model) were used to investigate IoT diffusion of 762 business cases over five years. The overall conclusion was that IoT diffusion between various sectors occurs at different rates.

Singh et al. (2017) and Tu (2018) proposed an IOT-TAM model to investigate what factors influence the adoption rate of IoT technologies within the corporate sector of India. Similar to the constructs used in TAM, four independent variables (perceived usefulness of IoT, external organization variables, internal organization variables and perceived ease of use of IoT technology) were used to evaluate the dependent variable behavioral intention to use IoT. Findings from the study indicated that all for constructs positively influence IoT adoption.

Tu (2018) used a mixed method approach. Grounded theory methodology was used as the foundation of the qualitative analysis while the TOE framework formed the basis for the quantitative analysis. Tu investigated what incentives and concerns behind firms' decisions to adopt IoT, and what are the determinant factors affecting IoT adoption in logistics and supply chain management. The results of the qualitative analysis determined that benefit cost, trustworthiness, and external factors influence the intention to adopt IoT. The results of the quantitative assessment showed that perceived benefits, perceived costs, and external pressure are significant determinants of IoT adoption intention, while technology trust is not.

Few researched used a combination of DOI and TOE framework in their investigation. Table 1 presents research that has been done using a combination of the

DOI theory and TOE framework. Research that used a combination of DOI theory and TOE framework did not focus on IoT adoption but instead investigated other concepts such as cloud adoption, Internet marketing, and knowledge management (Alkhalil et al., 2017; Shaltoni, 2017; Wang & Wang, 2016).

Table 1

Previous Research Using DOI Theory and TOE Framework.

Model/Theory	Author/Date	Technology/dependent variable
DOI and TOE	Alkhalil et al. (2017)	Cloud computing
DOI and TOE	Shaltoni (2017)	Internet marketing
DOI and TOE	Wang & Wang (2016)	Knowledge management system

Alkhalil et al. (2017) employed a mix method design using a combination of the DOI theory and TOE framework to explore the determinants for the decision to migrate existing resources to cloud computing. The outputs from a review of the literature and a phenomenological study were used to inform the theoretical model used in the study. Thirteen independent variables (relative advantage, complexity, trialability, risk, compatibility, size, readiness, internal social network, external social network, top management support, increasing providers configuration, regulation, and uncertainty regarding the market) were used to access the decision to adopt an innovation. The results of the study showed that seven variables (complexity, risk, compatibility, internal social network, increasing providers and configuration, regulation, uncertainty regarding the market) contribute to decision.

Shaltoni (2017) employed a mix method design using a combination of DOI theory and TOE framework to explore what factors influence the Internet marketing adoption in emerging Jordanian industrial markets. Shaltoni used unstructured exploratory interviews followed by a web survey which investigated six constructs (relative advantage, complexity, compatibility, innovativeness, competition level, and customer pressure) in their study. Results from the study showed that half of the investigated organizations are using the Internet as a one-way communication vehicle through static websites. The study also revealed that decision-makers in emerging industrial markets are enthusiastic about social media, particularly Facebook. Internet marketing adoption was positively related to perceived relative advantage, compatibility, organizational innovativeness, competitor, and customer pressure. Complexity negatively influenced adoption.

Wang and Wang (2016) employed a quantitative methodology using a combination of the DOI theory and TOE framework to investigate the determinant of firms' knowledge management system (KMS) implementation in Taiwan. Nine independent variables (perceived benefits, complexity, compatibility, sufficient resources, technology competency, top management support, organization culture, and competitive pressure) were used to investigate KMS implementation (Wang & Wang, 2016). The results showed that technological innovation factors (perceived benefits, complexity, and compatibility), organizational factors (top management support, organizational culture), and environmental factors (competitive pressure) are significant influences on KMS implementation in firms (Wang & Wang, 2016).

Few studies focused on IoT adoption at the organization level. The gap in the literature showed few studies using a combination of DOI theory or TOE framework. I did not identify any recent research studies using a combination of DOI theory and TOE framework investigation IoT adoption within the manufacturing sector.

IoT is an innovative technology that has the potential to increase an organization’s value while improving operational efficiencies (Hsu & Lin, 2016a; Voas, 2016). Organizations seek innovative technologies that bolster efficiencies and business profitability while lowering upfront cost to ensure their long-term survival. Organizations that fail to innovate are less agile, flexible, and competitive and thus fail to survive (Rosas et al., 2017; Taneja et al., 2016). My study reflects the growing need to use IoT to innovate within the manufacturing industry. Understanding the determinants of IoT is fundamental as organizations consider the adoption of IoT for business process transformation or to facilitate rapid application development to support business verticals, such as agriculture, healthcare, and manufacturing. Thus, it is hopeful that my study contributes to filling this gap.

Transition and Summary

The purpose of this quantitative, correlational study was to examine the relationship between corporate IT leaderships’ perceptions and their intent to adopt IoT within manufacturing organizations in the United States. IT adoption has been studied extensively at both the individual and organization level; however, organizations do not always adopt innovative technology, such as the IoT right away. DOI theory and the TOE framework are commonly used in innovation diffusion and adoption studies in organizations. Combining these two frameworks enhances the understanding of innovation adoption. As addressed in my analysis, IoT is a critical enabler to spur growth within the manufacturing sector. However, very few researchers have utilized a combination of DOI and TOE to conduct studies within the manufacturing sector. This lead to a gap in the literature, which can be characterized by a lack of research evaluating the factors influencing IoT adoption in the manufacturing sector.

Understanding the determinants of IoT is fundamental as organizations consider the adoption of IoT for business process transformation or to facilitate rapid application development to support business verticals. Presumably, economic growth that results from increased efficiency may create cost saving in manufacturing processes, thereby resulting in cost savings of goods and services offered to consumers. As profits increase, socially responsible organizations will provide increased wages and benefits to their employees, thus contributing to increased consumer spending powers. There is significance to IT practice as it may provide a practical model for understanding the determinants influencing the adoption of IoT technologies within the manufacturing sector. Future developers and IoT device manufacturers can use the findings from this study in the development of IoT devices and applications that better align with the needs of organizations, thus increasing IoT adoption rates. This study will help determine the relationship between corporate IT leaderships' perceptions and their intent to adopt IoT within manufacturing organizations in the United States.

Section 1 began with an introduction of the problem undertaken by this research via the background of the study. This section was a presentation of the problem statement, purpose statement, nature of the study, research questions, hypotheses, theoretical framework, and the significance of the study. This section was further expanded to include operation definitions, assumptions, limitations, delimitations. The literature review concluded this section with an in-depth discussion of the theoretical framework, methods, and instruments that will be used and their applicability to the problem under study.

Section 2 begins with a restatement of the purpose statement to provide the reader with a broad overview of the study. Section 2 continued with a discussion regarding the role of the researcher, participants, research method and design, which was then followed by the population and sampling strategy and protection of the study participants on the ethical research sections. Also included in Section 2 was a discussion of the data collection and analysis strategies, the choice of instruments, and finally, how to ensure study validity.

Section 3 presented an overview of the entire study and presented the findings that result from the data analysis of the collected surveys. Section 3 concluded with the application of the findings to professional practice, the implication for social change and recommendation for action and further study.

Section 2: The Project

In this section, I begin with a restatement of the purpose statement, followed by a discussion of my role as a researcher, and an overview of the participants. Next, I present a detailed description of the research method and research design, followed by discussions on population and sampling, ethical research concerns, research instrument, data collection, and analysis procedures, and validity of the study. This section concludes with a transition to Section 3

Purpose Statement

The purpose of this quantitative, correlational study was to examine the relationship between corporate IT leadership's perceptions of (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and intent to adopt IoT in manufacturing organizations. The dependent variable was the corporate IT leadership's intent to adopt IoT. The independent variables were corporate IT leadership's perceptions of (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support. Firm size was measured using a nominal scale, while relative advantage, complexity, compatibility, technology readiness, top management support, competitive pressure, and regulatory support were measured using a 5-point Likert scale ranging from *strongly disagree* to *strongly agree*. The population for the study was IT leadership with decision making authority working for manufacturing organizations in the United States. Organizations adopting IoT gain efficiencies, thereby creating cost savings of goods and services offered to consumers. The findings from this study may contribute to positive social change by contributing to economic growth that results from increased efficiency gained from the adoption of IoT in key business areas.

Role of the Researcher

The role of a researcher is multifaceted and evolves as the researcher progress through the study, from conceptualization through data gathering, analysis, and finally dissemination (Köhler, Landis, & Cortina, 2017; Osborne, 2017). Like other quantitative researchers, my role as a quantitative researcher changed as the study advanced from conceptualization through the presentation of the findings. Specifically, my role involved the selection to the topic of study, defining the research question and hypothesis, review of the relevant literature, collection, organization, and maintenance of the data, data analysis, and presentation of findings.

Researchers must be cognizant of bias. In qualitative research the personality of the researcher is intertwined with the research (McCusker & Gunaydin, 2014), there is an increased likelihood of subjectivity during data collection and data analysis (Twining, Heller, Nussbaum, & Tsai, 2017). Bias in research cannot be eliminated; I acknowledged that personal beliefs and values could influence my research and took precautions to minimize bias.

To further minimize bias, researchers employing quantitative methods should be detached and impartial. A quantitative researcher is independent of the research and achieves objectivity by being distant and independent of what is being researched (Quick & Hall, 2015c; Yates & Leggett, 2016). My goal during each phase of this study was to minimize direct contact with the participants, thus staying detached and impartial during the data collection, analysis, and presentation of findings.

As a researcher, my role was to ensure the reliability and validity of the study. Researchers using quantitative research seek reliable and valid results as a means of producing trustworthy and credible knowledge and evidence that can inform decisions (Hales, 2016). To increase the likelihood of reliable and valid results, a previously validated instrument was used and repurposed to align with the context of this study. Written permission to reuse the instrument is presented in Appendix B. Maintaining the integrity of the instrument and adherence to the research design will help ensure the validity of the results.

I have been working in the IT field for more than 15 years, with a primary focus on cybersecurity in support of homeland security. Before entering the IT field, my training was in clinical laboratory sciences, which is an evidence-based profession. Before being involved with this study, I had little knowledge of IoT devices, and zero knowledge of theories related to IT adoption. I had no prior involvement with the participants, nor did I influence the demographics of the study. To reduce my bias, I planned to be objective by being distant and independent of what was being researched; and by only drawing conclusions based on the analysis of the data that were collected.

Protecting the right of participants is essential in research. Adherence to the tenets in the Belmont Report (United States Department of Health & Human Services, 1979) was accomplished to ensure that the rights of the participants were not violated. Before embarking on this study, completion of the online course of the United States National

Institutes of Health's Office of Extramural Research on protecting human research participants was undertaken (Certificate Number 2146956).

Participants

I selected the eligibility criterion. Selecting participants in a study is one of the most important steps in research (Haegele, & Hodge, 2015). A researcher's ability to compare, contrast, and generalize to other studies is dependent on the inclusion criteria used for participant selection. Inclusion and exclusion criteria determine who can participate in the study. Researchers often specify specific characteristics that participants should have to participate in the study (Robinson, 2014). Specifying specific criteria narrows the eligible participants and increases the homogeneity of the sample while also disqualifying others from participation.

In this study, participants were IT decision-makers working for manufacturing organizations in the United States. The participants were knowledgeable about IoT. These decision-makers were responsible for making a recommendation to adopt IT technologies within their organizations and are familiar with their organization direction on IoT. The participants were between the ages of 18 and 65. I excluded minors as they were not necessary for this study. Health and Human Services (2009) stated in 45 CFR 46 Subpart D to limit minor participants unless necessary for the study.

I used an online panel. Online panels provide easy access to participants. Online panels provide many benefits to the researchers when collecting survey data such as access to diverse populations, cost-effectiveness, shorter sampling times, reduced time for data aggregation for analysis and study replicability (Hays, Liu, & Kapteyn, 2015).

These benefits and others have resulted in increased use of online panels to access participants, especially when targeting a subgroup. I accessed participants conveniently available through Qualtrics panel. Sample quality and data integrity are two concerns about the use of online panels. Smith, Roster, Golden, and Albaum (2016), in a study of online panels in the United States, concluded that the choice of vendor is critical to ensure data quality and researchers should include screening to access sample integrity data quality. As part of the data analysis, I screened the data to ensure that integrity was not compromised by examining characteristics such as respondents IP addresses, and pattern responses.

Roulin (2015) and Landers and Behrend (2015) both concluded that Qualtrics panels not only allow researches access to reliable data but that data are representative of the general labor force. They found that Qualtrics panels are comparable to other convenience sampling methods. Qualtrics panels have been used successfully by other researchers. In a study by Carneiro and Faria (2016), due to a low response rate using a self-administered online survey, the researchers recruited Qualtrics to administer their survey via a Qualtrics panel, which resulted in 310 completed surveys in 2 days. Balaji and Roy (2016) and Marakhimov and Joo (2017) also used Qualtrics panels to access participants for their study and achieved completed responses of 289 and 260, respectively.

