2017

Antecedents of Employees' Behavioral Intentions Regarding Information Technology Consumerization

Alain Ouattara
Walden University

Walden University

College of Management and Technology

This is to certify that the doctoral study by

Alain Ouattara

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

Review Committee
Dr. Steven Case, Committee Chairperson, Information Technology Faculty
Dr. Gail Miles, Committee Member, Information Technology Faculty
Dr. Jon McKeeby, University Reviewer, Information Technology Faculty

Chief Academic Officer
Eric Riedel, Ph.D.

Walden University
2017

Abstract

Antecedents of Employees' Behavioral Intentions Regarding Information Technology

Consumerization

by

Alain Ouattara

MS, University of Liverpool, 2013

BS, University of Ouagadougou, 1995

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Information Technology

Walden University

July 2017

Abstract

The majority of organizations worldwide have adopted IT consumerization. However, only a small percentage of them explicitly manage the dual use of personal devices and applications for work purposes. This correlational study used the extended unified technology acceptance and use technology model (UTAUT2) to examine whether employees' perceptions of habit, effort expectancy, performance expectancy, facilitating conditions, hedonic motivation, social influence, and price value can predict IT consumerization behavioral intentions (BI). A pre-existing UTAUT2 survey instrument was used to collect data from employees (N = 112) of small- and medium-sized organizations across different industries in Ontario, Canada. The regression analysis confirmed a positive statistically significant relationship between study variables and BI. Overall, the model significantly predicted BI, F (7, 100) = 76.097, $p < .001$, $R^2 = .842$. Performance expectancy ($\beta = .356$, $p < .001$), habit ($\beta = .269$, $p < .001$), and social influence ($\beta = .258$, $p < .001$) were significant predictors of BI at the .001 level whereas effort expectancy ($\beta = .187$, $p < .01$), facilitating conditions ($\beta = .114$, $p < .01$), hedonic motivation ($\beta = .107$, $p < .01$), and price value ($\beta = .105$, $p < .01$), were significant predictors at the .005 level. Using study results, chief information officers may be able to develop improved strategies to facilitate IT consumerization. Implications for positive social change include more flexibility and convenience for employees in managing their work and social lives.

Antecedents of Employees' Behavioral Intentions Regarding Information Technology Consumerization

by

Alain Ouattara

MS, University of Liverpool, 2013

BS, University of Ouagadougou, 1995

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of Doctor of Information Technology

Walden University

July 2017

Dedication

I dedicate this doctoral study to my beloved wife, Judith Koyenou Sanon, and my lovely children, Adan Iniboun and Sarah Ndjedim.

Acknowledgments

I am thankful to God Almighty who makes my dream to become a reality.

To my wonderful wife, Judith Sanon, my son, Iniboun Pinidie Adan Judicael, and my daughter, Ndjedim Marie Sarah, I am grateful every on you for never doubting in me and being my inspiration and your unwavering devotion and love during my doctoral journey. I value your love, patience, love, support, and sacrifices. Each one of you has given me reasons to make this possible. Hang on learning, and never give up. I believe my success had paved and you will use it as an example throughout your life.

My final thanks go to my chair, Dr. Steven Verle Case, who has guided me throughout my academic endeavor and provided useful support and advice. I am also grateful to my committee member, Dr. Gail Suzzette Miles, and my university research reviewer, Dr. Jon Walter McKeeby, for their valuable input.

Table of Contents

List of Tables

List of Figures

Section 1: Foundation of the Study

Niehaves, Köffer, and Ortbach (2013) considered IT consumerization as a diffusion of consumer information technology into organizations. According to the authors, the arrival of own consumer technologies drained much more attention from practitioner because of the unauthorized switch of the diffusion channel from employees to the organization. I examined in this doctoral study, factors that influence employees' IT consumerization behavioral intentions. I provided a background information as a foundation for lack of practitioner studies on strategies grounded theoretical framework that provide insights to organizational leaders and help them develop or implement better IT consumerization policies. I reviewed the literature to demonstrate the significance of this research and framed the research inquiry to addressing the gap in understanding the antecedents of IT consumerization through the lens of a technology acceptance model. I discussed IT consumerization from perspectives that surpass the mere fact of providing devices to employees or letting employees bringing their own devices into the organization. Based on the extended unified theory of acceptance and use technology (UTAUT2), which derived from technology acceptance model, I addressed a specific research question by testing hypotheses to examine whether a relationship exists between the seven key constructs of UTAUT2 and the employees' IT consumerization behavior. Based on the findings of this study, practitioners could make informed decisions on devising better strategies in implementing or adopting IT consumerization.

Background of the Problem

Information technology (IT) consumerization encompasses the dual use of devices and applications or services such as email services and cloud storage (Weeger, Wang, & Gewald, 2016). Consumer IT tools such tablets, smartphones, or social media are changing the way employees use technology to do their work (Köffer, Ortbach, Junglas, Björn, & Harris, 2015). For instance, employees can remotely use consumer devices for work purposes. Moreover, organizations have embraced employees' use of consumer IT tools for various reasons such as perceived increases in productivity and efficiency, reductions in administrative costs, and higher job satisfaction (Weeger et al., 2016). The use of such technology also has benefits for consumers. For instance, in the health care industry, IT consumerization makes remote consultation possible for patients and allows for personalized investigations of their health (Babu & Jayashree, 2016), which may enhance the quality of their health.

Although scholar practitioners' studies on IT consumerization post-adoption have increased, some gaps remain in many areas (Leclercq-Vandelannoitte, 2015). In fact, there is a need not only to conceptualize and operationalize IT consumerization but also to explore individual drivers leading to consumerization behavior (Leclercq-Vandelannoitte, 2015). Moreover, organizations have adopted various strategies to embrace IT consumerization. In fact, Steelman, Lacity, and Sabherwal (2016) suggested a four-wave model policy adoption whereas Astani, Ready, and Tessema (2013) proposed some organizational coping mechanisms about IT consumerization. Harris, Ives, and Junglas (2012) in the other hand suggested three strategies (Laissez-faire, middle ground, and authoritarian) in managing IT consumerization. However, Leclercq-Vandelannoitte (2015) argued that practitioners did not explore the underlying factors leading to the implementation of a particular policy. Thus, studies that focus on examining factors that influence IT consumerization are lacking.

Problem Statement

Approximately 60% organizations allow their employees to use their personal mobile devices for work purposes (Astani, Ready, & Tessema, 2013). However, only 12% of organizations have explicitly addressed or managed the dual use of personal devices and applications (Chun, Griffy-Brown, & Koeppel, 2014). The general IT problem of this study was that some organizations lack strategies for developing and revising policies for allowing and managing employees' use of personal devices and applications for work purposes. The specific IT problem was that some chief information officers (CIOs) lack information on the relationships between employees' habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value and their consumerization behavioral intentions. This knowledge is necessary to improve organizations' IT consumerization strategies.

Purpose Statement

The purpose of this quantitative correlational study was to examine the relationship between employees' habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value (the independent variables) and employees' IT consumerization behavioral intentions (the dependent variable). The study population consisted of employees working for small and medium-sized businesses in Ontario, Canada. Using research findings, CIOs of these organizations might be better able to develop and, or implement appropriate strategies or policies for IT consumerization. Findings may also help to foster a greater understanding on the part of CIOs of the underlying factors leading to employees' consumerization behavior. The trend toward IT consumerization increases the connection between social structures such family and friends, and IT because people expect to maintain contact (Carter, 2015). Thus, the research findings might contribute to positive social change by improving employees' social connectedness.

Nature of the Study

I used a quantitative method in this study because my objective was to examine whether a relationship exists between the identified independent variables and the dependent variable, employees' IT consumerization behavioral intentions. Use of a quantitative research methodology allows a researcher to examine the relationships among variables (Landrum & Garza, 2015; Frels & Onwuegbuzie, 2013) by measuring quantities (Spector, & Meier, 2014). A researcher using a qualitative method aims to explore, describe, or clarify the phenomenon by studying an individual or a group (Zachariadis, Scott, & Barrett, 2013). Because this was not my intention, I did not select a qualitative method for this study. Mixed-methods combine the use of qualitative and quantitative methods and allow a researcher to generate hypotheses, triangulate data, or expand research tools (Venkatesh, Brown, & Bala, 2013). To stay within the defined scope and purpose of my research study, I did not select a mixed-methods approach.

I used a correlational design in conducting my investigation. When researchers adopt a correlational design in a quantitative study, their primary objective is to describe and measure the relationship between two variables (Pinder, Prime, & Wilson, 2014). Because I wanted to examine the relationship between study variables to determine whether the identified independent variables predicted the dependent variable, I felt that a correlational design was appropriate. A researcher may use an experimental design to infer causal relationships (Spector, & Meier, 2014). Because I did not intend to explain any causes or effects related to employees' consumerization behavioral intentions, I did not use an experimental design. In a quasiexperimental design, a researcher may use uncontrolled exogenous variations of the dependent variable to estimate causal effect sizes (Rockers, Røttingen, Shemilt, Tugwell, & Bärnighausen, 2015). In this study, because I did not intend to determine any causal effect sizes, I did not use a quasiexperimental design.

Research Question

The research question of this study was, what is the relationship between employees' habit, performance expectancy, hedonic motivation, facilitating conditions, social influence, effort expectancy, and price value and employees' consumerization behavioral intentions?

Hypotheses

The research objective was to examine whether a relationship exists between employees' habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value and employees' IT consumerization behavioral intentions. The null hypothesis and the alternative hypothesis addressed in this study were

Null Hypothesis (H_0): There is no statistically significant relationship between employees' habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value and employees' consumerization behavioral intentions.

Alternative Hypothesis (H_1): There is a statistically significant relationship between employees' habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value and employees' consumerization behavioral intentions.

Theoretical Foundation

In 2012, Venkatesh, Thong, and Xu (2012) developed the unified theory of acceptance and use of technology 2 (UTAUT2) model to provide a comprehensive means of examining individuals' perceptions, attitudes, and intentions toward the use of technology. The model derived from the initial work of Venkatesh, Morris, Davis, and Davis (2003) who proposed the unified theory of acceptance and use of technology (UTAUT) based on eight theories to address technology acceptance (Venkatesh, et al., 2012). UTAUT2 has seven key constructs: performance expectancy, social influence, facilitating conditions, effort expectancy, hedonic motivation, price value, and habit, all of which can affect an individual's intention to use technology.

In developing UTAUT2, Venkatesh et al. (2012) theorized that age, gender, and experience, moderately influence seven key constructs, and the behavioral intention and the use of a given technology in the consumer context. The variables I examined in this study are the key constructs of the UTATUT2 model. Venkatesh et al. (2012) found that the model explained 74% of individuals' behavioral intention and 52% of technology use behaviors. Thus, I decided to use UTAUT2 as my theoretical.

Definitions of Terms

IT Consumerization: Dual use of devices and applications or services such as email services and cloud storage (Weeger et al., 2016).

Small and Medium-sized Businesses (SMBs): Commercial (for-profit) businesses with 100-499 employees, and less than $50 million in annual revenues (Statistics Canada, 2015).

Assumptions, Limitations, and Delimitations

Assumptions

Assumptions are opinions or beliefs that a researcher accepts as truths (Fan, 2013) and influence the research findings (Kirkwood & Price, 2013). Kirkwood and Price (2013) argued that assumptions are researcher's opinions that determine the scope of the research inquiry whereas Tabachnick and Fidell (2013) considered assumptions as norms a researcher accepts with no verification. Donaldson, Qiu, and Luo (2013) stated that assumptions might include population characteristics, the data collected, and research methodology. I had three assumptions regarding this study. First, I assumed that the respondents in the study would voluntarily participate, which will increase my response rate. Hence, I would get increase my sample sized and improve the statistical power as suggested in Sauermann and Roach (2013). Second, I assumed that respondents would fully and honestly complete the survey, which would increase the sample size. Third, I expected the participants to have some understanding of IT consumerization, which would allow them to provide an appropriate response when entering data.

Limitations

Limitations are defects or deficiency that are out of a researcher control (Tabachnick & Fidell, 2013; Horga, Kaur, & Peterson, 2014). Kaur and Peterson (2014) added that limitations impose some restriction on the methodology a researcher uses in a study and research findings. Moreover, Brutus, Aguinis, and Wassmer (2013) stated that a researcher should convey whether certain standards of the study were not met and consider any implications for the findings and the research area under study. For my quantitative correlational study, I relied on nonprobability convenience sampling because I selected only participant available on LinkedIn® and I used descriptive statistics to analyze the results. Hence, I did not consider using a randomized sample. My use of a convenience rather than random sample was a significant limitation to the study because it precluded me from generalizing my findings to the employee population in general. Furthermore, my response rate of 14.9% was relatively small might have reduced the statistical power as suggested in Sauermann and Roach (2013). Other limitations included the fact that respondents might not honestly or wholly answer the questions, might drop out of the study, or might misunderstand IT consumerization.

Delimitations

Delimitations refer to the boundaries of a research study (MartínezGraña, Goy, & Zazo, 2013). I restricted my analysis to comprehending how the independent variables might influence employees' behavioral intentions towards IT consumerization. My choice of organizational settings and participants were delimitations. Delimitations are also characteristics of the study, which the researcher can influence (Soilkki, Cassim, & Anis, 2014) or voluntarily impose (Dean, 2014). This study was geographically limited to Canadian-based small and medium-sized businesses (SMBs) in Ontario, Canada, which allows me to narrow the scope of the study based on the context and the type of participants. I drew my sample from employees working for these SMBs.

Significance of the Study

Contribution to Information Technology Practice

This study is significant to IT practice because CIOs might use its findings to expand their understanding of employees' consumerization behavioral antecedents. Furthermore, CIOs might use the findings to devise strategies to better plan and adopt IT consumerization within their organizations. Furthermore, CIOs might be able to discover the strengths and weaknesses of their IT consumerization implementation programs. Overall, CIOs might benefit from this research when introducing new technology or an in-house technology concerning planning processes or changes. Researchers and scholars might use the results of this study to identify how CIOs can make more informed decisions regarding IT consumerization adoption in their organizations

Implications for Social Change

Regarding implications for potential positive social change, this study might contribute to the successful adoption or implementation of IT consumerization in more organizations. Providing access to employees to use their own IT devices and applications in their work may improve individuals' social connectedness. As Ling (2014) noted, organizations that successfully adopt IT consumerization offer a workspace where parents have access to children, at home and at work, which allows parents to maintain a relationship with their children. Furthermore, with the adoption and implementation of IT consumerization policies in their organizations, employees might have more flexibility and convenience in managing their work and social lives, which mighty improve the overall quality of their lives.

A Review of the Professional and Academic Literature

The literature review provided the readers with information to evaluate the depth of inquiry. I began the literature with an in-depth discussion on IT consumerization, and the theoretical framework, UTAUT2, including various studies that utilized the theory, its extensions or a combination with other theories, alternative theories, and followed by rival theories. The literature review also provided information about the empirical evidence on the relationships that exist between the identified independent variables and the consumerization behavioral intention.

Overall, I organized the literature review by topic. The first section addressed the IT consumerization definition and its similarities with shadow IT and individual system information. This section emphasized the historical and definition of IT consumerization in the literature. I also discussed the similarities and differences between bring your own device (BYOD) and IT consumerization. The second section addressed the technology acceptance model using the extended unified technology acceptance and use technology model (UTAUT2) and its associated extensions such as UTAUT. This section informed the reader how various studies used the technology acceptance and a discussion on IT consumerization adoption factors. The third section provided the reader with a comprehensive view of the alternative theories. The fourth section provided the reader with a comprehensive view of the rival theories.

Literature Review Strategy

I compiled peer-reviewed articles and other scholarly journal articles, published dissertations, and books. I used Walden University's online library databases as the source of literature retrieval. The electronic databases included EBSCO Host's Business Source Complete, EBSCO Host's Applied Sciences Complete, ProQuest's ABI/INFORM Complete, ProQuest Central, ScienceDirect, Emerald Management Journals, Sage Journals, and Google Scholar. The total number of references in this study was 274. Of these articles, 251 (92%) were less than five years old, and 258 (94%) were peer-reviewed articles. The total number of references used in this literature review were 134. Of these references, 116 (87%) were within five years of my expected graduation, and 118 (88%) were peer-reviewed. All old references include theories from authors or seminal resources that added fundamental insights to the study. I used the following search key terms to collect the relevant literature: IT consumerization, IT consumerisation, consumerization of IT, consumerization of IT, UTAUT, UTAUT2, technology acceptance model, technology adoption, BYOD, BYOT, CYOD, and CYOT.

IT Consumerization

Historically, the consumerization of IT dated back in the 1980s (Leclercq-Vandelannoitte, 2015) with the emergence and constant growth of the market for consumer electronics, providing the same technologies applied in the corporate environment (Ruch & Gregory, 2014). This approach shifted in the mid-2000s from the top down to bottom up with the development of smartphones directly to the consumer market alongside with the expansion of web-based applications and services, such as maps or new, and interactive email frontends (Ruch & Gregory, 2014). Various scholars tried to define IT consumerization and determine its key components, but there is no consensus on the definitions or explicit conceptualizations of the phenomenon in the literature (Klesel, Mokosch, & Niehaves, 2015; Ruch & Gregory, 2014). Whereas one school considers the ownership of an artifact as the primary determinant, others take into consideration only the origin of technology (Klesel et al., 2015). While others restrict the scope to devices, some scholars broader their approaches to include applications, technologies, or artifacts (Ruch & Gregory, 2014).

According to Ruch & Gregory (2014), at least two independent views shared five dimensions of IT consumerization definition. These aspects concern the direction of innovation, the dual use of consumer technologies in the private and business contexts, the classification of consumer IT compared to enterprise or corporate IT, the ownership of consumer devices, and the potential impact or challenges of IT consumerization. Ownership is an important category for Niehaves, Köffer, Ortbach, and Reimler (2013) and Dernbecher, Beck, and Weber (2013) whereas the dual use of consumer technologies is an important category for Ortbach, Bode, and Niehaves (2013), and Weiß and Leimeister (2014). Köffer et al. (2015) provided broader and wider conceptualization of the phenomenon.

Based on the literature, Köffer et al. (2015) characterized IT consumerization as an overlapping and inter-influencing of three perspectives considered as sub-facets of the phenomenon, namely a market, an organizational, and an individual. The origin of the IT tools is at the center of the market perspective, where IT consumerization refers to tools initially made for the consumer marketplace and which slowly integrate the corporate environment. Thus, the difference between organizations' IT and individual's IT become blurred (Köffer et al., 2015). Regarding the organizational perspective, IT consumerization describes situations where enterprises officially approve the use of privately owned IT in the workplace such bring your own device (BYOD) program, forbid its use by employees, or choose to adopt a position between both extremes. Hence, authorization to introduce private IT within the enterprises and use it for job purpose is at the center of organizational perspective (Köffer et al., 2015). The individual standpoint, on the other hand, is based on the ownership of the IT tools. From that perspective, IT consumerization refers the process of people bringing into the organizations their IT experiences from their private world into the workplace and using it for business purpose (Köffer et al., 2015).

Nevertheless, although Ortbach et al. (2013) provided two different examples namely entertainment systems for consumer IT and customer relationship management (CRM) systems for corporate IT, it is not clearly stated in the literature when one is dealing with consumer IT or corporate IT. Furthermore, it is not possible based on the definitions from the literature to find an agreement among scholars whether the fact that employees bring their own devices into the work context is a consumerization or there has to be a dual use (Ruch & Gregory, 2014). Nevertheless, if an organization fails to adopt IT consumerization, the phenomenon will exemplify and, therefore, expand as a shadow IT (Weeger et al., 2015). According to Silic and Back (2014), shadow systems, shadow IT, rogue IT, feral systems, or workaround systems are different terms defining the same autonomous processes, developed systems, and organizational units developed without the knowledge, awareness, support, or acceptance, of an IT department. Greynet apps such as Google apps, content apps, and utility tools such code packages are some examples of IT tools are among shadow IT software (Silic & Back, 2014).

Although IT consumerization and Individual Information System (IIS) are very similar, researchers did not establish the differentiation between the two of them nor explain further their relationship (Ortbach, Köffer, Bode, & Niehaves, 2013). The authors characterized IT consumerization as a macro trend of adopting technologies originally developed for the consumer market for professional use in enterprises whereas IT consumerization occurring at a micro level refers to the consumerization behavior of an individual which is part of the formation process of an IIS.

BYOD Concept in IT consumerization

Based on Köffer et al.'s (2015) perspective views of IT consumerization, BYOD is a sub-facet of IT consumerization. BYOD fits in the organizational and individual perspectives of IT consumerization. According to Armando, Costa, Merlo, and Verderame (2015), BYOD is an organization's strategy grounded in a defined and enforced policy that binds the device user or owner and the organization. In other words, from an organization's perspective, BYOD is a policy, which allows employees to access and use their personal devices in the workplace for work-related activities. Hence, as one facet of IT consumerization, the organization implementing BYOD program, will not only allow employees to bring their own devices but they will have the authorization to carry out business activities on these devices.

From an individual perspective, Garba et al. (2015) argued that BYOD could refer to mobile or non-mobile such as tablets, smartphones, and personal laptops belonging to employees. While the device is the prime focus of the BYOD program in a corporate environment, IT consumerization goes beyond that restrictive view and encompasses any tools and services originally made for consumers.

The next section of the literature review informed the reader about the historical development of the theoretical framework. I also included the cross-cultural information, industries, and different type of business to illustrate the flexibility, adaptability, significance of the model, and the gap in the literature. This part of the literature review also provided information about the empirical evidence on the existing relationships between the identified independent variables the consumerization behavioral intention.

The Development of the UTAUT2 Model

UTAUT2 is the latest framework with regards to the evolution of theories concerning technology acceptation. At the core of UTAUT2 is UTAUT, which in turn emerged from the extensive synthesis work of Venkatesh et al. (2003) of prior technology acceptance research. From the evolution perspective, theories about technology acceptation start with TAM based on the work of Davis (1986). In the next paragraph, I discussed the development of theories technology acceptation, starting with the foundational theory, the technology of acceptance model (TAM). I followed with discussions on the paths from TAM to UTAUT, and then from UTAUT to UTAUT2.

Evolution of the Technology Acceptance Model. Davis (1986) developed and tested the first theoretical framework of the technology acceptance model (TAM) with the objective to understand the user acceptance process better and to put at the disposal of practitioners a theoretical framework for testing user acceptance methodology with regards to new systems before their implementation. Davis (1986) developed TAM based on the theoretical model of human behavior from psychology, Theory of Reasoned Action (TRA), which he modified by adding constructs from published literature in the Management Information Systems and Human Factors fields, and previous research. Davis (1986) hypothesized that an individual overall attitude on the usage of a given system is the primary predictor of the actual use of the system and that two major beliefs namely perceived ease of use (PEOU) and perceived usefulness (PU) influence attitude toward using.

TAM posits that behavioral intention (BI) predicts computer usage, and that attitude and PU determine BI. Davis (1986) argued that although design features directly influence PU and PEOU, as external variables, they only affect attitude or behavior indirectly through PU and PEOU. In TAM, use describes a person's direct usage of a system in a context of her job while attitude describes the degree of evaluative effect that a person correlates with the usage of the systems in her job. PU refers the degree to which an individual thinks that using a particular system would enhance her job performance whereas PEOU relates to the extent to which an individual believes that using a particular system would be physically and mentally effortless. Davis (1986) hypothesized that PEOU has a significant direct effect PU, considering that in the same situation where no external factors intervene or affect the system, a user performs better in her job when the system is easier. Davis (1986) also hypothesized that system design features or external variables indirectly influence PU through PEOU. Thus, TAM suggests that PEOU and PU mediate the effect of external variables on intentions.

The outer variables in the model is a group of variable such as training, objective system design characteristics, computer self-efficacy, user involvement in design, and the nature of the implementation process. However, Davis (1986) omitted subjective norm (SN) and behavioral intention (BI) from original TAM. The rationale is that there is no available information to participants on SN in the context of user acceptance testing, and on BI, intention represents the metal process of materialization of an individual action. In 1989, Davis sought to find better measurements for PU and PEOU by reviewing the theoretical reasoning behind the hypothesis suggesting the influence of PU and PEOU on system use. Although the author was not able to validate most of the subjective measures, and could not identify their relations to the system usage, he found that PU and PEOU are the important determinants of user’s BI. The author also found that attitude influence weakens over the time. Thus, he removed the attitude as a construct from TAM.

Marangunić and Granić (2015) identified three main paths of TAM extension, which introduced new factors and variables to the TAM and categorized as factors from detailed models, additional belief factors, and external variables. Regarding the elements from similar models, many studied incorporated subjective norm (Cheung & Vogel, 2013; Park, Baek, Ohm, & Chang, 2014), perceived behavioral control, and self-efficacy. Regarding the new belief, researchers borrowed variables from a diffusion of innovation literature related to belief construct such as trialability (Jackson, Mun, & Park, 2013), visibility, result demonstrability, and content richness (Chen, Shang, & Li, 2014; Lee & Lehto, 2013).

As for external variables, various studies using TAM extension integrated external variables or moderating variables to PU and PEOU introduced as well. In fact, Svendsen, Johnsen, Almås-Sørensen, and Vittersø (2013) and Venkatesh, Sykes, and Venkatraman (2014) added personality traits. Padilla-Meléndez, Del Aguila-Obra, & Garrido-Moreno (2013), and Venkatesh, Sykes, and Venkatraman (2014) integrated demographic characteristics whereas Lee and Lehto (2013) introduced computer self-efficacy to the model. Rondan-Cataluña, Arenas-Gaitán, and Ramírez-Correa (2015) stated that the implementation of TAM in various contexts other than the acceptance of computer in organization proves that model became a strong, powerful for predicting user acceptance. However, Marangunić, and Granić (2015) argued that the structure and main assumptions of these extended models stay the same as of the TAM because the key positions of PU and PEOU are identifiable in the models.

Venkatesh and Davis (2000) extended the initial TAM model with new constructs, namely social influence, and cognitive instrumental processes to explain PU and usage intentions. The newly added constructs as key determinants of PU and usage intention allow describing the changes in technology acceptance over time because individuals become experienced in using the given technology (Venkatesh & Davis, 2000). In TAM2, social influence processes include subjective norm, voluntariness, and image, and cognitive instrumental processes include output quality, job relevance, result demonstrability, and PEOU. In TAM2, the authors hypothesized that SN direct effect on intention over PU and PEOU will happen in mandatory system usage settings. Further, Venkatesh and Davis (2000) supposed that voluntariness moderates the relationship between SN and intention to use, and assumes voluntariness to differentiate between mandatory and voluntary compliance with organizational settings. The authors assumed that individuals' acquisition of knowledge will occur independently of the usage context being voluntary or compulsory. In other words, even in mandatory system usage settings, the individuals' perception of technology usefulness through persuasive social information will positively influence their intentions to adopt or use the system. Venkatesh and Davis (2000) hypothesized that identification such as internalization occurred independently of the system usage context.

In TAM2, the authors assumed that experience mediates the relation between SN and intentions, and the relationship between SN and PU (internalization). Venkatesh and Davis (2000) hypothesized that the relationship between SN and intention would be stronger in mandatory system usage settings and before the implementation or at early stages of use while the same connection would become weaker because of the experience gained during system usage. Further, Venkatesh and Davis (2000) hypothesized that experience would have the same effect on the relationship between SN and PU. However, the authors did not assume that experience would affect the relationship between image and PU (identification) or whether this connection might weaken over time. Regarding the cognitive instrumental process, Venkatesh and Davis (2000) hypothesized that individuals evaluate the usefulness of the system based on the similarity between the outcome of using the system or job relevance, and their job goals. TAM2 also posits that the effectiveness of demonstrability and output quality influence the PU of the system but the increase of experience has no effect on PU. Venkatesh and Davis (2000) validated TAM2 by conducting four longitudinal studies at three points in time on four different systems at four organizations. The authors found that TAM2 explained 34-52 percent of the variance in usage intention and up to 60 percent of the variance in perceived usefulness.

Venkatesh and Bala (2008) addressed the issue of TAM lacking actionable guidance to practitioners by proposing a new model TAM3. The authors stated that TAM3 presents an integrated nomological network of the determinants of individuals' technology adoption and use. Further, Venkatesh and Bala (2008) argued that the strength of TAM3 resides in the model's comprehensiveness and its potential for actionable guidance. However, the development of TAM3 leverages on the parsimonious aspect of TAM to add richness and insights the comprehension of user reactions to new technology in the work environment. In fact, on theory development, comprehensiveness and parsimony do have an important role to play (Venkatesh & Bala, 2008).

Comprehensiveness role is to make sure that the theory includes important factors whereas parsimony dictates the inclusion or not of factors that do not expand the understanding of the phenomenon under study (Venkatesh & Bala, 2008). According to the authors, TAM3 emphasizes the unique role and processes related to PU and PEOU and assumes that factors that decisively affect PU will not influence PEOU and vice versa. Venkatesh and Bala (2008) argued that this influence would become non-significant in the presence of other important social and cognitive constructs. Furthermore, TAM3 posits that experience moderates the relationships between PEOU and PU, computer anxiety and PEOU, and PEOU and behavioral intention.

From TAM to UTAUT. Venkatesh et al. (2003) argued that IT researchers disregard the contribution of alternative technology acceptance models intentionally because they either select a favored model or choose among multiple models and select variables across models. The authors conducted a study to review and compare eight technology acceptance models used to explain technology acceptance behavior and propose a unified view of individuals' technology acceptance, the Unified Theory of Acceptance Use of Technology (UTAUT). The models reviewed include Theory of Planned Behaviour (TPB), Theory of Reasoned Action (TRA), Diffusion of Innovations Theory (DOI). In addition to the Technology Acceptance Model (TAM), combined Theory of Planned Behavior and Technology Acceptance Model (TPB-TAM), Motivational Model (MM), Social and Cognitive Theory (SCT), and Model of Personal Computer Use (MPCU).

Venkatesh et al. identified and addressed five limitations of prior model tests and comparisons. These weaknesses include the simplicity and individual-oriented of the technologies studied compared to complex and sophisticated organizational technology, students used as participants in most of the studies, retrospective individual's reactions, cross-sectional measurement, and voluntary research settings preventing generalization to mandatory settings. Venkatesh et al. then conducted longitudinal field studies in four different organizations to compare the eight models. The authors theorized that performance expectancy, social influences, effort expectancy, and facilitating conditions have a direct effect on behavioral intentions and usage. However, they did not hypothesize that computer self-efficacy, attitude, and anxiety have a direct effect on behavioral intention. Venkatesh et al. stated that the UTAUT model accounted for 70% of the variance in usage intention. Nistor, Baltes, Dascălu, Mihăilă, Smeaton, and Trăușan-Matu (2014) stated that the UTAUT model provides a stable and reliable theoretical model, which allows having a greater understanding of technology acceptance in different contexts.

In fact, various studied used the UTAUT across industries and diverse cultures and with consistent results (El-Qirem, 2013; Faqih, 2013; Fonchamnyo, 2013). Lian and Yen (2014) conducted a study to understand the drivers and inhibitors of older consumers' intention to shop online. The authors examined the moderating effects of age and gender on consumers' intention to adopt online shopping in Taiwan through the lens of the UTAUT and innovation resistance theory in the context of five inhibitors: usage, value, risk, tradition, and image. Magsamen-Conrad, Upadhyaya, Joa, and Dowd (2015) conducted a study to determine the predictors of tablet devices adoption across multiple generations. Magsamen-Conrad et al. (2015) examined the moderating effects of age, gender, and user experience and the influence of performance expectancy, facilitating conditions, social influence, and effort expectancy on the behavioral intention to use tablets. Moghavvemi and Akma Mohd Salleh (2014) examined the inhibitory effects of external factors or hidden events entrepreneurs' intention to adopt and use information systems (IS). Cross-cultural and international studies such as e-learning and online banking in Taiwan (El-Qirem, 2013; Chu-Fen, 2013; Pham, Cao, Nguyen, & Tran, 2013) used UTAUT to examine similarities and differences in technology acceptance across and within industries. The authors found consistency in the capacity of PEOU and PU to predict technology adoption. Likewise, Dalhatu, Abdullah, Ibrahim, and Abideen (2014) found that developing countries and developed countries face similar adoption issues.

Although the UTAUT provides researchers with a useful framework to understand the use of technology (Taiwo & Downe, 2013), the model focuses on big organizations in mandatory setting environments. Also, unlike Diffusion of Innovation theory, UTAUT does not take into account the phases leading to the adoption of technology nor does it consider cultural aspects required for successful adoption of technology as constructs that affect technology acceptance (Bhattacherjee & Lin, 2015). Furthermore, in a critical review of technology acceptance models, including UTAUT, Bagozzi (2007) argued that the definition of acceptance is oversimplified and one-dimensional, which may be adequate to studying some information systems, but undermines the learning and collaboration aspects. More so, Bagozzi (2007) argued that researchers in social science research accept the assumption that there is a relationship between intention and behavior.

Also, according to Nistor et al. (2014), in many studies, researchers consider technology use intention as the prime indicator of acceptance indicator and ignore the actual use behavior. The authors added that common methods variance might inflate the correlational relationship between intention and behavior because of the few studies, which take into account the use behavior, use self-report in general. Correspondingly, de Oca and Nistor (2014) and Nistor et al. found weak or non-significant effects of participants' technology use intention on their actual usage behavior. Besides common methods variance, there are several possible explanations for the non-significant influence (Nistor et al., 2014). For instance, in a situation where users are more experienced in using a technology under study, experience as a moderator variable can lead to weaker intention–behavior effects (Venkatesh et al., 2012). Nistor, Göğüş, and Lerche (2013) suggested that cultural influence directly affects cultural masculinity and individualism on technology use behavior, which is another reason of weaker intention–behavior effects. Nonetheless, the UTAUT is a reliable theoretical model, which provides researchers a theoretical ground to thoroughly understand the technology acceptance in various contexts (Nistor et al., 2014).

Against this background, it appears that UTAUT served as a baseline model and many types of research used it to study a variety of technologies in organizational and non-organizational settings since. Many applications and replications of UTAUT or part of the model in organizational settings contributed to fortifying UTAUT generalizability

(Venkatesh et al., 2012). The authors grouped research studies that extend or integrate UTAUT into three categories. The first type of studies examined UTAUT in new contexts, such as new technologies, new user populations and new cultural settings whereas the second group focuses on extending UTAUT with new constructs to expand the scope of its outlined endogenous theoretical mechanisms. The third category concerns the integration of exogenous determinants of the UTAUT constructs. Venkatesh, Thong, and Xu (2016) in a comprehensive review of UTAUT literature from September 2003 until December 2014 examined the latest developments in research on technology acceptance and use, added another category, new outcome mechanisms such as individual performance. New outcome mechanisms describe the new impact or consequences of behavioral intention and technology use that researcher integrated to the original UTAUT (Venkatesh et al., 2016).

Some researchers (Venkatesh et al., 2003; Venkatesh et al., 2016) argued that UTAUT reached its practical limit of explaining individual technology acceptance and use decisions in organizations despite the theoretical contribution of the model. In fact, Venkatesh et al. (2012) considered that authors of UTAUT-based research made some efforts by applying UTAUT as is, combining it with other theories, or extending it to study different technologies in both organizational and non-organizational settings.

Despite the contribution of these extensive replications, applications, and extensions or integrations of UTAUT in expanding our knowledge of technology adoption and extending the theoretical boundaries of the theory, the majority of studies that used UTAUT examined only a subset of the constructs, particularly by dropping the moderators (Venkatesh et al., 2012). Hence, researchers should systematically investigate and theorize on the relevant factors in the context of consumer technology use (Venkatesh et al., 2012).

From UTAUT to UTAUT2. In examining factors influencing technology use in a range of settings Venkatesh et al. (2012) proposed the extended unified theory of the acceptance and use of technology 2 (UTAUT2) (Figure 1). The authors leveraged from Diffusion of Innovation Theory (discussed later as an alternative framework to UTAUT2), TAM, and the original UTAUT (Davis et al., 1989; Venkatesh et al., 2003). UTAUT2 includes seven constructs assumed to affect intention to use and use of technology in various contexts. The authors extended UTAUT to examine acceptance and use of technology in a consumer context. Venkatesh et al. (2012) incorporated three new constructs into UTAUT: hedonic motivation, price value, and habit. Further, the authors theorized that individual differences (age, gender, and experience) moderately affect the new constructs on behavioral intention and technology use. The authors tested the proposed new model UTAUT2 with data collected from a two-stage online survey. Venkatesh et al. (2012) argued that the extensions introduced in UTAUT2 provide a substantial improvement in the variance explained in behavioral intention (56 % to 74 %) and technology use (40 % to 52 %) compared to its predecessor UTAUT.

In the same line of ideas, Rondan-Cataluña, Arenas-Gaitán, and Ramírez-Correa (2015) analyzed chronologically the evolution of the main acceptance and use of technology models between 1970 and today to assess quantitatively how best each model explains use and intention to use a technology, and compared how assuming non-linear relationships in the models influence positively the appropriateness and the quality of the models. Rondan-Cataluña et al. found that UTAUT2 model had a better explanation power than the rest of technology acceptance models (TAMs). However, the authors noted that all models have a better explanation power using non-linear relationships than the traditional linear approach.

Various studies adopted UTAUT2 for exploring different issues such as healthcare industry, self-technology service, learning management software acceptance, e-banking, and smart mobile device adoption. In fact, Ramirez-Correa, Rondan-Cataluña, and Arenas-Gaitá (2015) conducted a study to explain behavioral intention to use mobile Internet. Ramirez-Correa et al. (2015)

examined the influence of the brand image on the intention to use mobile Internet using similar concepts defined in the UTAUT2, particularly self-image and price or value. The authors found that gender moderated the relationship and between Operating Systems and behavioral intention to use mobile Internet. Morosan and DeFranco (2016) used UTAUT2 as a theoretical framework to study consumers' intentions to use near field communication mobile payments (NFC-MP) in hotels. The authors expanded the model with new constructs such as reflecting privacy and security. Morosan and DeFranco (2016) found that the new model explained almost all the variability in consumers' intentions to use NFC-MP, in particular that performance expectancy is the highest predictor of intentions, while hedonic motivations, habit, and social influences have relatively lower effects. Hew, Lee, Ooi, and Wei (2015) examined the determinants of consumers' behavioral intention to use mobile applications through the lens of UTAUT2 as a theoretical framework. Except price value and social influence, Hew et al. (2015) found that performance expectancy, effort expectancy, facilitating conditions, hedonic motivation, and habit have significant relationships with students' behavioral intention to use mobile applications. Hew et al. identified habit as the main predictors of students' behavioral intention to use mobile applications. Additionally, the authors found gender and educational level to be insignificant moderators.

According to Venkatesh et al. (2016), the proliferation and diffusion of new information technologies in organizations and society has influenced to some extent the increased usage of the UTAUT-based models. Nevertheless, in most UTAUT-based models extensions studies including UTAUT2, researchers mixed new endogenous or moderation mechanisms together with new exogenous mechanisms and new outcome mechanisms (Venkatesh et al., 2016). Although researchers were prolific in the past decade with studies based on UTAUT model and its extensions, Venkatesh et al. (2016) by analyzing the literature, found that the Information System discipline had reached a level of saturation related to possible theoretical contributions from further research into technology acceptance and use. The authors argued that based on their analysis of UTAUT-based models, and the notions of the research context and cross-context theorizing, the first research should be adding libraries of new context effects from the environment, organization, location, and event dimensions. Thus, they proposed a multi-level framework to specify different libraries of context effects at different levels to make the theorizing of the contextual moderation.

Schwarz and Schwarz (2015) argued that researchers who used UTAUT-based models, explained technology post-adoption use through the "proxy view" of technology, which asserts that individual's perceptions of technology elucidate the extent to which he uses the technology. Despite that, there is a myriad of technology available to in knowledge workers to carry out every task they face (Schwarz & Schwarz, 2015). Hence, the authors argued that given two technologies able to perform both a given activity, it becomes impossible to explain why a manager decides to choose one technology over another based on the proxy view of technology. Schwarz and Schwarz (2015) stated that because UTAUT-based models are single technology oriented models, researchers should assess the influence other technologies on an individual's choice of one technology versus another. The authors acknowledged that perceptions and attitudes to some extent affect the behavior of choice, and assumed these perceptions are aspects of the choice behavior, but the single-technology, usage-centric views cannot determine their modus operandi. Another argument Schwarz and Schwarz (2015) put forward against UTAUT-based models on technology post-adoption is that they use a limited set of dependent variables such as continuance, usage, or intention. The authors proposed to expand this group to examine alternative outcomes, including the choice to be able to study post-adoption choice decision in multiple technology options' contexts.

Nevertheless, I decided to use UTAUT2 as the theoretical framework for this study because of its better predicting power over the other theories of technology acceptation. Furthermore, although others theories may apply to this study, it is important to choose a theory, which will provide guidance in fulfilling the purpose of the research, and help in answering the research question. Hence, I chose UTAUT2 to keep the focus on the objective of this study and to be able to respond to the research question.

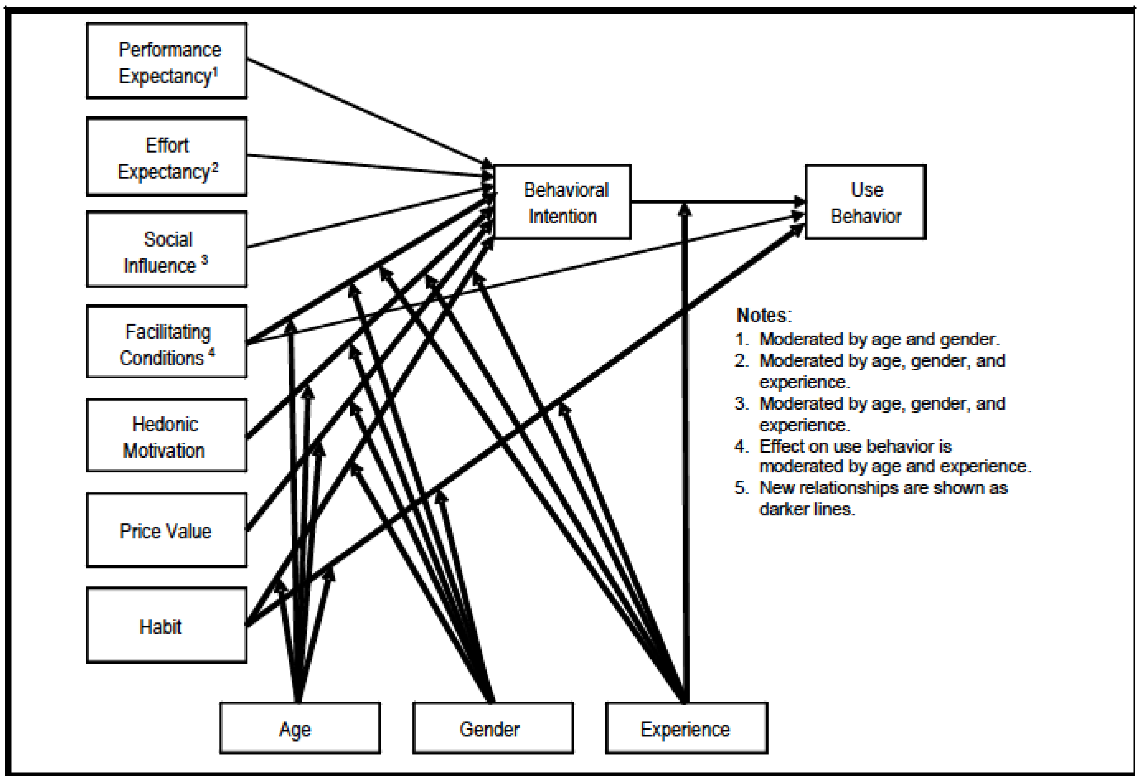


Figure 1. UTAUT2 model. Republished from "Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology," by V. Venkatesh, J. Y. L. Thong, and X. Xu, 2012, MIS Quarterly, p. 160. Copyright 2012 by MIS Quarterly.

Behavioral Intention Determinants

In the next paragraphs, I discuss the variables used in UTAUT2 and provided supporting evidence on their importance for this study. The discussion focused on UTAUT2 constructs namely, effort expectancy, performance expectancy, facilitating conditions, hedonic motivation, price value, habit, social influence, and behavioral intention.

Performance Expectancy. The reason why individuals use innovative technology is related to the perceived benefits rather than the adoption itself (Weeger et al., 2016). In fact, performance expectancy (PE) describes the degree to which an individual believes that using a technology allows him to get benefits in performing specific activities (Venkatesh et al., 2012). PE consists of four criteria: PU, the extrinsic motivation, the job fit, and the relative advantage. PU is to the extent to which individuals believe that using a new technology can ameliorate their job performance (Davis, 1989). Extrinsic motivation refers to the perceptions whether people would be interested in carrying out an activity provided that they perceive the activity to be instrumental in obtaining valued outcomes different from the activity itself. Job fit refers the perceived capabilities of new technology to increase individuals' job performance (Huang & Kao, 2015). Relative advantage relates to the benefit of adopting a new technology compared to the costs (Huang & Kao, 2015).

In previous research studies, researchers found PE to have a strong influence on behavioral intention (Venkatesh, et al., 2003). Recently, Weeger et al. (2016) showed PE has the most substantial positive impact on intention by examining factors that determine an employee's intention to participate in a corporate BYOD program. Huang and Kao (2015) also found that PE among the strongest determinant of individual's behavioral intention to use Phablet. Weeger et al. found that PE strongly affects intention to participate in a corporate BYOD program. Based on previous literature (Venkatesh & Morris, 2000; Venkatesh et al., 2012), gender and age moderate the influence of PE on behavioral intention.

Effort Expectancy. Effort expectancy (EE) is related to the usage of a new technology and represents the degree of the ease of use (Venkatesh et al., 2012). Across the literature, researchers used various constructs for EE, but there is a similarity between PEOU construct in TAM or the ease of use construct and the complexity construct of the diffusion of innovation theory. PEOU describes the extent to which an individual believes that using technology would be effortless (Venkatesh et al., 2003). Ease of use refers the extent to which an individual using an innovative technology perceived it as difficult or easy to use. According to Rogers (2003), the complexity is the degree to which an individual perceives an innovative technology as relatively difficult to use and understand. The more a new technology is complex, the more negatively it impacts on its acceptance rate (Rogers, 2003).

In previous empirical studies (Baptista & Oliveira, 2015; Venkatesh et al., 2003; Venkatesh et al., 2012), the authors found that EE influences the consumers' attitude of use in mandatory and voluntary usage. Furthermore, in the context of technology adoption, Davis (1989) found that EE is among the primary predictors for analyzing the technology usage behavior and the behavioral intention. Weeger et al. (2016) found that EE affects intention to participate in a corporate BYOD program. Based on the UTAUT, gender and age moderate the influence of EE on behavioral intention, and the effect is stronger for women, particularly for older women (Venkatesh et al., 2003)

Social Influence. Social influence (SI) represents the degree to which an individual perceives how important it is that ‘‘other people’’ believe he or she should use technology. Several researchers in their studies explored the concepts of the SI and showed that SI affects individuals' behaviors (Venkatesh & Davis, 2000; Venkatesh et al., 2003; Weeger et al., 2016). SI includes the subjective norm, the social factor, and the image. The subjective norms refer to informational influence and normative influence. The informational influence refers to people's obtaining of information from other people whereas the normative influence describes an individual's confirmation to the expectation of other people to gain a reward or avoid punishment. The social factor refers to a person's internalization from the social system's subjective culture (Huang & Kao, 2015). The image relates to the extent to which an individual finds that the using of an innovative technology can improve his status in a social organization (Huang & Kao, 2015).

Weeger et al. (2016) found that SI strongly affects intention to participate in a corporate BYOD program. Venkatesh & Davis (2000) found that SI significantly affects an individual's intention to use technology. Furthermore, Venkatesh et al. (2003) found that SI is a predictor of behavior intention to use technology and that gender and age moderate the relation between SI and behavioral.

Facilitating Conditions. Facilitating conditions (FC) refer to the degree to which individuals have confidence that the required supporting infrastructure is present in an organization for the use of technology (Venkatesh et al., 2003). From the authors' perspective, FC are similar to perceived behavioral control as defined in TPB. FC encompass many direct influencing factors of actual behavior directly, such as knowledge individuals obtained or the training, environmental impact on a person's perception of how easy or difficult it is to perform a task, etc.

Various studies tested FC in individuals’ attitudes towards technology, and the results provided supporting evidence that FC have a significant influence on behavioral intention to use technology. In fact, Escobar-Rodríguez and Carvajal-Trujillo (2014) found that FCs factor affects the online purchase intention and the online purchase use. Agudo-Peregrina, Hernández-García, and Pascual-Miguel (2014) found a similar result in the education context in a study where they examined factors influencing the acceptance of e-learning systems. Nonetheless, Venkatesh et al. (2003) suggested that EE captures FC such as support infrastructure, thus, in the presence of both PE and EE, FC do not significantly predict behavioral intention to use technology.

Hedonic Motivation. Hedonic motivation (HM) refers to the pleasure an individual has from using technology. Venkatesh et al. (2012) incorporated HM or intrinsic motivation constructs into the UTAUT2 model to complement UTAUT, which has only the extrinsic motivation or utilitarian value based on the performance expectancy construct. Various studies (Arenas-Gaitán et al., 2015; Baptista & Oliveira, 2015; Huang & Kao, 2015) found that HM operationalized as perceived enjoyment, to be among the primary determinants of technology acceptance and use.

Price Value. Unlike in mandatory organizational use settings where the organization bears the costs of the technology, the researchers applying UTAUT2 in a consumer use setting consider that consumers bear the monetary cost of technology use. Price value (PV) refers to the consumers’ cognitive trade-off between the perceived benefits of using a technology and the financial cost its usage (Venkatesh et al., 2012). It consists of criteria such as device cost, data service carriers’ costs (mobile Internet), application cost, service costs, and transaction fees, where necessary. According to Chang and Tseng (2013), the PV construct derives from the perceived value, often considered as a significant predictor of consumer's purchase behavior, which can affect a company's competitive advantage (Chang & Tseng, 2013). The higher the benefits of using a technology compared the monetary costs, the more positive is the PV is positive when the benefits of using technology are identified to be greater than the financial costs.

Venkatesh et al. (2012) argued that PV has a positive influence on intentions. However, there are mixed findings of such an argument. In fact, in a study, Baptista and Oliveira (2015) examined factors determining the mobile banking in Mozambique found that PV has no significant influence on behavioral intention. The authors argued that this may be because mobile banking users in this country perceive the service to be free of charges, without special fees, and with lower costs than other means or financial channels. Huang and Kao's (2015) finding on PV, on the other hand, is consistent with other studies (Escobar-Rodríguez & Carvajal-Trujillo, 2014; Venkatesh et al., 2012).

Habit. Researchers in various studies discussed the habit construct in different domains, such as psychology, education, health science, consumers' purchase behaviors and management. According to Venkatesh et al. (2012), habit describes the extent to which consumers tend to perform the usage of technologies or its products behaviors automatically because of learning. Habit also refers to past experiences' results (Venkatesh et al., 2012). Researchers who studied habitual intentions and habitual usage behaviors found that habit is a strong determinant of technology usages in a context of behavioral changes (Venkatesh et al., 2012). Baptista and Oliveira (2015) found that habit explains both the behavioral intention and usage behavior.

Behavioral Intention. One of the key objectives of the technology acceptance models is to study behavioral intention of new technologies (Ramirez-Correa et al., 2015). Researchers strive to demonstrate this fact through the proposition of various models such as TAM (Davis, 1986), UTAUT (Venkatesh et al., 2003), and UTAUT 2 (Venkatesh et al., 2012). In this study, behavioral intention (BI) is the dependent variable. BI relates to individual's subjective probability carry out a given behavior (Venkatesh et al., 2012). Researchers in various studies and contexts showed that intention influences behavior (Agudo-Peregrina, Hernández-García, & Pascual-Miguel, 2014; Ramirez-Correa et al., 2015; Tan, Ooi, Leong, & Lin, 2014).

Alternative Theories

In the following paragraphs, I provide details on the alternative theories that various researchers used to study technology adoption in different context including IT consumerization.

Theory of Reasoned Action (TRA). Ajzen and Fishbein (1980) relied on various theories and previous studies on attitudes such as expectancy-value theories, theories of attribution, the theory of cognitive dissonance, balance theory, and learning theories, and developed TRA with the objective to predict human behavior. Overall, TRA derived from the field of social psychology that studies the predictors of consciously intended behaviors (Ajzen & Fishbein 1980). The authors postulated that the rationality of individuals who will systematically make informed decisions based on the information at their disposal and take into consideration the consequences of their actions before performing or not a given behavior. Thus, behavioral intention is a salient predictor of behavior instead of attitude (Ajzen & Fishbein 1980). Furthermore, TRA posits that a person’s behavioral intention to accomplish a behavior determines his degree of success in achieving the particular behavior, and his attitude and subjective norm regarding the behavior determine his behavioral intention. In the model, behavioral intention is a measurement of the extent to which one's intention to accomplish a particular behavior whereas a person's positive or negative emotional state regarding the accomplishment of the target behavior, describes the attitude.

Subjective norm refers to the degree of social influence on an individual to perform or not a behavior such using a system (Venkatesh & Davis, 2000). Fishbein and Ajzen (1975) argued that the extent to which external constructs to the model influence the behavioral intention depend on the degree to which they affect attitude or subjective norms. The authors indicated three conditions should exist these external variables mediate the relationship between behavioral intention and behavior. The first condition dictates the measurement of behavioral intention should equate that of the behavior on their level specificity. The second conditionality is related to the fact that the behavioral intention should not change the time of measurement and the time of the accomplishment the behavior. The third condition specifies that a person performing the intention has the choice over his behavior.

Regarding usability, TRA is a general model with no specification on its applicability to a particular behavior or technology, thus it up to the research to determine salient beliefs with regards to the phenomenon under study (Rondan-Cataluña et al., 2015). From the information system research perspective, because external constructs influence behavior only through indirect influence on attitude, social norms, or their relative weights, the model provides a theoretical framework to examine the influence of external variables on user acceptance (Rondan-Cataluña et al., 2015).

In fact, many studies in the literature using TRA addressed different subject areas or extended the theory such as in (Ajzen & Fishbein 1980; Fishbein & Ajzen 1975; Head & Noar, 2014; Hinsz & Nickell, 2015; Mishra, Akman, & Mishra, 2014; Roberto, Shafer, & Marmo, 2014). The conditions of TRA are its primary cause of limitations, especially the assumption, based on the volitional control the behavior (Ajzen, 1991). Thus, research areas examining decisions that are not rational or usual actions, and unconscious behaviors cannot use TRA as a theoretical framework.

I did not select TRA because according to Ajzen (2012) TRA has some limitations in predicting behavior. Furthermore, not only TRA explicated only 40% of the variance of conduct, a gap between behavioral intention valuation and tangible performance evaluated exists (Ajzen 2012). Additionally, TRA is a prognostic model with individual forecasting behavior under certain conditions (Ajzen 2012). Moreover, TRA alleges that all behavior including technology acceptance are sets of salient beliefs whereas UTAUT2 defines fixed constructs as predictors of technology acceptance intention. Hence, because the objective of this study was to examine the relationship between the constructs described in UTAUT2, TRA was not suitable for this study.

Theory of Planned Behavior (TPB). TPB emerged as an extension of TRA because of the limitations of TRA in addressing an individual's behaviors over which he or she has no full volitional control (Ajzen, 1991). Also, as in the TRA, the behavioral intention in TPB remains a core construct of the theory. Furthermore, TPB posits that intentions, which are framing the degree of strength people invest willingly in performing a behavior, determine individual's behavior (Ajzen, 1991). The author argued that although globally the extent to which an individual performs is a function of the degree of strength of his behavioral intention, and as such, it is paramount that the person's behavioral intention occurs under volitional control for the accomplishment of the behavior. However, exogenous factors, representing individual's actual control over the behavior such as the available resources, do influence to some extent on most of the behaviors (Ajzen, 1991). Thus, the author argued that these factors combined would provide the individual with means to successfully perform the behavior.

The fundamental difference between TRA and TPB lies in the insertion to TPB of PBC as a construct, which semantically is closer to self-efficacy. PBC refers to what extent an individual perceives he can easily or with difficulty perform the behavior of interest whereas locus of control refers to expectancy in general term. Expectancy of success, on the other hand, relates to the perceived likelihood of achieving desired results of a given task, and perceived self-efficacy refers to individuals' subjective degree of control over what is happening to them or how well people can carry out actions that are necessary to address prospective situations. Regarding prediction, as identified clearly in TRA, in volitional control situations, the only construct need to predict behavior is intentions (Ajzen, 1991). However, the author argued that PBC solely predicts behavior when the behavioral intentions alone is a bit satisfactory regarding variance in behavior. Thus, the prevailing conditions determine, which construct predicts behavior.

Subsequently, intentions and PBC jointly can predict individuals' behavior performance (Ajzen, 1991). The author stated that there are three conditions attached to accurate prediction of behavior. First, there should be a correspondence or compatibility between measurements of intention and PBC with the behavior under interest in the same context. Secondly, because there is a probability that intervening events influence the states of intentions or PBC, the time between the measurements of both intentions and PBC and the observation of behavior should be stable. Thirdly, PBC should predict behavior to the degree to which PBC represents actual control. TPB posits that attitude, subjective norms, and PBC are conceptual and independent antecedents of intention and that behavior depends on salient beliefs appropriate to that behavior (Ajzen, 1991).

Various studies used TPB from multi-disciplinary perspective to predict different behaviors. In fact, Ortbach et al. (2013) used TPB in a context of IT consumerization. Phipps, Beatty, and Parker (2015) used TPB in a context of psychology, Carrington, Neville, and Whitwell (2014) used TPB in a context of sociology whereas Luca & Suggs, 2013, Zemore & Ajzen's (2014) study focused on health-related behavioral intention. Al Jardali, Abdallah, and Barbar (2015), and Jafarkarimi, Saadatdoost, Sim, and Hee (2016), on the other hand, concentrated on computer science and information systems disciplines. TBA alongside its extensions and ramifications with other intention theories is used to explore, explain and predict individual or groups' decisions of adoption, acceptance, and use of technology systems and IT related digital services. In fact, applications of TPB in information systems expand in many research areas such IT adoption (Chu & Chen, 2016). Also in IT acceptance, IT use, and continuance IT usage (Heirman, Walrave, Vermeulen, Ponnet, Vandebosch, & Hardies, 2016; Venkatesh, Morris, Al-Debei, Al-Lozi, & Papazafeiropoulou, 2013; Altawallbeh, Soon, Thiam, & Alshourah, 2015).

However and despite the fact that TPB received considerable attention and is still extensively adopted in the prediction of IT usage, criticisms remain against the theory (Sniehotta, Presseau, & Araújo-Soares, 2014). TPBs predictive ability is lower in the situations where the research used longitudinal designs, and sampled non-student participants, and when did not rely on self-report to as measurements instruments (Sniehotta et al., 2014). As an extension of TRA, TPB inherits implicit criticism directed to its predecessor regarding the balance between parsimony and validity (Sniehotta et al., 2014). In fact, Sheeran, Gollwitzer, & Bargh's (2013) argued that TPB is too rational reasoning oriented, thus ignoring irrational or unconscious impacts of behavior. Moreover, Sniehotta et al. (2014) reported that various studies questioned TPA ability to help to understand the cognitive behaviors and future behaviors because of its static explanatory nature. Taylor & Todd's (1995a) criticism was more related to TPB applicability in consumers' context. The authors argued that since TPB requires motivated individuals to carry out some typical behaviors, the theory is not fit when using it to examine consumer adoption behavior. Overall, Sniehotta et al. raised acerbic criticisms as the authors called for the retirement of TPB.

Ajzen (2015) took a stance against Sniehotta et al.'s (2014) criticisms towards TPB. Although the author recognized that TPB does not account entirely for the variance in intentions, he argued that fallibility of the constructs is partly causing variance issue with regards to reliability and on construct validity. Regarding the limited predictive validity of the TPB, as another, Ajzen (2015) argued that Sniehotta et al. failed to recognize that the prediction performance of TPB relies on intentions from attitudes, subjective norms, and PBC, attested in most applications. However, although the author acknowledged that potential problems affect the prediction of behavior from intentions, he argued that researchers can expand TPB with new predictors, and the presence of PBC as a construct in this model is a justification of the feasibility. Furthermore, rejecting the criticism rationalism in TPB, Ajzen (2015) argued that TPB does not propose that people are rational or that they behave in a reasonable manner. Hence from his perspective, the acerbic criticism from Sniehotta et al. about TPB inability to provide an appropriate foundation for behavior change interventions, is wrong. In fact, Sniehotta et al. argued that the lack of guidance in TPB on how cognitions change leads to the impossibility to successfully find appropriate ways to modify attitudes, subjective norms, and PBC. The authors added that TPB failed to sustain empirical tests of behavior change interventions. Ajzen (2015) argued that TPB can be used as a framework to design appropriate change behavior interventions, it is not a behavioral change theory rather a theory, which role is helping to predict and explain individuals' intentions and behavior.

I did not select TPB because it shares the same limitations as TRA. In fact, according to Ajzen (2012), TPB has some limitations in predicting behavior. Furthermore, not only TPB explicated only 40% of the variance of conduct, a gap between behavioral intention valuation and tangible performance evaluated exists (Ajzen

2012). Additionally, TPB is a prognostic model with individual forecasting behavior under certain conditions (Ajzen 2012). Moreover, like TRA, TPB alleges that all behavior including technology acceptance are sets of salient beliefs whereas UTAUT2 defines fixed constructs as predictors of technology acceptance intention. Hence, because the objective of this study was to examine the relationship between the constructs described in UTAUT2, TPB was not suitable for this study.

Decomposed Theory of Planned Behavior (DTPB). Taylor and Todd (1995a) conducted an empirical assessment to examine the antecedents of behavioral intention in a context of the consumer. The authors compared TRA and three versions of TPB as defined in Ajzen (1991) but by extending one with full specification of belief structures, and the other two respectively with decomposition and crossover refinements. Taylor and Todd (1995a) derived an extension of TPB called DTPB based on the constructs from the diffusion of innovation literature by adding new constructs such as perceived ability, the influence of significant others, and control, which Ajzen (1991) found to be the primary determinants of IT usage behavior. TPB posits the three determinants of behavioral intention are attitude, subjective norm, and PCB, and underlying belief structures, which are attitudinal beliefs, normative beliefs, and control beliefs, in turn, determine each determinant respectively. Taylor and Todd (1995a) argued that one of the criticisms raised against both TRA and TPB is the aggregation of the belief structures into unidimensional constructs integration of beliefs, and previous studies shown that monolithic belief sets may not always be related to attitude or subjective norm. The authors argued DTPB provides a framework thoroughly to examine the dimensions of normative, control, and attitudinal beliefs into multidimensional belief variables because of its advantages. The decomposition of beliefs structures contributes to clarity and to improve the understanding of the relationship between those structures and the determinants of behavioral intentions, thus directing to the specific factors that may influence behavior (Taylor & Todd, 1995a).

Furthermore, by decomposition of the attitudinal belief structures, the authors added that it solves the issue of operationalization raised against TRA and TPB because it can provide steady groups of beliefs applicable across various research settings. From the consumer adoption perspective, Taylor & Todd (1995a) suggested using a group attitudinal belief dimensions, such as relative advantage, complexity, and compatibility, which are the three essential characteristics of an innovation that influence attitude adoption in the process of adoption decision. The authors also hypothesized that the possible divergence of opinion among the referent groups, influence the decomposition for normative belief structure. From their perspective, normative belief structure can encompass three essential referent groups in an organization setting such as peers, superiors, and subordinates, with every referent group probability having its opinions on the use of IT. Taylor and Todd, (1995a) hypothesized that attitudinal beliefs influence subjective norm, or normative beliefs affect attitude, thus creating a crossover effects.