Qualtrics panels are an effective means to gain access to participants for a study. Using a Qualtrics panel was a viable choice to gain access to participants for this study. Access to participants was via purposeful sampling, an extension of the nonprobabilistic sampling methodology, by selecting participants (IT leaders with decision-making authority) conveniently available through a Qualtrics panel.

Establishing a working relationship with participants was critical for data collection. The way participants are approached could affect the sample (Twining et al., 2017). Asking for consent, being transparent about the research methods and potential risk, while also respecting anonymity, and confidentiality builds trust and a working relationship (Rothstein, 2015). As part of the invitation to participants, an informed consent form was utilized to inform participants about the nature of the research topic, the purpose and use of the data collected, and a notification that questionnaire was administered anonymously. The goal was to ensure anonymity and confidentiality while instilling trust with the participants.

Research Method and Design

Before selecting the research method for this study, I assessed which research methods were most suitable. Researchers typically employ one of three research methods: quantitative, qualitative, and mixed methods (McCusker & Gunaydin, 2014). While all three methods are viable for research, a quantitative method allowed the examination of the relationship between and among variables used in this study (Yates & Leggett, 2016). A quantitative method was selected for this study.

I also assessed research designs to identify the most suitable quantitative research design. There are three main research design approaches available to quantitative researchers: (a) descriptive, (b) experimental, and (c) relational or correlation (Haegele & Hodge, 2015). While each design has its strengths and weaknesses, the selected design should be chosen to complement the context of the study by addressing the research question and hypothesis. Correlation designs focus on finding linkages or associations between variables (Reio, 2016). A quantitative, correlational method was determined to be more appropriate for this study because it allows the examination of the relationship between IT leadership's perceptions and the intent to adopt IoT in manufacturing organizations. The research method and design were chosen to align with the problem statement, purpose, research question, and assess the hypothesis. In the following paragraphs, I provide a detailed rationale to support the chosen research method and design.

Method

In this study, I employed a quantitative methodology. Researchers use quantitative research to examine the relationship between independent and dependent variables within a population (Yates & Leggett, 2016). By analyzing varying factors, researchers can determine how they relate to each other, generalize to other similar situations, provide explanations of predictions, and explain causal relationships. In this study, I examined the relationship between IT leadership's perceptions of eight independent variables and the dependent variable: Intent to adopt IoT.

Central to quantitative research is the logic of hypothesis testing (Haegele & Hodge, 2015). Researchers conduct statistical analyses of numeric data collected to assess the probability of accepting or rejecting the null hypothesis. I used quantitative methods to evaluate if there is a statistically significant relationship between corporate IT leadership's perceptions of their intent to adopt IoT. Included in Section 1 are a null and an alternate hypothesis.

Quantitative methods involve numbers, logic, objectivity, and positivist concepts. Quantitative methods involve the production and evaluation of numerical data and emphasize objectivity by encouraging researchers to distance themselves from participants (Quick, & Hall, 2015c; Twining et al., 2017).

Using surveys allows researchers the ability to solicit measurable characteristics of the population while distancing themselves from participants, thus facilitating objectivity. Responses to surveys that employ Likert-scales produce numerical data which can then analyzed. Like other researchers, such as Wang and Wang (2016), I used surveys to collect data anonymously from participants and to statistically analyze numerical data collected from Likert-scale responses to the survey questions.

A quantitative method was appropriate for the study because the purpose of the study was to statistically analyze numerical data collected from Likert-scale responses to the survey questions and make inferences to manufacturing organizations considering the adoption of IoT.

Qualitative methods focus on the why and how of a phenomenon. Barnham (2015) asserted that qualitative methods focus on why and who, but does not facilitate enumeration (Palinkas, 2014). Researchers use qualitative methods to explore problems by using open-ended why and who questions, rather than explain relationships between variables statistically. Because my goal for this study was to identify the relationship between variables of interest, a qualitative method was inappropriate. Another characteristic of qualitative methods is the entanglement of the researcher in the study to gain a more in-depth understanding of the topic. When researchers require a more in-depth analysis of attitudes, motivations, and behaviors, and numerical representation is inadequate, a qualitative approach is appropriate (Ograjenšek & Gal, 2015; Quick & Hall, 2015a). Unlike in quantitative research, where the researcher distances themselves from the participants, researchers conducting qualitative studies immerse themselves into the environment under study to gain a more personal understanding of the environment, culture, social interactions, and so on, they become the instrument and form a close relationship with the participants. Because quantitative studies emphasize objectivity by encouraging researchers to distance themselves from participants, a qualitative method was inappropriate for this study.

Qualitative methods are best suited when gathering contextual information. According to Ograjenšek and Gal (2015), some events cannot be understood without the contextual meaning being discovered and incorporated as part of the analysis. Contextual information includes unique cultural and social interactions, symbols, and others which cannot be discovered by casual observations. To gather such in-depth information, the researcher is required to immerse themselves and have close interaction with the participants. The need to collect contextual information to answer the research question is deemed unnecessary. A qualitative approach was not selected for this study.

Mixed methods studies combine the attributes of both qualitative and quantitative approaches. The real value of the mixed methods approaches manifest when there is an integration of both quantitative and qualitative data resulting in a more significant insight of a phenomenon (Makrakis & Kostoulas-Makrakis, 2016; Yardley & Bishop, 2015). By approaching the problem from multiple viewpoints, researchers employing mixed method approaches can close the knowledge gap and gain a more comprehensive understanding, which is lacking when quantitative or qualitative research are employed independently. A holistic view and a more profound understanding are accomplished by the incorporation of contextual and empirical information with the study (Ingham-Broomfield, 2016).

The concept of triangulation is central to mixed method approaches. Mixed methods help a researcher triangulate result via the use of a combination of qualitative and quantitative data (Flick, 2016). The integration of data from qualitative and quantitative analyses provides a more comprehensive analysis of the subject under study. Although mixed methods are a valid approach since it incorporated aspects of qualitative methods, I deemed it not appropriate.

Mixed method research has a high price. Some concerns using the mixed method approach are, integration is difficult, typically completed poorly, and they demand a considerable amount of time and resources (Guetterman, Fetters, & Creswell, 2015; Raich, Müller, & Abfalter, 2014). Mixed methods approach involves higher risk, due in part to combining two research methodologies; also, it demands a greater length of time to complete and the involvement of more resources, resulting in a higher cost. Due to the likelihood of increasing cost and risk, a mixed method approach was not chosen.

I selected a quantitative approach over qualitative and mixed method approaches because I desired to statistically examine relationships between the IT corporate leadership’s perceptions of the independent variables and their intention to adopt IoT and to test the hypothesis.

Design

The research design selected should address the research question and hypotheses. Four main quantitative research design methods rely on the quantification of observations; namely, descriptive, correlational, quasi-experimental, and experimental (Norris, Plonsky, Ross, & Schoonen, 2015). However, according to Cokley and Awad (2013), only three of them identify relationships between the independent and dependent variables; namely correlational, quasi-experimental, and experimental. Each design has its strengths and weaknesses; therefore, selection should align with the context of the study. I chose a correlation design for this study.

Experimental research designs can be subdivided into true-experimental research and quasi-experimental research. True-experimental research designs assume equivalency between the study and control groups and randomness in participant’s assignment (Quick & Hall, 2015c; Rockers, Røttingen, Shemilt, Tugwell, & Bärnighausen, 2015), whereas in quasi-experimental research, participants are not randomly assigned (Haegele & Hodge, 2015; Rockers et al., 2015). Both true-experimental research and quasi-experimental research involve the manipulation of variables. However, researchers using quasi-experimental research assert more control over the assignments; hence, quasi-experimental research is more applicable to the real world.

Experimental designs are viable in instances where researchers need to test for cause and effect. Alternative designs such as experimental designs are appropriate when a researcher seeks to assess causal effects (Bleske-Rechek, Morrison, & Heidtke, 2014; Haegele & Hodge, 2015). Researches manipulate the independent variable and evaluate its effect on the dependent variable, which enables them to collect data which can identify the cause of a phenomenon. These types of design are more complicated than those of descriptive and correlational designs. The purpose of this study was not to seek cause and effect; the experimental and quasi-experimental designs were not suitable for this study. Multiple groups are involved in experimental designs. Experimental design typically involves at least two groups of participants; one or more groups receive an intervention while one group act as the control group (Haegele & Hodge, 2015). Experimental designs are more rigorous than other types of research, and the inclusion of a control group increases the likelihood of identifying the cause of a phenomenon. As this study involves the use of a control group and direct interaction and control of the participants, this renders experimental designs inappropriate.

The goal of this study was to evaluate the relationship between the variables under study. Correlation designs are used to examine the size and direction of the relationship between variables under study (Bosco, Aguinis, Singh, Field, & Pierce, 2015; Curtis, Comiskey, & Dempsey, 2016). A positive correlation indicates that variables move in the same direction, while a negative correlation indicates that variables move in opposite directions; in either case, there is a relationship. However, no correlation is indicative of the absence of a relationship among variables. The goal of this study was not to predict outcomes. A weakness of correlation designs is that causation cannot be determined as in experimental designs (Bleske-Rechek et al., 2014; Curtis et al., 2016). Correlation does not imply causation, and this study does not plan to investigate the cause for the lack of adoption.

This study did not involve the manipulation of the independent variable. A correlation is employed by researches in cases when they do not want to manipulation of the independent variable or when it is not possible (Curtis et al., 2016). Nonexperimental design, such as correlation designs does not involve directly influencing the variables under study. For this study, I chose not to manipulate the independent variable. A correlation design was most suitable for this study since this study will evaluate the relationship between the variables under study in a nonexperimental situation. In this study, because the primary purpose was to examine the relationship between the IT corporate leadership's perceptions of independent variables and the intention to adopt IoT, a quantitative correlation design was chosen.

Population and Sampling

The first task in sampling was defining the population. According to Haegele and Hodge (2015), a population is the group of people whom the researcher hopes to infer the findings from the study. The target population for this study consisted of IT Leaders working in manufacturing organizations in the United States. Specifically, IT Leaders with decision-making authority who were knowledgeable about IoT, and working for manufacturing organizations in the United States. Similar to Oliveira et al. (2014), the planned target population included IT leader include positions such as chief information officers, chief technology officers, IT directors, IT managers, and information system managers. According to the United States Census Bureau (2015), there was 296,995 manufacturing organization in the U.S. To narrow the sample frame; I used Qualtrics to recruit a panel of participants that aligned with my eligibility criteria. The relevance of the population in this study rest on the participant's knowledge of IoT adoption within their respective organization.

Sampling is the process of selecting representative units from the population. There are two general sampling methods, probability, and nonprobability, that are used to ensure sampling representativeness (Emerson, 2015; Rao et al., 2017). Probability sampling also referred to as random sampling describes the fact every member of the population has an equal chance of being selected as part of the sample (Haegele & Hodge, 2015; Quick & Hall, 2015c). In random sampling, the selected participants have the same characteristics as the target population. However, according to the authors, random sampling is difficult since every member has to be identified and is not useful when a unique characteristic from the larger demographic is required. Random sampling is also research intensive (Valerio et al., 2016). Alternatively, nonprobability or nonrandom sampling describes the fact that every member of the population does not have an equal chance of being selected as part of the sample. (Haegele & Hodge, 2015). Nonprobability sampling is the preferred strategy when targeting a unique subset of a population. According to Valerio et al. (2016), there are four nonprobability sampling strategies, namely, purposive, convenience, snowball, and respondent drive sampling. When targeting hard to reach participants, optimal sampling strategies should be employed. I chose a purposive sampling strategy.

Purposeful sampling, a nonprobability sampling technique, is a widely used strategy in quantitative research when criteria for selecting key informants have been established (Barratt, Ferris, & Lenton, 2014; Valerio et al., 2016). In this study, because I have identified knowledge of IoT as an eligibility criterion for the participants, a purposive sampling strategy was most appropriate. Some limitation of purposeful sampling includes the loss of generalizability, limitations in the number and type of data analysis techniques, and an increased opportunity for researchers to choose incorrect inclusion criteria. (Haegele & Hodge, 2015; Palinkas et al., 2013). Nevertheless, despite the limitations of purposeful sampling, it was a suitable method for this study. Employing a purposeful sampling strategy ensured that hard to reach participants can be recruited what meet the inclusion criteria for this study.

Three factors are used to calculate the sample size (*n*) (a) effect size, (b), alpha level, and (c) power level. According to Cohen (1992), a small effect size is .02, a medium effect size is .15, and a large effect size is .35 for both multiple and multiple partial correlations. Effect size estimations indicate the strength between variables. I selected a medium effect size of ($f = 0.15$) as used in similar studies (Bosco et al., 2015; Green, 1991; Yang, Sun, Zhang, & Wang, 2015).

Researchers aim to limit Type I errors. Alpha in quantitative studies is typically set to .05, which mean that the researcher is 95% confident of the actual estimate of a variable (MacNell, Driscoll, & Hunt, 2014; Whelan & DuVernet, 2015). While using a smaller value for alpha reduces Type I errors, the likelihood of Type II errors increases. An alpha of .05 was selected for this study. Conversely, power is the probability of Type

II errors. Cohen (1992) suggested that researchers use a statistical power of .80. Reducing Type II errors while ensuring that the sample size is achievable in a timely and cost-effective manner was a goal of this study. According to Cohen (1992), values smaller than .80 increase the risk of Type II errors., however, more significant values could result in an enormous sample size. A statistical power of .80 was chosen for this study.