In another study, Taylor and Todd (1995b) found similar results about DTPB when they contrasted three models of IT usage namely, the Technology Acceptance Model (TAM), and TPB, and DTPB. Taylor and Todd (1995b) discovered that TAM, TPB, and DTPB models lead to similar results regarding the ability of the models to explain comparable information technology behavioral usage. But, regarding behavioral prediction, Taylor and Todd (1995b) found that TPB and DTPB have better explanatory power over TAM. Nevertheless, the authors found that TAM has better prediction power regarding behavioral technology usage and that TPB, as found in Taylor & Todd (1995a), has better explanation power regarding comprehending behavioral usage and intention. Taylor and Todd (1995b) argued that the influence of decomposition of social norms, self-efficacy, PBC, the three models' constructs measurements from the three models explain the predictive power of DTPB. Taylor & Todd (1995b) added that the decomposition the belief structure improves the model's ability to explain the behavioral intention better.

Related to DTPB, Pavlou and Fygenson (2006) extended TPB by decomposing beliefs to explain and predict the process of e-commerce adoption by online consumers. The authors added trust as an attitudinal belief predictor and a control belief for the behaviors of the two interrelated behaviors, getting information and purchasing, and product value, perceived ease of use, perceived usefulness as attitudinal beliefs in the extension of TPB model. Pavlou and Fygenson (2006) theorized that perceived ease of use would influence self-efficacy and controllability, thus PBC. But the authors chose download delay, time resources, and website navigation, which are technological characteristics as a controllability set of antecedents for getting information, whereas monetary resources, product diagnosticity, and information protection represented the controllability set of precursors for the purchasing. In the extended model of TPB, Pavlou & Fygenson (2006), considered both getting information and purchasing skills as antecedents for self-efficacy while habit, experience, product price, web vendor reputation, and demographics represented control variables. The authors found supporting empirical evidence that PBC plays a second-order formative structure through self-efficacy and controllability. Subsequently and despite the variability of self-efficacy and controllability across behavior, PBC applies to any behavior.

Various studies examined different approaches towards decomposing beliefs into multidimensional constructs to explain the relationships between intention belief structures and antecedents. Hsieh (2015) used DTPB model to explain physicians' acceptance of electronic medical records exchange systems. Mäntymäki and Riemer (2014) show the DTPB model's explanatory power to examine psychological gratifications and social influences in predicting teenagers' intention to engage in the social virtual world. Dos Santos and Okazaki (2015) and Khasawneh (2015) also used DTPB in education area to examine the prominent potential factors related to e-learning adoption.

I did not select DTPB because of was is not aligned with the purpose of this research study. In fact, DTPB suggests that attitude, subjective norms or social influence and PBC, along with their decomposed structures, influence both the intentional and accidental behaviors (Taylor &Todd, 1995a). However, the objective of this study was the examine the relationship between employees' habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value, and employees' IT consumerization behavioral intentions. Hence, I did not select DTPB as the theoretical framework for this study.

Diffusion of Innovation (DOI) Theory. Diffusion research seeks to explain why some innovations diffuse through a social system at a faster rate than others do. Scholars credit the work of Everett M. Rogers with developing most of the principles of diffusion of innovation theory research and being the pioneers in the field. Rogers (2003) stated that the innovation-decision process evolves different steps, which begin with the individual receiving first knowledge of innovation. The next stage is having a supporting decision taking a position to adopt or reject the implementation of innovations (Rogers, 2003). Rogers identified innovation, communication, time, and social systems as components of DOI theory in technology adoption in the context of social systems, companies, or individuals. The author did address not only the technology aspect of the innovation but also introduced its concept. Rogers argued that innovations could be either tangible or intangible, and processes, methodologies, or new techniques are examples of innovations.

Rogers (2003) identified fours elements that influence an individual decision making. These elements include the type of innovation-decision, the nature of the social system or business in which the innovation is diffusing, the nature of communication channels diffusing the innovation at different stages in the process, and the extent of change agent promotion efforts in spreading the innovation. According to the author, the innovation process involves five stages: knowledge, persuasion, decision, implementation, and confirmation. Knowledge refers to a situation when an individual or other decision-making unit experiences the effect of an innovation and gets and an understanding of how it works.

Rogers identified three categories of knowledge: Awareness-knowledge, how-to knowledge, and principles knowledge. Awareness-knowledge refers to an individual looking for information confirming the existence of innovation. This action may stimulate a person's interest in seeking how-to-knowledge or principles-knowledge at persuasion and decision stages of the innovation process. How-to-knowledge refers to a person looking for required information necessary to adequately use an innovation. A person may reject an innovation or discontinue its usage if he lacks an adequate level of knowledge before trying and adopting the innovation (Rogers, 2003). Principles-knowledge refers to an individual looking for information related to the functioning principles of innovation such as microelectronics, the Internet, and consumer electronics. Rogers argued that although an individual can adopt an innovation without principles-knowledge, the likelihood of him misusing a new idea exists, a situation, which may result in discontinuance. Also, individuals understanding of the principles knowledge improves their ability in judging the effectiveness of innovation. Rogers argued people can achieve their awareness-knowledge by using mass media, and that change agent in the innovation-decision process can play a distinctive and important role at the trial or decision stage because of how-to knowledge. According to the author, the principles-knowledge task is more appropriate in a context of formal education.

Persuasion refers to a situation when an individual forms a favorable attitude towards the innovation. At this stage, people are more engaged in a search of information about the innovation. Thus, they make an informed decision about the sources of information and develop a global perception of the innovation (Rogers, 2003). The author added that to reduce the scale of uncertainty around the new idea, individuals use their peers as a source of information. Rogers theorized that in this stage, an individual's attitude towards an innovation leads to a subsequent change in opened behavior. Despite that and in general, there may be a disparity in people's attitude and actions, which means that a favorable or unfavorable attitude formed about an innovation may lead indirectly or directly to rejection or an adoption of that innovation (Rogers, 2003).

Decision refers to an individual's actions to create a situation where he must make a choice to reject or to adopt an innovation. In general, individuals proceed to the trial of the innovation at small scale and later decide on whether to adopt it or not (Rogers, 2003). Thus, the relative advantage of trying leads an individual to accept or reject new ideas. According to Rogers, the rejection decision can occur at any stage of the innovation-decision process, and even after a prior adoption decision. The author added that this type of discontinuance could be an active rejection or a passive refusal. An active rejection refers to an individual who considers the adoption but decides not to adopt it while in a passive rejection case, the person never considers using the innovation.

Implementation refers to a situation when a person effectively uses an innovation. This stage is the materialization of the implementation of a person's mental innovation-decision process except for the real trial part, a situation where he manifests his overt behavior change as the innovation is put to use. The original innovation may be re-invented in the course of this stage due to (Rogers, 2003). The author added some reasons behind such situation include complexity and difficulty to understand, a variety of possible applications, and adopters' ignorance and inadequate learning.

Confirmation refers to a situation when individual attempts to reinforce prior innovation-decision, which conflicting messages about the new ideas may change. However, dissonance may occur at the confirmation stage on the adoption of innovations, which individuals may attempt to avoid (Rogers, 2003). Furthermore, Rogers argued that the clear distinction between each stage is not possible, and individuals may not be aware of the changes occurring when going through the innovation-decision phases. Also, innovation attributes and innovators' characteristics are partly creating the variation in innovations adoption time among individuals (Rogers, 2003).

Diffusion research has focused on individuals' differences on innovation while analyzing innovation differences did not get enough investment (Rogers, 2003). According to the author, past research analysis did not make any distinction between innovations, which is incorrect and an oversimplification. Nonetheless, Rogers acknowledged the need for a standard classification scheme of innovations' perceived attributes but advocated for the development of scales of perceived attributes on each diffusion study instead of using existing measurements from prior research. Rogers argued that individuals' perceived attributes of innovation rather than experts or change agents' objective perceived attributes affect the speed at which people adopt innovations. The author added that five characteristics could influence the probability and the rate of adoption: relative advantage, compatibility, trialability, observability, and complexity. Furthermore, Rogers stated that adoption rate is a function of the individuals' views of these attributes. In fact, the above mentioned the five perceived attributes of an innovation explain 49-87 % of the variance in the speed of adoption (Rogers, 2003).

However, some characteristics are inherent to the innovation while others are adopters characteristics and their use of the innovation. According to Rogers, there is an empirical interrelation between the perceived innovation attributed although each of them is conceptually different, and past research and a desire for maximum generality and succinctness determine their selection.

Relative advantage refers the extent to which an individual perceives that innovation is better than the idea it replaces (Rogers, 2003). In other words, innovation must introduce improvements. Compatibility is the degree to which an individual perceives an innovation to be consistent with existing values, needs, past experiences of potential adopters (2003). The author argued that organizations adopt innovations, which are compatible with their needs. Complexity is the extent to which an individual perceives an innovation to be relatively difficult to understand and use (Rogers, 2003). Trialability relates to the degree to which a person may be able to experiment or test an innovation in a short period (Rogers, 2003). Observability on the other refers to the extent to which others can witness the results of innovation (Rogers, 2003).

Rogers (2003) argued that the adoption patterns are different among individuals, and categorized adopters into five ideal types, namely innovators, early adopters, early majority, late majority, and laggards, using abstraction from empirical studies. The author stated that the innovators are venturesome, individuals who understand and utilize sophisticated technical knowledge, and individuals useful in introducing new ideas into a social system. In contrast, the early adopter's salient characteristic is respect. They serve as opinion leaders or role model in the social system. The first majority adopts innovations before the average member of the system. Their behavior is deliberate while the majority is hesitant and skeptical to adopting new ideas (Rogers, 2003). Laggards will embrace innovations after ensuring their successful implementation. Overall, DOI theory posits that innovation characteristics and organizational characteristics influence innovations' adoption. At the organization level, Rogers (2003) identified characteristics such as centralization, size, slack, formalization and interconnectedness to affect the adoption of innovations.

Several studies adopted or extended Rogers' perceived attributes of innovation, particularly those concentrating on the potential users' perceptions of IT innovation and its influence on adoption. In fact, the literature on diffusion of innovations is prolific and very fragmented (Karakaya, Hidalgo, & Nuur, 2014). Notwithstanding, one can find the various approaches, which use different perspectives and focuses each of specific aspects of the theory, even though the significant contributions are from marketing, economics, sociology and anthropology (Karakaya et al., 2014). The authors added that economists explained the diffusion of new products and particular technologies based on costs and past behavior of the consumers using econometric models whereas marketing studies took a range of different research instruments oriented to explain the buyer behavior. Social studies, on the other hand, examined the sociological and psychological factors that influence the diffusion of innovations, and most of the anthropological studies used case studies' approach of the diffusion of innovations, communities, or doctrines and information in villages.

More multidisciplinary emerged examining the dissemination of medical, educational, and other policy innovations (Karakaya et al., 2014). Among these, Eder, Mutsaerts, and Sriwannawit (2015) conducted a study using DOI theory as the as a framework to analyze the factors influencing the adoption of renewable electricity from individual households' perspectives. Oliveira, Thomas, and Espadanal (2014) examined the determinants of the adoption of cloud computing through the lenses of both DOI theory and technology-organization-environment (TOE) framework. The authors found that five factors influence the adoption of cloud computing: complexity, relative advantage, technological readiness, company size, and top management support. Islam (2014) examined the factors predicting households' adoption time probabilities of photovoltaic solar panels using discrete choice experiments and an innovation diffusion model. Oliveira, Thomas, Baptista, and Campos (2016) conducted a quantitative study to identify the primary predictors in a context of mobile payment adoption and the intention to recommend this technology through the lens of UTAUT2. The authors extended the model with three constructs from the DOI theory namely perceived security and innovativeness and compatibility. Oliveira et al. found supporting evidence that compatibility, perceived technology security, performance expectations, innovativeness, and social influence have significant direct and indirect effects of the adoption of mobile payment and the intention to recommend this technology.

DOI theory tries to explain the innovation-decision process, categories of adopters, factors determining the rate of adoption. The theory contributes in predicting the likelihood rate of adoption of innovation. Rogers (2003) stated that rejection decisions could happen at any stage in the decision process. Furthermore, the author added people develop their attitudes along the way in the knowledge-reinforcement path, but he did elaborate on how the role innovation attributes could play in shaping these attitudes. However, it is important to remember that innovation has different categories of adopters and it is not realistic to expect one model to be able to generalize how individuals develop positive or negative attitudes in respect of innovation attributes, stages of adoption and categories of adopters. Although TAM and DOI theory originated in different disciplines, the two theories have obvious similarities.

Although DOI theory supports innovative technology as a determinant to disruptive innovation for a competitive strategy change, I could not select it to examine the relationship between employees’ habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value, and employees' IT consumerization behavioral intentions. The rationale was that it was fit for the purpose of this study. In the next section, I discussed the social cognitive theory (SCT), which concentrates on the possibility of making changes in people's behavior.

The Social Cognitive Theory. The model of causation is the foundation of the social cognitive theory (SCT) (Bandura, 1989). According to the author, unidirectional causation researchers used to explain human behavior regarding unidirectional causation, whereby environmental influences or internal dispositions shaped and controlled behavior. SCT shifted the approach to a model of causation involving triadic reciprocal determinism whereby behavior, cognition and environmental influences, and other personal factors all operate as interacting determinants that affect each other bidirectionally (Bandura, 1989). The author argued that there is no simultaneity of the occurrences of all the reciprocal influences, and the mutual causation does not imply an equality of the various sources of influence. Furthermore, Bandura (1989) argued that due to the bidirectionality of influence between behavior and environmental circumstances, individuals are products as well as producers of their environment. Hence, a great deal of potential environmental influences and their future forms depend on behavior, and to some extent which forms of behavior are developed, and activated depend on environmental influences (Bandura, 1989). The author found that some sources of influence are stronger than others, and an individual, the given behavior of interest, and the particular situation in which the behavior occurred differentiate the interaction between the three factors.

SCT posits that careful thinking, which is related to outcomes of a given action taken, controls human motivation and action. However, many crucial factors such as goals, perceived impediments and opportunity structures, perceived self-efficacy, and outcome expectancies that influence behavior but perceived self-efficacy and outcome expectancies are the core constructs of SCT (Bandura, 1989). Perceived self-efficacy refers to individuals' beliefs in their capabilities to carry out a given action needed to achieve the desired outcome whereas outcome expectancies refer individuals' beliefs regarding potential consequences of their behaviors. Thus, individuals whose self-efficacy is pessimistic with respect their accomplishments and personal development. Self-efficacy is directly related to behavior.

In the area of individual behavior, Compeau and Higgins (1995a) considered SCT as a valid model, which accepted and empirically validated, especially the role of self-efficacy in encouraging or deterring certain behaviors. In fact, previous studies considered self-efficacy along with other factors in the domain of information systems and IT to explain individuals' acceptance or adoption of various technologies. For instance, Compeau and Higgins (1995a) developed and validated a measure of computer self-efficacy and examined its impact as well as its antecedents using SCT to identify the linkages between cognitive determinants. Compeau and Higgins (1995a) found that individuals' social cognitive perspective on computing behavior and self-efficacy influence their feelings and behaviors. Also, the authors found that outcome expectations on job performance has a significant influence on affect and use of computers. Likewise, Compeau and Higgins (1995a) concluded that affect and anxiety influence significantly computer use. What is more, the authors found that self-efficacy and outcome expectations play a mediating role in the processing of environmental information, and that verbal persuasion and others' actual use of computers influence a behavior indirectly through their influence on self-efficacy and outcome expectations. Compeau and Higgins (1995a) found a negative influence of support on self-efficacy and outcome expectations.

Various research introduced self-efficacy as a primary construct into the TAM structure for technology adoption studies, and researchers found a strong association between computer self-efficacy and the TAM construct of PEOU. Tarhini, Hone, and Liu (2013) extended the TAM model with social norms, quality of work life, computer self-efficacy, and facilitating conditions in a context of e-learning systems. Faqih (2013) investigated the influence of perceived risk and Internet self-efficacy on the consumers' intentions to use online channels for purchases. The author used an extended model of TAM with the above constructs and a non-probability sampling to collect data using f a self-administered questionnaire. Faqih (2013) found that perceived risk, PU, and PEOU directly influence the consumers' behavioral intention to use online channel for purchase. Further, the author found that the Internet self-efficacy does directly influence consumers' intention to shop online. However, Faqih (2013) found that Internet self-efficacy indirectly affects consumers' behavioral intention to use online channel for purchase through PU and PEOU. Hsia, Chang, and Tseng (2014) extended TAM with locus of control, computer self-efficacy to explain employee acceptance of e-learning systems. The authors found that computer self-efficacy directly influences PEOU and behavioral intention to use.

I did not select SCT as the theoretical framework for this study because its core constructs are different from the core construct defined in UTAUT2. Hence, choosing SCT would make impossible to fulfill the objective of this study and answering the research question. In the next section, I discussed the motivational model theory, which links Davis' technology acceptance model and self-determination theory (SDT).

The Motivational Model. The concept of intention is at the center of most current motivation theories (Deci, Vallerand, Pelletier, & Ryan, 1991). According to the authors, these theories address factors that promote individuals' comprehension of behavior-outcome instrumentalities and taking part in effective behavior to achieve those outcomes. In contrast to the other theories, Self-Determination Theory (SDT) is also concerned about behaviors that are intentional and motivated (Deci et al., 1991).

However, the authors added that SDT makes a difference between self-determined and controlled types of deliberate regulation. According to Deci et al. (1991), motivational actions are self-determined to the degree to which one endorses and engages in the entire volitional sense of self while individuals control actions if interpersonal or intrapsychic force compels them. On the other hand, an individual demonstrates a self-determined behavior in situations where the regulatory process is a choice, but when the regulatory process is compliance, individuals control their behavior. SDT postulates that individuals have inherent basic psychological needs, and focuses on needs for competence, autonomy or self-determination, and relatedness (Deci et al., 1991). Competence refers to comprehending the process of achieving various external and internal outcomes, and effective in carrying out the requisite actions while relatedness refers the social relationship one develops and maintains in his community. Autonomy or self-determination describes ones’ self-initiating and self-regulating actions.

Deci et al. stated that circumstances are contributing to achieving any of the basic human needs for competence, relatedness, and autonomy or self-determination, influence individuals’ motivation. Nevertheless, the authors argued that the satisfaction of the autonomy need is required for individuals to be self-determined rather than controlled. In SDT, behavior is either intrinsic or extrinsic. People engage in intrinsic behaviors because of the satisfaction and pleasure they get from their performance whereas extrinsically motivated behaviors are related to some separable consequence. SDT provides an explanatory framework for understanding the reasons why individuals look for specific goals and behaviors (Gard, Sanchez, Starr, Cooper, Fisher, Rowlands, & Vinogradov, 2014).

Overall, SDT emphasizes that there are no intrinsic and extrinsic factors when individuals set goals and engage in behaviors to achieve three objectives: intrinsic motivation, extrinsic motivation, or disconnection–disengagement with motivated behavior and its relationship with the environment (Gard et al., 2014). Venkatesh et al. (2003) considered extrinsic motivator such as PU to be the most important predictor of information system use. However, they considered perceived joyfulness as an intrinsic motivator for the information system. In fact, researchers in empirical studies demonstrated that intrinsic motivators influence technology acceptance and use across contexts. Hanus and Fox (2015) studied intrinsic influence in a context of game-based training. Zalma (2014) studied intrinsic influence in the context of human and technology interaction whereas Chou, Lin, Lu, Chang, and Chou's (2014) focus was on information systems. D'Lima, Winsler, and Kitsantas (2014) studied intrinsic influence in a context of education. I did not select the model as the theoretical framework because it does not support the purpose of this study.

The Model of PC Utilization. Recognizing that human behavior may not be rational, Triandis (1979) extended TPB to include emotive and habitual dimensions through his Theory of Interpersonal Behavior. According to the author, four dimensions namely intention, affect, habit, and facilitating conditions determine individuals' behavior. Intention describes the person's motivation on the behavioral performance, and the individual's attitudes, emotions or norms can influence it (Triandis, 1979). The author considered norms as social rules about engaging actions or not whereas facilitating conditions refer to objective factors, which can facilitate the behavior or harder to do. Habit, on the other hand, describes the level of routinized behavior. Triandis (1979) argued that behavior always depends partly on the intention, to some extent on the habitual responses, and to some extent on the situational constraints and conditions. According to the author, interpreted consequences of individuals' behaviors reinforce them, and that reinforcement affects the behavioral perceived consequences by changing the behavioral perceived probabilities and the value of these probabilities. People only perceive part of the behavioral consequences, which can be either perceived consequences or actual consequences (Triandis, 1979).

The former refers to individuals' anticipated effects while the latter concerns interpreted post-behavior consequences as desirable or undesirable depending on the situation. Furthermore, the author argued that the behavior-consequence reinforcement sequence would probably create revisions of perceived consequences and their value, feeds back into the person-system. Also, the author argued that social, affective factors and rational deliberations influence individuals' intentions by social and emotional factors and rational considerations. However, the influence of these constructs on intention is neither sufficiently deliberative nor fully automatic (Triandis, 1979). Another construct fundamental in Triandis' framework is behavior.

Based on Triandis' proposed framework, Thompson, Higgins, & Howell (1991) conducted an initial test of a model of personal computer (PC) utilization using part of Triandis' framework. In fact, Thompson et al. (1991) argued that individuals' feelings or affect toward using PCs, habits, social norms, the expected consequences, and the facilitating conditions influence the utilization of a PC. The author examined the direct effects of affect, perceived consequences, social factors, and facilitating conditions on behavior. However, they did not consider behavioral intentions because they were more interested in actual rather than predictive use. Thompson et al. did not add habits as a construct in their model because of measurement issues. In their study, Thompson et al. did not find supporting evidence of effect and facilitating conditions to influence PC use.

According to Venkatesh et al. (2003), although the Model of PC Utilization predicts PC utilization behavior, it is suitable to predict acceptance and use of a range of information technologies at the individual level. However, the Model of PC Utilization posits that intention, affect, habit, and facilitating conditions determine individuals' behavior. Hence, the model because it does not support the objective of this study. Therefore, the Model of PC Utilization was not suitable for this research study.

Rival Theories to the UTAUT2 Model

In this section, I identified two competing theories for this study, which were: the task-technology fit theory and the switching theory. Researchers might use these theories to provide different approaches to developing some explanations for comprehending IT consumerization. I included in the next sections an overview of the opposing theories of my adopted conceptual framework.

Task-technology fit (TTF) Theory. Goodhue and Thompson (1995) developed the TTF adoption model based on user attitudes as determinants of utilization and task fit technology as a determinant of performance. TTF posits that the use of a new technology and its capability to allow an individual to carry the tasks related to his jobs activities positively influence the individual's performance. In other words, an individual will adopt a new technology if it best fits the efficient execution of the daily tasks. Goodhue and Thompson's model uses four constructs, namely task characteristics, technology characteristics, task-technology fit, and use. Goodhue and Thompson argued that technology characteristics and the task characteristics determine the task-technology fit, which in turn influences the adoption and use of the information system.

Previous studies used TTF as a theoretical framework to explain technology adoption. Lu and Yang (2014) used a hybrid model combining TTF and social capital theory to examine and compare the impact of social, and task, and technology characteristics on individuals' intentions in using social network sites. Oliveira, Faria, Thomas and Popovič (2014) combined TTF model, UTAUT, and initial trust model (ITM) explore the factors affecting mobile banking adoption. Tate, Evermann, and Gable (2015) used TTF in online context to examine the determinants and consequences of an individual's successful task completion. According to Goodhue and Thompson (1995), previous research found that the utilization construct is an appropriate surrogate in the context of voluntary use whereas user evaluations are adequate in a mandatory use context. Furthermore, the author pointed out that either construct might be a good surrogate in mandatory context. Thus, I did not consider TTF for this study because this study was focusing on technology acceptance in the non-mandatory settings at the individual level.

Switching Theory. The switching theory derived from push–pull–mooring (PPM) framework, which is a dominant paradigm of the migration theory of humans moving from one geographic location to another (Bansal, Taylor, & James, 2005). PPM switching model posits that people migrate because of negative factors at the origin whereas positive factors at the destination pull people towards them (Bansal et al., 2005). The authors added that mooring variables, which refer to personal and social factors can make the migrations easier or can inhibit them.

Bhattacherjee, Limayem, and Cheung (2012) expanded the PPM to explain different switching patterns from a group of adopters to another one. The authors suggested that personal innovativeness that moderated the relationship between the user dissatisfaction and relative advantage of new technology, and the switching intention. Furthermore, Bhattacherjee et al. (2012) introduced another construct, namely habit, which has not only a moderating effect but also directly influences switching behavior. According to the authors, an individual habitual usage of technology will decrease the probability of him switching to another product. Hence, concerning IT consumerization, especially the dominant ownership facet, people will more likely hold on their technologies and switch from their organizations' IT tools to their private technologies to carry out their job-related activities (Dernbecher et al., 2013).

In prior studies, researchers used the PPM switching model or combined it with other models to examine switching behavior in post-adoption various contexts. Dernbecher et al. (2013) applied a switching theory to study consumerization on an individual level. Bhattacherjee and Park (2014) investigated the reasons behind users switching from the traditional client-centric model of computing to cloud computing. Chang, Liu, and Chen (2014) focused on virtual migration for social networking sites, Lin and Huang (2014) examined the determinants of consumers' intentions in a context IT standards, and Lai and Wang (2015) studied middle-aged and elderly switching attitudes in a context of healthcare cloud services.

Bhattacherjee et al. (2012) stated researchers lack an overall theoretical framework to guide for IT switching research to guide them in choosing appropriate constructs and hypotheses suitable for switching research, and the relation between the constructs. In fact, depending on the model and the context, the habit construct has either a direct effect of switching behavior such as in Dernbecher et al. (2013) or the switching intention such as in Bhattacherjee et al. (2012). Nevertheless, the choice of the model depends on three factors: the researchers' preferences, research problem, and research context (Nimako, Ntim, & Mensah, 2014). The switching theory does not support the objective of this study and does not contribute to answering the research question. Thus, I decided not to select switching theory.

Gaps in the Literature

Previous studies on IT consumerization focused on its effects and antecedents. In fact, some researchers examined the effect of IT consumerization and developed theory on the relationship between IT consumerization and job satisfaction (Giddens & Tripp, 2014) and job attractiveness (Weeger et al., 2016). Some researchers studied the effect of IT consumerization effect on work-life balance (Köffer, Junglas, et al., 2014), stress (Niehaves et al., 2013; Ortbach, Köffer, Müller, et al., 2013). Other researchers looked into the performance aspect (Chung, Lee, & Choi, 2015; Giddens & Tripp, 2014; Köffer, Ortbach, & Niehaves, 2014; Niehaves et al., 2013). Regarding the antecedents, researchers adopted various theoretical frameworks to explain IT consumerization behavior at the individual level. Dernbecher et al. (2013) used switching theory, Weeger and Gewald (2014) applied perceived risk theory, and Hopkins, Sylvester, and Tate (2013), Lee et al. (2013) and Ortbach, Köffer, Bode et al. (2013) used TRA or TPB. Other researchers focused on organizational reactions to IT consumerization (Leclercq-Vandelannoitte, 2015), or approached it from a mobile device management perspective (Ortbach et al., 2014).

Weeger, et al. (2016) in research on employees' participation in a corporate BYOD program called for future studies to examine individual's relationship with technology, and considered constructs such as "joy of use", "playfulness" and "enjoyment". Furthermore, Hopkins et al. (2013) argued that many studies on IT consumerization focused on the phenomenon's effects, particularly its security and governance issues, but some gap remains on the psychological issues associated with the trend. Other researchers (Dernbecher et al., 2013; Ruch & Gregory, 2014) insisted that studies on IT consumerization remain inconclusive enough considering the multi-faceted nature of the phenomenon, and called for more research work to comprehend it. Ruth & Gregory (2014) argued that although some studies exist that have examined the antecedents or consequences of IT consumerization, a clear understanding of IT consumerization is lacking, including its antecedents and consequences. The authors insisted that existing research did not address the cognitive and behavioral changes that are related to the phenomenon. Also, Dernbecher et al. (2013) argued that the investigation on antecedents of IT consumerization on an individual level is lacking.

Another gap that emerges from the literature is the lack of strategical approaches based on sound theoretical foundations to IT consumerization adoption (Leclercq-Vandelannoitte, 2015). Although some studies proposed some strategies based on a case study, they lack sound theoretical foundation. In fact, Marshall's (2014) study BYOD implementation in healthcare settings based on a case study. Based on cases studies, Steelman, Lacity, and Sabherwal (2016) demonstrated how organizations are adopting BYOD policies through a four-wave model of BYOD evolutions. Astani, Ready, and Tessema (2013) highlighted organizational strategies in coping with BYOD based on a survey.

This study addressed some of these research gaps on IT consumerization, and its findings might provide sound ground for practitioners to develop better adoption strategies. In fact, the study focused on the antecedents leading to IT consumerization. In this study, the objective was to answer the question: what is the relationship between employees' habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value, and employees' IT consumerization behavioral intentions? Therefore, I examined factors determining an employee's IT consumerization behavioral intention. I decided to approach the study from the perspective of technology acceptance research in the consumer context using the extended UTAUT model, UTAUT2, as the theoretical framework.

Transition and Summary

The following were the steps I took in Section 1. I started by providing the background of the problem followed by the problem and purpose statements, the research question, and the hypotheses. After doing so 1, I reviewed the literature to provide the reader with in-depth information regarding current and past research on IT consumerization and its subfacet, BYOD. The literature review in this study contains a detailed description of the theoretical foundation UTAUT2 that I used. Section 1 ends with a discussion the gap in the literature on IT consumerization that I sought to address with my investigation.

In Section 2, I detail the role of the researcher, the participants, and the research method and design. I continue twith a description of the population of the study, the sampling method, and data collection and data analysis techniques. I conclude Section 2 with a discussion of the reliability and validity, including internal and external validity, of the study and a transition into Section 3.

Section 2: The Project

In this study, I focused on developing a better understanding of the relationship between the independent variables and the dependent variable, behavioral intention. I used Venkatesh et al.'s (2012) extended UTAUT2 model in my effort to understand my correlational findings. In this section, I begin with a restatement of my purpose statement followed by a discussion of my role as the researcher and an overview of the participants in my study. A description of my research method and design follows, which includes supporting evidence gathered from the literature review and previous research. Next, I discuss the population and sampling technique; ethical research concerns; instrumentation, data collection, and analysis procedures; and validity of the study. I conclude with a transition to Section 3.

Purpose Statement

The objective of this quantitative correlational study was to examine the relationship between the independent variables and the dependent variable. The dependent variable was employees' consumerization behavioral intentions, and the independent variables were habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value. My study population consisted of employees working for small and medium-sized businesses in the province of Ontario in Canada. Study findings may help expand CIOs' understanding of the underlying determinants for employees' consumerization behavior. CIOs might use the findings of this study to develop appropriate strategies and/or policies for IT consumerization in their organizations. Implementation of such changes may contribute to positive social change by improving employees' social connectedness. IT consumerization increases the intertwinement of social structures in the sense that people to maintain contact with their peers (Carter, 2015).

Role of the Researcher

Unlike in a qualitative study where the researcher is a primary instrument in the data collection process (Yilmaz, 2013), a quantitative researcher should strive to remain detached and impartial and have an outsider's point of view during the research process (Yilmaz, 2013). However, Darlington and Dobson (2013) stated that there are two opposing schools regarding value neutrality in research. Some scholars maintain that a researcher should be detached from all values, and should focus on theoretical facts (Darlington & Dobson, 2013)). Other scholars see value neutrality as a principle guiding researchers' behaviors but acknowledges that, in situations, researchers will maintain their values (Darlington & Dobson, 2013). Researchers must not let their values interfere with the research or attempt to promote them in their investigations, according to this school of thought (Darlington & Dobson, 2013). Darlington and Dobson stated that it is impossible to conduct research, which is value-free, or entirely impartial because a researcher's personal beliefs and values influence the research focus; research questions; data collection, analysis, and interpretation procedures; and, subsequently, the research findings.

However, Darlington and Dobson (2013) argued that research's findings are not related to a researcher's deliberate avoidance of his or her personal beliefs. The authors added that reseach’s findings are objective if the researcher evaluates hypotheses based on evidence that derive from measurement such population sample representativeness and verification, validity, and reliability.

I adhered to tenets in the Belmont Report (United States Department of Health & Human Services, 2015) to ensure that I did not violate participants’ rights. I also successfully took the online course of the United States National Institutes of Health’s Office of Extramural Research on protecting human research participants.

In my study, I used UTAUT2 from Venkatesh et al. (2012) as my theoretical foundation; with the authors’ permission, I also modified and used their survey items for my data collection instrument (see permission letter in Appendix D). I conducted the statistical tests of collected data using SPSS®, after which I analyzed and interpreted the results. After graduation, I plan to collaborate with my mentor to publish the findings in an academic journal.

I have been working in the information technology field for more than 20 years. I have extensive experience in providing corporate remote access to users, especially corporate email using enterprise-owned and employee-owned laptops. In 2010, I deployed for my organization, one of the first Blackberry server pilot project to provide email access on 100 Blackberry handheld devices to users. Overall, I am very familiar with IT consumerization. Although I share Darlington and Dobson’s view on the impossibility to conduct a research that is value-free, in this study, I strove to remain objective. I acknowledge that that striving to remain objective in this study might not have prevented potential bias on my part, especially in the interpretation of the findings.

Nevertheless, I did not perceive my IT experience on IT consumerization to pose a material bias to this research study. Furthermore, Darlington and Dobson (2013) recommended that a researcher uses evidence-based analysis rather than a deliberate biased assertions based on predilections. Therefore, I drew my conclusions in this study based on analysis the data I collected instead of biased assertions.

Participants

The participants of this study were employees working across various industries in SMBs based in Ontario province in Canada. Furthermore, nonprofit and government organizations, schools, hospitals, subsidiaries, cooperatives, and finance and leasing companies were not part of the study. I selected the participants based on their availability and my convenience. A sample is convenient when the participants do not have an equal chance of being selected (Raschke et al., 2013). Furthermore, to reduce the size of the sample frame, I recruited employees using the social platform LinkedIn®. My strategy of selecting participants included criteria related to IT consumerization.

In fact, the final data of the survey included only responses from participants who use at least one of the consumer's technologies in the course of their daily routine. In other words, any employee belonging the selected subgroup of organization could participate in the survey, but I retained only those satisfying the usage criteria at the final stage for analysis. Hence, in the final stage, I considered two criteria. The first criterion was related to the devices used in the course of their daily routine. I took into account employees who use smartphones, netbooks, and tablets irrespective of the software and services. I did not include those who use desktops and laptops unless they satisfy the second criterion. The rationale is that I follow the idea of Köffer et al. (2015) who argued that desktops and laptops are traditional IT tools used widely by organizations before the appearance of the term IT consumerization in the literature.

The second inclusive criterion was related to the usage of software and services. Today, employees use wearable devices, smartphones and tablet computers, equipped with a myriad of applications. Employees can use these devices to have ubiquitous Internet access that can support numerous work tasks. Therefore, my choice of participants included employees using consumer software. IT consumerization encompasses the use of consumer software in the workplace (Köffer et al., 2015). Hence, the participants included employees who use consumer software, services, or applications for work-related activities. Steelman, Lacity, and Sabherwal (2016) proposed sample of consumers technologies. They related to cloud storage (e.g. Dropbox, iCloud, Box), chat systems (e.g. Facetime, Skype, instant messaging). Also, online collaboration tools (e.g. Google Docs, Office 365), social networking sites (e.g. Facebook, Twitter, Instagram), online app stores (e.g. Apple App Store, Google Play), and customized consumer applications.

I ensured anonymity and confidentiality to all participants in compliance with Walden University's Internal Review Board (IRB), but I did not offer any incentives for taking part of this study. I invited the participants on LinkedIn® to take one online survey. Apart from the information on anonymity and confidentiality to all participants, displayed to the participants in the survey, they were able to read the scope and purpose of the study, and each participant had the opportunity to withdraw from the study. Furthermore, each participant should acknowledge his/her consent before participating in the survey. I projected to encrypt and store the data collected from the survey on a memory stick. I also planned to encrypt the memory stick and store it in a safe deposit box at a financial institution for five years. I would discard the data after the five years as per the IRB safety guidelines.

Sample Size. Sample selection bias can threaten research validity (Pye, Taylor, Clay-Williams, and Braithwaite, 2016). To ensure an appropriate sample size in the study, I used two approaches. The first used Green's (1991) formula for estimating sample size. Green (1991) suggested that to determine a population sample size in multiple regression analysis; the researcher could use the equation sample size = 50 + 8 (m), whereby m designates the number of independent variables. With seven independent variables, the results of the formula gave an estimate sample size of 106 participants. In the second approach, I used G*Power 3.1.9.2 for OSX to determine the sample size. In a quantitative meta-meta-analysis of effect sizes in a context of marketing research, Eisend (2015) demonstrated the appropriateness of medium effect size in measuring scientific knowledge. Bosco, Singh, Aguinis, Field, and Pierce (2015) confirmed the relevance of the medium effect size in research. Therefore, I conducted a computation using an a priori power analysis, assuming a medium effect size ($f = .15$, $a = .05$). I obtained a minimum sample size of 103 participants to achieve a power of .80 using multiple linear regressions F-test. When I increased the sample size to 153, the power rose to .95. Hence, the population sample size estimated for this study is between 103 and 153 as shown in Figure 2 below. The estimate sample size obtained based on Green's (1991) formula was closer to the minimum sample size calculated using a priori power analysis. Thus, in term of sample size range, the lower would be 103 and the upper bound 153. Hence, I sought a minimum sample size of 103 participants.

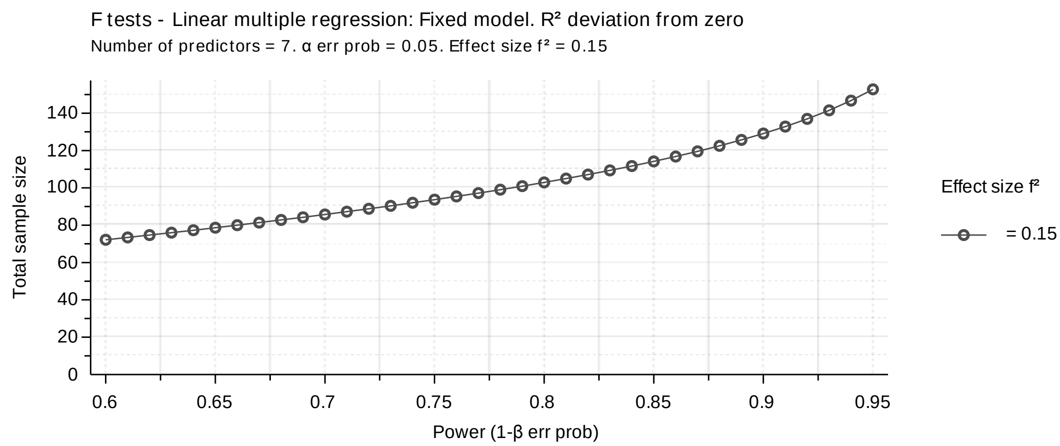


Figure 2. Power as a function of sample size.

Research Method and Design

Several studies in the field of research on human services used quantitative and qualitative, and some examples of mixed-methods (Venkatesh et al., 2013). But for the researcher to decide which of the three methodologies to adopt depends on the research questions, the purpose, and the context (Frels & Onwuegbuzie, 2013). According to the authors, because of the intertwining of research questions to environmental settings, which comprise beliefs and theories, a researcher examines the worldviews at the beginning of the research study to derive the data collection strategy. I examined in this study, the relationship between employees' IT consumerization behavioral intentions and the seven constructs defined in the UTAUT2 model namely habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value. Thus, the driving research paradigm for this study was a quantitative methodology.

Method

The main differences between quantitative and qualitative research designs are in their epistemological, theoretical, and methodological underpinnings (Yilmaz, 2013). According to the author, quantitative research approaches are based on objectivist epistemology whereas qualitative methods use constructivist epistemology. Researchers and scholars use qualitative methods instead of quantitative methodologies as a narrative approach (Gilstrap, 2013) or to explore a phenomenon, which does not rely on enumeration, numerical or statistical analysis (McCusker & Gunaydin, 2015; Palinkas, 2014). Furthermore, qualitative research is excellent in eliciting the view of the group or individuals under study whereas a quantitative study is a better approach when a theory exists to allow the researcher to test the hypotheses (Palinkas, 2014). In qualitative research, the researcher seeks to provide answers to questions regarding the ‘what’, ‘how', or ‘why' of a phenomenon of interest, while quantitative methods allow him to aim to answer the questions about the ‘how many' or ‘how much' (Palinkas, 2014). I did not select the qualitative method because the objective of this study was to examine the relationship between the defined independent variables and the behavioral intention in the context of IT consumerization. Mixed-methods combine both quantitative and qualitative research methods (Frels & Onwuegbuzie, 2013; Venkatesh et al., 2013). Unlike with qualitative and quantitative methods, a mixed-methods study allows the researchers to address confirmatory and exploratory research questions using a single research inquiry (Venkatesh et al., 2013). Even though a mixed method as a merit (Venkatesh et al., 2013), because the researcher using this approach will combine both quantitative and qualitative (Frels & Onwuegbuzie, 2013; Venkatesh et al., 2013), I did not select it.

I decided that a quantitative method would be appropriate to address the research question. Previous studies provided enough supporting evidence to my decision to conducting a quantitative study research. For instance, Yuan, Ma, Kanthawala, & Peng (2015) used a quantitative method and a survey as a data collection instrument to examine the determinants of continued use of health and fitness apps based on the theoretical framework UTAUT2. Escobar-Rodríguez and Carvajal-Trujillo (2014) examined through the lens of the UTAUT2 framework the determinants of purchasing flights from low-cost carrier websites using a quantitative approach to a survey instrument. Arenas-Gaitán et al. (2015) conducted a study to explain Internet banking usage by the elderly. The authors used UTAUT2 as a theoretical model and statistically tested the constructs with the data collected through a survey of 415 individuals over 55 years. Nair, Ali, & Leong (2015) conducted a quantitative study to explain the factors affecting students' acceptance and usage of a lecture capture system using UTAUT2 as a theoretical framework for data collected using a survey approach.

Three distinct objectives characterize surveys used in research (Pinsonneault & Kraemer, 1993). The first one is to provide quantitative descriptions of some characteristics of the population under study. A researcher may mainly use a survey to analyze either the relationships between variables or to forecast the findings descriptively to a population under study. Secondly, a researcher uses a survey in research as a data collection instrument using structured and predefined questions. Thirdly, a researcher collects data with the objective of generalization. But the data are related only to a subset of the population under study. In this study, I collected the data based on a survey to examine the employees' behavioral intentions on IT consumerization.

Research Design

The objective of a research design was to answer the research questions or test the hypotheses (Pinsonneault & Kraemer, 1993). According to the authors, survey designs may either be cross-sectional or longitudinal based on time dimension consideration or not. A cross-sectional design allows the research to collect data at one point in time, and he can generalize findings to the population (Pinsonneault & Kraemer, 1993). However, the authors stated that a cross-sectional design limits the possibility of the researcher to infer causally because of the time dimension. Conversely to a cross-sectional design, in a longitudinal design, the researcher collects data for two points in time at a minimum (Pinsonneault & Kraemer, 1993). The authors added that a longitudinal design provides a greater possibility to the researcher to causally infer than a cross-sectional design because it makes it easy to set temporal priority. This study used cross-sectional design because I collected the data at one point in time, and I had no intention to establish causal inferences. More precisely, I conducted a quantitative cross-sectional correlational study focusing on describing and measuring the relationships between the independent variables and the dependent variable. In fact, the purpose of the study was to determine the extent to which habit, effort expectancy, performance expectancy, hedonic motivation, facilitating conditions, social influence, price value would relate to the employees' consumerization behavioral intentions.

Previous studies used this method, design, and instrument to examine the relationships between UTAUT2 variables and the dependent variable. For instance, Yuan, Ma, Kanthawala, and Peng (2015) conducted a study to examine the determinants of continued use of health and fitness apps based on the theoretical framework UTAUT2 using a correlation design with a questionnaire as a data collection instrument. Escobar-Rodríguez and Carvajal-Trujillo (2014) conducted a quantitative correlation study to examine the determinants of purchasing flights from low-cost carrier websites based on an extension of UTAUT2 with two new constructs perceived trust and consumers' innovativeness and renamed price value to price saving. Similarly, based on UTAUT2 and a survey instrument, but in a different context, Yang (2013) conducted a quantitative correlation study to examine the relationships between the modified UTAUT2 constructs and undergraduate students' intention to adopt m-learning. Morosan and DeFranco (2016) conducted a quantitative correlation study to explain consumers' intentions to use near field communication mobile payments in hotels through the lens of UTAUT2. The authors used a survey to collect data from 794 hotel consumers selected from the United States general population to empirically validate the augmented model.

Population and Sampling

In this study, the general population was employees working in the private sector for small and medium-sized businesses in Canada with the focus on enterprises based in the province of Ontario as a geographic area. According to Statistics Canada, as of December 2015, there were 1.14 million medium-sized businesses in Canada. Of these businesses, 415, 612 were based in Ontario. To narrow down the sample frame, I included in this study only employees present on the social media LinkedIn®. The relevance of the population in this study rests on the variety of the business types. In fact, the population will include SMBs from various industries. The sample representativeness depends on the sampling methodology, sample size, and the response rate (Acharya, Prakash, Saxena, & Nigam, 2013). Broadly, two categories of sampling methods exist, namely nonprobability sample and probability sample (Acharya et al., 2013; Raschke, Krishen, Kachroo, & Maheshwari, 2013).

Probability sampling methods, namely simple random sampling, systematic random sampling, stratified random sampling, cluster sampling, multiphase sampling, and multistage sampling describe the fact that each participant has equal chance to be selected in the survey (Acharya et al., 2013; Raschke et al., 2013). Hence, the generalization to the target population appears to be the main benefit of probability sampling methods (Acharya et al., 2013; Raschke et al., 2013). Nonetheless, the authors stated that probability sampling methods are resource-consuming in terms of time and money. Unlike probability sampling methods, nonprobability sampling methods classified as convenience or purposive sampling, quota sampling, and snowball sampling refer to the fact is each participant does not have a known probability to be selected in the survey (Acharya et al., 2013; Raschke et al., 2013). Thus, researchers using nonprobability sampling methods will not be able to generalize the results of the study, and they will not be able to measure or control the variability and bias (Acharya et al., 2013; Raschke et al., 2013). But, the authors added that non-probability sampling methods have the advantage of being less costly, and the researcher will not need a list of all the whole population.

Researchers use non-probability sampling methods when they lack enough information about the population (Raschke et al., 2013). Hence, I used a nonprobability sampling method in this study to determine the participants not only to save time and money but because I lacked enough information about the participants. Furthermore, researchers use non-probability sampling methods because of the accessibility to the participants, and other non-statistical criteria (Raschke et al., 2013). Nevertheless, despite that random sampling method being a better approach on sampling, the size of the SMBs in Ontario and its dispersion prevented from using this method as a viable one for the study.

Furthermore, regarding sampling methods, Acharya et al. (2013) stated that they must be systematic and defined in such a way that the researcher should be able to derive valid inferences from the sample. Thus, I used a convenience sample by considering only the available participants willing to take part in the survey. I conveniently selected the respondents by sending solicitations through LinkedIn® email or contact features to get the survey the employees directly. I used a power analysis using G*Power software and the formula suggested in Green (1991) to estimate the sample sized which, was between 103 and 153 participants.

Regarding the response rate, Sauermann and Roach (2013) argued that detailed survey leads to smaller rates of around 10-25%, which reduces sample size and statistical power. The authors added that low response rate could create nonresponse bias and affect the validity of survey results independently of the sample size. In their study, the authors found that that personalization increases the odds of responding by as much as 48%, whereas lottery incentives approach enhances the chance of returning by 30%. Furthermore, Sauermann and Roach (2013) found that by changing the wording of reminders over the survey life cycle, the response rate could increase by over 30%. However, the authors did not find that changes in contact timing (day of the week or hour of the day) had significant benefits. Hence, because I was not planning to pay any incentives to the participants, I invested in the wording of reminders throughout the survey lifecycle and added personalized features on the message to potential respondents to improve the response rate. I sent out 723 surveys and obtained 108 valid responses, yielding a valid response rate of 14.9%.

Ethical Research

Scholarly researchers abide by the rules and procedures to guarantee the rights and safety of the participants (Resnik, Miller, Kwok, Engel, & Sandler, 2015; Rothstein, 2015). Hence, preserving the confidentiality of the participants is paramount. As an academic researcher, I strived to remain credible and trustworthy in the course of my research activities. I used encryption software to secure the collected data, stored it in a portable device, encrypted the whole content of the drive, and safely preserved it from the third party for a minimum of 5 years. It is also the responsibilities of researchers to abide by ethical practices (Vanclay, Baines, & Taylor, 2013). According to Rothstein (2015), one of the researchers' ethical practices concerns the communication of the research objectives with participants before collecting the data.

Furthermore, Walden University research protocols recommend that doctoral students guarantee participants' rights and safety and inform them of the study's objectives. I complied with Walden University IRB requirements. I included in the survey instructions section related to the informed consent, and I provided an option to the participants to acknowledge and accept it before proceeding to the survey. Furthermore, Scott and Olikowski (2014) argued that a researcher ensures privacy if it is impossible to identify a participant based on the data collected. I took action to preserve the privacy of the respondents, and make sure that the data gathered through the survey could not contain any piece of information related their personal information or their organization names.

I also included in the survey a section that displayed a confidentiality statement together with the information on the background of the study, and how to complete the questionnaire. This section also highlighted the voluntariness of the survey and the process of withdrawal from the study. I dedicated another section where I stated that there was no compensation for contributing to the research and that I would strive to guarantee the confidentiality of the information provided.

Data Collection

I used a web-based survey instrument to collect data for this study. I considered the data collected as the prime source to examine the relationship between variables. The raw data collected was not be included in the final paper. I encrypted the data and stored it on a USB drive and encrypted the whole drive. I put the USB drive in a safe deposit box place at my residential house for five years after which, I would dispose of it. The USB drive would service as a data source, and I would make it available upon request.

Instruments

For this study, I used a UTAUT2 survey instrument and implemented it as an online survey using SurveyMonkey®. I adapted and altered the wording of the items accordingly to relate the elements in IT consumerization context. To operationalize IT consumerization behavioral intention, I replaced the behavioral intention construct of Venkatesh, et al. (2012) with IT consumerization behavioral intention. In fact, researchers such as Weeger et al. (2016) altered the wording to link the items to the BYOD context. Survey changes and adjustments concerned the replacement of references to mobile Internet with consumer's IT tools.

Researchers who adopt quantitative designs rely on tests and closed-ended questionnaires to collect, analyze and interpret the data (Zohrabi, 2013). Subsequently, the items in this study consisted of close-ended questions submitted to the participants. The questionnaire contained twenty-eight (28) question items. According to Escobar-Rodríguez and Carvajal-Trujillo (2014), researchers use a Likert scale to measure variables, which they cannot directly observe or quantify. Because the variables I used to capture the participants' responses were not directly quantifiable, an ordinal 7-point Likert-type scale was appropriate to measure them. I employed a Likert scale ranging from 1 to 7, where 1 means strongly disagree, 2 means moderately disagree, 3 means somewhat disagree, 4 means neutral (neither disagree nor agree), 5 means somewhat agree, 6 mean moderately agree, and 7 means strongly agree. Use did not vary from the scale from UTAUT2. Hence, I used anchors of the seven-point scale ranging from 'never' to 'many times' per day. Moreover, Panda and Narayan Swar (2013) stated that Likert-type scale measures the extent to which each participant agrees with each question. Hence, by using a Likert scale, I was able to measure every response to each survey question whereby a higher score indicated a greater degree of IT consumerization intention. This process allowed me to measure the independent variables (habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value) and the dependent variable (IT consumerization intention). I included demographic questions about age and gender. I measured the scale for age in years, and that of gender consisted of 0 or 1, with 0 represented women. I included the survey instrument in the table of contents as Appendix C and the authorization to use and modify the UTAUT2 survey as Appendix D.

Many researchers adjusted survey items from the technology acceptance model in their studies. In fact, Yuan et al. (2015) used a modified UTAUT2 survey instrument in a context of health and fitness application systems in the United States. Alazzam, Basari, Sibghatullah, Doheir, Enaizan, and Mamra (2015) used a modified UTAUT2 survey instrument in their study of electronic health records acceptance in Jordan. Morosan et al. (2016), and Oliveira, Thomas, Baptista, and Campos (2016) modified UTAUT2 survey instrument to adapt to a mobile context payment. I will also adjust survey UTAUT2 items to adapt to IT consumerization context. Furtheremore, Weeger et al.

(2016) claimed that researchers adopt items from previous technology adoption research to safeguard measurement validity. Hence, by adopting UTAUT2 survey instrument, which Venkatesh et al. (2012) tested in a context of mobile Internet context, it might maintain the measurement validity. Wong, Wei-Han Tan, Loke, & Ooi (2014) added that researchers chose UTAUT2 because of the model's validity and reliability in influencing technology acceptance.

Reliability and validity are the key fundamental issues to address to interpreting measurement results from administering a survey (Barry, Chaney, Piazza-Gardner, & Chavarria, 2014). However, the authors argued that validity and reliability are not related to the survey or a scale itself, but to the scores. These scores derive from survey/scale based on certain conditions, among a given sample, which provides evidence to supporting validity and reliability claims (Barry et al., 2014). Thus, researchers should talk about the reliability and the quality of the data produced instead of the instrument itself (Barry et al., 2014). According to the authors, reliability refers to a scale's consistency and the validity relates to the accuracy or the trustworthiness of the output scores. Moreover, validity usually involves three elements namely content validity, construct validity, and criterion-related validity (Barry et al., 2014). Content validity relates to the extent to which a survey's items, as a whole, is representative of the necessary content (Barry et al., 2014; Venkatesh et al., 2013; Zachariadis, Scott, & Barrett, 2013). Construct validity, refers to how accurately a scale measures a relevant theoretical construct (Barry et al., 2014; Venkatesh et al., 2013; Zachariadis, Scott, & Barrett, 2013). Criterion-related validity, which includes predictive, discriminant, and concurrent validities, refers to the comparison of scores on a new/developed instrument and the scores from another relevant and reputable scale (Barry et al., 2014). However, instead of a trinity concept, researchers conceptualize validity as a unitary concept (Barry et al., 2014). According to Barry et al. (2014), and Reeves and Marbach-Ad (2016), the unitary concept is related to a combined body of validity evidence in five areas: response processes, test content, internal structure, and consequences of testing, and relations to other variables.

Researchers use Cronbach's alpha to measure the internal consistency of the reliability of a psychometric test (Ain, Kaur, & Waheed, 2015; Bonett & Wright, 2015; Dunn, Baguley, & Brunsden, 2014; Kazman, Galecki, Lisman, Deuster, & O'Connor, 2014; Peters, 2014). Cronbach's alpha is an index of a scale's reliability and internal consistency, which provides an estimate proportion of variability in the scale score of the measured variable, in relation with the total variance within the participants' responses (Dunn et al., 2014; Kazman et al., 2014). According to Kazman et al. (2014), Cronbach's alpha has different classifications. However, researchers consider values of .60 as unacceptable, while values bigger than .80 are excellent. Nevertheless, researchers believe alpha measures of .70 or above are satisfactory (Kazman et al., 2014). The reliability of the UTAUT2 survey instrument also rests with the frequency in which technology adoption studies used similar instruments (Alazzam et al., 2016; Morosan et al., 2016, Oliveira et al., 2016; Venkatesh et al., 2012). Furthermore, prior studies have consistently shown alpha to be above the level of .70 (Alazzam et al., 2016; Morosan et al., 2016, Oliveira et al., 2016; Venkatesh et al., 2012).

Some criticisms rose against the use of Cronbach's alpha as an indicator of reliability. Dunn et al. (2014) stated that alpha depends on the number of various factors and the index can be biased. However, the authors recognized that if the researchers report the degree of certainty that alpha provides and consider the characteristics of the data set under study, they could explain better point estimates in psychometric applications. Nevertheless, Dunn et al. (2014) argued that despite Cronbach's alpha being among the predominant statistics in studies relying on psychometric scales, the fundamental limitation in estimating the degree of error of a scale is that a researcher cannot confidently get the actual value of a test's reliability in a particular situation. Peters (2014) stated that there are two main problems with using Cronbach's alpha as an index of scale reliability and internal consistency. From their perspective, not only there is no relation between Cronbach's alpha and a scale's internal consistency and an estimate of its reliability, but also researchers' assumption of repeated measurements of scale items, which is not respected and a difficult condition to fulfill. Nevertheless, Bonett and Wright (2015) argued that although some researchers are cautious about the small value of alpha for a response variable or a predictor variable in statistical analysis, there is no recognized little value for alpha. The author recommended that when reporting Cronbach's alpha, a researcher should supplement it with an interval of confidence. In the same line of ideas, Dunn et al. (2014) argued confidence intervals provide a better way of including precision of an estimate into a statistical summary considering that they are easy to comprehend and are a reference for rigorous statistical reporting. In this study, I used the Cronbach's alpha coefficient to assess the reliability of the scales of the instrument and report its value together with the confidence intervals.

Barry et al. (2014) argued that all other measurement characteristics become relatively void without validity. Hence addressing the score validity of the instrument is paramount. The measurement instrument used in the study relied on validated scales from previous studies. In fact, Huang and Kao (2015), Parameswaran, Kishore, and Li (2015), and Weeger et al. (2016) assessed the scales for the UTAUT constructs for their psychometric properties, including the reliabilities and validities, and found they exhibit satisfactory measurement properties. Moreover, Parameswaran, et al. (2015) found that scales for the UTAUT constructs are invariant. Thus, researchers could use them in future technology acceptance studies and get valid and similar results. Venkatesh et al. (2012) used and validated the seven constructs that I used in this study in a context of mobile Internet usage. Moreover, in various studies (Ain et al., 2015; Wong et al., 2014; Yuan et al., 2015), the authors adopted UTAUT2 measurements with minor changes and the instrument remains valid regarding reliability and construct validity. However, Barry et al. argued that since changes to an item's wording, structure or content/construct focus could affect respondent comprehension and interpretation, researchers should report validity of scales. Hence, in this study, I statistically estimated and indicated the validity of the UTAUT2 constructs although the alteration on survey items was minor.

In previous studies, Arenas-Gaitán, et al. (2015), and Parameswaran, et al.(2015), Oliveira et al. (2016) adapted surveys/scales to quantify and measure relevant participant characteristic. The authors validated the scale scores by assessing and reporting convergent validity and discriminant validity regarding factor loadings and average variance extracted (AVE). AVE is an estimation of the sum of all the square of factor loadings for a particular construct, divided by the total number of items measuring the construct (Henseler, Ringle, & Sarstedt, 2015; Nimako et al., 2014). Discriminant validity assesses whether a group of items is not related to a criterion (Arenas-Gaitán, et al., 2015; Barry et al., 2014; Nimako et al., 2014). Researchers can assess the convergent validity and discriminant validity using AVE (Nimako et al., 2014). Researchers determine discriminant validity by comparing the AVE of each construct with the shared variance between constructs (Ramirez-Correa et al., 2015). An AVE higher than .70 indicates discriminant validity (Arenas-Gaitán, et al., 2015; Oliveira et al., 2016; Ramirez-Correa et al., 2015; Venkatesh et al. 2012) whereas an AVE higher or equal to .50 indicates convergent validity (Nimako et al., 2014). Hence, to assess the validity, I assessed the convergent validity and the discriminant validity of the measurements.

Other researchers (Arenas-Gaitán et al., 2015; Choi et al., 2015; Nimako et al., 2014) used confirmatory factor analysis (CFA) test to assess the validity. CFA is an estimate of the common variance among a group of items using their linear relations to latent variables (Van der Eijk & Rose, 2015). With CFA, it is assumed the following: the existence of multivariate, normality, randomized sample, the presence of sufficient sample size, and the existence of correct prior model specification (Choi, et al., 2015; Feldt, 2014; Shan, Hu, Wang, & Liu, 2014). Furthermore, Van der Eijk and Rose (2015) argued that CFA required interval variables and that researchers should not conduct CFA on Likert items, which are ordered categorical, and as such violate this assumption of interval-level measurement. Although using CFA to assess convergent and discriminant validity is common, it is not the best approach to verify discriminant validity (Van der Eijk & Rose, 2015). Furthermore, the sample size in this study will be convenient. Therefore, to assess the validity, I did not use CFA in this study.

The purpose of the study was to examine the relationship between employees' habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value, and their consumerization behavioral intentions. As such, I measured these concepts using the survey instrument and elicited appropriate information to the independent constructs as predictors of employees' IT consumerization behaviors. I would the raw data collected available by request for five years after publication. Furthermore, I aligned the design of the survey questions with the research question and the constructs examined in the study. The survey questions aligned with the UTAUT2 model by addressing the model independent variables, and the dependent variable, IT consumerization behavioral intention. The first UTAUT2 variable, performance expectancy aligned with the survey instrument section one item questions 1 through 4. The second UTAUT2 variable, effort expectancy aligned with the survey instrument section two questions 1 through 4. The third UTAUT2 variable, social influence aligned with the survey instrument section three questions 1 through 3. The fourth UTAUT2 variable, facilitating conditions aligned with the survey instrument section four questions 1 through 4. The fifth UTAUT2 variable, hedonic motivation aligned with the survey instrument section five questions 1 through 3. The sixth UTAUT2 variable, price value aligned with the survey instrument section six questions 1 through 3. The seventh UTAUT2 variable, habit aligned with the survey instrument section seven questions 1 through 4. The dependent variable, IT consumerization behavioral intention, aligned with the survey instrument section seven questions 1 through 3. Section 8 is related the use construct of the UTAUT2 model. I included the survey instrument in the table of contents as Appendix C.

Data Collection Technique

Researchers use a questionnaire or self-administered questionnaire in a survey to collect data from the participants (Rowley, 2014). More so, the author added that self-administered questionnaires are made up of set open and closed questions. Researchers use questionnaires in conducting quantitative research where researchers need to collect data different predictive and analytical studies to examine any relationships between variables (Rowley, 2014). Hence, in this study, I used in this study, a survey with a questionnaire as a data collection tool. Furthermore, literature provides evidence to use a self-administered survey. In fact, in UTAUT2 studies (Tang, Lai, Law, Liew, & Phua, 2014; Nimako et al., 2014; Wong, Tan, Loke, & Ooi, 2015), the authors used self-administered surveys to collect data and demonstrated the reliability and validity of their instruments. The main advantage of questionnaires is that they provide an easy way to get responses from a considerable number of people (Rowley, 2014). However, the author added that with questionnaires, researchers do not have any certainty that the respondents have understood the questions, or whether response provided are accurate data. However, web-based surveys contribute to reliable data collection (Cardamone, Eboli, & Mazzulla, 2014). In fact, except for research costs reduction, the shortening of response times in the data phase, web-based surveys are efficiency data collection instruments (Bakla, Cekic, & Kosksai, 2013). Furthermore, in prior research, many researchers used a web-based survey to collect the data. In fact, Tang et al. (2016) relied on data collected through a web-based survey to explore the predictors of Gen Y's behavioral intention towards mobile wallet adoption based on UTAUT2. Tavares and Oliveira (2016) used a web-based survey to collect data to examine the main determinant to patients' decision to adopt or not electronic heath record portals. Yang (2013) relied on UTAUT2 to examine undergraduate students' mobile learning acceptance in a consumer context based on data collected from 182 undergraduate students using a web-based survey. Hence, I built a web-based questionnaire in a SurveyMonkey® form and distributed the link to the survey through emails to collect the data for this study.

I collected the data during four weeks after getting the authorization from Walden University IRB to conduct the research. I allowed two days for participants to complete the survey by providing their responses using the questionnaire. I kept on monitoring the data entry, and two days after sending out the survey, I sent out a reminder to the participants those who received the initial email. I expanded the survey life span until I reached the minimum sample of 103 participants required. As soon as I obtained the required minimum number of 103 participants, I closed down the survey. I will not conduct a pilot test after the IRB approval. I included the survey questions used in this study in Appendix C.