A power analysis, using G*Power version 3.1.9 software, was conducted to determine the appropriate sample size for the study. I conducted an *F*-Test for multiple linear regression to calculate a priori sample size given a medium effect size of (f=0.15), the error probability of (α=0.05), the power of 0.80 and eight predictors (Figure 6). The G*Power analysis indicated that a minimum sample size of 109 participants is required to achieve a power of .80. Increasing the power to .95 resulted in a sample size of 160 participants. Based on the G*power analysis, a minimum of 109 participants to a maximum of 160 participants are required for the study, as shown in Figure 7.

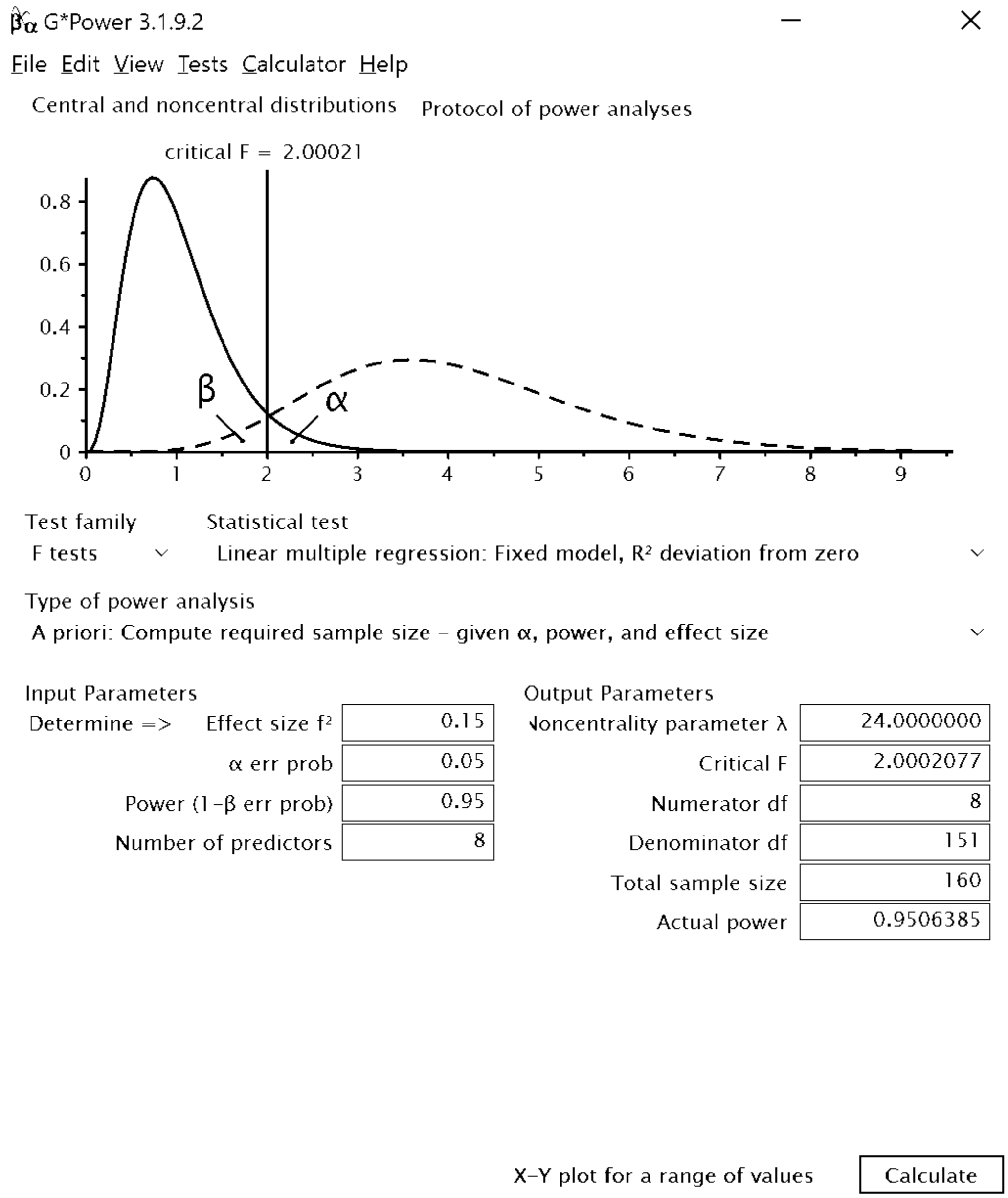

Figure 6. G*power analysis to compute the required sample size.

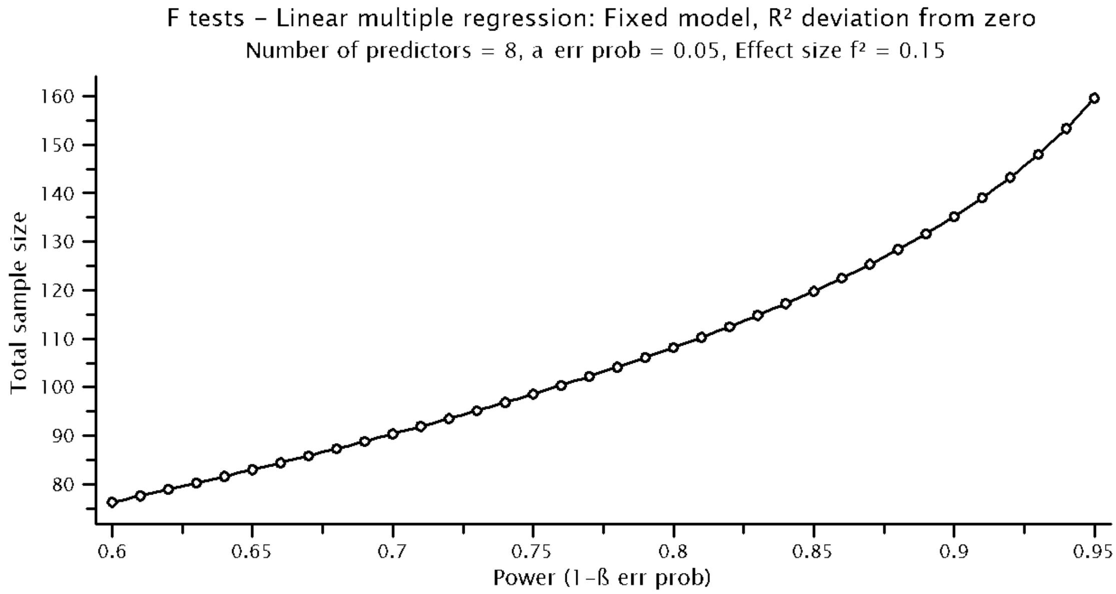

Figure 7. Power as a function of sample size.

An alternative method of determining appropriate sample size suggested in Green (1991), uses the formula $N \geq 50 + 8(m)$ = sample size where m is the number of independent variables to be examined because the independent variables being examined are; relative advantage, complexity, compatibility, technology readiness, top management support, firm size, competitive pressure, and regulatory support, that meant that m was equal to 8 and the formula $N \geq 50 + 8\ (8) = 114$. The estimated sample size required for the study based on the formula is 114 participants. Based on the result of the sample size analyses, the sample range is 114 to 160 with the former being above .80. For this study, a minimum sample of114 was the target.

The response rate has an impact on the validity of the study. The response rate from similar studies conducted by Alkhalil et al. (2017), Oliveira et al. (2014), and Shaltoni (2017) ranged from 10% to 22%. Because of the historic low response rate, a survey window of six weeks was used to ensure a maximum number of responses. Every two weeks, a reminder e-mail was sent to the potential participants to remind them to complete the survey. The survey was closed when 160 completed surveys were received.

Ethical Research

Researchers can potentially encounter ethical issues during a study. Researchers employ best practices, rules, and procedures to ensure the rights and safety of participants (Osborne, 2017). Best practices allow researchers to employ a standard set of ethical protection regardless of their experience while maintaining high research standards. My objective was focused on incorporating measures to protect the rights of the participants in this study.

There are some ethical research principles that researchers use to protect the rights of participants. According to Quick and Hall (2015a), ethical consideration falls into three categories; informed consent, voluntary participation, anonymity, and confidentiality, aimed at protecting participant's, dignity, rights, interest, and safety. Protecting the rights of participants is a researcher's moral obligation. In this study, I followed best practices by incorporating ethical principles.

Researchers should obtain consent from all participants. Ethical conduct of scientific research requires a researcher to gain informed consent (Twining et al., 2017). Informed consent is a means of communicating the intent, risk, and procedure of a study to prospective participants (Ko, LaToza, & Burnett, 2013) and provide a full disclosure which eliminates perceived coercion (Quick & Hall, 2015b). To comply with the Walden University research protocol and Walden University IRB requirements, a consent form was presented to participants before the start of the survey. As part of the consent form, a checkbox needed to be checked to acknowledge that they understood and agreed to participate in this research study.

Participant's participation should be voluntary. According to Quick and Hall (2015a), participants should be notified that their participation is voluntary, and withdrawal from the study is allowed. As part of the consent agreement, the participants were informed that their participation is voluntary and that they can leave the survey at any time before submission of the survey. The participants were informed that once the survey has been submitted, they could not withdraw and their answers to the survey question could not be removed as the survey will be anonymous; there was no way to know which survey belong to them.

Preserving the confidentiality and anonymity of participants was essential. The violation of confidentiality and anonymity are two ethical considerations that researchers must minimize during online survey research (Roberts & Allen, 2015) Before the start of the survey; the participants were informed that any data collected will be removed from the online survey service after the closure of the survey. To protect the confidentiality of the participants, an encrypted USB flash drive was used to store all the collected data. To ensure the integrity of the data, a checksum of all the collected data were generated and stored on the encrypted USB flash drive. The encrypted USB flash drive is stored in a safe for five years, after which all data will be safely destroyed.

Some researchers offer participants incentives for taking part in their study. Motivating potential participants to respond to online surveys is difficult due partly to survey fatigue, which increases the likelihood of nonresponse (Göritz & Neumann, 2016). Offering incentives foster motivation by offering a benefit to the participants, which result in an increased response rate. (Göritz & Neumann, 2016; Hsu, Schmeiser, Haggerty, & Nelson, 2017). The decision to offer incentives can positively influence the response rate. To increase the likelihood of participants response, an incentive was offered for participation. Within the consent agreement of this study I highlighted that participants will be compensated.

To protect the rights of participants, I adhered to the tenants in the Belmont Report (United States Department of Health & Human Services, 1979) to ensure that I did not violate the rights of the participants. I completed the online course of the United States National Institutes of Health's Office of Extramural Research (No. 2146956) on protecting human research participants.

Data Collection Technique

Data collection was a critical step toward answering the research question. In quantitative studies, researchers use an instrument as the data collection tool (Quick & Hall, 2015a). Researchers conducting quantitative research can employ several techniques such as analysis of data, structured observations, surveys, and questionnaires to acquire data for a study (Quick & Hall, 2015c). Combining the research instruments along with the appropriate data collection technique allows a researcher to collect information related to the topic under study, which can subsequently be analyzed to answer the research question. For this study, I used an instrument created by Oliveira et al. (2014), which was distributed via an online survey. The following subsections describe the instrument an elaborate on the data collection process used for this quantitative study.

Instruments

For this study, I used the DOI-TOE survey instrument created by Oliveira et al. (2014), which was based on a combination of the DOI theory and TOE frameworks. Permission to use the survey instruments was granted (Appendix B). The survey instrument used in my study is provided in Appendix A. For this study, the survey instrument was administered as an online survey via Qualtrics. An invitation was e-mailed to participants containing the link to the survey.

The survey instrument measured ten constructs related to IoT adoption, namely security concerns, cost saving, relative advantage, complexity, compatibility, technology readiness, top management support, firm size, competitive pressure, regulatory support. IoT adoption was the single dependent variable. The survey instrument I used, contained all the question, is provided in Appendix A. The constructs measured by the instruments were discussed in detail in Section 1. The survey instrument consists of 34 close-ended questions which were used to collect data from the participants. The use of close-ended questions allows responses from participants to be quantified (Quick & Hall, 2015c). The use of scales such as Likert facilitates the quantifications of participants opinion to the question presented in the instrument. Because the variables I planned to use were not directly quantifiable, the use of a Likert scale for measurement was appropriate.

To be consistent with the previous source, the survey question uses an ordinal scale of measurement via a five-point Likert scale ranging from 1=*strongly disagree* to

5=*strongly agree.* The number of questions for the ten independent constructs varied to form a minimum of two questions to a maximum of five questions. The dependent construct has two questions which measure are using the nominal scale.