Data Organization Techniques

I used SurveyMonkey® to implement the questionnaire, collected and aggregated the data. I downloaded from SurveyMonkey® into Microsoft Excel format and uploaded the data into SPSS® package software, a statistical software program, to analyze, and interpret it. I presented the data in a narrative format in Section 3.

I encrypted and maintained the survey data safely in storage for five years as per Walden University IRB safety guidelines. If questions emerge regarding the study, the safeguarded data would be use as a source of data. Furthermore, I maintained ethical research protocols and ensured that each participant data collected and aggregated using SurveyMonkey® did not provide any identification.

Data Analysis Technique

Before analyzing data, researchers should check questionnaires for completion, discard incomplete surveys, transfer the data into a data analysis software, check and clean the data set, and group the data per variable type (Rowley, 2014). Thus, I verified the questionnaires to make sure that respondents fully completed them, and I discarded those with missing data. I also ensured that the data did not contain any omissions or mistakes due to the process of importing the data from the survey tool into the data analysis software.

The data analysis process focused on testing the hypotheses to provide answers the research question. Examining the relationship between habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value, and employees’ IT consumerization behavioral intentions, was the overarching purpose that underlies the undertaking of this quantitative correlation study. The following research question addressed the relationship between the independent variables and the dependent variable and provided a guide for this research: What is the relationship between employees' habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value, and employees' IT consumerization behavioral intentions? The null and alternative hypotheses related to the research question were

Null Hypothesis (H_0): There is no statistically significant relationship between employees' habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value, and employees' IT consumerization behavioral intentions.

Alternative Hypothesis (H_1): There is a statistically significant relationship between employees' habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value, and employees' IT consumerization behavioral intentions.

Various software tools exist to analyze data such as Microsoft Excel®, and Statistical Package for the Social Sciences (SPSS®) (Rowley, 2014). In prior UTAUT2 research (Ain, Kaur, & Waheed, 2015; Hsu & Lin, 2015; Lu, Liu, & Wei, 2016; Nimako et al., 2014; Sheng & Zolfagharian, 2015; Wong et al., 2014), the authors used SPSS® in the correlation analysis. Hence, I usedSPSS® to analyze the data. I also addressed the research question by testing the stated hypotheses, and I reported the results in the way that was consistent with the theoretical framework adopted in this study.

In prior studies, researchers relied on UTAUT and its extensions as a theoretical framework and used different types of structural equation modeling (SEM) to assess the relationship between variables. In fact, many researchers (Arenas-Gaitán, et al., 2015; Baptista & Oliveira, 2015; Escobar- Escobar-Rodríguez et al., 2014; Hsu & Lin, 2015; Nair, Ali, & Leong; 2015; Ramirez-Correa, et al., 2015) used partial least squares (PLS). Researchers such as Olasina, and Mutula (2015), and Tan and Lau (2016) used Pearson's correlation in their studies. Jung and Lee (2015), Khechine, Lakhal, Pascot, and Bytha (2014), Olasina, and Mutula (2015), and Slade, Williams, Dwivedi, and Piercy (2015), on the other hand, relied on multiple regression analysis. Other methods used in UTAUT and its extensions studies include analysis of variance (Magsamen-Conrad, Upadhyaya, Joa, & Dowd, 2015). In other studies, researchers used descriptive analysis and path analysis (Thakur & Srivastava, 2014).

According to Arenas-Gaitán, et al. (2015), researchers chose PLS because of it can be used for both reflective and formative scales, and it does not have a normal distribution and sample size constraints. Furthermore, researchers used PLS to model latent variables and assess parameters of entire theories simultaneously (Dijkstra, & Henseler, 2015). In this study, there was no modeling of latent constructs or a development of a theory. Thus, I did not use PLS. A path analysis involves examining the direct and indirect effects of the independent variables on the dependent variable (Blackwell, Lauricella, & Wartella, 2014; Liu, Fan, Xu, & Chen, 2014). In this study, I did not evaluate the effects of the independent variables. Thus, it did not include path analysis. Pearson’s correlation allows the researcher to determine the degree of linear relationship between two constructs (Choon, Sulaiman, & Mallasi, 2014). The primary test in this study concerned the hypothesis of the combined linear relationship between seven independent variables and one dependent variable. Hence, I did not use the correlation analysis.

Researchers use multiple regression analysis to examine the predictive power of at least two independent variables over the dependent variable (Woodside, 2013). According to Hopkins and Ferguson (2014), the main difference between multiple regression and the other such as hierarchical or stepwise regression is the order in which the independent variables get into the regression equation. In traditional multiple regression, all independent variables are entered simultaneously into the regression equation (Hopkins & Ferguson, 2014). I did not consider either hierarchical multiple regression nor stepwise multiple regression to analyze the data for this study. The rationale of not choosing hierarchical multiple regression analysis is that it evaluates the influence of control variables of other independent variables on the dependent variable prior to examining the relationship between them (Feldt et al., 2014; Hopkins & Ferguson, 2014; Martinez & Scott, 2014; Newton & Teo, 2014). Stepwise multiple regression analysis, on the other hand, allows the researchers to identify a group of independent variables that contribute the most toward predicting the dependent variable by removing the weakest correlated variable each time (Elzamly & Hussin, 2014; Hopkins & Ferguson, 2014; Huihua et al., 2015). Multiple regression analysis was suitable for this study because the objective was to examine the relationship between the independent variables and the dependent variable, and I evaluated independent variables simultaneously.

Nevertheless, Woodside (2013) noted that multiple regression analysis has three main limitations. First, researchers conducting multiple regression analysis will not be able to draw any conclusion regarding the interaction between dependent and independent variables. Second, Woodside (2013) added that multiple regression analysis excludes possible asymmetric relations between variables because of the symmetrical approach of the test. Third, it is not possible to rely on correlation coefficients to explain non-linear relations between constructs. Furthermore, researchers should be aware of the foundational requirements when they decide to use standard multiple regression analysis. In fact, there are assumptions of normality, linearity, multicollinearity, and homoscedasticity on the variables when using standard multiple regression analysis (Hassan, Farhan, Mangayil, Huttenen, & Aho, 2013; Hopkins & Ferguson, 2014; Suki, 2015; Zainodin & Yap, 2013).

The assumption of normality dictates a normal distribution of variables (Hopkins & Ferguson, 2014). The linearity assumption is that there is a linear relationship between the dependent variable and the coefficients of the model (Hopkins & Ferguson, 2014). To assess the existence of linearity between constructs, I tested for non-linearity. The most common approach to detecting non-linearity was to plot the residuals as a function of standardized predicted values (Hopkins & Ferguson, 2014). Researchers consider residual values as linear if the data points are to some degree tightly distributed around a diagonal line (Hopkins & Ferguson, 2014). Statistical packages such as SPSS® are useful to plot the residuals. The homoscedasticity assumption or constant variance of the error terms is that the random errors have the equal constant variance across independent variables (Hopkins & Ferguson, 2014). To test homoscedasticity, researchers can use statistical tests such as Durbin-Watson, Brown-Forsythe, and Levene (Hopkins & Ferguson, 2014. I used Durbin-Watson test, which is available in the SPSS® package to assess homoscedasticity assumption, and I used scatter plot and residuals plot to examine homoscedasticity visually.

The multicollinearity the assumption is that each predicted variable is independent of all other predicted variables (Baciu & Parpucea, 2013; Hopkins & Ferguson, 2014; Midi & Arezoo, 2013; Slade et al., 2015; Zainodin & Yap, 2013). If the violation of the multicollinearity assumption or independent error terms occurs, it will probably result in higher levels of Type I error (Bedeian, 2014; Hopkins & Ferguson, 2014), which means the increase of the likelihood of rejecting a true null hypothesis (Hopkins & Ferguson, 2014). The author argued that although a high R^2 value with a nonsignificant t-statistic indicates multicollinearity, the simplest way to detect potential issue multicollinearity is to check any high pairwise correlation between any two constructs. Another way to assess multicollinearity is to use the variation influence factor (VIF). VIF value above 10 indicates a multicollinearity problem (Hopkins & Ferguson, 2014; Slade et al., 2015), and a value between 5 and 10 indicates a possibility of a multicollinearity problem (Hopkins & Ferguson, 2014). VIF value can be calculated using SPSS® (Hopkins & Ferguson, 2014). A researcher can use Durbin–Watson statistic as a step to correct the problem involving multicollinearity (Hopkins and Ferguson, 2014). Hence, I evaluated the existence of independent error terms by noting the correlation coefficients among the predictor constructs and assessed the problem by calculating the VIF value.

There are other quantitative statistical analyses, which I did not consider appropriate for this study. These statistical analysis approaches encompass bivariate linear regression, factor analysis, and discriminant analysis. I did not use bivariate linear regression because this study concerned seven variables. Researchers use discriminant analysis to classify individuals into groups based upon one or more measures (Buettner, 2015). The purpose of this study did not include classifying groups and, therefore, discriminant analysis was not an appropriate analysis technique for the study. Researchers use factor analysis to lower large groups of overlapping measured variables to smaller groups, which often represent unobserved latent variables (Grassi-Oliveira, Cogo-Moreira, Salum, Brietzke, Viola, Manfro, Kristen, & Arteche, 2014). In this study, I did not use latent variables. Therefore, factor analysis was not appropriate.

Various researchers in their quantitative studies (Motamedi Joybari, Gholipour, & Yazdani Charati; 2013; Wang & Wang; 2014) used SPSS® to analyze the data. Researchers (Lira, Ripoll, Peiro, & Zornoza, 2013; Otte, Bngerter, Britsch, & Wuthrich, 2014) also generated descriptive statistics in SPSS® on the data collected in their quantitative studies to describe the essential features of the studies. I used SPSS® to generate descriptive statistics to provide summaries about the sample, representative scores, the amount of variation in the data, and normality detail, and I carried out multiple regression tests. I included descriptive statistics and the multiple regression analysis test results in tables and Section 3.

Reliability and Validity

Reliability and validity of measures are the prime validation issues researchers need to address in quantitative research (Venkatesh et al., 2013). In the following paragraphs, I explained the steps I took to ensure that this study is reliable and valid.

Reliability

The validity of a quantitative research depends on the reliability of the research instruments (Venkatesh et al., 2013). The author added that a research instrument is reliable when it produces quality results in a repeatedly. According to Šumak and Šorgo, (2016), a researcher can reduce the possibility of errors in measurement by adapting questionnaire items from previous studies. Therefore, I used the survey instrument from Venkatesh et al. (2012) to reduce errors in measurement. Furthermore, according to Topaloglu, Caldibi, and Oge (2016), researchers use Cronbach's alpha to assess the quality of instrument measurements when the scale is Likert-type and administered only once. Because I used an ordinal 7-point Likert-type scale to measure the respondents' answers, using Cronbach's alpha was appropriate in this study, to address the threats to reliability.

Validity

Research validity refers to the accuracy of the findings (Venkatesh et al., 2013). The authors identified three types of validity in quantitative studies, namely measurement, design validity, and inferential validity. Measurement validity encompasses reliability and construct validity, and refers to how efficiently an instrument measures what it is supposed to measure regarding the definition of the construct

(Venkatesh et al., 2013; Yilmaz, 2013). I used Cronbach's alpha to measure the internal consistency of the reliability of the measures to establish the instrument reliability. According to Henseler et al. (2015), because threats to construct validity derive from different sources, researchers have to use various construct validity subtypes such as convergent validity, discriminant validity, and criterion validity to assess their results. Therefore, to address threats to the construct validity, I assessed the convergent validity and the discriminant validity of the measurements.

Design validity relates to both internal and external validity (Venkatesh et al., 2013). Internal validity refers to the existence of cause-effect or causal relationships in a scientific inquiry (Aguinis & Edwards, 2014; Neall & Tuckey, 2014; Pirog, 2014; Venkatesh et al., 2013; Yilmaz, 2013). The objective of this study was to examine the relationship between the independent and dependent variables. Hence, I did address internal validity in this study. External validity relates to the extent to which research findings are generalizable to other settings and populations (Lancsar & Swait, 2014; Krupnikov & Levine, 2014; Landers & Behrend, 2015; Venkatesh et al., 2013; Yilmaz, 2013). According to Landers and Behrend (2015), researchers' approach to threats to external validity has to be systematic and scientific. Furthermore, the authors added that sampling strategy critically impacts the validity of a researcher's findings. Hence, if the sample is not adequately selected to represent the target population, it will become the major threat to external validity (Bevan, Baumgartner, Johnson, & McCarthy, 2013; Pye et al., 2016).

In this study, I used a convenience sampling strategy. Researchers such as Acharya et al. (2013), Krupnikov and Levine (2014), and Raschke et al. (2013) argued that nonprobability sampling would not allow the researcher to generalize the research findings from the sample to the desired population. Landers and Behrend (2015) claimed that when a researcher chose a convenient sample, he would need more than the probability to make a case of sample representativeness. The authors added that convenience sampling means getting a randomized sample from a convenient population and rationally proving that the convenient population is very similar to the targeted population. Hence, convenient samples' external validity hinge on the sample particular characteristics and the research setting and procedures (Landers & Behrend, 2015). To address external validity in this study, I developed the following strategies. In various studies (Anderson & Levitt, 2016; Duffey, Haberstroh, Ciepcielinski, & Gonzales, 2016), the authors used a priori power analysis to estimate sample size. Likewise, I conducted a power analysis using G*Power with seven level of the independent variable, an alpha of .05, an effect size of .15, and a power of .80. I got a minimum projected sample size of 103 participants. The rationale is that Balkin and Sheperis (2011) suggested G*Power as appropriate tools for conducting power analysis to estimate the research sample size before the data collection. The next approach I took to minimize threats to the external validity was to ensure that the data collection instrument is valid and reliable. In fact, several researchers (Alazzam et al. 2015; Morosan et al., 2016; Oliveira et al., 2016; Venkatesh et al., 2012) showed that UTAUT2 instrument scales are reliable and valid. Furthermore, the AVE estimate contributed to establishing external validity. The third approach was related to the population characteristics. SMBs in Ontario share similar characteristics to other SMBs within the province but also across Canada. Nevertheless, Peterson and Merunka (2014) stated that scientific recommend that statistical conclusions have to be limited to the populations from which the researcher derives samples. Therefore, the findings from this study might be generalizable to the population of SMBs located in the Ontario province.

Inferential or statistical conclusion validity refers to inferences based covariation between the independent and dependent variables (Gibbs & Weightman, 2014; Rideout & Gray, 2013; Venkatesh et al., 2013). Neall and Tuckey (2014), and Rodriguez (2013) stated false positive and false negative arguments regarding the relation between variables are threats statistical conclusion validity. Furthermore, Kennedy (2015) added that the sample size, the effect size, the alpha, and the power are the four components that influence inferential. I conducted a power analysis to estimate the sample size before data collection, an action, which would contribute to minimizing threats to inferential and make a case for the study validity. In fact, effect size provides an estimate of the magnitude of the relationship between variables and informs study design and statistical analysis (Bosco et al., 2015; Eisend, 2015). Furthermore, researchers such as Šumak, & Šorgo (2016), de Sena Abrahão, Moriguchi, and Andrade (2016) showed that is appropriate to use a medium effect size in quantitative research in the context of technology acceptance. Researchers such as de Sena Abrahão et al. (2016), Olalekan and Tajudeen (2015), and Šumak and Šorgo (2016), used a significance level of .05 in quantitative studies to reject the null hypothesis. Hence, the use of a medium effect size (f

= .15, a = .05) to get a minimum sample size of 103 participants and achieve a power of .80, contributed to minimizing threats to statistical conclusion validity in this study. Another strategy I used to reduce the impact of the threats to the findings was the use of multiple regression analysis to understand the strength the relationship between variables. In fact, several researchers (Bettis, Gambardella, Helfat, & Mitchell, 2014; Collard, Ruttle, Buchanan, & O'Brien, 2013; Elzamly & Hussin, 2014; Mohapatra & Das, 2013) stated that regression analysis could help achieve both the rejection of alternative explanations and the correlation between variables.

Transition and Summary

The purpose of this study was to investigate thoroughly the propensity of employees working for SMBs in the province of Ontario to embrace IT consumerization. In Section 1, I discussed the background of the study, the problem statement, the purpose statement, and the nature of the study. I included in this section, my assumption as a researcher, the research limitations, and delimitations. The section continued with the research question, the hypothesis, and a discussion on a theoretical framework. The academic literature review closed this section. I began Section 2 by restating the purpose of providing a reader with a broad perspective of the nature of the project. I also discussed the role of the researcher to inform the reader of what role I played in this research process. I continued in Section 2 with a discussion of the research method and design. I followed up with the description of the population and sampling strategy. Additionally, I included the process I implemented regarding the data storage and security to make sure that I guaranteed the ethical measures required for the approval of the study. In Section 3, I discussed the research findings. I also addressed the study effects on the professional community and the implications for social change. The section continues with a discussion on recommendations for actions and further research, reflections and a conclusion.

Section 3: Application to Professional Practice and Implications for Change

In Section 1, I discussed the background of the study, presented the problem and purpose statements, and described the nature of the study. I included in that section the research question, the hypothesis, and a discussion of the theoretical framework I used. I closed this section with a review of the relevant academic literature. I discussed the research process I used to conduct my quantitative study of the relationship between employees' habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value and employees' consumerization behavioral intentions in Ontario, Canada. In Section 3, I present an overview of the study and a summary of study findings. I also explore how the findings relate to IT practice. I also discussed the impact of the findings on CIOs' decisions to implement IT consumerization policies. I follow up by discussing the implications of my research for social changes and offering recommendations for action and further study. The section ends with my reflections and a conclusion.

Overview of Study

The purpose of this quantitative correlation study was to examine the relationship between employees' habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value and employees' consumerization behavioral intentions. I used inferential statistics (specifically, Pearson's coefficient and multiple linear regression analysis) to test for the existence of a relationship between habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value, the independent variables, and the dependent variable, consumerization behavioral intention.

To ensure that the results were statistically valid, I chose 0.05 as the *p*-value for this test. The Pearson's coefficient (r) analysis showed a significant correlation between employees' consumerization behavioral intentions and all of the independent variables except for facilitating conditions. Results of the tests showed significant correlations between employees' consumerization behavioral intentions and effort expectancy, $r(108) = .661$, $p < .001$, performance expectancy, $r(108) = .699$, $p < .001$, habit, $r(108) = .754$, $p < .001$, price value, $r(108) = .232$, $p < .001$, hedonic motivation, r(108) = .570, $p < .001$, social influence, $r(108) = .523$, $p < .001$, and facilitating conditions, $r(108) = .399$, $p < .001$.

The test of results of the multiple regression indicated that the independent variables were statistically significant in predicting employees' consumerization behavioral intentions [F (7, 100) = 58.524, $p < .001$, $R^2 = .842$, adjusted $R^2 = .831$]. The results accounted for approximately 84% of the variance in employees' consumerization behavioral intentions. Performance expectancy ($\beta = .356$, $p < .001$), habit ($\beta = .269$, $p < .001$), and social influence ($\beta = .258$, $p < .001$) were significant at the .001 level as predictors of employees' consumerization behavioral intentions. Effort expectancy ($\beta = .187$, $p < .01$), facilitating conditions ($\beta = .114$, $p < .01$), hedonic motivation ($\beta = .107$, $p < .01$), and price value ($\beta =.105$, $p < .01$), were significant at the .005 level as predictors of employees' consumerization behavioral intentions. I found all seven key variables to predict employees' consumerization behavioral intentions. Hence, I rejected the null hypothesis because the results of the study confirmed a positive relationship between employees' habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value and employees' consumerization behavioral intentions.

Presentation of the Findings

In this study, I chose a quantitative correlational design. I also used a standard multiple regression analysis to examine the relationship between employees' habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value and employees' consumerization behavioral intentions. Following are my research question and corresponding hypotheses

What is the relationship between employees' habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value and employees' consumerization behavioral intentions?

The null hypothesis and the alternative hypothesis addressed in this study were

H_0: There is no statistically significant relationship between employees' habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value and employees' consumerization behavioral intentions.

H_1: There is a statistically significant relationship between employees' habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value and employees' consumerization behavioral intentions.

To answer the research question, I collected data using a web-based survey which I administered via the social media platform LinkedIn®. The participants were employees from SMBs based in the province of Ontario, Canada. Seven hundred and twenty three eligible participants received e-mails soliciting their participation in the study. Selected participants received follow-up reminders to participate in the study over a period of 4 weeks following approval from Walden University's IRB. I received 112 completed surveys but excluded four because they were incomplete. This left 108 usable surveys. This number (108) exceeded the required minimum sample size of 103 or 106 participants that I calculated using G*Power 3.1 software analysis and Green's formula (Green, 1991) for sample size determination. I ended data collection after receiving sufficient completed surveys to complete my analysis.

Participant Characteristics

The descriptive statistics indicated that 53.7% (58) of the participants were women and 50 participants (46.3%) were men. Table 1 displays the participants by age.

Table 1

Age of Participants

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	23	3	2.8	2.8	2.8
	24	7	6.5	6.5	9.3
	25	5	4.6	4.6	13.9
	26	3	2.8	2.8	16.7
	27	6	5.6	5.6	22.2
	28	5	4.6	4.6	26.9
	29	4	3.7	3.7	30.6
	30	3	2.8	2.8	33.3
	31	5	4.6	4.6	38.0
	32	10	9.3	9.3	47.2
	33	2	1.9	1.9	49.1
	34	3	2.8	2.8	51.9
	35	6	5.6	5.6	57.4
	36	7	6.5	6.5	63.9
	37	3	2.8	2.8	66.7
	38	4	3.7	3.7	70.4
	39	3	2.8	2.8	73.1
	40	2	1.9	1.9	75.0
	41	1	.9	.9	75.9
	42	3	2.8	2.8	78.7
	43	2	1.9	1.9	80.6
	44	2	1.9	1.9	82.4
	45	4	3.7	3.7	86.1
	46	3	2.8	2.8	88.9
	47	1	.9	.9	89.8
	50	1	.9	.9	90.7
	51	3	2.8	2.8	93.5
	52	2	1.9	1.9	95.4
	53	1	.9	.9	96.3
	55	2	1.9	1.9	98.1
	56	1	.9	.9	99.1
	60	1	.9	.9	100.0
	Total	108	100.0	100.0	

Survey Instrument Characteristics

I used a validated survey instrument (see Appendix C) to collect the data from employees working for SMBs in the province of Ontario, Canada. I recruited the participants on LinkedIn®. The survey included 28 items based on a Likert-type scale ranging from 1 (strongly disagree) to 7 (strongly agree).

Validity and Reliability Test Results

As discussed in Section 2, the measurement instrument I used relied on validated scales from previous studies. The scales for the UTAUT constructs are invariant and can be used in other technology acceptance studies to produce similar, valid results, according to Parameswaran et al. (2015). Although Venkatesh et al. (2012), tested and validated the seven key constructs used in this study, because I replaced “mobile Internet” with “consumer IT tools” in the questions’ wording of my survey instrument, I followed Barry et al.’s (2014) suggestion, and I assessed the validity of scales. To evaluate the validity of the measurement, I tested convergent and discriminant validity of the measurement instrument. Table 2 displays the results of the validity test from the 28 questions in the electronic survey relating to the seven key constructs of the UTAUT2 model. The values of the AVE for each component for the entire dataset was higher than .50, which indicates convergent and discriminant validity.

Table 1

Validity Statistics

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% Variance	AVE	Total	% of Variance	AVE
PE1	2.599	64.979	.650	2.599	64.979	.650
PE2	.879	21.966	.220			.22
PE3	.420	10.503	.105			.11
PE4	.102	2.552	.026			.03
EE1	2.737	68.418	.684	2.737	68.418	.684
EE2	.599	14.985	.150			.15
EE3	.385	9.614	.096			.10
EE4	.279	6.983	.070			.07
SI1	2.406	80.196	.802	2.406	80.196	.802
SI2	.469	15.626	.156			.16
SI3	.125	4.178	.042			.04
FC1	2.265	56.613	.566	2.265	56.613	.566
FC2	.878	21.941	.219			.22
FC3	.618	15.454	.155			.15
FC4	.240	5.992	.060			.06
HM1	2.807	93.577	.936	2.807	93.577	.936
HM2	.139	4.622	.046			.05
HM3	.054	1.801	.018			.02
PV1	2.227	74.242	.742	2.227	74.242	.742
PV2	.712	23.737	.237			.24
PV3	.061	2.021	.020			.02
HT1	2.070	51.742	.517	2.070	51.742	.517
HT2	1.283	32.082	.321			.32
HT3	.415	10.378	.104			.10
HT4	.232	5.798	.058			.06
BI1	2.278	75.940	.759	2.278	75.940	.759
BI2	.604	20.121	.201			.20
BI3	.118	3.938	.0391			.04

Note PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitating conditions, HM = hedonic motivation, PV = price value, BI = behavioral intention, and HT = habit.

Alazzam et al. (2015), Morosan et al. (2016), Oliveira, et al. (2016) and Yuan et al. (2015) had validated and used their studies. However, Chiu, Hsueh, Hsieh, and Hsieh (2014) recommended to testing the validity and reliability of the survey instrument before using it to assess the relationships between variables. Hence, I performed a Cronbach's alpha test using SPSS® to evaluate the reliability of the UTAUT2 instrument. The value for Cronbach's alpha for the entire dataset was 0.898, based on unstandardized items. I used Cronbach's alpha to measure the internal consistency of the scales and demonstrated that a group of measured indicators rely on only one underlying construct. This result indicated that the instrument was a reliable instrument to measure the behavioral intentions of employees from SMBs based in the Province of Ontario. Table 3 indicates that the values for all of the item variables involved are above 0.7, hence, considered as reliable. However, I note that except for PE1, FC4, HT2, HT3, the removal of any other item variable would result in a lower Cronbach's alpha than the one of the entire dataset.

Table 3

Cronbach’s Alpha Items (Total Statistics)

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PE1	147.55	243.689	.120	.899
PE2	147.85	226.240	.647	.891
PE3	147.90	228.391	.557	.893
PE4	147.95	224.587	.639	.891
EE1	147.82	232.688	.552	.894
EE2	147.83	233.318	.568	.894
EE3	147.82	236.520	.454	.895
EE4	148.02	230.205	.595	.893
SI1	148.84	233.125	.388	.896
SI2	148.89	233.408	.388	.896
SI3	148.86	229.429	.599	.892
FC1	147.82	232.371	.397	.896
FC2	148.29	234.319	.418	.895
FC3	148.00	234.336	.360	.896
FC4	147.97	238.308	.219	.899
HM1	148.60	224.747	.618	.891
HM2	148.59	228.075	.558	.893
HM3	148.76	224.502	.626	.891
PV1	147.92	229.423	.507	.894
PV2	148.19	234.027	.304	.898
PV3	148.18	234.838	.315	.898
HT1	148.81	199.728	.692	.891
HT2	151.54	238.419	.167	.901
HT3.	150.14	252.644	-.233	.906
HT4	149.26	220.624	.551	.893
BI1	147.71	220.169	.772	.888
BI2	147.95	227.091	.689	.891
BI3	147.93	219.079	.740	.888

Note PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitating conditions, HM = hedonic motivation, PV = price value, BI = behavioral intention, and HT = habit.

After performing the Cronbach’s alpha test, I computed the scale for each construct by calculating the average of all the items’ scale of each construct for each participant. The value for Cronbach’s alpha was 0.794. This result indicates that the instrument was a reliable instrument to measure the behavioral intentions of employees from SMBs based in Ontario, Canada. Table 5 shows that the values for all of the variables involved are above 0.7. Thus they are accepted as reliable. However, I note that except for price value, the removal of any other variable would result in a lower Cronbach's alpha than the Cronbach's alpha calculated for entire UTAUT model.

Table 5

Cronbach’Alpha Items-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PE	37.8117	17.363	.512	.570	.769
EE	37.8418	17.951	.578	.518	.764
SI	38.8449	18.033	.399	.373	.786
FC	37.9622	18.049	.412	.370	.784
HM	38.6011	15.948	.520	.467	.770
PV	38.1381	18.858	.195	.298	.825
HT	39.9159	16.348	.685	.673	.743
BI	37.9715	15.093	.877	.842	.710

Note PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitating conditions, HM = hedonic motivation, PV = price value, BI = behavioral intention, and HT = habit.

Following the validity and reliability tests, I performed standard multiple regression tests, $\alpha = 0.05$ (two-tailed), to examine the efficacy of employees' habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value in predicting, employees' IT consumerization behavioral intentions.

Descriptive statistics.

I received 112 survey responses, and discarded four records due to missing data, resulting in 108 records used in the analysis. Table 6 presents descriptive statistics of the study variables.

Table 6.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
PE	108	3.50	7.00	6.0579	.86913
EE	108	5.00	7.00	6.0278	.69320
SI	108	3.00	7.00	5.0247	.88802
FC	108	4.00	7.00	5.9074	.86508
HM	108	4.00	7.00	5.2685	1.11579
PV	108	3.00	7.00	5.7315	1.07309
HT	108	2.25	5.25	3.9537	.85663
BI	108	4.33	7.00	5.8981	.87596

Note PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitating conditions, HM = hedonic motivation, PV = price value, BI = behavioral intention, and HT = habit.

Test of Assumptions.

In this section, I present results of tests of the assumptions of multicollinearity, normality, and linearity. This section also contains test results of the assumptions of independence of residuals and homoscedasticity.

Multicollinearity. The assumption of multiple regression posits that there is no collinearity among independent variables (Zainodin & Yap, 2013). According to Baciu and Parpucea (2013) and Midi and Arezoo (2013) argued that multicollinearity exists if a correlation between two or more independent variables exists. I examined the correlation table for evidence of multicollinearity among the constructs as shown in Table 7. I calculated Pearson correlations to identify the relationships between the variables. I computed the average score of the multi-items for a construct because multiple items measured a single construct in the questionnaire. The highest correlation between the constructs was 0.754.

Table 7.

Correlations Statistics

		PE	EE	SI	FC	HM	PV	HT	BI
PE	Pearson Correlation	1	.478**	.191*	.166	.278**	.097	.541**	.699**
	Sig. (2-tailed)		.000	.048	.087	.004	.318	.000	.000
	N	108	108	108	108	108	108	108	108
EE	Pearson Correlation	.478**	1	.249**	.094	.504**	.048	.630**	.661**
	Sig. (2-tailed)	.000		.009	.334	.000	.623	.000	.000
	N	108	108	108	108	108	108	108	108
SI	Pearson Correlation	.191*	.249**	1	.269**	.286**	.085	.296**	.523**
	Sig. (2-tailed)	.048	.009		.005	.003	.379	.002	.000
	N	108	108	108	108	108	108	108	108
FC	Pearson Correlation	.166	.094	.269**	1	.200*	.486**	.245*	.399**
	Sig. (2-tailed)	.087	.334	.005		.038	.000	.011	.000
	N	108	108	108	108	108	108	108	108
HM	Pearson Correlation	.278**	.504**	.286**	.200*	1	.014	.636**	.570**
	Sig. (2-tailed)	.004	.000	.003	.038		.886	.000	.000
	N	108	108	108	108	108	108	108	108
PV	Pearson Correlation	.097	.048	.085	.486**	.014	1	.017	.232*
	Sig. (2-tailed)	.318	.623	.379	.000	.886		.863	.015
	N	108	108	108	108	108	108	108	108
HT	Pearson Correlation	.541**	.630**	.296**	.245*	.636**	.017	1	.754**
	Sig. (2-tailed)	.000	.000	.002	.011	.000	.863		.000
	N	108	108	108	108	108	108	108	108
BI	Pearson Correlation	.699**	.661**	.523**	.399**	.570**	.232*	.754**	1
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.015	.000	
	N	108	108	108	108	108	108	108	108

Note PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitating conditions, HM = hedonic motivation, PV = price value, BI = behavioral intention, and HT = habit.
*. Correlation is significant at the 0.05 level (2-tailed)
**. Correlation is significant at the 0.01 level (2-tailed).

To reduce multicollinearity among the variables, I mean-centered variable with r > .50 as in Venkatesh et al. (2012). To further test for multicollinearity, I calculated and examined the values of the independent variables' VIFs to validate the assumption of absence of multicollinearity. All values below were lower than the conservative threshold of 5, thus suggesting that multicollinearity was not a major issue in the study. Table 8 shows the calculated VIF values that ranged from 1.175 to 2.597, which is below the common VIF threshold of 10. Therefore, there was multicollinearity issue among the variables (Hopkins & Ferguson, 2014; Slade et al., 2015). Moreover, all the predictors were below 0.5, hence, indicates no possibility of a multicollinearity problem.

Table 8.

Correlations Coefficients Among Study Predictors Variables

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	-.682	.294		-2.319	.022	-1.265	-.099		
	PE	.359	.050	.356	7.242	.000	.260	.457	.655	1.527
	EE	.237	.068	.187	3.464	.001	.101	.372	.540	1.852
	SI	.254	.043	.258	5.979	.000	.170	.339	.851	1.175
	FC	.115	.049	.114	2.336	.022	.017	.213	.664	1.506
	PV	.084	.042	.107	2.011	.047	.001	.168	.554	1.805
	HM	.086	.038	.105	2.280	.025	.011	.161	.738	1.355
	HT	.276	.066	.269	4.206	.000	.146	.406	.385	2.597

Note PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitating conditions, HM = hedonic motivation, PV = price value, , and HT = habit.

a. Dependent Variable: BI: behavioral intention

Outliers, normality, linearity, homoscedasticity, and independence of residuals. I evaluated the outliers, normality, linearity, homoscedasticity, and independence of residuals by examining the normal probability plot of the regression standardized residual (Figure 3), the histogram of the standardized residuals (Figure 5), and the scatterplot of the standardized residuals shown in Figure 4. By reviewing the unusual data pattern using a random sample of a population, researchers can visually assess the existence of outliers (Astill, Harvey, & Taylor, 2013; Ghapor, Zubairi, Mamum, & Imon, 2014). The output showed that some of the outcome variables deviated from normality. Ghapor et al. suggested a bootstrapping testing to evaluate the outliers. Hence, I used bootstrapping analysis to examine the influence of assumption violations. I used bootstrap regression based on 2,000 random samples to ensure robustness of variable estimates. The objective was to evaluate the assumption violations using based 95 % confidence intervals and derive p values, avoiding any normality-based assumption associated with the t-distribution used in the standard linear regression.

The examinations indicated no major violations of these assumptions. The tendency of the points indicated that violation of the assumption of normality was not present. It is observable that the absence of a regular pattern in the scatterplot of the standardized residuals (Figure 3) supported the assumptions being satisfactory.

Figure 3. Normal probability plot (P-P) of the regression standardized residual.

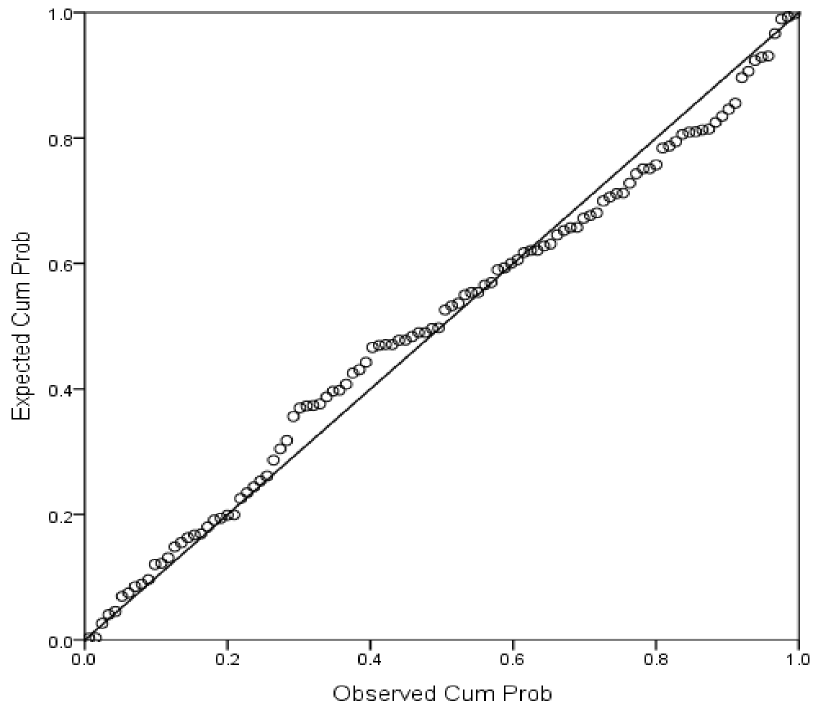


Figure 4. Scatterplot of the standardized residuals.

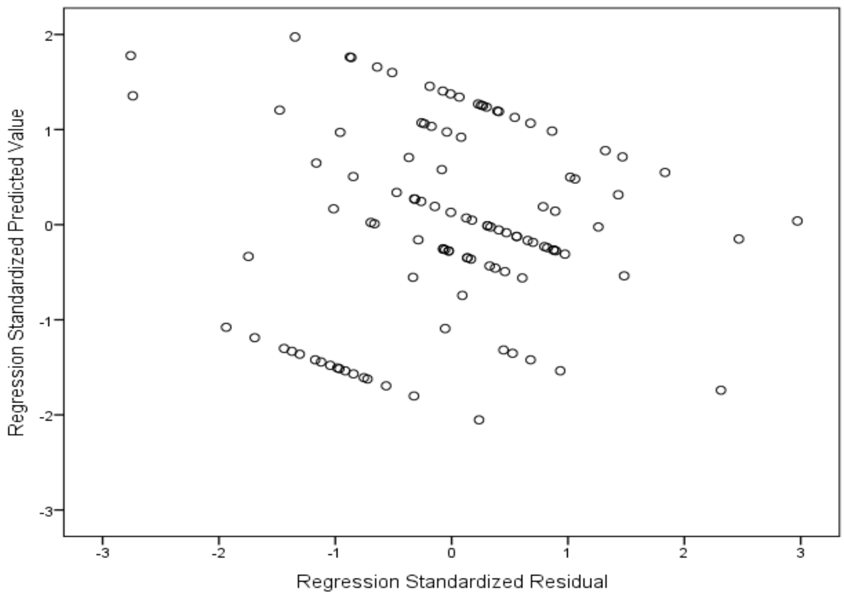
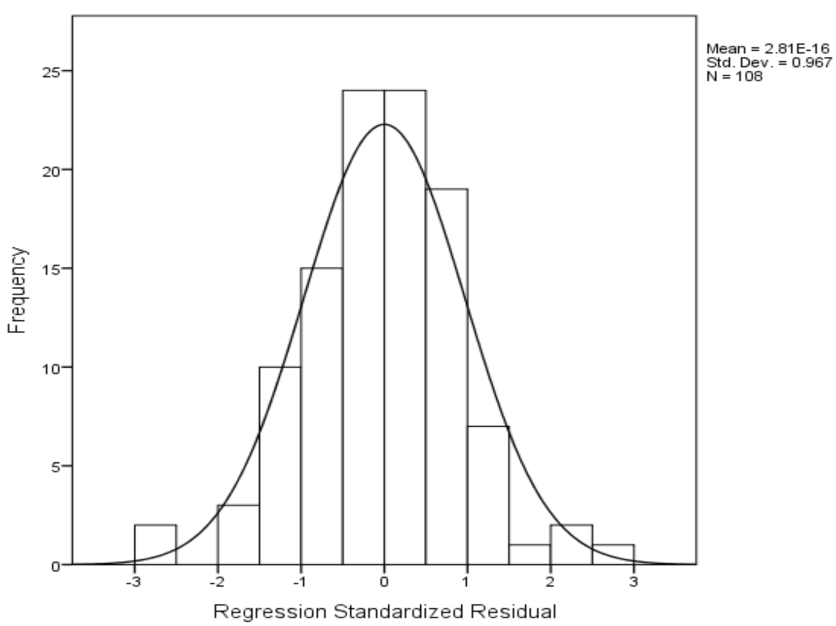


Figure 5. Histogram of the regression standardized residual.



I examined and analyzed the skewness and kurtosis values of the data them to look for any normality issue. The cutoff values for skewness and kurtosis to assume normality are ±3 and ±10 respectively (Blanca, Arnau, López-Montiel, Bono, & Bendayan, 2015; Garner, Moses, & Waajid, 2013). After analyzing the normality test results, the values of each variable's skewness and kurtosis test result came within the advised measures of normality. In fact as shown in Table 9, the skewness test values varied from -1.106 to 0.720, and the kurtosis test values ranged from -1.405 to 1.351 for all variables.

Table 9.

Descriptive Statistics Skewness And Kurtosis

						95% CI	
			Statistic	Bias	Std. Error	Lower	Upper
	N	108		0	0	108	108
PE	Skewness	-1.106	.233	.043	.193	-1.406	-.622
	Kurtosis	1.351	.461	-.116	.483	.319	2.205
	N	108		0	0	108	108
EE	Skewness	-.015	.233	.003	.116	-.245	.211
	Kurtosis	-1.066	.461	.028	.169	-1.340	-.658
	N	108		0	0	108	108
SI	Skewness	.720	.233	-.010	.177	.346	1.063
	Kurtosis	-.084	.461	.023	.427	-.789	.892
	N	108		0	0	108	108
FC	Skewness	-.425	.233	.007	.151	-.716	-.118
	Kurtosis	-.594	.461	.008	.240	-.983	-.041
	N	108		0	0	108	108
HM	Skewness	.148	.233	.000	.144	-.141	.421
	Kurtosis	-1.405	.461	.024	.089	-1.538	-1.188
	N	108		0	0	108	108
PV	Skewness	-.182	.233	.009	.164	-.496	.150
	Kurtosis	-1.090	.461	.009	.210	-1.418	-.600
	N	108		0	0	108	108
HT	Skewness	-.684	.233	.001	.145	-.978	-.392
	Kurtosis	-.556	.461	.044	.352	-1.088	.260
	N	108		0	0	108	108
BI	Skewness	-.510	.233	-.004	.125	-.761	-.275
	Kurtosis	-.701	.461	.046	.283	-1.147	-.058
Valid N (listwise)	N	108		0	0	108	108

Note. PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitating conditions, HM = hedonic motivation, PV = price value, BI = behavioral intention, HT = habit, and CI = confidence interval.

Consequently, the data collected were considered normal and there was no need for transformation. An insignificant violation would be permitted, and the efficiency of the survey is certain when the size of the sample is larger than 100 participants (Barker & Shaw, 2015). Hence, for this study with a sample size as large as 108 participants, Pearson's correlation coefficient analysis and multiple linear regression analysis may perhaps bear minor deviations from the assumption of normality and would be considered appropriate. To validate the homoscedasticity assumption, I used Durbin-Watson test and examined the residual scatter plot as discussed in Section 2. The Durbin-Watson value of 1.757 was higher than the upper limit 1.587 and below 2. Therefore the homoscedasticity assumption was met.

Inferential Results. I used a standard multiple linear regression, $\alpha = .05$ (two-tailed), to examine whether employees' habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value were able to predict SBMs' employees' consumerization behavioral intentions in the province of Ontario, Canada. Before conducting the regression test, I assessed the possible existence of the assumptions of multiple regression analysis, by investigating multicollinearity, normality, linearity, homoscedasticity, and independence of residuals. There were no violations of assumptions after the test. The model was statistically significantly to predict the SBMs' employees' consumerization behavioral intentions in the province of Ontario, F (7, 100) = 76.097, $p < .001$, and accounted for approximately 84% of the variance in employees' behavioral consumerization intentions ($R^2 = .842$, adjusted $R^2 = .831$). The R^2 of .842 showed that seven major variables, namely habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value defined 84% of the variance in the employees' consumerization behavior intentions. I rejected the null hypothesis. The p-value for each construct, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit was below 0.05. Therefore, all the seven constructs were statistically significant predictors of employees' consumerization behavior intentions.

The positive slope for performance expectancy, effort expectancy, social influence, hedonic motivation, facilitating conditions, price value, and habit as predictors of the employees' consumerization behavior intentions (BI) indicated that an increase of each of these constructs led to an increase of the intention to adopt consumers' IT tools. However, performance expectancy, social influence, habit, and effort expectancy, had a stronger impact on employees intention to adopt consumers' IT tools than facilitation conditions, hedonic motivation, and price value. Appendix D contains SPSS® output for this study.

I tested the influence of age and gender to assess their effect on the relations between facilitating conditions and BI, hedonic motivation and BI, price value and BI, and habit and BI. Table C9 in Appendix C infers that age moderated the relationships between the four constructs, habit, facilitating conditions, hedonic motivation, price value, and behavior intention.

Analysis Summary. I examined in this study, the relationship employees' habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value and their behavioral intentions in the context of IT consumerization. Hence, I conducted standard multiple linear regression tests to assess this relationship. Despite the absence of any serious violations of the assumptions surrounding the multiple regressions analysis, I used bootstrapping test with a sample of 2000 samples and 95% confidence interval to address any potential violations of the statistical assumption. I calculated question items' AVE values to verify the validity of UTAUT2 measurement instrument and a Cronbach's alpha test to evaluate the reliability of the instrument. Since all 28 items 'alpha of the UTAUT 2 were above 0.80, which indicated the UTAUT2 Instrument was reliable in measuring SBMs' employees' consumerization behavioral intentions in the province of Ontario. The value for Cronbach alpha value for the entire dataset was 0.898, which indicated the UTAUT2 Instrument was a reliable instrument. The findings supported the arguments of Yuan et al. (2015), Alazzam et al. (2015), Morosan et al. (2016), Oliveira et al. (2016), and Venkatesh et al. (2012) that the UTAUT2 model is appropriate to measure the behavioral intentions. Overall, the seven key constructs of the UTAUT2 model predicted SMBs employees' behavioral intentions with regards to IT consumerization in Ontario, Canada , F (7, 100) = 76.097, $p < .001$, $R^2 = .842$. Further, although I found all the seven predictors significantly associated with the SBMs' employees' IT consumerization behavioral intentions, some constructs had a stronger influence when compared. In fact, the analysis of the beta (β) values showed that performance expectancy, social influence, habit, and effort expectancy, tend to be stronger in influencing employees intention to adopt consumers' IT tools than hedonic motivation, facilitation conditions, and price value.

Theoretical conversation on findings

I used in this study the UTAUT2 model developed in Venkatesh et al. (2012) as a theoretical model for this study. Venkatesh et al. suggested that habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value, are the key construct predictors of behavior intention and use behavior of the UTAUT 2 model. The results for the validity (AVE above 0.50) and reliability (Cronbach alpha value = 0.794) tests indicated that the UATUT2 model was relevant to measure SMBs' employees' IT consumerization behavioral intentions in the province of Ontario. The validity and reliability results supported the arguments from Alazzam et al. (2015), Oliveira et al. (2016), Yuan et al. (2015), and Venkatesh et al. (2012) that the UTAUT2 model is appropriate to measure the behavioral intentions. In fact, Venkatesh et al.'s findings suggested that UTAUT2 was able to produce a substantial improvement in the variance explained in the behavioral intention of 74%. The results were in line with Venkatesh et al.'s argument improvement in the variance explained in the behavioral intention of 84%.

As discussed in section 1, Hew, Lee et al. (2015), and Morosan and DeFranco (2016) found positive associations between behavioral intentions to adopt a technology and habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value. In this study, the regression test analysis supported Morosan and DeFranco's (2016) findings that performance expectancy is the highest predictor of intentions, while hedonic motivations, habit, and social influences have relatively lower effects. The results of this study also corroborated Hew et al.'s

(2015) findings that performance expectancy, facilitating conditions, effort expectancy, hedonic motivation, and habit have significant relationships with behavior intentions. However, unlike in Hew et al., in this study, price value and social influence were statistically significant in influencing employees' intention to adopt consumers' IT tools. I also found like in Hew et al. (2015) that gender and age were insignificant moderators. Particularly, the findings in this study were in support of Venkatesh et al.'s (2012) that age moderated the relationships between the four constructs, facilitating conditions, hedonic motivation, price value, and habit and behavior intention. However, I found that gender only moderated relationships between hedonic motivation and behavior intention, and habit and behavior intention.

Overall, the findings of this study supported previous studies' results and suggested a positive and statistically significant relationship between the seven key contracts used as independent variables and the behavioral intention to adopt consumers' IT tools, the dependent variable. Therefore, when those constructs increased, the employees' intent to embrace consumers' IT Tools increased. Moreover, this positive relationship between the seven constructs of UTAUT2 model, and the employees' consumerization behavioral intentions was consistent with prior studies discussed in the literature review of new technology adoption theories. The findings of this study showed an indication that performance expectancy, social influence, habit, and effort expectancy, had a stronger impact on the employees' intent to adopt consumers' IT tools than facilitation conditions, hedonic motivation, and price value. Moreover, there is an indication from results of the multiple regression the alternative hypothesis was correct.

The alternative hypothesis was that there is a statistically significant relationship between employees' habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value, and employees' consumerization behavioral intentions. Although all variables studied were statistically significant, performance expectancy was the primary predictor between the seven key variables.

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 employees' IT consumerization behavioral intentions habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value. Leclercq-Vandelannoitte (2015) argued that IT consumerization adoption lacks sound theoretical foundations to back up the implementation strategies. In this study, I found that habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value had a positive impact on the employees' intention to adopt consumer IT tools in the province of Ontario in Canada. Moreover, the findings were grounded in a reliable and valid theoretical model as demonstrated in Venketesh et al. (2012), which I confirmed in this study through the regression analysis.

There are several implications for practitioners based on this research. First, I was able to demonstrate that performance expectancy, social influence, habit, and effort expectancy, had a stronger positive impact on employees intention to adopt consumers' IT tools, while facilitation conditions, hedonic motivation, and price value positive effect were also positive but relatively lower. Moreover, I showed that performance expectancy was the leading key driver of consumerization behavior intentions of the employees. Hence, CIOs will need to design policies that consider providing the employees with technologies of their choice. CIOs should seek balance in their IT policy strategies because a far more restrictive policy regarding the use of consumers' IT tools can lower the consumerization behavioral intention of the employees, hence the work productivity. Moreover, based on the strong association between performance expectancy and consumerization behavior intention, the likelihood of employees explore and experiment with consumers' IT tools increase if the tools provide valuable or useful utilities to perform. Thus, in designing their strategies towards IT consumerization, CIOs can introduce some flexibility by prioritizing consumers' IT tools that offer useful features, which may increase the performance of the employees.

Second, as I was able to show, the impact of social influence as related to the consumerization behavior of others important to employees significantly affected the consumerization behavioral intentions. Hence, this positive relationship between social influence and behavior intention significant in the context of implementing strategies related to the IT consumerization. In fact, the employees' tendency to adopt the consumerization behavior of others appears as an important parameter to consider increasing the likelihood of the success of such strategies. Third, although facilitation conditions were not as strong predictor as performance expectancy, there was an indication from the findings of this study that it had a positive effect on employees' behavioral intention. Thus, CIOs need to consider from the work compatibility perspective, the specific needs of employees when developing their strategy to adopt IT consumerization. Aside from that, as I showed that facilitation conditions increase positively IT consumerization behavior, CIOs should be careful when strategizing the adoption of IT consumerization policies. The rationale is that if consumers' IT tools is an organization initiative, CIOs should put high consideration on compatibility issues because of the probability of seeing the implementation policy failure increases due frustration after compatibility issues.

Fourth, I found habit to be the third constructs with a stronger positive impact on employees' consumerization behavioral intentions after performance expectancy and social influence. Therefore, regarding policy strategies, CIOs should integrate that variable and could elaborate strategies that consider consumers' IT tools use habits of employees. Moreover, Venkatesh et al. (2012) pointed out the possibility to change habits. Hence, CIOs can identify risky behaviors of employees using consumers IT tools and devise appropriate strategies, which leverage less risky consumers' IT tools use habit and lessen the negative effect of unsafe habits by targeting their underpinning beliefs. Finally, CIOs can use the findings of this study to develop IT policies that take into account various groups of users base on the fact the by mean of social influence, the likelihood workers to positively affect other employees' intentions to adopt consumers' IT tools as found in this study.

Implications for Social Change

It is unlikely that organization will be able to put an end to the trend towards IT consumerization (Harris et al., 2012). Moreover, organizations are adjusting to new context IT consumerization, which impulses significant shift in prior organization driven IT management policies. In fact, previous studies (Astani et al., 2013; Marshall, 2014; Steelman et al., 2016), the authors discussed various strategies to embrace IT consumerization from the organization perspective. However, these approaches lack sound theoretical backup (Leclercq-Vandelannoitte, 2015). Through the findings of this study, CIOs have at their disposal a theoretical ground, which can help them develop better their IT consumerization policy strategies, hence facilitate the adoption of consumers' IT tools. Subsequently, a successful adoption of IT consumerization can provide better work environment. As Ling (2014) pointed out, in such environment, parents will be able to access to children, at home and work, hence better parenting (Ling, 2014). Moreover, considering the positive effect of social influence, habit, and effort expectancy on behavioral intention as I was able to demonstrate in this study, and the subsequent relation with work productivity, with successful IT consumerization adoption, employees' social lives improve. In fact, friends, coworkers, and family members or closed social groups can be able to manage their work and social lives integrally with improved flexibility and convenience, hence, intertwinement of social structures due to an increase of the internalization and the expectations of maintaining contact (Carter, 2015).

Recommendations for Action

Based on the this study's findings analysis, which showed the positive impact of the seven key constructs of the UTAUT2 model on consumerization behavior intention, CIOs should implement effective IT consumerization management policy. They can effectively adopt IT consumerization by not leaving the consumers' IT tools unmanaged but, by developing IT strategies that leverage on prioritized IT tools that increase employees' productivity and while leaving the freedom of choice. As organizations respond to security threats and data privacy issues associated with IT consumerization by deploying corporate policy governance (Crossler, Long, Loraas, & Trinkle, 2014), CIOs should take appropriate actions to ensure that employees comply with such a policy for it to be more efficient. Based on their findings on employees' compliance with BYOD policy, Crossler et al. (2014) suggested that CIOs ensure policy governance through training that focuses on three key elements. According to the authors, these elements are: increasing perceived response efficacy using the explanation of each policy as an effective response to security and data privacy threats, increasing employees' self-efficacy va-a-vis compliance behavior, and informing employees regarding the severity of potential unsecure BYOD behavior related threats. Moreover, as I found out in this study, habit positively influenced consumerization behavior intention. Because training employees can change habits (Venkatesh et al., 2012), CIOs can increase employees' compliance behavior through habits. Another recommendation for action is that CIOs should balance their IT consumerization policies not only to improve employees' compliance behaviors but also to avoid hinder their performance expectancy.

Furthermore, I projected to conduct an after-graduation work in collaboration with my mentor to publish the findings in an academic journal.

Recommendations for Future Study

This study is subject to some limitations. First, I recruit participants in social media, namely LinkedIn® to solicit the IT consumerization behavior intention. Although the relevance of the population in this study rests on the variety of the business types, recruiting through a social, which some employees may consider as a consumer's IT tool may have had an influence on the participants' characteristics. Moreover, the solicited participants' IT consumerization behavioral intention was not observed. Hence, there is a possibility that of discrepancy between daily routine behavioral intention and self-reported behavior. Nevertheless, the sample population of this study was compliant with Walden IRB requirements as related to the data collection. Hence, I did not collect any personal identification of any participants. Therefore, guaranteeing anonymity in the process was not subject to significant motivation, which may lead to misrepresenting the IT consumerization behavior. Second, I relied on the geographic location of the respondents and the organizations, and the classification of these organizations as SMBs for which the participants worked for as provided in LinkedIn®. Hence, I obtained the data from some employee respondents, who work for organizations based in the province of Ontario, in Canada at the time of the data collection. Despite this limitation, I found statistically significant positive results for the seven variables measured in this study.

In fact, I discovered in this study that habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value had a statistically significant positive impact on employees' IT consumerization behavioral intentions. However, others researchers could undertake future studies an investigation on the relationship between the individual constructs of UTAUT2 model and behavior in other geographical areas, and examine the influence of the model core constructs on behavior intention and use behavior over the time. Notably, Venkatesh and Morris (2003) found that within a period of three months of using a new technology, the effect of social influence decrease because individuals internalized what others expect from them. Hence, in the future, researchers could examine if temporal limits social influence and effort expectancy could affect the explanatory power of the findings of this study.

Moreover, despite the contribution of these extensive replications, applications, and extensions or integrations of UTAUT2 and its extensions some avenues remain for future research. In fact, researchers could conduct future research using an experimental design to examine the behavior intention in association with the actual use of consumers' IT tools as outlined in the UTAUT2 model. Also, in the future, researchers could examine how IT consumerization behavior evolves into use behavior over an extended period and assess if IT consumerization behavior intention could not have any influence on use behavior. Finally, future researchers can validate the explanatory power of the findings of this study by using other categories of participants, different sample sizes, different geographic areas, and different research designs.

Reflections

Although challenging, I had great and wonderful learning experience of the research process at Walden University. Sometimes overwhelmed by the demand, I had to draw from my personal beliefs to sustain my resilience because of hectic revisions at certain of phase as I advanced throughout the journey to complete my doctoral study. I expanded my understanding and knowledge of the fundamentals around my project topic, namely the multifaceted aspect of IT consumerization, various theories of technology acceptance and social theories interconnection. Although I did have some basic understanding of different research approaches, I had expanded my knowledge of the quantitative research process and research designs in such way that I was able to use it as in this study and can do so in further research.

Moreover, I started this project without a sound understanding of the UTAUT2 model and how the authors derived the various constructs as predictors of behavior intention. But, I progressed through the different phases of the project and by reading many author’s articles and multiple peers reviews research base on the same model or its extensions, I gained a thorough understanding of the theory as its complex association with IT consumerization behavior intention. Hence, I developed a deep awareness of how important is the model to the research findings in the context of IT consumerization.

Initially, I went through a complicated process of IRB application because of it revision process as it appeared that different evaluators were assessing the compliance requirements at each version submission. Moreover, based on my initial recruitment plan, I should have gotten signed letters from community partners before commencing the data collection. My attempt to contact by phone or emails the identified organization yield no success for a week. I had to change data approach by focusing only on the small and medium-sized organization, which employees were on the social media LinkedIn®. Nevertheless, I went through a valuable data collection period of 4 weeks, and I was able to reach the minimum sample size required to conduct the data analysis.

It is with no preconceived biases that I began this research to examine the degree of the significance of the relationship between employees' IT consumerization behavioral intentions habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value. The results indicated that habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value influence positively the employees' intention to adopting consumers' IT tools in the province of Ontario in Canada. The findings of this study provide some indications to CIOs to improve their IT consumerization adoption strategies and can inspire future researchers.

Summary and Study Conclusions

I conducted a quantitative research method using a non-experimental cross-sectional survey design was employed to look into the degree of significance of the relationship between employees' IT consumerization behavioral intentions habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value. I used a predictive UTAUT2 framework and pretested survey instrument for the purpose of this study. I conducted the data collection using an online survey built with Survey Monkey. I sent out 723 surveys over a period of four weeks, and I received 112 responses among which, four surveys were incomplete, and I discarded them. The response rate was 15, 49%. The data collected were exported from Survey Monkey and imported into SPSS software. I performed in SPSS the descriptive statistics, the instrument reliability and validity analysis, and a standard multiple regression analysis to test the hypothesis derived from the question.

The analysis of the statistical results supported the null hypothesis. I found that performance expectancy, social influence, habit, and effort expectancy, had a stronger positive impact on employees' intention to adopt consumers' IT tools, while facilitation conditions, hedonic motivation, and price value positive effect were also positive but relatively lower. Moreover, I found that performance expectancy was the first leading key driver of consumerization behavior intentions of the employees. I found habit to be the third constructs with a stronger positive impact on the employees' consumerization behavioral intentions after performance expectancy and social influence. Despite some limitations of this research, CIOs can use the findings and make informed decisions on how to develop better strategies to adopt IT consumerization. The objective of this study was to use the seven key constructs of the UTAUT2 model to assess their influence on employees' IT consumerization behavioral while providing CIOs the sound theoretical ground to devise better strategies in their decisions to adopt IT consumerization.

References

Acharya, A. S., Prakash, A., Saxena, P., & Nigam, A. (2013). Sampling: Why and how of it. *Indian Journal of Medical Specialties, 4*(2), 330-333. doi:10.7713/ijms.2013.0032

Agudo-Peregrina, Á. F., Hernández-García, Á., & Pascual-Miguel, F. J. (2014). Behavioral intention, use behavior, and the acceptance of electronic learning systems: Differences between higher education and lifelong learning. *Computers in Human Behavior*, *34*, 301-314. doi:10.1016/j.chb.2013.10.035

Ain, N., Kaur, K., & Waheed, M. (2015). The influence of learning value on learning management system use: An extension of UTAUT2. *Information Development*, *32*(5), 1306-13216. doi:10.1177/0266666915597546

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

Ajzen, I. (2001). Nature and operation of attitudes. *Annual review of psychology*, *52*(1), 27-58. doi:10.1146/annurev.psych.52.1.27

Ajzen, I. (2012). Martin Fishbein's legacy: The reasoned action approach. *ANNALS of the American Academy of Political and Social Science, 640*(1), 11-27. doi:10.1177/0002716211423363

Ajzen, I. (2015). The theory of planned behaviour is alive and well, and not ready to retire: A commentary on Sniehotta, Presseau, and Araújo-Soares. *Health Psychology Review, 9*(2), 131-137. doi:10.1080/17437199.2014.883474

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. Prentice-Hall, Englewood Cliffs, N.J

Al Jardali, H., Abdallah, F., & Barbar, K. (2015). Measuring intentions among employees toward the use of a balanced scorecard and information system: A conceptual approach using the theory of planned behavior and the technology acceptance model. *Procedia Economics and Finance, 26*, 1146-1151. doi:10.1016/S2212-5671(15)00944-2

Alazzam, M. B., Basari, A. S. H., Sibghatullah, A. S., Doheir, M., Enaizan, O. M., & Mamra, A. H. K. (2015). EHRs acceptance in Jordan hospitals by UTAUT2 model: Preliminary result. *Journal of Theoretical and Applied Information Technology*, *78*(3), 473. Retrieved from http://www.jatit.org

Al-Debei, M. M., Al-Lozi, E., & Papazafeiropoulou, A. (2013). Why people keep coming back to Facebook: Explaining and predicting continuance participation from an extended theory of planned behaviour perspective. *Decision Support Systems, 55*(1), 43-54. doi:10.1016/j.dss.2012.12.032

Aljukhadar, M., Senecal, S., & Nantel, J. (2014). Is more always better? Investigating the task-technology fit theory in an online user context. *Information & Management, 51*(4), 391-397. doi:10.1016/j.im.2013.10.003 0378

Altawallbeh, M., Soon, F., Thiam, W., & Alshourah, S. (2015). Mediating role of attitude, subjective norm and perceived behavioural control in the relationships between their respective salient beliefs and behavioural intention to adopt e-learning among instructors in Jordanian universities. *Journal of Education and Practice, 6*(11), 152-159. Retrieved from http://iiste.org/Journals/index.php/JEP

Anderson, R. S., & Levitt, D. H. (2015). Gender self confidence and social influence: Impact on working alliance. *Journal of Counseling & Development*, *93*(3), 280-288. doi: 10.1002/jcad.12026

Astill, S., Harvey, D., & Taylor, A. (2013). A bootstrap test for additive outliers in non-stationary time series. *Journal of Time Series Analysis, 34*, 454-465. doi:10.1111/jtsa.12033

Arenas-Gaitán, J., Peral, B., & Jerónimo, M. A. (2015). Elderly and Internet banking: An application of UTAUT2. *Journal of Internet Banking and Commerce*, *20*. Retrieved from http://www.arraydev.com/commerce/jibc/

Arendacká, B. (2012). A note of fiducial generalized pivots for σ in one-way heteroscedastic ANOVA with random effects. Statistics, 46, 489-504. doi:10.1080/02331888.2010.540669

Armando, A., Costa, G., Merlo, A., & Verderame, L. (2015). Formal modeling and automatic enforcement of Bring Your Own Device policies. *International Journal of Information Security*, *14*(2), 123-140. doi:10.1007/s10207-014-0252-y

Arpaci, I., Yardimci Cetin, Y., & Turetken, O. (2015). A cross-cultural analysis of smartphone adoption by Canadian and Turkish organizations. *Journal of Global Information Technology Management*, *18*(3), 214-238. doi:10.1080/1097198X.2015.1080052

Astani, M., Ready, K., & Tessema, M. (2013). BYOD issues and strategies in organizations. *Issues in Information Systems, 14*(2), 195-201. Retrieved from http://www.iacis.org/

Babu, R., & Jayashree, K. (2016). Prominence of IoT and Cloud in health care. *International Journal of Advanced Research in Computer Engineering & Technology, 5*(2), 420-424. Retrieved from http://www.ijarcet.org/

Baciu, O., & Parpucea, I. (2013). A model to minimize multicollinearity effects. *Annals of the University of Oradea, Economic Science Series, 22*(1), 699-706. Retrieved from http://anale.steconomiceuoradea.ro

Bagozzi, R. P. (2007). The legacy of the technology acceptance model and a proposal for a paradigm shift. *Journal of the Association for Information Systems, 8*(4), 244–254. doi: 10.1.1.361.5863

Bakla, A., Cekic, A., & Kosksai, O. (2013). Web-based surveys in educational research. *International Journal of Academic Research, 5*(1), 5-13. doi:10.7813/2075-4124.2013/5-1/B.1

Balkin, R. S., & Sheperis, C. J. (2011). Evaluating and reporting statistical power in counseling research. *Journal of Counseling & Development, 89,* 268–272. doi:10.1002/j.1556-6678.2011. tb00088.x

Baptista, G., & Oliveira, T. (2015). Understanding mobile banking: The unified theory of acceptance and use of technology combined with cultural moderators. *Computers in Human Behavior, 50,* 418-430. doi:10.1016/j.chb.2015.04.024

Bandura, A.(1989). Human agency in social cognitive theory. *American Psychologist, 4,* 1175-1184.