Included were demographics questions about age, gender, location in the U.S., and job title. The scale for age was measured in years, while the scale of gender consisted of 0 or 1, with 0 representing women. Oliveira et al. (2014) used a five-point Likert scale to evaluate the theoretical constructs used. Garrison, Wakefield, and Kim (2015) used a five-point Likert scale in their study to measure the participants level of agreement. Also, Hsu and Lin (2016b) used a five-point Likert scale to measure the constructs in their study. The scales and measures I selected for use in my study are consistent with similar studies conducted by other researchers. By using a Likert scale, I was able to measure and access the degree of IoT Adoption intention, with higher scores indicating a higher degree of IoT Adoption intent.

Researchers have used this instrument and similar instruments to evaluate technology adoption within other populations. Quantitative researchers often use or adapt previously used instruments (Rowley, 2014) Weeger, Wang, and Gewald (2015) claimed that researchers who adopt items from previous studies could protect the measurement validity--adopting a previously tested and validated instrument allowed for the comparison of research findings to that of similar studies. The following researchers have successfully modified and used a combination of the DOI and TOE instrument: Martins et al. (2016) conducted an empirical analysis to assesses the determinants of SaaS diffusion in firms in Portugal. Ji and Liang (2016) explored the determinants affecting E-

Government cloud computing adopting in China. Oliveira et al. (2014) assessed the determinants of could computing adoption within the manufacturing and services industries in Portugal. Wang and Wang (2016) conducted an empirical study of business in Taiwan to assess the determinants of firms' knowledge management system implementation.

This study required an instrument that was reliable and valid. According to Quick and Hall (2015c), reliability and validity are two fundamental concepts that can be used to describe the strength and credibility of the research results. Oliveira et al. (2014) used Smart-PLS software to test the reliability and validity of the measurement model. The result of their analysis concluded that the instrument was both reliable and valid.

Oliveira et al. (2014) used composite reliability to test the reliability of the scales. According to researchers a result greater than .7 suggests scales are reliable (Ali, Rasoolimanesh, Sarstedt, Ringle, & Ryu, 2018; F. Hair Jr, Sarstedt, Hopkins, & G. Kuppelwieser, 2014; Henseler, Hubona, & Ray, 2016). Oliveira et al.'s analysis of the full samples showed values higher than .7. The results of the composite reliability tests show that the DOI-TOE survey instrument maintains its reliability, thus makes it useful for this study. Test for construct validity was conducted. Construct validity is the degree to which an instrument truly measures the constructs; and are typically expressed as convergent validity and discriminant validity (Ali et al., 2018; Hair Jr et al., 2014; Henseler et al., 2016).

Construct validity is the degree to which an instrument truly measures the constructs and are typically expressed as convergent validity and discriminant validity

(Ali et al., 2018; F. Hair Jr et al., 2014; Henseler et al., 2016). According to Shin (2017), convergent validity confirms the extent to which the results are compatible and aligned with the theoretical or conceptual values. The average variance extracted (AVE) values of .5 and greater support convergent validity. While according to F. Hair, Jr et al. (2014), discriminant validity represents the extent to which a construct differs from other constructs and measures what it was intended to measure. Assessment of discriminant validity is traditionally conducted using Fornell-Lackner criterion or cross-loadings. Oliveira et al. (2014) analyzed convergent validity, and the AVE values for full and subsample were greater the .5. Test for the discriminant validity of the constructs using Fornell-Lackner criteria and cross-loadings show both values are satisfied for the full and industry-specific sample. Both validity tests show that each construct is independent of its measures. Test for both reliability and validity of the survey instrument used by Oliveira et al. (2014) confirmed its reliability and validity, making it suitable to be sued for this study.

I did have to adapt the DOI-TOE survey instrument for this study. I adapted and changed the wording of items the survey questions to align with the context of my study by replacing the cloud computing adoption construct with an IoT adoption construct. Similarly, researchers such as Ji and Liang (2016), Hsu and Lin (2016b) and Oliveira et al. (2014) altered the wording of their instrument to align with the context of their study. Although the changes to the instrument were minor, the reliability and validity scores could be affected. Reproducibility and credibility are the core concepts of quantitative research (Claydon, 2015), and threats can affect generalizability (Haegele & Hodge, 2015). I reaffirmed both the reliability and validity of the instrument used in this study utilizing and techniques such as factor analysis and test for Cronbach’s coefficient alpha.

The raw data collected during the survey were downloaded and stored on an encrypted USB drive for five years in a safe. Data from the site hosting the survey will be deleted to eliminate the risk of loss or accidental spillage of information. I will make raw data available to researchers by request within the five years that it will be stored.

Data Collection Technique

Electronic questionnaires are an accessible means for researchers to collect data. Researchers engaged in quantitative studies use questionnaires consisting of close-ended questions to collect data from participants (Quick & Hall, 2015c). The electronic distribution of questionnaires via online surveys allows for greater access to participants while maintaining anonymity. The use of a closed-ended question enables researchers’ conduction quantitative studies to quantify participants responses (Rowley, 2014). For this quantitative study, an online survey consisting of a questionnaire consisting of close-ended questions was used to collect data from the participants. The literature provides evidence for the use of online surveys. In fact, in DOI-TOE studies (Martins et al., 2016; Oliveira et al., 2014; Wang & Wang, 2016), the author’s used online self-administered surveys for data collections.

There are some advantages and disadvantages of using online surveys. The main advantage of using online surveys is the ability to obtain responses from a large number of people (Rowley, 2014). Greater the response the accessible population increase the likelihood of researchers to generalize their finding. However, a limitation is that researchers are unable to validate if participants understood the question or provided accurate data (Rowley, 2014). Online surveys are not only convenient for the respondent, but it also reduces the data entry time for a researcher (Hollier, Pettigrew, Slevin, Strickland, & Minto, 2016). Online surveys provide easy access to respondents to participate, and since data is typically stored in a format that can be imported to a data analysis tool such, it potentially reduces the researcher's data entry time. However, while there is an increased convenience to respondents, online surveys typically have low response rates (Rice, Winter, Doherty, & Milner, 2017). A respondent's interest in the topic and the length of the survey influence response rates. Providing an incentive to participants positively influence response and retention rates (Rice et al., 2017). In this study, I ensured that the length of the survey took no longer than 15 minutes and providedd an incentive to ensure increased response rates.

For this study, an online survey was used to collect data from the participants. I built a web-based questionnaire via Qualtrics online tool and distributed it by e-mailing the link to the survey to the Qualtrics panel. I collected data for two weeks to allow responses to reach or surpass the maximum sample of 160 participants needed. I sent out weekly reminders to participants to complete the survey.

Pilot studies allow for pre-verification and fine-tuning of the data collection method before executing the primary study (Norris et al., 2015). While a pilot study can enhance the quality of the survey instrument, I chose not to conduct a pilot test after IRB approval. The survey question to be used in this study are in Appendix A.

Data Analysis Technique

This research intends to answer what is the relationship between corporate IT leadership's perceptions of (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and intent to adopt IoT. The null and alternative hypothesis related to the research questions are:

$H1_0$: There is no statistically significant relationship between corporate IT leaderships' perceptions of (a) relative advantage, (b) complexity, (c) compatibility (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and intent to adopt IoT.

$H1_a$: There is a statistically significant relationship between corporate IT leaderships' perceptions of (a) relative advantage, (b) complexity, (c) compatibility (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and intent to adopt IoT.

Several tests evaluate the relationships between variables. Common test such as *t*-test, analysis of variance (ANOVA), Person product-moment correlation, and regression can be used to explore the relationship among variable (Curtis et al., 2016). However, the test selected as the basis for the inferential statistical test should align with the study design. The use of the *t*-test, ANOVA are appropriate for studies comparing mean scores for multiple groups (Curtis et al., 2016; Jupiter, 2017). This study is evaluating the adoption intention with a single group of participants and does not assess causal effects; therefore, *t*-test and ANOVA were deemed not appropriate. Multiple regression analysis extends simple linear regression to evaluate the relationships between a dependent variable and multiple independent variables (Ray-Mukherjee et al., 2014). I used multiple regression analysis to determine if the eight independent variables have a significant relationship with the intent to adopt IoT.

Eliminating invalid responses reduces error resulting in more stable and consistent results. Before conducting data analysis, researchers should screen questionnaire and discard incomplete surveys which reduce biases and calculation errors (Curran, 2016; Rowley, 2014). Data cleaning was performed to eliminate incomplete responses before importing data into SPSS. Once data has been imported into SPSS, validation of the data was performed by crosschecking the entered data with the source data to ensure that no missing, incorrectly coded, or incorrectly transcribed data exists.

Outliers should be eliminated as part of the data cleaning effort. According to Niven and Deutsch (2012), outliers are the observation that deviated from other members in a sample and can be trimmed before performing data analysis. Outliers can negatively impact correlation results; thus, they will be eliminated as part of the data cleaning. Boxplots and scatter plots can be used to identify outliers visually. (Hazra & Gogtay, 2016) I inspected the results from the scatter plot to identify outliers and removed them from the dataset.

Descriptive Statistics

The survey instrument included four demographic questions on age, gender, location in the US, and job title. I did not use location or job title for analysis other than to gain general insight where in the US the data were collected and what jobs participants held at the time of the survey. I used the participant's age and gender to reveal general insights into the potential relationship between the independent and dependent variables. I used SPSS to calculate descriptive statistics such as frequency, percentage, mean, and standard deviations, along with the total number of participants.

Inferential Statistics

I conducted this research to examine if there is a relationship between corporate IT leadership’s perceptions of (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and intent to adopt IoT. Because the hypothesis includes more than two independent variables, multiple regression was appropriate for testing. I used SPSS to evaluate eight hypotheses using multiple regression analysis to determine the significance of any relationships.

Researchers use SPSS to conduct data analysis. While inferential data analysis is possible in a tool like Excel, statistical passages such as SPSS allows researchers direct import of data into the tool and permitting more advanced analyses to be conducted (Norkett, 2013). Various researchers conducting quantitative studies use SPSS for data analysis (Alkhalil et al., 2017; Haddud et al., 2017; Leong et al., 2017; Topaloglu, Caldibi, & Oge, 2016). Researchers (Alkhalil et al., 2017; Haddud et al., 2017) also generated descriptive statistics in SPSS to describe the critical features of the data. Other researchers (Haddud et al., 2017; Leong et al., 2017; Topaloglu et al., 2016) used SPSS to assess the reliability and validity of the research instrument. I used SPSS version 25 statistical analysis software for PC/Windows, to generate descriptive statistics, assess reliability and validity, and conduct a correlation analysis of the data. Results of the study will be presented in Section 3.

Study Validity

This study involved examining four threats to validity: external, internal, statistical conclusion, and construct and reliability. To ensure reliability, and trustworthiness of the study, researchers use validity test such as external validity, internal validity, construct validity and statistical conclusion validity to evaluate the suitability tools, process, and data (Leung, 2015). Researchers using quantitative research seek reliable and valid results as a means of producing trustworthy and credible knowledge and evidence that can inform decisions. The following paragraphs explain the steps taken to ensure the validity and reliability of the study.

Threats to External Validity

Generalizability is an essential aspect of this study. Using a convenience sample may have threated the external validity of this study. While convince sampling allows for quicker sample collection, its main limitation is the loss of generalizability (Valerio et al., 2016). To improve the external validity of the study, I distributed the survey instrument to IT leaders in manufacturing organizations across the US to increase the likelihood of generalizability to the larger population.

There are two techniques researchers can employ to minimize the effects of external validity; reduce the influence on participants and sufficient power. Using an online survey reduces the interaction and influence of the research on the participant's responses (Walter, Dunsmuir, & Westbrook, 2015). By having sufficient power increases the likely-hood that significance is detected. For this study, I employed a quantitative approach and used online surveys to ensure that I distance myself from the participants and I also set the statistical power to .95, which means there is a 95% chance of observing a statistically significant effect when it occurred. Because this study was nonexperimental and did not have a pretest-posttest design, these factors were not relevant and will not threaten the external validity of this study.

Threats to Internal Validity

Internal validity is not a significant threat to this study. Experimental and quasi-experimental designs are susceptible to 8 threats to internal validity namely; (a) selection, (b) selection by maturation, (c) statistical regression, (d) mortality, (e) maturation, (f) history, (g) testing, and (h) instrumentation (Haegele & Hodge, 2015). Internal validity is relevant to studies trying to establish causal relationships. Because this study used a correlation design, a nonexperimental design, to investigate the relationship, potential correlations, between dependent and independent variables; and there was no manipulation of the study variable. Internal validity is not a threat to this study.

Threats to Construct Validity

Construct validity is the degree to which an instrument truly measures the constructs and are typically expressed as convergent validity and discriminant validity (Ali et al., 2018). According to Shin (2017), convergent validity confirms the extent to which the results are compatible and aligned with the theoretical or conceptual values. Average variance extracted (AVE) values of .5 and outer loadings are higher than 0.7 support a sufficient degree of convergent validity. While according to Hair Jr et al.

(2014), discriminant validity represents the extent to which a construct differs from other constructs and measures what it was intended to measure. Fornell-Larcker criteria and cross-loadings are used to assess discriminant validity. This study utilized a survey instrument created by Oliveira et al. (2014), which was tested for both convergent and discriminant validity; reliability and validity were confirmed. To evaluate construct validity, I evaluated the correlation matrix and part of the multiple regression analysis using SPSS.