Bansal, H.S., Taylor, S.F., and James, Y.S. (2005). "Migrating" to new service providers: Toward a unifying framework of consumers' switching behaviors. *Journal of the Academy of Marketing Science, 33*(1), 96-115.

Barry, A. E., Chaney, B., Piazza-Gardner, A. K., & Chavarria, E. A. (2014). Validity and reliability reporting practices in the field of health education and behavior a review of seven journals. *Health Education & Behavior*, *41*(1), 12-18. doi: 10.1177/1090198113483139

Bedeian, A. G. (2014). “More than meets the eye”: A guide to interpreting the descriptive statistics and correlation matrices reported in management research. *Academy of Management Learning & Education, 13*(1), 121-135. doi: 10.5465/amle.2013.0001

Bettis, R., Gambardella, A., Helfat, C., & Mitchell, W. (2014). Quantitative empirical analysis in strategic management. *Strategic Management Journal*, *35*(7), 949-953. doi:10.1002/smj.2278

Bevan, S., Baumgartner, F. R., Johnson, E. W., & McCarthy, J. D. (2013). Understanding selection bias, time-lags and measurement bias in secondary data sources: Putting the encyclopedia of associations database in broader context. *Social science research*, *42*(6), 1750-1764. doi: 10.1016/j.ssresearch.2013.08.003

Bhattacherjee, A., Limayem, M., & Cheung, C. M. (2012). User switching of information technology: A theoretical synthesis and empirical test. *Information & Management*, *49*(7), 327-333. doi:10.1016/j.im.2012.06.002

Bhattacherjee, A., & Park, S. C. (2014). Why end-users move to the cloud: a migration-theoretic analysis. *European Journal of Information Systems*, *23*(3), 357-372. doi:10.1057/ejis.2013.1

Blackwell, C. K., Lauricella, A. R., & Wartella, E. (2014). Factors influencing digital technology use in early childhood education. *Computers & Education,77*, 82-90. doi: 10.1016/j.compedu.2014.04.013

Bonett, D. G., & Wright, T. A. (2015). Cronbach's alpha reliability: Interval estimation, hypothesis testing, and sample size planning. *Journal of Organizational Behavior*, *36*(1), 3-15. doi: 10.1002/job.1960

Bosco, F. A., Aguinis, H., Singh, K., Field, J. G., & Pierce, C. A. (2015). Correlational effect size benchmarks. *Journal of Applied Psychology,100*(2), 431. doi: 10.1037/a0038047

Brown, S. A., Venkatesh, V., & Goyal, S. (2014). Expectation confirmation in information systems research: A test of six competing models. *MIS Quarterly*, *38*, 729-756. Retrieved from http://www.misq.org/

Brutus, S., Aguinis, H., & Wassmer, U. (2013). Self-reported limitations and future research in scholarly reports: Analysis and recommendations. *Journal of Management, 39*, 1490-1528. 10.1177/0149206312455245

Buettner, R. (2015). Analyzing the problem of employee internal social network site avoidance: Are users resistant due to their privacy concerns?. *In System Sciences (HICSS), 2015 48th Hawaii International Conference on,* 1819-1828.

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

Carrington, M. J., Neville, B. A., & Whitwell, G. J. (2014). Lost in translation: Exploring the ethical consumer intention–behavior gap. *Journal of Business Research, 67*(1), 2759-2767. doi: 10.1016/j.jbusres.2012.09.022

Carter, R., & Auken, H. (2006). Small firm bankruptcy. *Journal of Small Business Management, 44*, 493-512. doi:10.1111/j.1540-627X.2006.00187.x

Carter, M. (2015). Me, my self, and I(T): Conceptualizing information technology identity and its implications. *MIS Quarterly*, *39*, 931-957. Retrieved from http://www.misq.org/

Chang, I., Liu, C. C., & Chen, K. (2014). The push, pull and mooring effects in virtual migration for social networking sites. *Information Systems Journal*, *24*(4), 323-346. doi: 10.1111/isj.12030

Chang, E.-C., & Tseng, Y.-F. (2013). Research note: E-store image, perceived value and perceived risk. *Journal of Business Research*, *66*(7), 864–870. doi:10.1016/j.jbusres.2011.06.012

Chaparro-Peláez, J., Agudo-Peregrina, Á. F., & Pascual-Miguel, F. J. (2016). Conjoint analysis of drivers and inhibitors of e-commerce adoption. *Journal of Business Research, 69(4), 1277-1282*. doi: 10.1016/j.jbusres.2015.10.092

Chen, M. F., & Tung, P. J. (2014). Developing an extended theory of planned behavior model to predict consumers' intention to visit green hotels. *International Journal of Hospitality Management*, *36*, 221-230. doi: 10.1016/j.ijhm.2013.09.006

Chen, Y. C., Shang, R. A., & Li, M. J. (2014). The effects of perceived relevance of travel blogs' content on the behavioral intention to visit a tourist destination. *Computers in Human Behavior*, *30*, 787-799. doi: 10.1016/j.chb.2013.05.019

Cheng, H. H., & Huang, S. W. (2013). Exploring antecedents and consequence of online group-buying intention: An extended perspective on theory of planned behavior. *International Journal of Information Management*, *33*(1), 185-198. doi: 10.1016/j.ijinfomgt.2012.09.003

Cheung, R., & Vogel, D. (2013). Predicting user acceptance of collaborative technologies: An extension of the technology acceptance model for e-learning. *Computers & Education*, *63*, 160-175. doi:10.1016/j.compedu.2012.12.003

Cho, E., & Kim, S. (2014). Cronbach's coefficient alpha well known but poorly understood. *Organizational Research Methods*, *18*(2) 207-230. doi: 10.1177/1094428114555994

Choi, H., & Shi, S. (2014). Design of safe internal network with the use of active tracking system. *International Journal of Security and Its Applications, 8,* .291-300. doi:10.14257/ijsia.2014.8.2.30

Choon, T. G., Sulaiman, A., & Mallasi, H. (2014). Intention to use green IT among students. *Int. J. Res. Bus. Technol, 4*(2), 439-445. Retrieved from http://www.ijrbtonline.com/index.php/ijrbt

Chou, H. W., Lin, Y. H., Lu, H. S., Chang, H. H., & Chou, S. B. (2014). Knowledge sharing and ERP system usage in post-implementation stage. *Computers in Human Behavior,33,* 16-22. doi:10.1016/j.chb.2013.12.023

Chun, M. W., Griffy-Brown, C., & Koeppel, H. (2014). The New Normal: Fundamental Shifts for 21st Century Organizations and for the CIOs Who Lead Them. *The Journal of Applied Business and Economics, 16*(5), 27. Retrieved from http://www.na-businesspress.com/jabeopen.html

Chung, S., Lee, K. Y., & Choi, J. (2015). Exploring digital creativity in the workspace: The role of enterprise mobile applications on perceived job performance and creativity. *Computers in Human Behavior*, *42*, 93-109. doi: 10.1016/j.chb.2014.03.055

Chu, T. H., & Chen, Y. Y. (2016). With good we become good: Understanding e-learning adoption by theory of planned behavior and group influences. *Computers & Education, 92,* 37-52. doi: 10.1016/j.compedu.2015.09.013

Collard, M., Ruttle, A., Buchanan, B., & O'Brien, M. (2013). Population size and cultural evolution in nonindustrial food-processing societies. *Plos One, 8*(9), 1. doi:10.1371/journal.pone.0072628

Compeau, D., and Higgins, C. (1995a) Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly, 19*, 189-211. Retrieved from http://www.misq.org/

Compeau, D., and Higgins, C. (1995b) Application of social cognitive theory to training for computer skills. *Information Systems Research, 6*(2) 118 -143. doi: 10.1287/isre.6.2.118

Davis, F. D. (1986). *A technology acceptance model for empirically testing new end-user information systems: Theory and results* (Doctoral dissertation), Massachusetts Institute of Technology). Retrieved from http://hdl.handle.net/1721.1/15192

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*, 319-340. doi: 10.2307/249008

Darlington, R., & Dobson, J. (2013). Objective but not detached: Partisanship in industrial relations research. *Capital & Class*, *37*(2), 285-297. doi: 10.1177/0309816813489936.

Deci, E., Vallerand, R., Pelletier, L., and Ryan, R. (1991) Motivation and education: The self-determination perspective. *Educational Psychology, 26* (3and 4) 325-246. doi: 10.1080/00461520.1991.9653137

Dean, J. (2014). Personal protective equipment: An antecedent to safe behavior? *Professional Safety, 59* (2), 41-46. Retrieved from http://www.asse.org/professional-safety/

Dernbecher, S., Beck, R., & Weber, S. (2013). Switch to your own to work with the known: An empirical study on consumerization of IT. *In Proceedings Research: 19th Americas Conference on Information Systems*. Chicago, USA.

de Oca, A. M. M., & Nistor, N. (2014). Non-significant intention–behavior effects in educational technology acceptance: A case of competing cognitive scripts?.*Computers in Human Behavior*,*34*, 333-338. doi:10.1016/j.chb.2014.01.026

de Sena Abrahão, R., Moriguchi, S. N., & Andrade, D. F. (2016). Intention of adoption of mobile payment: An analysis in the light of the unified theory of acceptance and use of technology (UTAUT). *RAI Revista de Administração e Inovação*,*13*(3), 221-230. doi: 10.1016/j.rai.2016.06.003

Dijkstra, T. K., & Henseler, J. (2015). Consistent partial least squares path modeling. *MIS quarterly*, *39*, 297-316. Retrieved from http://www.misq.org

de Vries, H., Dijkstra, M., & Kuhlman, P. (1988). Self-efficacy: The third factor besides attitude and subjective norm as a predictor of behavioural intentions. *Health Education Research*, *3*, 273–282. doi: 10.1093/her/3.3.273

Disatnik, D., & Sivan, L. (2014). The multicollinearity illusion in moderated regression analysis. *Marketing Letters*, *27*(2), 403-408. doi: 10.1007/s11002-014-9339-5

Dos Santos, L. M. R., & Okazaki, S. (2013). Understanding e-learning adoption among Brazilian universities: An application of the decomposed theory of planned behavior. *Journal of Educational Computing Research*, *49*(3), 363-379. doi:10.2190/EC.49.3.e

D'Lima, G. M., Winsler, A., & Kitsantas, A. (2014). Ethnic and gender differences in first-year college students' goal orientation, self-efficacy, and extrinsic and intrinsic motivation. *The Journal of Educational Research*, *107*(5), 341-356. doi:10.1080/00220671.2013.823366

Duffey, T., Haberstroh, S., Ciepcielinski, E., & Gonzales, C. (2016). Relational- cultural theory and supervision: Evaluating developmental relational counseling. *Journal of Counseling & Development,94*(4), 405-414. doi: 10.1002/jcad.12099

Dunn, T. J., Baguley, T., & Brunsden, V. (2014). From alpha to omega: A practical solution to the pervasive problem of internal consistency estimation. *British Journal of Psychology, 105*(3), 399-412. doi:10.1111/bjop.12046

Eder, J. M., Mutsaerts, C. F., & Sriwannawit, P. (2015). Mini-grids and renewable energy in rural Africa: How diffusion theory explains adoption of electricity in Uganda. *Energy Research & Social Science, 5*, 45-54. doi:10.1016/j.erss.2014.12.014

Eisend, M. (2015). Have we progressed marketing knowledge. A meta-meta-analysis of effect sizes in marketing research. *Journal of Marketing, 79*(3), 23-40. doi:10.1509/jm.14.0288

Elzamly, A., & Hussin, B. (2014). A comparison of fuzzy and stepwise multiple regression analysis techniques for managing software project risks: Implementation phase. *International Management Review, 10*(1), 43-54. Retrieved from http://www.usimr.org

Erlingsson, C., & Brysiewicz, P. (2013). Orientation among multiple truths: An introduction to qualitative research. *African Journal of Emergency Medicine, 3*, 92–99. doi:10.1016/j.afjem.2012.04.005

Escobar-Rodríguez, T., & Carvajal-Trujillo, E. (2014). Online purchasing tickets for low cost carriers: An application of the unified theory of acceptance and use of technology (UTAUT) model. *Tourism Management*, *43*, 70-88. doi: 10.1016/j.tourman.2014.01.017

Falk, C. F., & Savalei, V. (2011). The relationship between unstandardized and standardized alpha, true reliability, and the underlying measurement model. *Journal of personality assessment*, *93*(5), 445-453. doi: 10.1080/00223891.2011.594129

Fan, X. (2013). The test is reliable; the test is valid: Language use, unconscious assumptions, and education research practice. *The Asia-Pacific Education Researcher*, *22*, 217–218. doi:10.1007/s40299-012-0036-y

Faqih, K. M. (2013). Exploring the influence of perceived risk and internet self-efficacy on consumer online shopping intentions: Perspective of technology acceptance model. *International Management Review*, *9*(1), 67-77. Retrieved from http://usimr.org

Fedlt, R. (2014). Gender invariance of item-cluster subcomponents of the NEO-FFI: A multigroup confirmatory factor analysis. *Individual Differences Research, 12*, 59-68. Retrieved from http://ores.su/en/journals/individual-differences-research/

Fishbein, M., & Ajzen, I.(1975). *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research*. Addison-Wesley, Reading, MA

Fleming, M. L., Barner, J. C., Brown, C. M., Shepherd, M. D., Strassels, S., & Novak, S. (2014). Using the theory of planned behavior to examine pharmacists' intention to utilize a prescription drug monitoring program database. *Research in Social and Administrative Pharmacy, 10*(2), 285-296. doi: 10.1016/j.sapharm.2013.05.009

Frels, R. K., & Onwuegbuzie, A. J. (2013). Administering quantitative instruments with qualitative interviews: A mixed research approach. *Journal of Counseling & Development*, *91*(2), 184-194. doi: 10.1002/j.1556-6676.2013.00085.x

Garba, A. B., Armarego, J., Murray, D., & Kenworthy, W. (2015). Review of the information security and privacy challenges in bring your own device (BYOD) Environments. *Journal of Information Privacy and Security*, 11(1), 38–54. doi:10.1080/15536548.2015.1010985

Gard, D. E., Sanchez, A. H., Starr, J., Cooper, S., Fisher, M., Rowlands, A., & Vinogradov, S. (2014). Using self-determination theory to understand motivation deficits in schizophrenia: the ‘why’of motivated behavior. *Schizophrenia research, 156*(2), 217-222. doi: 10.1016/j.schres.2014.04.027

Gibbs, N., & Weightman, W. (2014). An audit of the statistical validity conclusion of clinical superiority in anesthesia journal. *Anaesthesia & Intensive Care, 42*, 599-607. Retrieved from http://www.aaic.net.au

Giddens, L. & Tripp, J. (2014). It’s my tool, i know how to use It: A theory of the impact of BYOD on device competence and job satisfaction. In *Proceedings Research:*

20th Americas Conference on Information Systems (AMCIS), Savannah, GA, USA.

Gilstrap, D. L. (2013). Quantitative research methods in chaos and complexity: From probability to post hoc regression analyses. *Complicity: An International Journal of Complexity & Education, 10(*1/2), 57-70. Retrieved from http://www.complexityandeducation.ualberta.ca/journal.htm

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly, 19*, 213–236. Retrived from http://www.misq.org/

Grassi-Oliveira, R., Cogo-Moreira, H., Salum, G. A., Brietzke, E., Viola, T. W., Manfro, G. G., Kristen, C. H., & Arteche, A. X. (2014). Childhood trauma questionnaire (CTQ) in Brazilian samples of different age groups: Findings from confirmatory factor analysis. *PloS one, 9*(1), e87118. doi:10.1371/journal.pone.0087118

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

Hanus, M. D., & Fox, J. (2015). Assessing the effects of gamification in the classroom: A longitudinal study on intrinsic motivation, social comparison, satisfaction, effort, and academic performance. *Computers & Education*, *80*, 152-161. doi:10.1016/j.compedu.2014.08.019

Hassan, S., Farhan, M., Mangayil, R., Huttunen, H., & Aho, T. (2013). Bioprocess data mining using regularized regression and random effects. B*MC Systems Biology, 7*(1), 1-7. doi:10.1186/1752-0509-7-s1-s5

Head, K. J., & Noar, S. M. (2014). Facilitating progress in health behaviour theory development and modification: The reasoned action approach as a case study. *Health Psychology Review*, *8*(1), 34-52. doi: 10.1080/17437199.2013.778165

Heirman, W., Walrave, M., Vermeulen, A., Ponnet, K., Vandebosch, H., & Hardies, K. (2016). Applying the theory of planned behavior to adolescents' acceptance of online friendship requests sent by strangers. *Telematics and Informatics*, *33*(4), 1119-1129. doi: 10.1016/j.tele.2016.01.002

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115-135. doi: 10.1007/s11747-014-0403-8

Hew, J-J., Lee, V-H., Ooi, K-B., Wei, J. (2015). What catalyses mobile apps usage intention: an empirical analysis. *Industrial Management & Data Systems*, *115*(7), 1269-1291.doi:10.1108/IMDS-01-2015-002

Hopkins, N., Sylvester, A. and Tate, M. (2013). Motivations for BYOD: An investigation of the contents of a 21st century school bag. In *Proceedings Research: 21st European Conference on Information Systems (ECIS)*. Utrecht, Netherlands.

Hinsz, V. B., & Nickell, G. S. (2015). The prediction of workers' food safety intentions and behavior with job attitudes and the reasoned action approach. *Revista de Psicología del Trabajo y de las Organizaciones*, *31*(2), 91-100. doi: 10.1016/j.rpto.2015.03.001

Hsia, J. W., Chang, C. C., & Tseng, A. H. (2014). Effects of individuals' locus of control and computer self-efficacy on their e-learning acceptance in high-tech companies. *Behaviour & Information Technology*, *33*(1), 51-64. doi: 10.1080/0144929X.2012.702284

Hsieh, P. J. (2015). Physicians' acceptance of electronic medical records exchange: An extension of the decomposed TPB model with institutional trust and perceived risk. *International journal of medical informatics*, *84*(1), 1-14. doi: 10.1016/j.ijmedinf.2014.08.008

Hsu, C. L., & Lin, J. C. C. (2015). What drives purchase intention for paid mobile apps?–An expectation confirmation model with perceived value. *Electronic Commerce Research and Applications*, *14*(1), 46-57. doi: 10.1016/j.elerap.2014.11.003

Huang, C. Y., & Kao, Y. S. (2015). UTAUT2 based predictions of factors influencing the technology acceptance of phablets by DNP. *Mathematical Problems in Engineering*. doi:10.1155/2015/603747

Hopkins, L., & Ferguson, K. E. (2014). Looking forward: The role of multiple regression in family business research. *Journal of Family Business Strategy*,*5*(1), 52-62. doi: 1016/j.jfbs.2014.01.008

Huihua, L., Xu, Y., Han, L., & Zhou, F. (2015). Scale-dependence effects of landscape on seasonal water quality in Xitiaoxi catchment of Taihu Basin, China. *Water Science & Technology*, *71*, 59-66. doi:10.2166/wst.2014.463

Humayun, S., Ashar, A., & Ahmad, A. (2014). Student's perception of labor room learning environment. *Pakistan Armed Forces Medical Journal*, *64*, 277-286. Retrieved from http://www.pafmg.org

Islam, T. (2014). Household level innovation diffusion model of photo-voltaic (PV) solar cells from stated preference data. *Energy Policy*, *65*, 340-350. doi:10.1016/j.enpol.2013.10.004

Jackson, J. D., Mun, Y. Y., & Park, J. S. (2013). An empirical test of three mediation models for the relationship between personal innovativeness and user acceptance of technology. *Information & Management*, *50*(4), 154-161. doi:10.1016/j.im.2013.02.006

Jafarkarimi, H., Saadatdoost, R., Sim, A. T. H., & Hee, J. M. (2016). Behavioral intention in social networking sites ethical dilemmas: An extended model based on theory of planned behavior. *Computers in Human Behavior*, *62*, 545-561. doi:10.1016/j.chb.2016.04.024

Jung, I., & Lee, Y. (2015). YouTube acceptance by university educators and students: a cross-cultural perspective. *Innovations in Education and Teaching International*, *52*(3), 243-253. doi: 10.1080/14703297.2013.805986

Karakaya, E., Hidalgo, A., & Nuur, C. (2014). Diffusion of eco-innovations: A review. *Renewable and Sustainable Energy Reviews*, *33*, 392-399. doi:10.1016/j.rser.2014.01.083

Kautonen, T., Gelderen, M., & Fink, M. (2015). Robustness of the theory of planned behavior in predicting entrepreneurial intentions and actions. *Entrepreneurship Theory and Practice, 39*(3), 655-674. doi: 10.1111/etap.12056

Kazman, J. B., Galecki, J. M., Lisman, P., Deuster, P. A., & O'Connor, F. G. (2014). Factor structure of the functional movement screen in marine officer candidates. *The Journal of Strength & Conditioning Research*, *28*(3), 672-678. Retrieved from http://journals.lww.com/nsca-jscr/pages/default.aspx

Khasawneh, M. (2015). Factors influence e-learning utilization in universities-academic staff perspectives. *Procedia-Social and Behavioral, 210,* 170-180. *doi: 10.1016/j.sbspro.2015.11.356*

Kennedy, J. E. (2015). Beware of inferential errors and low power with Bayesian analyses: Power analysis is needed for confirmatory research. *The Journal of Parapsychology*, *79*(1), 53. Retrieved from http://www.rhine.org/what-we-do/journal-of-parapsychology.html

Khechine, H., Lakhal, S., Pascot, D., & Bytha, A. (2014). UTAUT model for blended learning: The role of gender and age in the intention to use webinars. *Interdisciplinary Journal of E-Learning and Learning Objects*, *10*(1), 33-52. Retrieved from http://www.ijello.org/Volume10/IJELLOv10p033-052Khechine0876.pdf

Kirkwood, A., & Price, L. (2013). Examining some assumptions and limitations of research on the effects of emerging technologies for teaching and learning in higher education. *British Journal of Education Technology*, *44*, 536-543. doi:10.1111/bjet.12049

Klesel, M., Mokosch, G., & Niehaves, B. (2015). Putting flesh on the duality of structure: the case of IT consumerization. In *21st Americas Conference on Information Systems (ACIS).* San Juan, Puerto Rico.

Kroshus, E., Baugh, C. M., Daneshvar, D. H., & Viswanath, K. (2014). Understanding concussion reporting using a model based on the theory of planned behavior. *Journal of Adolescent Health, 54*(3), 269-274. doi:10.1016/j.jadohealth.2013.11.011

Krupnikov, Y., & Levine, A. S. (2014). Cross-sample comparisons and external validity. *Journal of Experimental Political Science*, *1*, 59. doi:10.1017/xps.2014.7

Köffer, S., Ortbach, K., Junglas, I., Björn, N., & Harris, J. (2015). Innovation Through BYOD? The Influence of IT Consumerization on Individual IT Innovation Behavior. *Business & Information Systems Engineering*, *57*(6), 363-375. doi:10.1007/s12599-015-0387-z

Köffer, S., Junglas, I., Chiperi, C. and Niehaves, B. (2014). Dual use of mobile IT and work-to-life conflict in the context of IT consumerization. In *Proceedings Research: 35thInternational Conference on Information Systems (ICIS),* Auckland, New Zealand.

Köffer, S., Ortbach, K. and Niehaves, B. (2014). Exploring the Relationship between IT Consumerization and Job Performance: A theoretical framework for future research. *Communications of the Association for Information Systems*, *35*(1). 261-

283. Retrieved from http://aisel.aisnet.org/cais/vol35/iss1/14

Lai, J. Y., & Wang, J. (2015). Switching attitudes of Taiwanese middle-aged and elderly patients toward cloud healthcare services: An exploratory study. *Technological Forecasting and Social Change*, *92*, 155-167. doi:10.1016/j.techfore.2014.06.004

Lancsar, E., & Swait, J. (2014). Reconceptualising the external validity of discrete choice experiments. *Pharmacoeconomics*, *32*(10), 951-965. doi: 10.1007/s40273-014-0181-7

Landers, R. N., & Behrend, T. S. (2015). An inconvenient truth: Arbitrary distinctions between organizational, Mechanical Turk, and other convenience samples. *Industrial and Organizational Psychology*, *8*(2), 142-164. doi:10.1017/iop.2015.13

Landrum, B., & Garza, G. (2015). Mending fences: Defining the domains and approaches of quantitative and qualitative research. *Qualitative Psychology, 2*, 199 –209. doi:10.1037/ qup0000030

Leclercq-Vandelannoitte, A. (2015). Managing BYOD: how do organizations incorporate user-driven IT innovations? *Information Technology & People, 28*(1), 2–33. doi:10.1108/ITP-11-2012-0129

Lee, D. Y., & Lehto, M. R. (2013). User acceptance of YouTube for procedural learning: An extension of the technology acceptance model. *Computers & Education*, *61*, 193-208. doi: 10.1016/j.compedu.2012.10.001

Lian, J. W., & Yen, D. C. (2014). Online shopping drivers and barriers for older adults: Age and gender differences. *Computers in Human Behavior*, 37, 133–143. doi:10.1016/j.chb.2014.04.028

Lin, T. C., & Huang, S. L. (2014). Understanding the determinants of consumers' switching intentions in a standards war. *International Journal of Electronic Commerce, 19*(1), 163-189. doi: 10.2753/JEC1086-4415190105

Ling, R. (2014). From ubicomp to ubiex (pectations). *Telematics and Informatics, 31*(2), 173-183. doi:10.1016/j.tele.2013.09.001

Lira, E., Ripoll, P., Peiro, J., & Zornoza, A. (2013). The role of information and communication technologies in the relationship between group potency and group maintenance outcome: A longitudinal study. *Behaviour & Information Technology, 32*, 147-155. doi:10.1080/0144929x.2011.630421

Lu, J., Liu, C., & Wei, J. (2016). How Important Are Enjoyment and Mobility for Mobile Applications?. *Journal of Computer Information Systems*, 1-12. doi: 10.1080/08874417.2016.1181463

Lu, H-P., & Yang, Y-W. (2014). Toward an understanding of the behavioral intention to use a social networking site: An extension of task-technology fit to social-technology fit. *Computers in Human Behavior, 34*, 323-332. doi:10.1016/j.chb.2013.10.020

Luca, N. R., & Suggs, L. S. (2013). Theory and model use in social marketing health interventions. *Journal of health communication, 18*(1), 20-40. doi: 10.1080/10810730.2012.688243

Magsamen-Conrad, K., Upadhyaya, S., Joa, C. Y., & Dowd, J. (2015). Bridging the divide: Using UTAUT to predict multigenerational tablet adoption practices. *Computers in Human Behavior*, 50, 186–196. doi:10.1016/j.chb.2015.03.032

Mandy, W. & Roughan, L. & Skuse, D. (2014). Three dimensions of oppositionality in autism spectrum disorder. *J Abnorm Child Psychol, 42*,291–300. doi:10.1007/s10802-013-9778-0

Mäntymäki, M., & Riemer, K. (2014). Digital natives in social virtual worlds: A multi-method study of gratifications and social influences in Habbo Hotel. *International Journal of Information Management, 34*(2), 210-220. doi: 10.1016/j.ijinfomgt.2013.12.010

Marshall, S. (2014). IT consumerization: A case study of BYOD in a healthcare setting.*Technology Innovation Management Review*,*4*(3). Retrieved from http://timreview.ca/article/771

Martins, C., Oliveira, T., & Popovič, A. (2014). Understanding the Internet banking adoption: A unified theory of acceptance and use of technology and perceived risk application. *International Journal of Information Management, 34*(1), 1-13. doi: 10.1016/j.ijinfomgt.2013.06.002

Marangunić, N., & Granić, A. (2015). Technology acceptance model: A literature review from 1986 to 2013. *Universal Access in the Information Society*, *14*(1), 81-95. doi: 10.1007/s10209-014-0348-1

Martinez, C., & Scott, C. (2014). In search of the meaning of happiness through flow and spirituality. *The International Journal of Health, Wellness, & Society*, *4*(1), 37-49. Retrieved from http://www.ijw.cgpublisher.com

Martínez-Graña, A. M., Goy, J. L., & Zazo, C. (2013). Cartographic-environmental analysis of the landscape in natural protected parks for his management using GIS. Application to the natural parks of the "las Batuecas-Sierra de Francia" and "quilamas" (central system, Spain). *Journal of Geographic Information System*, *5*(1), 54–68. doi:10.4236/jgis.2013.51006

McCusker, K., & Gunaydin, S. (2015). Research using qualitative, quantitative or mixed methods and choice based on the research. *Perfusion*, *30*(7) 537–542.10.1177/0267659114559116

Midi, H., & Bagheri, A. (2013). Robust multicollinearity diagnostic measures based on minimum covariance determination approach. *Economic Computation & Economic Cybernetics Studies & Research*, *47*(4), 1-15. Retrieved from http://www.ecocyb.ase.ro/

Mishra, D., Akman, I., & Mishra, A. (2014). Theory of reasoned action application for green information technology acceptance. *Computers in human behavior*, *36*, 29-40. doi: 10.1016/j.chb.2014.03.030

Mohapatra, S., & Das, S. (2013). Information technology outsourcing risks in banks: A study of perception in the Indian banking industry. *Vilakshan, XIMB Journal 10*(2), 61-72. Retrieved from http://www.ximb.ac.in/

Moghavvemi, S., & Akma Mohd Salleh, N. (2014). Effect of precipitating events on information system adoption and use behaviour. *Journal of Enterprise Information Management*, *27*(5), 599–622. doi: 10.1108/JEIM-11-2012-0079

Motamedi Joybari, M., Gholipour, A., & Yazdani Charati, J. (2013). Effects of components of organizational culture and information technology on the implementation of knowledge management in Mazandaran University of Medical Science. *Journal of Mazandaran University of Medical Sciences, 23*(102), 58-65. Retrieved from http://jmums.mazums.ac.i

Morosan, C., & DeFranco, A. (2016). It's about time: Revisiting UTAUT2 to examine consumers' intentions to use NFC mobile payments in hotels. *International Journal of Hospitality Management, 53*, 17-29. doi:10.1016/j.ijhm.2015.11.003

Nair, P. K., Ali, F., & Leong, L. C. (2015). Factors affecting acceptance & use of ReWIND: validating the extended unified theory of acceptance and use of technology. *Interactive Technology and Smart Education*, *12*(3), 183-201. doi: 10.1108/ITSE-02-2015-0001

Neall, A. M., & Tuckey, M. R. (2014). A methodological review of research on the antecedents and consequences of workplace harassment. *Journal of Occupational and Organizational Psychology, 87*(2), 225-257. doi:10.1111/joop.12059

Newton, C., & Teo, S. (2014) Identification and occupational stress: A stress-buffering perspective. *Human Resource Management, 53*, 89-113. doi:10.1002/hrm.21598

Niehaves, B., Köffer, S., & Ortbach, K. (2013). The effect of private IT use on work performance-towards an IT consumerization theory. In Wirtschaftsinformatik:

11th International Conference on Wirtschaftsinformatik. Leipzig, German.Nimako, S. G., Ntim, B. A., & Mensah, A. F. (2014). Effect of mobile number portability adoption on consumer switching intention. *International Journal of Marketing Studies*, *6*(2), 117. doi:10.5539/ijms.v6n2p117

Nistor, N., Baltes, B., Dascălu, M., Mihăilă, D., Smeaton, G., & Trăuşan-Matu, Ş. (2014). Participation in virtual academic communities of practice under the influence of technology acceptance and community factors. A learning analytics application. *Computers in Human Behavior, 34,* 339-344. doi: 10.1016/j.chb.2013.10.051

Nistor, N., Göğüş, A., & Lerche, T. (2013). Educational technology acceptance across national and professional cultures: A european study. *Educational Technology Research and Development, 61*(4), 733-749. doi: 10.1007/s11423-013-9292-7

Olasina, G., & Mutula, S. (2015). The influence of national culture on the performance expectancy of e-parliament adoption. *Behaviour & Information Technology, 34*(5), 492-505. doi: 10.1080/0144929X.2014.1003326

Oliveira, T., Thomas, M., Baptista, G., & Campos, F. (2016). Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology. *Computers in Human Behavior*, *61*, 404-414. doi: 10.1016/j.chb.2016.03.030

Oliveira, T., Thomas, M., & Espadanal, M. (2014). Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors. *Information & Management*, *51*(5), 497-510. doi:10.1016/j.im.2014.03.006

Oliveira, T., Faria, M., Thomas, M. A., & Popovič, A. (2014). Extending the understanding of mobile banking adoption: When UTAUT meets TTF and ITM. *International Journal of Information Management*, *34*(5), 689-703. doi:10.1016/j.ijinfomgt.2014.06.004 0268

Ortbach, K., Bode, M., & Niehaves, B. (2013). What influences technological Individualization?–An analysis of antecedents to IT consumerization behavior. In *Proceedings Research*: *19th Americas Conference on Information Systems*. Chicago, USA.