Threats to Statistical Conclusion Validity

The goal of a researcher is to produce credible results that can inform decisions Statistical conclusion validity is the extent to which the conclusions made are credible (García-Pérez, 2012; Neall & Tuckey, 2014; Suter & Suter, 2015). Threats to statistical conclusion validity are concerned with factors that can increase Type I and Type II errors (Neall & Tuckey, 2014; Suter, & Suter, 2015). Researchers could make incorrect decisions regarding rejection or accepting the null hypothesis due to incorrect collusion being drawn from the data. Threats to statistical conclusion validity could originate from such as the sampling process, statistical power, and statistical analysis methods used (García-Pérez, 2012; Neall & Tuckey, 2014). The paragraphs below discuss the reliability of the instrument, data assumptions, and sample size, discussion the steps taken to address threats to statistical conclusion validity.

Reliability of the Instrument

In a quantitative analysis's reliability is an expression of consistency and repeatability (Leung, 2015). In this research, I employed a survey instrument used by

Oliveira et al. (2014) that had been successfully validated. Oliveira et al. used composite reliability to test the reliability of the scales, which resulted in values greater than .7. According to researchers a result greater than .7 for both Cronbach's alpha and composite reliability suggests consistent internal reliability (Ali et al., 2018; Hair Jr et al., 2014; Henseler et al., 2016). The instrument used by Oliveira et al. was reliable. Because I slightly adapted and changed the wording of items the survey questions to align with the IoT adoption context of this study, the reliability of the instrument may have been threatened. As such, the reliability of the instrument used in my study should be reported. I used SPSS to re-affirm the internal reliability of the instrument via factor analysis, and Cronbach's coefficient alpha analysis to validate the scales for each of the test variables.

Data Assumptions

Researchers should be aware of the underlying assumptions for the type of statically analysis being employed. Since I used multiple regression, assumptions of normality, linearity, multicollinearity, and homoscedasticity were evaluated (Hopkins & Ferguson, 2014). If these assumptions are violated results from the regression analysis may be inaccurate. However, the absence of any violation justifies the use of multiple regression testing.

Normality must be accessed to ensure the correct statistical test is used. The assumption of normality for multiple regression analysis assumes normality between the independent and dependent variables (Hopkins & Ferguson, 2014). I tested for nonnormality by plotting residuals via SPSS. Researchers can access nonnormality by plotting the error distribution against the normal distribution (Hopkins & Ferguson, 2014).

The assumption of linearity assumes a linear relationship between the dependent variable and the coefficients of the model (Hopkins & Ferguson, 2014). Similar to testing for normality, I tested for nonlinearity by plotting residuals via SPSS and evaluated if the data points are distributed close to the diagonal line; which is an indication of linearity.

The homoscedasticity assumption assumes constant variance of random error (Hopkins & Ferguson, 2014). Heteroscedasticity, opposite of homoscedasticity, is the absence of equal scatter or variances are often an indication of other influences than randomness (Alih & Ong, 2015). Homoscedasticity is one indication of uniformity. According to Alih and Ong (2015), distortion such as outliers makes dataset heteroscedasticity. Scatter plots can be used to detect heteroscedasticity visually. To test for homoscedasticity, researchers can also use tests such as Durbin-Watson, Brown-Forsythe, and Levene (Barker & Shaw, 2015; Hopkins & Ferguson, 2014). In addition to visual analysis, I also used the Durbin-Watson test available in SPSS to assess the homoscedasticity assumption; also, I used scatter plots and residual plots to detect heteroscedasticity visually. When multiple variables measure the same things, meaning those variables are highly correlated is defined as multicollinearity (Mwalumbwe & Mtebe, 2017).

The multicollinearity assumption is that each predicted variable is independent of all other variables (Hopkins & Ferguson, 2014). Failure to detect and report multicollinearity could lead to misinterpretation of results; as a violation could result in increased Type 1 errors which increase the probability of rejecting the null hypothesis. Researchers can test for multicollinearity by conducting statistical tests such as variance inflation factor (VIF) and condition number (Alves, Cargnelutti Filho, & Burin, 2017). VIF values exceeding10 indicate a high degree of multicollinearity (Hanse, Harlin, Jarebrant, Ulin, & Winkel, 2015); whereas valued between three and 10 indicate multicollinearity problems (Hanse et al., 2015; Hopkins & Ferguson, 2014). A researcher can use the Durbin–Watson statistic as a step to correct for multicollinearity (Hopkins & Ferguson, 2014). Since SPSS can calculate VIF; I tested for the presence of multicollinearity using VIF.

Researchers should plan to address violations as appropriate. Bootstrapping enables the ability to increase accurate analysis despite assumption violation via resampling (Montoya & Hayes, 2017). Bootstrapping provide an effortless way to overcome violations. Since there was no violation of the assumptions, bootstrapping was not used.

Sample Size

Sample size influences the significance and generalizability of results. Effect size estimations indicate the strength between variables (Bosco et al., 2015). Small sample sizes could lead to Type II errors and possible inflated effect sizes and have low power (Schweizer, & Furley, 2016). Small sample sizes have a higher chance of producing false positives, and not yielding a significant test. Because I had control of demining the sample size, I conducted a power analysis to estimate the sample size before data collection, with a medium effect size of (f=0.15) and a power of .95. Based on the result of the sample size analysis, I sought to obtain completed surveys from 114 to160 participants.

Transition and Summary

The purpose of this quantitative, correlational study was to examine the relationship between corporate IT leadership's perceptions of (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and intent to adopt IoT in manufacturing organizations. Section 2 began with a discussion regarding the role of the researcher, participants, research method and design, which was then followed by the population and sampling strategy and protection of the study participants on the ethical research sections. Also included in Section 2 was a discussion of the data collection and analysis strategies, the choice of instruments, and finally, how to ensure study validity. Section 3 presented an overview of the entire study and presented the findings that resulted from the data analysis of the collected surveys. Section 3 concluded with the application of the findings to professional practice, the implication for social change and recommendation for action and further study.

Section 3: Application to Professional Practice and Implications for Change

In this study, I used a correlation quantitative research method to analyze the relationships between corporate IT leadership's perceptions of (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and intent to adopt IoT. In this section, I present the results of the analysis of the data gathered through the online surveys completed by the participants of the study.

Overview of Study

The purpose of this quantitative, correlational study was to examine the relationship between corporate IT leadership's perceptions of (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and intent to adopt IoT in U.S. manufacturing organizations. I gathered data from 168 IT Leaders via a Qualtrics panel which satisfied the sample size requirement. With 168 participants, the power achieved was .96. The response rate was 12%. Multiple linear regression analysis was used to assess the existence of the relationship between the independent and dependent variables.

The results of the multiple regression were significant, $F(8,157) = 15.22$, $p < .001$, $R^2 = 0.44$, indicating that approximately 44% of the variance in intent to adopt IoT could be explained by (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support. Technology readiness ($\beta = .41$, $p < .004$), top management support (β

= .29, $p < .004$), and competitive pressure ($\beta = .33$, $p < .016$) were significantly at .05 level as predictors of IT leadership's intent to adopt IoT. Three of the eight independent variables, technology readiness, top management support, and competitive pressure predict intention to adopt IoT were the most significant factors influencing the intent to adopt IoT. Hence, I rejected the null hypothesis because the results of the study confirmed a relationship between the independent variables and IT leadership's intent to adopt IoT.

Presentation of the Findings

Descriptive and inferential statistics were used to draw conclusions from the sample collected. Multiple regression analysis was used to evaluate the research question and hypotheses. The research question was:

RQ1: What is the relationship between corporate IT leadership's perceptions of (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and intent to adopt IoT?

The null and alternative hypothesis addressed in the study were:

$H1_0$: There is no statistically significant relationship between corporate IT leadership's perceptions of (a) relative advantage, (b) complexity, (c) compatibility (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and intent to adopt IoT.

$H1_1$: There is a statistically significant relationship between corporate IT leadership's perceptions of (a) relative advantage, (b) complexity, (c) compatibility (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and intent to adopt IoT.

As a prerequisite to data analysis, I evaluated the collected data for missing data, outliers, normality, linearity, homoscedasticity, and multicollinearity. Subsequently, I conducted a multiple regression analysis to determine if there were any significant relationships between the variables of interest. Reported below are the results of the data analysis.

Descriptive Statistics

Data were collected from a sample of 168 IT leaders in the manufacturing sector within the United States. (N = 168). Displayed in Table 2 are the frequency and percent statistics of participants' gender and age. The most frequently observed category of gender was male (n = 94, 56%), while women accounted for (n = 73, 43%). Age of the participants ranged from 18 to 65 years. The most frequently observed category of age was 25 - 34 (n = 49, 29%). A total of 78.6 % of participants were between the age of 24 – 54.

Table 2

Frequency and Percent Statistics of Participants' Gender and Age

Demographic	Frequency (*n*)	%
Gender		
Female	73	43.4
Male	94	56
Unknown	1	0.6
Total	168	100
Age		
18 - 24	11	6.5
24 - 34	49	29.2
35 - 44	36	21.4
45 - 54	47	28
55 - 65	25	14.9
Total	168	100

Note. Total N = 168

Table 3 shows the frequency of distribution of demographics job role and the number of employees per participants organization. There were 168 accepted participants’ responses with roles ranging from Analyst/Associate to the executive level. Analysis of the descriptive statistics conducted on the job roles revealed that the highest percentage of participants responses worked either as an Analyst/Associate or Manager, (26.2 %). The analysis revealed that the highest percentage of employee category (n = 39, 23.2%) was between 11 and 249 employees.

Table 3

Frequency and Percent Statistics of Participants' Job Role and Number of Employees

Demographics	Frequency (*n*)	%
Job Title		
Analyst / Associate	44	26.2
Manager	44	26.2
Senior Manager	12	7.1
Director	19	11.3
Vice President	4	2.4
Senior Vice President	2	1.2
C level executive (CIO, CTO, COO, CMO, Etc)	13	8.9
President or CEO	1	.6
Owner	8	4.8
Other	19	11.3
Total	100	100.0
Employees		
1 to 10 employees	9	5.4
11 to 249 employees	39	23.2
250 - 499 employees	25	14.9
500 -999 employees	29	17.3
1,000 to 2,499 employees	28	16.7
2,499 to 4,999 employees	13	7.7
5,000 to 9,999 employees	13	7.7
10,000 employees or more	12	7.1
Total	168	100.0

Note. Total *N* = 168

Table 4 shows the Annual Business Volume in U.S. dollars for each participants' organization. The most frequently observed category was more than $ 1 million (*n* = 106, 63%). Additionally, Table 4 shows the frequency and percent statistics for the participant's organization's location by U.S, region. The most frequently observed location was East North Central (*n* = 37, 22%).

Table 4

Frequency and Percent Statistics of Participants' Organizations' Annual Business Volume and U.S Region

Variable	Frequency (*n*)	%
Annual Business Volume in U.S. Dollars		
Less than $10,000	2	1.2
$10,000 - $49,999	2	1.2
$50,000 - $99,999	6	3.6
$100,000 - $499,000	15	8.9
$50,000 - $99,999	37	22.0
More than $ 1 million	106	63.1
Total	168	100.0
U.S. Region		
New England	10	6.0
Mid-Atlantic	24	14.3
East North Central	37	22.0
West North Central	22	13.1
South Atlantic	33	19.6
East South Central	6	3.6
West South Central	11	6.5
Mountain	7	4.2
Pacific	18	10.7
Total	168	100.0

Note. Total N = 168

Table 5 shows the frequency distribution observed of participants' organization current IoT engagement and plan to adopt IoT. The most frequently observed category of current IoT engagement was, have evaluated and plan to adopt this technology (n = 50, 30%). The most frequently observed category of future plan to adopt IoT was between two and five years (n = 43, 26%).

Table 5

Frequency and Percent Statistics of Participants' Organizations Current IoT engagement and Future Plan to Adopt IoT

Variable	*n*	%
Current IoT Engagement		
Not considering	18	10.7
Currently evaluating, e.g., in a pilot study	42	25.0
Have evaluated but do not plan to adopt this technology	18	10.7
Have evaluated and plan to adopt this technology	50	29.8
Have already adopted IoT	40	23.8
Total	168	100.0
Future Plan to Adopt IoT		
Not considering	13	7.7
Less than 1 year	26	15.5
Between 1 and 2 years	38	22.6
Between 2 and 5 years	43	25.6
More than 5 years	15	8.9
Have already adopted IoT	33	19.6
Total	168	100.0

Note. Due to rounding errors, percentages may not equal 100%.

Testing of Hypothesis

Hypothesis was tested using multiple regression analysis to determine if there were any significant relationship between corporate IT leadership's perceptions of (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and the dependent variable intent to adopt IoT in manufacturing organizations. Composite scores were calculated for the independent and dependent variables by averaging case scores related to each construct.

Data Cleaning

Before evaluating the research question, data were screened for missing values and univariate outliers. Missing data were evaluated using frequency count, and one case missed/skipped one survey item related to gender. This case was not removed. The data was screened for univariate outliers visually using box plots and by calculating the standard deviations. According to Tabachnick and Fidell (2013), an outlier was defined as any value which falls outside the range of +/- 3.29, standard deviations from the mean (Tabachnick & Fidell, 2013). Univariate outliers were found and removed from further analyses; relative advantage had two outliers (cases: 58, 149) while compatibility had one outlier (case: 58). Using the number of cases analyzed for relative advantage was (n = 166*)*, and compatibility was (n = 167), respectively. Displayed in Table 6 are the descriptive statistics of the covariates used to evaluate the research question.

Table 6

Descriptive Statistics of Dependent and Independent Variables

Variable	*M*	*SD*	*n*	SE_M	Skewness	Kurtosis
Relative advantage	4.04	0.65	166	0.05	-0.38	-0.52
Complexity	2.71	0.82	168	0.06	0.18	-0.45
Compatibility	3.73	0.78	167	0.06	-0.35	-0.38
Technology readiness	3.54	0.93	168	0.07	-0.69	0.25
Top management support	3.75	0.87	168	0.07	-0.74	0.26
Firm size	4.73	1.22	168	0.09	-0.22	0.17
Competitive pressure	3.49	0.81	168	0.06	-0.24	-0.15
Regulatory support	3.47	0.83	168	0.06	0.02	-0.21
Intent to adopt IoT	3.60	1.33	168	0.10	-0.19	-0.82

Validity and Reliability Assessment

As discussed in Section 2, the measurement instrument I used relied on validated scaled from a previous study. Although Oliveira et al. (2014), tested and validated the constructs used in this study, because I adapted the DOI-TOE survey instrument to align with the context of my study by replacing the cloud computing adoption construct with an IoT adoption construct, I assessed the validity and reliability of the scales.

Reliability analysis. A Cronbach alpha coefficient was calculated for the dependent and each independent variable. Reliability analysis allows one to study the properties of measurement scales and the items that compose the scales (Tabachnick & Fidell, 2013). Scale reliability is assumed if the coefficient is ≥ .70. The Cronbach's alpha coefficient was evaluated using the guidelines suggested by George and Mallery (2016) where > .9 excellent, > .8 good, > .7 acceptable, > .6 questionable, > .5 poor, and ≤ .5

unacceptable. As shown in Table 7, the items for relative advantage and intent to adopt IoT indicated excellent reliability; items for compatibility and technology readiness, indicated good reliability; items for complexity, technology readiness, and top management support indicated acceptable reliability; items complexity, competitive pressure, and regulatory support indicated acceptable reliability; while items for firm size indicted unacceptable reliability. Thus, except for firm size, the dependent and independent variables were found to be sufficiently reliable.

Table 7

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

Scale	No. of Items	α
Relative advantage	5	.86
Complexity	4	.71
Compatibility	4	.83
Technology readiness	3	.78
Top management support	3	.73
Firm size	2	.36
Competitive pressure	3	.68
Regulatory support	2	.67
Intent to adopt IoT	2	.85

Validity analysis. A variety of authors suggest different benchmarks to determine a sufficient sample size for CFA. Some authors use benchmarks based on the overall sample size. A common rule of thumb for determining sufficient sample size is 300 observations (Tabachnick & Fidell, 2013). Other authors use the ratio (*N:q*) of an overall sample size to the number of free parameter estimates (latent variable, indicator, variance, covariance, or any regression estimates) included in the model. Kline (2015) recommends that the *N:q* ratio should be about 20 to 1. Schreiber, Nora, Stage, Barlow, and King (2006) suggested that the consensus for a sufficient *N:q* ratio is 10:1. On the lower end of the ratio, Bentler and Chou (1987) suggested that an acceptable *N:q* ratio is 5:1. The participant to item ratio for this analysis was approximately 3 to 1, where the sample size was 168 according to the *N:q* ratio rule-of-thumb, the given sample size is insufficient for CFA. Also, CFA cannot be conducted accurately with less than three observed variables, as this results in negative degrees of freedom calculation, which is nonsensical (Kline, 2015). To test for the validity of the constructs, I first used Pearson product-moment correlations by correlation the mean of each construct with the total score.

By comparing the value of the significance with critical *r* table, product moment validity can be accessed for each subscale's relationship with intent to adopt IoT. If the significance value is greater than the critical *r*-value, the construct is significantly related in a bivariate relationship. Any such significant findings indicate criterion validity, as the subscales are shown to correlate with the theoretically related outcome of intent to adopt IoT. The critical value was $r = \pm.15$ for an alpha of .05, an N of 168, and two tails. The results of the analysis show that all constructs were significantly related to intent to adopt IoT in bivariate analyses except for firm size (see Table 8). Because firm size was not significant, the construct may not be a reasonable measure of the actual size of firms in the sample, as firm size should theoretically be related to the intent to adopt IoT (Rogers, 2003).

Table 8

Test for Criterion Validity of Constructs

Constructs	*N*	*p*	*r*
Relative advantage	168	< .001	.47
Complexity	168	.001	-.25
Compatibility	168	< .001	.52
Technology readiness	168	< .001	.57
Top management support	168	< .001	.53
Firm size	168	.252	.09
Competitive pressure	168	< .001	.49
Regulatory support	168	< .001	.36

Individual items from each scale were measured for their correlation with the overall scale they composed. As seen in Table 9, all items were at least strongly correlated with their overall score. However, firm size appeared to be mostly related to the first firm size question, which asked participants how many employees their business had. The second firm size question was less representative of the overall construct and asked about business volume in USD. Based on the results of both the relationship with IoT adoption, and the lack of consistency when measuring an overall construct, firm size did not reflect a valid scale, and may not be a useful construct. Though all other scales showed significant bivariate relationships with the intent to adopt IoT, Table 9 indicates which items on each scale were less consistent with their overall score and shows which items may be considered for removal in future studies, should reliability or validity not be met.

Table 9

Test for Construct Validity With Each Item for Each Subscale

Item	*p*	*r*
Relative Advantage		
RA1	< .001	.83
RA2	< .001	.80
RA3	< .001	.77
RA4	< .001	.81
RA5	< .001	.78
Complexity		
CX1	< .001	.59
CX2	< .001	.81
CX3	< .001	.82
CX4	< .001	.70
Compatibility		
C1	< .001	.84
C2	< .001	.84
C3	< .001	.83
C4	< .001	.76
Technology readiness		
TR1	< .001	.84
TR2	< .001	.84
TR3	< .001	.82
Top management success		
TMS1	< .001	.84
TMS2	< .001	.80
TMS3	< .001	.78
Firm size		
FS1	< .001	.92
FS2	< .001	.63
Competitive pressure		
CP1	< .001	.77
CP2	< .001	.79
CP3	< .001	.81
Regulatory support		
RS1	< .001	.85
RS2	< .001	.88

Evaluation of Statistical Assumptions

The assumptions of normality of residuals, homoscedasticity of residuals, the absence of multicollinearity, and the lack of outliers were assessed. I evaluated independence, linearity, and homoscedasticity using scatterplots, and no violations were observed. This section presents the result of the test of assumptions.

Normality. Normality was evaluated using a P-P scatterplot (Hopkins & Ferguson, 2014). In the P-P scatterplot, normality can be assumed if the points form a relatively straight line. No significant deviations from normality were observers (see Figure 8).

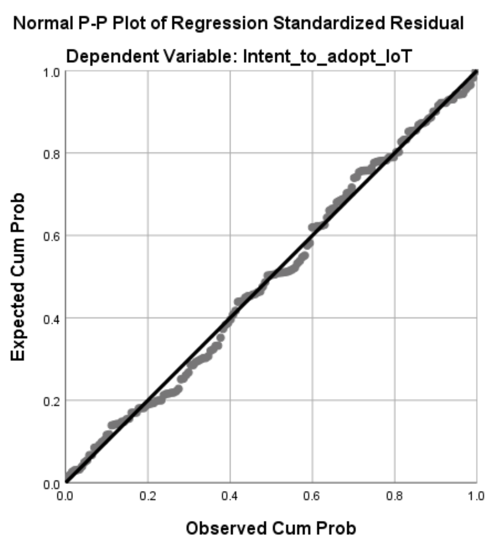

Figure 8. P-P scatterplot of regression standardized residual testing normality.

Homoscedasticity. Homoscedasticity was evaluated by plotting the residuals against the predicted values (Bates, Mächler, Bolker, & Walker, 2014). The assumption of homoscedasticity is met if the points appear randomly distributed with a mean of zero and no apparent curvature. The assumption of homoscedasticity was met (Figure 9).

Also, to validate the homoscedasticity assumption, I used the Durbin-Watson test. The Durbin-Watson d = 2.036, which is between the two critical values of 1.5 < d < 2.5. There is no first order linear auto-correlation in our multiple linear regression data.

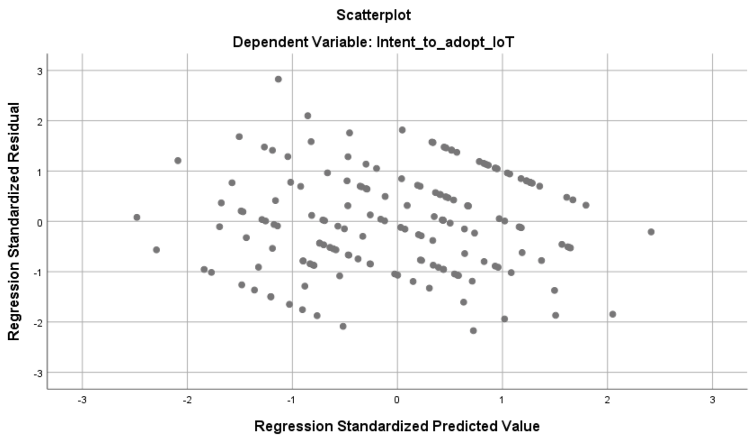

Figure 9. Residuals standardized predicted value testing for homoscedasticity.

Multicollinearity. To test for multicollinearity, I calculated and examined the VIF to validate the absence of multicollinearity between predictors. High VIFs indicate increased effects of multicollinearity in the model. All values were lower than 10, and the tolerance score was less than three, suggesting that multicollinearity was not a significant issue in the study. Table 10 shows the calculated VIF value for each independent variable.

Outliers. To identify outliers, I examined the residual scatterplot, Figure 9 for observation greater than three standard deviations. The examination indicated no significant violation of assumptions.

Table 10

Variance Inflation Factor for Independent Variables

Variable	VIF
Relative advantage	2.28
Complexity	1.21
Compatibility	2.90
Technology readiness	2.59
Top management support	2.15
Firm size	1.10
Competitive pressure	1.77
Regulatory support	1.60

The examinations of the assumptions for multiple linear regression indicated no major violations; consequently, the data collected were considered normal, and there was no need for transformation. Hence inferential statistics using multiple linear regression were conducted.

Inferential Results

To approach the research questions, multiple linear regression analysis was conducted to evaluate the prediction of Intent to adopt IoT from (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support. The “Enter” variable selection method was chosen for the linear regression model, which includes all of the selected predictors.

Research Question: What is the relationship between corporate IT leadership’s perceptions of (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and intent to adopt IoT?

H1_0: There is no statistically significant relationship between corporate IT leadership's perceptions of (a) relative advantage, (b) complexity, (c) compatibility (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and intent to adopt IoT.

H1_1: There is a statistically significant relationship between corporate IT leadership's perceptions of (a) relative advantage, (b) complexity, (c) compatibility (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and intent to adopt IoT.

The results the linear regression model were significant, $F(8,157) = 15.22$, $p < .001$, $R^2 = 0.44$, indicating that approximately 44% of the variance in intent to adopt IoT could be explain by (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support. The results of the multiple linear regression analysis revealed relative advantage, complexity, compatibility, firm size, and regulatory support not to be statistically significant predictors to the model ($p > .05$). However, the results of the multiple linear regression revealed a statistically significant association between technology readiness ($\beta = .41$, $p < .004$), top management support ($\beta = .29$, $p < .034$), competitive pressure ($\beta = .33$, $p < .016$) and were significantly at .05 level as predictors of IT leadership's intent to adopt IoT (Table 11). I rejected the null hypothesis.

Table 11

Multiple Regression Analysis Among Study Predictors

Variable	*B*	*SE*	95% CI	β	*t*	*p*
(Intercept)	-0.02	0.72	[-1.45, 1.41]	0.00	-0.02	.981
Relative advantage	0.04	0.18	[-0.33, 0.40]	0.02	0.21	.831
Complexity	-0.21	0.11	[-0.42, 0.00]	-0.13	-1.93	.055
Compatibility	0.07	0.17	[-0.27, 0.42]	0.04	0.41	.683
Technology readiness	0.41	0.14	[0.13, 0.68]	0.28	2.93	.004
Top management support	0.29	0.14	[0.02, 0.56]	0.19	2.14	.034
Firm size	-0.05	0.07	[-0.18, 0.09]	-0.04	-0.66	.509
Competitive pressure	0.33	0.13	[0.06, 0.60]	0.19	2.44	.016
Regulatory support	0.08	0.12	[-0.16, 0.31]	0.05	0.63	.530

Note. Results: $F(8,157) = 15.22$, $p < .001$, $R^2 = 0.44$
a. Dependent Variable: Intent to Adopt IoT

To access the impact that firm size on the overall model, I also conducted a multiple linear regression with firm size removed. The results of the linear regression model were significant, $F(7,158) = 17.39$, $p < .001$, $R^2 = 0.44$, indicating that approximately 44% of the variance in intent to adopt IoT could be explain by (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) competitive pressure, and (g) regulatory support. The results of the multiple linear regression analysis revealed relative advantage, complexity, compatibility, and regulatory support not to be statistically significant predictors to the model (p > .05). However, the results of the multiple linear regression revealed a statistically significant association between technology readiness ($\beta = .41$, $p < .004$), top management support ($\beta = .28$, $p < .040$), competitive pressure ($\beta = .31$, $p < .019$) and were significantly at .05 level as predictors of IT leadership’s intent to adopt IoT. There was no significant difference between the two models as $R^2 = 0.44$ as the same, thus firm size was retained.

Analysis Summary

I examined in this study the relationship between corporate IT leadership's perceptions of (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and the dependent variable intent to adopt IoT in manufacturing organizations in the U.S. A multiple linear regression analysis was conducted to assess this relationship as there was no violation of the assumption. Cronbach's Alpha was calculated to evaluate the reliability of the instrument. All items of the DOI-TOE survey instrument were above .7 except for firm size, which indicated the instrument was reliable for all scales except firm size. Validity test indicated that all constructs were valid except for firm size and showed that the first item on the firm size scale (i.e., number of employees) was a more useful measure of the size of a firm than the second item (i.e., business volume in USD). I kept firm size as one of the constructs in the multiple linear regression analysis. Overall the nine constructs of the DOI-TOE model predicted IT leadership's intention to adopt IoT in the manufacturing sector within the U.S. $F(8,157) = 15.22$, $p < .001$, $R^2 = 0.44$. I found by accessing the beta (β) that technology readiness, top management support, and competitive pressure tend to be the most influential factor influencing IT leadership intention to adopt IoT.

Theoretical Conversation on Findings

The literature review indicated a lack of information about IoT adoption within U.S. Manufacturing organizations. Using DOI theory and the TOE framework as guidance, I used a quantitative instrument to survey IT leaders from the U.S. Manufacturing sector to gain insight into their view of what determinants influence the adoption of IoT. These used constructs were categorized as innovation characteristics, technology context, organizational context, an environmental context.

The empirical evidence obtained in this study supported accepting of the alternative hypotheses. The results for RQ1 indicated that approximately 44% of the variance in intent to adopt IoT could be explained by (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support (R^2 = 0.44). I rejected the null hypothesis.

The findings indicated that none of the innovation characteristics were significant, while at least one factor from technology context, organizational context, an environmental context was significant. One possible reason for the findings is that DOI addresses diffusion innovation over time while TOE addresses the relationship between organizational adoption of technology innovation (Shaltoni, 2017).

Innovation characteristics. Although five variables were used to describe the innovation characteristics construct, relative advantage, security, cost, complexity, and compatibility, only three, relative advantage, complexity, and compatibility, were used to assess the hypothesis. The findings that emerged from the study indicated that none of the innovative characteristics made significant contributions in explaining IT leaderships' intent to adopt IoT. The findings differ from Rogers (2003) claimed that the attributes of innovation, namely relative advantage, compatibility, complexity could explain a significant percentage of innovation adoption.

Relative advantage. An outcome of the analysis is that relative advantage had no significant relationship with the intent to adopt IoT in the U.S. manufacturing sector. Although the results disconfirmed Rogers's (2003) DOI theory and also differs from previous DOI-TOE studies (AlBar & Hoque, 2017; Chiu, Chen, & Chen, 2017; Haberli, Oliveira, & Yanaze, 2017; Ilin, Ivetić, & Simić, 2017; Oliveira et al., 2014; Shaltoni, 2017; Wang & Wang, 2016), where relative advantage was a significant determinant for technology adoption, however, it confirmed results of Alkhalil et al. (2017) and Puklavec, Oliveira and Popovič (2018) who found no correlation between the independent variable relative advantage and the intent to adopt technology. One explanation for this is that because participants of this study were familiar with the concept of IoT and its relative benefits, such as increasing productivity and increased operational efficiencies. It may have lessened the perceived relative advantage IoT brings to manufacturing organizations. In relation to earlier studies, the results for relative advantage are mixed; thus, additional research is needed before reaching more definite conclusions.

Complexity. Another outcome of the analysis is that complexity had no significant relationship with the intent to adopt IoT in the U.S. manufacturing sector. Although the results disconfirmed Rogers's (2003) DOI theory and also differs from previous DOI-TOE studies (AlBar & Hoque, 2017; Oliveira et al., 2014; Wang & Wang, 2016) where complexity was a significant determinant for technology adoption, however, it confirmed results of Chiu et al. (2017), Oliveira et al. (2014) and Shaltoni (2017), who found no correlation between the independent variable complexity and the intent to adopt technology. One explanation for this is that participants in this study were familiar with IoT and how it integrated into their environment; this supposition is supported by the result in Table 5 where it indicates that approximately 11 % and 8 % of participants current IoT engagement and future plan to adopt IoT respectively are not considering adoption of IoT. Thus, in relation to earlier studies, the results for complexity are mixed; thus, additional research is needed before reaching more definite conclusions.

Compatibility. Compatibility was also found to have no significant relationship with the intent to adopt IoT in the U.S. manufacturing sector. Although the results disconfirmed Rogers's (2003) DOI theory and also differs from previous DOI-TOE studies (Alkhalil et al., 2017; Chiu et al., 2017; Oliveira et al., 2014; Shaltoni, 2017; Wang & Wang, 2016) where compatibility was a significant determinant for technology adoption, however it confirmed results of AlBar and Hoque (2017) and Oliveira et al. (2014) who found no correlation between the independent variable complexity and the intent to adopt technology. One explanation for the non-significance is that participants in this study were familiar and had knowledge that IoT technology was well-matched and easily integrated into their environment; this supposition is possibly supported by the result in Table 5 where it indicates that approximately 54% and 20% of participants current IoT engagement and future plan to adopt IoT respectively, are planning or have already adopted IoT. In relation to earlier studies, the results for compatibility are mixed; therefore, additional research is needed before reaching more definite conclusions.

Finding in the literature regarding innovative characteristics are mixed. In relation to earlier studies, the results for relative advantage, complexity, and compatibility are mixed, as different types of organizations have different attitudes for the application and adoption of innovative technologies (Chiu et al., 2017). Roger's (2003) conjectures that innovation is an idea, practice, or item that is perceived as new by the adopting entity. Based on the results shown in Table 5, approximately 89% of participants have evaluated IoT technology; it is conceivable that US manufacturing organization do not perceive IoT as an innovation. Because I targeted the decision makers; perception of IoT was mostly likely decided. According to Rogers (2003), innovation adoption progress through a five-step decision process (knowledge, persuasion, decision, implementation, and confirmation); the result in Table 5 suggest that many participants have progressed past the awareness stage; thus IoT is not viewed as an innovation. Puklavec et al. (2018) in their study to understanding the determinants of business intelligence system adoption stages, confirm that the influence of determinants differs as organization progress through the phases of evaluation, adoption, and use. Within the U.S. manufacturing sector, IoT can be regarded and an established innovation with organizations being cognizance of IoT's relative advantage, complexity, and compatibility.

Technology context. The technology context describes facets of an organization, its organizational structure, and the availability of knowledgeable and skilled human resources (Tornatzky & Fleischer, 1990). The results of the study indicated that technology readiness had a significant relationship with the intent to adopt IoT. Tornatzky and Fleischer (1990) argued that the fit of the new technology with the existing technology, is as important as the availability of the technology, also that compatibility and complexity of the technology related to the integration with the current environment influence innovation adoption; due in part to the uniqueness of each organization technology implementation and the relevance of the technology. This significant relationship indicates that on average, as organizations become more technology ready, competent, and have skilled resources which are knowledgeable about IoT, the more likely there are to adopt IoT (Kiel et al., 2017; Martins et al., 2016). Previous studies have suggested that technology readiness does not influence technology adoption.

Alkhalil et al. (2017) found technology readiness irrelevant for organization decision to migrate existing resources to the cloud, while Low et al. found technology readiness unimportant for organizations in the technology sector. The results of this study support the alternative; technology readiness does influence technology adoption. For example, Oliveira et al. (2014) in accessing the determinants of cloud computing adoption in the service and manufacturing sectors, found technology readiness as an influential determinant. Other DOI-TOE studies conducted by (Haberli et al., 2017; Puklavec et al., 2018; Wang & Wang, 2016) support the finding that technology readiness will positively influence the decision to adopt IoT. The finding of this study indicates that organizations must ensure that their technology infrastructure and the availability of skilled and knowledgeable workers are available before the adoption and integration of IoT solutions into business operations.

Organizational context. In this study, two variables described the organization context construct, namely: top management support and firm size.

Top management support. The results of the study indicated that top management support had a significant relationship with the intent to adopt IoT. Top management support plays a vital role in IoT adoption because it guides the allocation of resources, the integration of services, and the re-engineering of processes (Hsu & Yeh, 2016; Martins et al., 2016; Wang & Wang, 2016). Top management support does not influence technology adoption. Oliveira et al. (2014) in accessing the determinants of cloud computing adoption in the manufacturing sectors found top management support not to be an influential determinant. Other studies by Alkhalil et al. (2017) and Puklavec et al. (2018) also found top management support not to be influential in technology adoption; plausible explanation could include the lack of top management understanding of the technology being adopted. However, the finding of this study indicates that top management support is significant to U.S. manufacturing organizations. This finding is supported by other studies (Chiu et al., 2017; Haberli et al., 2017; Ilin et al., 2017; Oliveira et al., 2014; Wang & Wang, 2016) where top management support was found to influence technology adoption significantly. Top management support can reduce resistance and help overcome barriers related to technology adoption (Hsu & Yeh, 2016; Martins et al., 2016; Wang & Wang, 2016). Without the influence and support of top management, the organization is likely to resist the adoption of IoT (Wang & Wang, 2016).

Firm size. The results of the study indicated that firm size did not have a significant relationship with the intent to adopt IoT. Large firms tend to have an advantage over small ones because they have more resources and can take more significant risks associated with innovation adoption (Carcary et al., 2014). Studies have shown that small firms, although more adaptable, do not have the resources or knowledge to readily adopt newer technologies (Carcary et al., 2014). In related studies, Oliveira et al. (2014) found firm size to be a facilitator of cloud computing in both the manufacturing and service sectors. However other studies by Alkhalil et al. (2017), Chiu et al. (2017), and Ilin et al. (2017) found firm size not to be a facilitator of technology adoption. The finding of this study contradicts studies that found that firm size to be a contributing factor in technology adoption. According to Ilin et al. (2017), firm size being nonsignificant should not discourage organizations, regardless of size, from taking the initiative to adopt IoT; as shown in Table 3-Employees, approximately 44% of participants were from organizations with less than 500 employees. Chiu et al. (2017) suggested that although larger organizations typically have the financing and skilled resources, the bureaucracy of more massive origination could negatively influence technology adoption, while smaller organizations have more flexibility and ability to adapt to technological change. A possible explanation for the findings in this study is that U.S. manufacturing organizations, regardless of the size, have adequate knowledge and resources and finances in place to adopt IoT technology. In relation to earlier studies, the results for firm size are mixed; thus, additional research is needed before reaching more definite conclusions.

Environmental context. In this study, two variables describe the organization context construct: competitive pressure and regulatory support.

Competitive pressure. The results of the study indicated that competitive pressure had a significant relationship with the intent to adopt IoT. In related studies, Shaltoni (2017) and Wang and Wang (2016) found that competitive pressure influenced technology adoption. This finding is consistent with results from earlier studies on the adoption of innovative technologies (Shaltoni, 2017; Wang & Wang, 2016). The results of this study indicated that competitive pressure from competitors and others in competing industries often lead the organization to innovate. According to Wang and Wang, when an organization partner or competitors adopt new technology, the organization may feel pressured to implement the technology to maintain a competitive edge. The results from this study suggest that when organizations feel intense competition, they tend to adopt technology to stay competitive; they believe that adopting IoT technology is a strategy to stay competitive. However, Oliveira et al. (2014) and Haberli et al. (2017) found competitive pressure not to be a facilitator of cloud computing in both the manufacturing and service sectors, suggesting that competitive pressure from business partner and competitors did not positively influence technology adoption. The results of this study indicate that competitive pressure is a determinant of IoT adoption and that organizations are aware of their competitor’s technology adoption trends and thus follow suit to stay competitive.

Regulatory support. The results of the study indicated that regulatory support was not significant to the adoption of IoT. Government regulations can influence organizations in IoT adoption. In related studies, Oliveira et al. (2014) found regulatory support not to be a facilitator of cloud computing in both the manufacturing and service sectors, while AlBar and Hoque (2017) in their study of factors affecting ERP adoption found regulatory environment was a significant contributor to ERP adoption. The nonsignificant result does not mean that firms disregard prevailing standards and regulations, but rather that IoT regulation is in its infancy (Ahlmeyer & Chircu, 2016; Atzori et al., 2017; Hosek et al., 2017); regulations may not have been embraced by the organizational IT leaders. According to Oliveira et al. regulations are essential to instill the sense of trust necessary for organizations to adopt new technologies, and also facilitate removal of governmental or legislative barriers that can hinder adoption of technologies.

Applications to Professional Practice

The standard multiple regression analysis results and the choice of a quantitative correlation design were valuable to determine the degree of the significance of the relationship between corporate IT leadership’s perceptions of (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and intent to adopt IoT in U.S. manufacturing organizations. In this research, two theoretical perspectives (the DOI theory and the TOE framework) were integrated to develop the research model to assess the determinants that influence IoT adoption. Very few studies were identified in the literature that evaluated the combined effects of the innovation characteristics and the contextual factors (technology, organizational, and environmental). This study is significant to IT practice in that it may give a practical model for understanding the determinants influencing the adoption of IoT technologies. Practitioners can adopt the model and the instrument for use in other innovation studies.

In this study, technology readiness, followed by competitive pressure and then top management, was the most influential determinants for intention to adopt IoT in the U.S. manufacturing sector. The findings were grounded in a reliable and valid theoretical model, as demonstrated in Oliveira et al. (2014), which I confirmed in this study through the regression analysis. There are several implications for practitioners based on this research.

Technology readiness was the leading driver of IoT adoption by IT leaders. IT leaders should design strategies that ensure that first, the origination's infrastructure is kept up to date to facilitate user integration of IoT key devices into the environment. Organizations should ensure that personnel have the requisite knowledge, skill, and are available to implement and operate IoT technologies (Tornatzky & Fleischer, 1990). An organization that meets these two characteristics has a higher degree of technological readiness and competency are in a better position for the adoption of IoT (Kiel et al., 2017; Martins et al., 2016).

Top management support plays a vital role in IoT adoption because it guides the allocation of resources, the integration of services, and the re-engineering of processes (Hsu & Yeh, 2016; Martins et al., 2016; Wang & Wang, 2016). Without the influence and support of top management, and the origination is likely to resist the adoption of IoT (Wang & Wang, 2016). IT leaders should include early, and frequent top management engagement to obtain their buy-in and support when considering IoT adoption within their organization.

Competitive pressure from competitors and others in supporting industries often lead the organization to innovate (Hsu & Yeh, 2016). An organization that fails to innovate grows less competitive and fail to survive (Rosas et al., 2017; Taneja et al., 2016). IT leaders should be aware that organizations are likely to adopt IoT as a strategy to improve competitiveness (Rosas et al., 2017) and should implement strategies that with the support of top management that allow their organization to remain agile and adaptable as possible, and a means to ensure continued competitiveness (Balaji & Roy, 2016; Ferretti & Schiavone, 2016; Rosas et al., 2017). Organization implementation strategies that anticipate future trends are more successful (Caputo et al., 2016). Competitiveness represents the key to success. Manufacturing organizations considering the adoption of IoT for business process transformation or to facilitate rapid application development to support business success and longevity should develop their strategies around on these three determinants.

Developers and IoT device manufacturers can use the findings from this study in the development of IoT devices and applications that better integrate with organizations existing capabilities, thus increasing IoT adoption rates. There is an opportunity for both developers and IoT device manufacturers to increase IoT adoption by educating their customers on how to utilize best and implement IoT technologies.

Implications for Social Change

I explored the relationship between eight independent variables ((a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support) and a dependent variable: Intent to adopt IoT in U.S manufacturing sector. The results of the study revealed the independent variables (technology readiness, top management support, and competitive pressure) did have a significant relationship to the intent to adopt IoT in the U.S manufacturing sector. This knowledge can be used to refine organizational strategies to spur IoT adoption.

Implications of this study for social change can be voiced in terms of operational efficiency for manufacturing organizations, and the area of cost improvements for consumers. IoT adoption creates a significant opportunity for manufacturing organizations to improve or optimize their legacy technologies resulting in increased efficiency in key business areas. The efficiencies gained may create cost saving in manufacturing processes, thereby resulting in cost savings of goods and services offered to consumers. As profits increase, socially responsible organizations will provide increased wages and benefits to their employees, thus contributing to increased consumer spending powers.

Recommendations for Action

I explored the relationship between eight independent variables (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and a dependent variable: intent to adopt IoT in U.S manufacturing sector. The results of the study revealed five of the independent variables (relative advantage, complexity, compatibility, firm size, and regulatory support) did not have a significant relationship to the intent to adopt IoT in the U.S manufacturing sector. This knowledge can be used to refine the predictive model for evaluating the intent to adopt IoT within the targeted market sector.

Adoption of IoT in the manufacturing sector is relatively new with limited guidance or studies providing best-practices approaches or strategies to evaluate determinants for IoT adopters in the manufacturing sectors. Because this study is one of only a few which examined the determinants that influence the intent to adopt IoT in the manufacturing sector, it is recommended that further studies be conducted in this area. Because this study is limited to the U.S. manufacturing sector, there may also be the need to further conduct simial studies in other countries to validate the study of hypothesis and to compare results.

Recommendations for Further Study

There were several limitations identified in the study. First, participants were limited to IT leaders working in the manufacturing sector in the U.S. According to Oliveira et al. (2014), different sectors have different determinants which influence technology adoption. Future studies could expand the sample population by including IT leaders in other industries within and outside the U. S.

All participants were obtained via Qualtrics panels. Participants were incentivized to take the survey; as such, these participants may not adequately represent the views of all manufacturing sector IT leaders. The generalizability of results is restricted only to IT leaders with demographics similar to participants from this study. Future studies could target participants responses via other voluntary collection methods, such as LinkedIn who are not incentivized for participation.

Another limitation is the possibility the DOI-TOE model used excluded factors which could influence IoT adoption. While the analysis supported the use of the integrative DOI-TOE framework at predicting the intent to adopt IoT, the study revealed that three constructs were main contributors. Future researchers can conduct research by incorporating additional independent such as security (SathishKumar & Patel, 2014; Whitmore, Agarwal, & Da Xu, 2014), privacy (SathishKumar & Patel, 2014; Whitmore et al., 2014) and cost (Lin et al., 2016; Tu, 2018). Another alternative could be to include other dependent variables such as firm size and data complexity, similar to the model used by Kim, Hebeler, Yoon, and Davis (2018). It is possible that by using additional factors in an integrative model could lead to greater insights on if there are other factors which influence IoT adoption in the US manufacturing sector.

Another identified limitation of this study was related to potential sampling bias resulted from poorly worded research questions and a limited ability of participants to ask for clarification, and the occasional influence of the participants' answers to the survey questions. Although I used an existing survey instrument, it was modified to focus on IoT adoption; I did not conduct a pilot study. Results from this study indicated that firm size might not be a reasonable measure of the actual size of firms in the sample, as firm size should theoretically be related to the intent to adopt IoT (Rogers, 2003). Future researchers could conduct a pilot study using this instrument and review the results to ensure that they are no concerns about structure, wording, or sequence of the questions, thus mitigating this limitation. Also, conducting a pilot study could further develop an understanding of if additional factors should be considered, leading to a possible expansion of the model.

Future researchers can also use this study as a source that would allow them to research technologies other than IoT and possibly include other independent variables that could help in predicting the intention to use a specific technology. Researchers could apply this model to investigate the determinant for IoT adoption in different industries within the U.S., or different industries in other countries.

Reflections

Although challenging at times, I had a wonderful learning experience at Walden University. This doctoral study allowed me to learn how to conduct research in academia, and I gained knowledge of the quantitative research process and research designs and applied it to this study. This acquired knowledge will allow me to conduct further research.

I began this journey without any understanding of the DOI and TOE frameworks and their associated constructs. My understanding grew as I progressed through the various stages of the study and by reading multiple peered review articles. I developed a deeper understanding of the DOI and TOE framework and their importance to the research finding in the context of IoT adoption.

I had no preconceived biases when I began this research to examine the relationship between (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and the dependent variable intent to adopt IoT in manufacturing organizations in the U.S. The results indicate that there is a significant relationship between (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and corporate IT leadership's perceptions of intent to adopt IoT. The findings of this study provide some indication to corporate IT leadership' on the determinants that most influence IoT adoption within U.S manufacturing organizations.

Summary and Study Conclusions

I conducted a quantitative, correlational study to examine the relationship between corporate IT leadership's perceptions of (a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support and intent to adopt IoT in manufacturing organizations. I gathered data from 168 IT Leaders via a Qualtrics panel which satisfied the sample size requirement. The response rate was 12%. I performed in SPSS descriptive statistics, the instrument reliability and validity analysis, and standard multiple regression analysis to test the hypothesis derived from the question.

The analysis of the statistical results supported the alternative hypothesis. Three of the eight independent variables; technology readiness, top management support, and competitive pressure contributed to predicting intention to adopt. Despite some limitations, IT leaders’ in U.S manufacturing organizations can use these findings to make an informed decision on what the determinants most influence IoT adoption. This study makes significant contributions to the body of research on the adoption of new technologies and IoT.

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Appendix A: IoT Adoption Survey for U.S Manufacturing Sector Survey Instrument

This survey will address the extent to which IT Leadership perception of a) relative advantage, (b) complexity, (c) compatibility, (d) technology readiness, (e) top management support, (f) firm size, (g) competitive pressure, and (h) regulatory support influence the intent to adopt IoT in manufacturing organizations. The data analysis will allow comprehending the strength of the relationship. This survey has 11 sections, with each section corresponding to the variables. For each statement, please respond on a scale of 1 to 5. The definition of the scale is as follows. 1 = strongly disagree, 2 =disagree, 3 = neutral (neither disagree or disagree), 4 = agree, 5 = strongly agree. *Note:* All items are based on a 5-point scale except those noted *.

Demographic

What is your Age? *(between 18 -100)

What is your Gender? * (Man -1; Woman =0)

In which state does your organization reside? *

- New England - Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont
- Middle Atlantic - New Jersey, New York, Pennsylvania
- East North Central - Illinois, Indiana, Michigan, Ohio, Wisconsin
- West North Central - Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota
- South Atlantic - Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia

- East South Central - Alabama, Kentucky, Mississippi, Tennessee
- West South Central - Arkansas, Louisiana, Oklahoma, Texas
- Mountain - Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming
- Pacific - Alaska, California, Hawaii, Oregon, Washington

What is your Job Title? *

Security Concerns

SC1 – The organization is concerned with IoT data security

SC2 – The organization is concerned about customers IoT data security

SC3 – The organization is concerned about IoT privacy

Cost Savings

CS1 – The benefits of IoT are greater than the costs of this adoption

CS2 – With IoT there is a reduction of energy costs and environmental costs

CS3 – Maintenance costs of IoT are very low

Relative Advantage

RA1 – IoT allows you to manage business operations in an efficient way.

RA2 – The use of IoT services improves the quality of operations

RA3 – Using IoT allows you to perform specific tasks more quickly

RA4 – The use of IoT offers new opportunities

RA5 – Using IoT allows you to increase business productivity

Complexity

CX1 – The use of IoT requires a lot of mental effort

CX2 – The use of IoT is frustrating

CX3 – The use of IoT is too complex for business operations

CX4 – The skills needed to adopt IoT are too complex for employees of the firm.

Compatibility

C1 – The use of IoT fits the work style of the company

C2 – The use of IoT is fully compatible with current business operations

C3 – Using IoT is compatible with your company's corporate culture and value system.

C4 – The use of IoT will be compatible with existing hardware and software in the company

Technology Readiness

TR1 – The percentage of employees who are knowledgeable about IoT

TR2 – The company knows how IoT can be used to support operations

TR3 – Within the company, there are the necessary skills to implement IoT

Top Management Support

TMS1 – The company's management supports the implementation of IoT.

TMS2 – The company's top management provides strong leadership and engages in the process when it comes to information systems.

TMS3 – The company's management is willing to take risks (financial and organizational) involved in the adoption of IoT.

Firm Size

FS1* – The number of company employees

FS2* – Annual business volume

Competitive Pressure

CP1 – Our firm thinks that IoT has an influence on competition in their industry

CP2 – Our firm is under pressure from competitors to adopt IoT

CP3 – Some of our competitors have already started using IoT

Regulatory Support

RS1 – There is legal protection in the use of IoT

RS2 – The laws and regulations that exist nowadays are sufficient to protect the use of IoT

IoT Adoption

IoTA1*– At what stage of IoT adoption is your organization currently engaged?

- Not considering;
- Currently evaluating (e.g., in a pilot study);
- Have evaluated, but do not plan to adopt this technology;
- Have evaluated and plan to adopt this technology;
- Have already adopted IoT.

IoTA2* – If you are anticipating that your company will adopt IoT in the future. When do you think it will happen?

- Not considering;
- More than 5 years;
- Between 2 and 5 years;
- Between 1 and 2 years;
- Less than 1 year;
- Have already adopted IoT.

Note: *All items are based on a 5-point scale except those noted

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