Ortbach, K., Köffer, S., Bode, M., & Niehaves, B. (2013). Individualization of information systems-analyzing antecedents of IT consumerization behavior, In *Proceedings Research*: *34th International Conference on Information Systems*. Milan, Italy.

Padilla-Meléndez, A., Del Aguila-Obra, A. R., & Garrido-Moreno, A. (2013). Perceived playfulness, gender differences and technology acceptance model in a blended learning scenario. *Computers & Education*, *63*, 306-317. doi:10.1016/j.compedu.2012.12.014

Palinkas, L. A. (2014). Qualitative and mixed methods in mental health services and implementation research. *Journal of Clinical Child & Adolescent Psychology*, *43*(6), 851-861. doi: 10.1080/15374416.2014.910791

Panda, R., & Narayan Swar, B. (2013). Online shopping: An exploratory study to identify the determinants of shopper buying behavior. *International Journal of Business Insights & Transformation*, *7*(1), 52-59. Retrieved from http://www.ijbit.org/

Parameswaran, S., Kishore, R., & Li, P. (2015). Within-study measurement invariance of the UTAUT instrument: An assessment with user technology engagement variables. *Information & Management*, *52*(3), 317-336. doi: 10.1016/j.im.2014.12.007

Pardamean, B. E. N. S., Suparyanto, T. E. D. D. Y., & Kurniawan, R. I. F. K. Y. (2013). Assessment of graph theory e-learning utilizing learning management system. *Journal of Theoretical and Applied Information Technology*, *55*(3), 353-358. Retrieved from http://www.jatit.org

Park, E., Baek, S., Ohm, J., & Chang, H. J. (2014). Determinants of player acceptance of mobile social network games: An application of extended technology acceptance model. *Telematics and Informatics*, *31*(1), 3-15. doi:10.1016/j.tele.2013.07.001

Pavlou, P. and Fygenson, M. (2006) Understanding and predicting electronic commerce adoption: An extension of the theory of planned behaviour. *MIS Quarterly*, *30*, 115- 149. Retrieved from http://www.misq.org/

Peters, G. J. Y. (2014). The alpha and the omega of scale reliability and validity: Why and how to abandon Cronbach's alpha and the route towards more comprehensive assessment of scale quality. *European Health Psychologist*, *16*(2), 56-69.

Peterson, R. A., & Kim, Y. (2013). On the relationship between coefficient alpha and composite reliability. *Journal of Applied Psychology*, *98*, 194-198. doi:10.1037/a0030767

Peterson, R. A., & Merunka, D. R. (2014). Convenience samples of college students and research reproducibility.*Journal of Business Research*,*67*(5), 1035-1041. doi:

10.1016/j.jbusres.2013.08.010

Phipps, D. L., Beatty, P. C., & Parker, D. (2015). Standard deviation? The role of perceived behavioural control in procedural violations. *Safety science, 72*, 66-74. doi:10.1016/j.ssci.2014.08.009

Pinder, P., Prime, G., & Wilson, J. (2014). An exploratory quantitative study comparing and correlating parental factors with environmental science achievement for Black American and Black Caribbean students in a mid-atlantic state. *The Journal of Negro Education, 83*(1), 49-60. doi: 10.7709/jnegroeducation.83.1.0049

Pinsonneault, A., & Kraemer, K. L. (1993). Survey research methodology in management information systems: An assessment. *Journal of Management Information Systems, 10*(2), 75-105. doi: 10.1080/07421222.1993.11518001

Pye, V., Taylor, N., Clay-Williams, R., & Braithwaite, J. (2016). When enough is enough. Understanding and solving your sample size problem in health services research. *BMC Research Notes, 9*, 1-7. doi: 10.1186/s13104-016-1893-x

Ramirez-Correa, P. E., Rondan-Cataluña, F. J., & Arenas-Gaitá n, J. (2015). Predicting behavioral intention of mobile Internet usage. *Telematics and Informatics, 32*(4), 834–841. doi:10.1016/j.tele.2015.04.006

Raschke, R., Krishen, A., Kachroo, P., & Maheshwari, P. (2013). A combinatorial optimization based sample identification method for group comparisons. Journal of Business Research, 66, 1267–1271. doi:10.1016/j.jbusres.2012.02.024

Reeves, T. D., & Marbach-Ad, G. (2016). Contemporary test validity in theory and practice: a primer for discipline-based education researchers. *CBE-Life Sciences Education*, *15*(1), rm1. doi: 10.1187/cbe.15-08-0183

Renda dos Santos, L. M., & Okazaki, S. (2015). Planned e-learning adoption and occupational socialisation in Brazilian higher education. *Studies in Higher Education*. doi:1 0.1080/03075079.2015.1007940

Resnik, D., Miller, A., Kwok, R., Engel, S., & Sandler, D. (2015). Ethical issues in environmental health research related to public health emergencies: Reflections on the Gulf study. (2015). *Environmental Health Perspectives, 123*, A227-A231. doi:10.1289/ehp.1509889

Rideout, E. C., & Gray, D. O. (2013). Does entrepreneurship education really work? A review and methodological critique of the empirical literature on the effects of university-based entrepreneurship education. *Journal of Small Business Management, 51*(3), 329-351. doi: 10.1111/jsbm.12021

Roberto, A. J., Shafer, M. S., & Marmo, J. (2014). Predicting substance-abuse treatment providers' communication with clients about medication assisted treatment: A test of the theories of reasoned action and planned behavior. *Journal of substance abuse treatment*, *47*(5), 307-313. doi:10.1016/j.jsat.2014.06.002

Rockers, P. C., Røttingen, J-R., Shemilt, I., Tugwell, P., & Bärnighausen, T.(2015). Inclusion of quasi-experimental studies in systematic reviews of health systems research. *Health Policy, 119*, 511-521. doi:10.1016/j.healthpol.2014.10.006

Rodriguez, A. (2013). The Latino assumption: A research note. *Leisure Sciences, 35*, 184-189. doi:10.1080/01490400.2013.761917

Rogers, E. M. (1983). *Diffusion of innovations* (3rd ed.). New York, NY: Free Press

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

Rondan-Cataluña, F. J., Arenas-Gaitán, J., & Ramírez-Correa, P. E. (2015). A comparison of the different versions of popular technology acceptance models. *Kybernetes, 44*(5), 788-805. doi: 10.1108/K-09-2014-0184

Rothstein, M. (2015). Ethical Issues in big data health research. Journal of Law, Medicine & Ethics, 43,425-429. doi:10.1111/jlme.12258

Rowley, J. (2014). Designing and using research questionnaires. *Management Research Review*, *37*(3), 308-330. doi: 10.1108/MRR-02-2013-0027

Ruch, T., & Gregory, R. (2014). Consumerization of IT– Where is the theory? In *Proceedings Research: 18th Pacific Asia Conference on Information Systems (PACIS)*. Chengdu, China.

Sauermann, H., & Roach, M. (2013). Increasing web survey response rates in innovation research: An experimental study of static and dynamic contact design features. *Research Policy, 42*, 273–286. doi: 10.1016/j.respol.2012.05.003

Scott, S., & Orlikowski, W. (2014). Entanglements in practice: Preforming anonymity through social media. *MIS Quarterly, 38*, 873-893. Retrieved from http://www.misq.org

Sheng, X., & Zolfagharian, M. (2014). Consumer participation in online product recommendation services: augmenting the technology acceptance model. *Journal of Services Marketing*, *28*(6), 460-470. doi: 10.1108/JSM-04-2013-0098

Shan, H., Hu, E., Wang, L., & Liu, G. (2014). Study on antecedent variable of dual commitment in the transitional economy. Pakistan Journal of Statistics, 30, 935-955. Retrieved from http://www.pakjs.com

Sheeran, P., Gollwitzer, P. M., & Bargh, J. A. (2013). Nonconscious processes and health. Health Psychology, 32, 460-473. doi: 10.1037/a0029203

Silic, M., & Back, A. (2014). Shadow IT–A view from behind the curtain. *Computers & Security*, *45*, 274-283. doi: 10.1016/j.cose.2014.06.007

Siponen, M., Adam Mahmood, M., Pahnila, S. (2014). Employees' adherence to information security policies: An exploratory field study. *Information & Management*, *51*(2), 217–224. doi:10.1016/ j.im.2013.08.006.

Slade, E., Williams, M., Dwivedi, Y., & Piercy, N. (2015). Exploring consumer adoption of proximity mobile payments. *Journal of Strategic Marketing, 23*(3), 209-223. doi: 10.1080/0965254X.2014.914075

Spector, P. E., & Meier, L. L. (2014). Methodologies for the study of organizational behavior processes: How to find your keys in the dark. *Journal of Organizational Behavior, 35*(8), 1109-1119. doi: 10.1002/job.1966

Soilkki, K. K., Cassim, N., & Anis, M. K. (2014). An evaluation of the factors influencing the performance of registered nurses at the national referral hospital in Namibia. *Australian Journal of Business and Management Research, 4*(2), 47-60. Retrieved from http://www.ajbmr.com

Sniehotta, F. F., Presseau, J., & Araújo-Soares, V. (2014). Time to retire the theory of planned behaviour. *Health Psychology Review, 8*(1), 1-7. doi: 10.1080/17437199.2013.869710

Steelman, Z. R., Lacity, M., & Sabherwal, R. (2016). Charting Your Organization's Bring-Your-Own-Device Voyage. *MIS Quarterly Executive*, *15*, 85-104. Retrieved from http://www.misq.org/

Suki, N. M. (2015). An empirical study of factors affecting the Internet banking adoption among Malaysian consumers?. *The Journal of Internet Banking and Commerce*. Retrieved from http://www.arraydev.com/commerce/jibc/

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

Svendsen, G. B., Johnsen, J. A. K., Almås-Sørensen, L., & Vittersø, J. (2013). Personality and technology acceptance: the influence of personality factors on the core constructs of the technology acceptance model. *Behaviour & Information Technology*, *32*(4), 323-334. doi: 10.1080/0144929X.2011.553740

Szalma, J. L. (2014). On the application of motivation theory to human factors/ergonomics motivational design principles for human–technology interaction. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *56*(8), 1453-1471. doi: 10.1177/0018720814553471

Tan, E., & Lau, J. L. (2016). Behavioural intention to adopt mobile banking among the millennial generation. *Young Consumers, 17*(1). doi:10.1108/YC-07-2015-00537

Tan, G. W. H., Ooi, K. B., Leong, L. Y., & Lin, B. (2014). Predicting the drivers of behavioral intention to use mobile learning: A hybrid SEM-Neural Networks approach. *Computers in Human Behavior, 36,* 198-213. doi:10.1016/j.chb.2014.03.052

Tang, C. Y., Lai, C. C., Law, C. W., Liew, M. C., & Phua, V. V. (2014). Examining key determinants of mobile wallet adoption intention in Malaysia: an empirical study using the unified theory of acceptance and use of technology 2 model. *International Journal of Modelling in Operations Management, 4*(3-4), 248-265. doi 10.1504/IJMOM.2014.067383

Tate, M., Evermann, J., & Gable, G. (2015). An integrated framework for theories of individual attitudes toward technology. *Information & Management*, *52*(6), 710-727. doi: 10.1016/j.im.2015.06.005 0378

Thakur, R., & Srivastava, M. (2014). Adoption readiness, personal innovativeness, perceived risk and usage intention across customer groups for mobile payment services in India. *Internet Research*, *24*(3), 369-392. doi: 10.1108/IntR-12-2012-0244

Tavares, J., & Oliveira, T. (2016). Electronic Health Record Patient Portal Adoption by Health Care Consumers: An Acceptance Model and Survey. *Journal of medical Internet research, 18*(3). doi:10.2196/jmir.5069

Taylor, J., & Bates, T. (2013). A discussion on the significance associated with Pearson's correlation in precision agriculture studies. *Precision Agriculture, 14*, 558-564. doi:10.1007/s11119-013-9314-9

Taylor, S., & Todd, P. (1995a). Decomposition and crossover effects in the theory of planned behaviour: A study of consumer adoption intentions. *International Journal of Research in Marketing, 12*(2), 137-155. doi:10.1016/0167-8116(94)00019-K

Taylor, S., & Todd, P. (1995b). Understanding Information Technology Usage: A Test of Competing Models. *Information Systems Research, 6*(2), 144-176. doi:10.1287/isre.6.2.144

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

Tarhini, A., Hone, K., & Liu, X. (2013). User acceptance towards web-based learning systems: Investigating the role of social, organizational and individual factors in European higher education. *Procedia Computer Science,17*, 189-197. doi:10.1016/j.procs.2013.05.026

Tchatoka, F. (2015). On bootstrap validity for specification tests with weak instruments. *Econometrics Journal, 18*, 137–146. doi: 10.1111/ectj.12042

Terry, D. J., & O'Leary, J. E. (1995). The theory of planned behaviour: The effects of perceived behavioural control and self-efficacy. *British Journal of Social Psychology, 34*, 199–220. doi: 10.1111/j.2044-8309.1995.tb01058.x

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

Triandis, H. C. (1979). Values, attitudes, and interpersonal behavior. *Nebraska symposium on motivation, 27*, 195-259.

Topaloglu, M., Caldibi, E., & Oge, G. (2016). The scale for the individual and social impact of students' social network use: The validity and reliability studies.*Computers in Human Behavior, 61*, 350-356. doi:10.1016/j.chb.2016.03.036

United States Department of Health & Human Services. (2015). Belmont Report 1979. Retrieved from http:// www.hhs.gov

Upadhaya, B., Munir, R., & Blount, Y. (2014). Association between performance measurement systems and organisational effectiveness. *International Journal of Operations & Production Management*, *34*(7), 853-875. doi:10.1108/IJOPM-02-2013-0091

Van der Eijk, C., & Rose, J. (2015). Risky business: factor analysis of survey data–assessing the probability of incorrect dimensionalisation. *PloS one*, *10*(3), e0118900. doi: 10.1371/journal.pone.0118900

Vanclay, F., Baines, J. T., & Taylor, C. N. (2013). Principles for ethical research involving humans: Ethical professional practice in impact assessment, Part I. *Impact Assessment and Project Appraisal, 31*, 243-253. doi:10.1080/14615517.2013.850307

Venkatesh,V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, *39*(2), 273–315. doi:0.1111/j.1540-5915.2008.00192.x

Venkatesh, V., Brown, S. A., & Bala, H. (2013). Bridging the qualitative-quantitative divide: Guidelines for conducting mixed methods research in information systems. *MIS Quarterly*, *37*, 21-54. Retrieved from http://www.misq.org/

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly 27*, 425-478. Retrieved from http://www.misq.org/

Venkatesh, V., Sykes, T. A., & Venkatraman, S. (2014). Understanding e- government portal use in rural India: Role of demographic and personality characteristics. *Information Systems Journal*, *24*(3), 249-269. doi: 10.1111/isj.12008

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology : Extending the unified theory. *MIS Quarterly, 36*, 157–178. Retrieved from http://www.misq.org/

Venkatesh, V., Thong, J. Y., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems*, *17*(5), 328.

Wang, C., & Wang, S. (2014). Use behavior research of information security technology based on TAM. *International Journal of Security & its Application*, *8*(2)203-209. doi:10.14257/ijsia.2014.8.2.21

Weeger, A. & Gewald, H. (2014). Factors Influencing future employees decision-making to participate in a BYOD program: Does risk matter? In *Proceedings Research: 22nd European Conference on Information Systems (ECIS)*. Tel Aviv, Israel.

Weeger, A., Wang, X., & Gewald, H. (2016). IT Consumerization: Byod-program acceptance and its impact on employer attractiveness. *Journal of Computer Information Systems, 56*(1), 1-10. doi:10.1080/08874417.2015.11645795

White, K. M., Terry, D. J., & Hogg, M. A. (1994). Safer sex behavior: The role of attitudes, norms, and control factors. *Journal of Applied Social Psychology, 24*, 2164–2192. doi: 10.1111/j.1559-1816.1994.tb02378.x

Wong, C. H., Tan, G. W. H., Loke, S. P., & Ooi, K. B. (2015). Adoption of mobile social networking sites for learning?. *Online Information Review,39*(6), 762-778. doi: 10.1108/OIR-05-2015-0152

Wong, C. H., Wei-Han Tan, G., Loke, S. P., & Ooi, K. B. (2014). Mobile TV: a new form of entertainment?. *Industrial Management & Data Systems*, *114*(7), 1050-1067.doi: 10.1108/IMDS-05-2014-0146

Woodside, A. G. (2013). Moving beyond multiple regression analysis to algorithms: Calling for adoption of a paradigm shift from symmetric to asymmetric thinking in data analysis and crafting theory. *Journal of Business Research, 66*(4), 463-472. doi: 10.1016/j.jbusres.2012.12.021

Yang, S. (2013). Understanding undergraduate students' adoption of mobile learning model: A perspective of the extended UTAUT2. *Journal of convergence information technology*, *8*(10), 969. doi:10.4156/jcit.vol8.issue10.118

Ye, X., Yao, Z., Liu, W., Fan, Y., Xu, Y., & Chen, S. (2014). Path analysis to identify factors influencing health skills and behaviour in adolescents: A cross-sectional survey. *Plos One, 9*(8), e104406. doi:10.1371/journal.pone.0104406

Yilmaz, K. (2013). Comparison of Quantitative and Qualitative Research Traditions: epistemological, theoretical, and methodological differences. *European Journal of Education*, *48*(2), 311-325. doi: 10.1111/ejed.12014

Yuan, S., Ma, W., Kanthawala, S., & Peng, W. (2015). Keep using my health apps: Discover users' perception of health and fitness apps with the UTAUT2 model. *Telemedicine and e-Health*, *21*(9), 735-741. doi:10.1089/tmj.2014.0148.

Zainodin, H., & Yap, S. (2013). Overcoming multicollinearity in multiple regression using correlation coefficient. In *Proceedings of the International Conference on Mathematical Sciences and Statistics* (pp. 416-419). Kuala Lumpur, Malaysia: AIP Publishing

Zachariadis, M., Scott, S., & Barrett, M. (2013). Methodological implications of critical realism for mixed-methods research. *MIS Quarterly, 37*, 855-879. Retrieved from http://www.misq.org/

Zahadat, N., Blessner, P., Blackburn, T., & Olson, B. A. (2015). BYOD security engineering: A framework & its analysis. *Computers & Security,55*, 81-99. doi:10.1016/j.cose.2015.06.011.

Zemore, S. E., & Ajzen, I. (2014). Predicting substance abuse treatment completion using a new scale based on the theory of planned behavior. *Journal of substance abuse treatment, 46*(2), 174-182. doi:10.1016/j.jsat.2013.06.011

Zohrabi, M. (2013). Mixed method research: Instruments, validity, reliability and reporting findings. *Theory and Practice in Language Studies*, *3*(2), 254. doi:10.4304/tpls.3.2.254-262

Appendix A: Letter Requesting Employees' Participation in the Survey

To:

From:

Date:

Dear Sir/Madam: I am Alain Ouattara, a Doctor of Information Technology student at Walden University. I am seeking permission for employees to participate in the quantitative study on the relationship between habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value, and employees' consumerization behavioral intentions. The population for the study is employees working for small and medium-sized businesses (SMBs) located in the province of Ontario, Canada.. The name of your organization will not be required.

. The survey will be web-based. I will use SurveyMonkey® to collect the data. The web-based survey may require 15 to 20 minutes of the respondent's time.

Maintaining confidentiality of the survey responses is critical, so an encrypted USB drive in a safety deposit box will contain the data for five years after the completion of the study. The responses to the electronic survey are crucial in helping to design appropriate strategies towards IT consumerization. Employees may opt to withdraw from the research at their convenience, and I will destroy the data they provided.

The doctoral study chairperson for this proposed study is Dr. Steve Case. If you have questions, you may contact me, or my supervising faculty member using the contact information. Alain Ouattara| [address redacted]| Mobile Phone: [redacted]| Email: [redacted], Dr. Steve Case| E-mail: [redacted].

Your response and time are greatly appreciated thank you.

Sincerely,

Alain Ouattara

Appendix B: Survey Questions

Introduction

This survey will address the extent to which the employees' IT consumerization behavioral intention is related to habit, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, social influence, and price value. IT consumerization describes the use of devices and applications or services such as email services and cloud storage in private life and workplace. Consumers' IT tools can encompass cloud storage (e.g. Dropbox, iCloud, Box), chat systems (e.g. Facetime, Skype, instant messaging). They can also be online collaboration tools (e.g. Google Docs, Office 365), social networking sites (e.g. Facebook, Twitter, Instagram), online app stores (e.g. Apple App Store, Google Play), and customized consumer applications. The responses will be used to determine the level of IT consumerization activities of your employees. The data analysis will allow comprehending the strength of the relationship. This survey has eight sections, with each section corresponding to the variables mentioned above. For each statement on, please provide a response on a scale of 1 to 7. The definition of the scale is as follows. 1 = strongly disagree, 2 = moderately disagree, 3 = somewhat disagree, 4 = neutral (neither disagree nor agree), 5 = somewhat agree, 6 = moderately agree, and 7 = strongly agree

Demographic

Age (between 18-100)

Gender (Man = 1; Woman = 0)

Performance Expectancy

PE1. I find consumer’s IT tools useful in my daily life.

PE2. Using consumer’s IT tools increases my chances of achieving things that are important to me.

PE3. Using consumer’s IT tools helps me accomplish things more quickly.

PE4. Using consumer’s IT tools increases my productivity.

Effort Expectancy

EE1. Learning how to use consumer’s IT tools is easy for me.

EE2. My interaction with consumer’s IT tools is clear and understandable.

EE3. I find consumer’s IT tools easy to use.

EE4. It is easy for me to become skillful at using consumer’s IT tools.

Social Influence

SI1. People who are important to me think that I should use consumer’s IT tools.

SI2. People who influence my behavior think that I should use consumer’s IT tools.

SI3. People whose opinions that I value prefer that I use consumer’s IT tools.

Facilitating Conditions

FC1. I have the resources necessary to use consumer’s IT tools.

FC2. I have the knowledge necessary to use consumer’s IT tools.

FC3. Consumer’s IT tools are compatible with other technologies I use.

FC4. I can get help from others when I have difficulties using consumer’s IT tools.

Hedonic Motivation

HM1. Using consumer’s IT tools is fun.

HM2. Using consumer’s IT tools is enjoyable.

HM3. Using consumer’s IT tools is very entertaining

Price Value

PV1. Consumer’s IT tools are reasonably priced.

PV2. Consumer’s IT tools is a good value for the money.

PV3. At the current price, consumer’s IT tools provide a good value.

Habit

HT1. The use of consumer’s IT tools has become a habit for me.

HT2. I am addicted to using consumer’s IT tools.

HT3. I must use consumer’s IT tools.

HT4. Using consumer’s IT tools has become natural to me.

Behavioral Intention

BI1. I intend to continue using consumer’s IT tools in the future.

BI2. I will always try to use consumer’s IT tools in my daily life.

BI3. I plan to continue to use consumer’s IT tools frequently.

Use

Please choose your usage frequency for each of consumer’s IT tools.

Note: Frequency ranged from “never” to “many times per day.”

Appendix C: Tabular Presentation of Key Findings

Table C1

Descriptive Statistics Regression

	Mean	Std. Deviation	N
PE	6.0093	.96669	108
EE	5.7500	1.22950	108
SI	4.9907	1.01848	108
FC	4.6713	.89171	108
HM	5.2315	1.09037	108
PV	4.3148	1.99367	108
HT	3.9491	.98811	108
BI	6.1759	1.12598	108

Note. PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitating conditions, HM = hedonic motivation, PV = price value, BI = behavioral intention, and HT = habit.

Table C2

Model Summary with the Dependent Variable Behavioral Intention

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.918[a]	.842	.831	.36023	1.757

Table C3

Bootstrap for Model Summary with the Dependent Variable Behavioral Intention

Model	Durbin-Watson	Bias	Std. Error	95% Confidence Interval	
				Lower	Upper
1	1.757	-.526	.174	.904	1.587

Table C4

ANOVA with the Dependent Variable Behavioral Intention

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	69.125	7	9.875	76.097	.000[a]
	Residual	12.977	100	.130		
	Total	82.102	107			

Table C5

Correlation Coefficients Among Study Predictor Variables

Model		Unstandardized Coefficients		Standardized Coefficients			95% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	-.682	.294		-2.319	.022	-1.265	-.099		
	PE	.359	.050	.356	7.242	.000	.260	.457	.655	1.527
	EE	.237	.068	.187	3.464	.001	.101	.372	.540	1.852
	SI	.254	.043	.258	5.979	.000	.170	.339	.851	1.175
	FC	.115	.049	.114	2.336	.022	.017	.213	.664	1.506
	HM	.084	.042	.107	2.011	.047	.001	.168	.554	1.805
	PV	.086	.038	.105	2.280	.025	.011	.161	.738	1.355
	HT	.276	.066	.269	4.206	.000	.146	.406	.385	2.597

Note. PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitating conditions, HM = hedonic motivation, PV = price value, BI = behavioral intention, and HT = habit.
.

Table C6

Bootstrap for Coefficients

Model			Bias	Std. Error	Sig. (2-tailed)	95% CI Lower	95% CI Upper
1	(Constant)	-.682	-.012	.348	.052	-1.387	-.033
	PE	.359	.007	.050	.000	.270	.475
	EE	.237	-.005	.074	.004	.095	.390
	SI	.254	-.001	.051	.000	.156	.351
	FC	.115	.002	.058	.045	.007	.232
	HM	.084	.002	.041	.041	.007	.168
	PV	.086	-.001	.039	.027	.010	.164
	HT	.276	.002	.066	.000	.140	.401

Note. PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitating conditions, HM = hedonic motivation, PV = price value, BI = behavioral intention, HT = habit, and CI = confidence interval.

Table C7

Residual Statistics with the Dependent Variable Behavioral Intention

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-1.6496	1.5867	.0000	.80376	108
Residual	-.99362	1.07057	.00000	.34825	108
Std. Predicted Value	-2.052	1.974	.000	1.000	108
Std. Residual	-2.758	2.972	.000	.967	108

Note. PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitating conditions, HM = hedonic motivation, PV = price value, BI = behavioral intention, and HT = habit.

Table C8

Bootstrap Independent Variables and Moderators with the Dependent Variable Behavioral Intention

		Statistic	Bias	Std. Error	95% CI Lower	95% CI Upper
Predicted Value	Minimum	-1.6496				
	Maximum	1.5867				
	Mean	.0000	.0012	.0838	-.1667	.1605
	Std. Deviation	.80376	.00045	.05131	.69608	.90003
	N	108	0	0	108	108
Residual	Minimum	-.99362				
	Maximum	1.07057				
	Mean	.00000	.00000	.00000	.00000	.00000
	Std. Deviation	.34825	-.01509	.02764	.27911	.38573
	N	108	0	0	108	108
Std. Predicted Value	Minimum	-2.052				
	Maximum	1.974				
	Mean	.000	.000	.000	.000	.000
	Std. Deviation	1.000	.000	.000	1.000	1.000
	N	108	0	0	108	108
Std. Residual	Minimum	-2.758				
	Maximum	2.972				
	Mean	.000	.000	.000	.000	.000
	Std. Deviation	.967	.000	.000	.967	.967
	N	108	0	0	108	108

Note. CI = confidence interval

Table C9

Bootstrap Independent Variables and Moderators with the Dependent Variable Behavioral Intention

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	-.102	.056		-1.828	.070	-.212	.009		
	PE	.359	.050	.356	7.242	.000	.260	.457	.655	1.527
	EE	.237	.068	.187	3.464	.001	.101	.372	.540	1.852
	SI	.254	.043	.258	5.979	.000	.170	.339	.851	1.175
	FC	.115	.049	.114	2.336	.022	.017	.213	.664	1.506
	HM	.084	.042	.107	2.011	.047	.001	.168	.554	1.805
	PV	.086	.038	.105	2.280	.025	.011	.161	.738	1.355
	HT	.276	.066	.269	4.206	.000	.146	.406	.385	2.597
2	(Constant)	-.016	.052		-.318	.751	-.119	.086		
	PE	.327	.046	.325	7.076	.000	.236	.419	.508	1.970
	EE	.264	.058	.209	4.540	.000	.149	.380	.504	1.983
	SI	.209	.037	.212	5.716	.000	.136	.282	.779	1.284
	FC	.146	.041	.144	3.538	.001	.064	.228	.644	1.554
	HM	.133	.041	.169	3.256	.002	.052	.213	.397	2.516
	PV	.035	.033	.043	1.050	.296	-.031	.100	.652	1.533
	HT	-.031	.072	-.031	-.431	.667	-.175	.113	.213	4.689
	FC*BI*Age	.007	.002	.230	4.445	.000	.004	.010	.398	2.511
	HM*BI*Age	-.005	.002	-.144	-2.197	.030	-.009	.000	.248	4.027

table continues

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95% Confidence Interval for B Lower Bound	Upper Bound	Collinearity Statistics Tolerance	VIF
	PV*BI*Age	-.002	.001	-.076	-1.985	.050	-.005	.000	.734	1.363
	HT*BI*Age	-.005	.002	-.146	-2.342	.021	-.009	-.001	.274	3.651
3	(Constant)	-.027	.047		-.576	.566	-.121	.066		
	PE	.287	.043	.285	6.654	.000	.202	.373	.478	2.093
	EE	.245	.054	.194	4.565	.000	.138	.351	.487	2.052
	SI	.224	.034	.227	6.559	.000	.156	.292	.730	1.370
	FC	.151	.038	.149	3.956	.000	.075	.227	.616	1.624
	HM	.101	.038	.129	2.673	.009	.026	.176	.377	2.651
	PV	.024	.030	.029	.786	.434	-.036	.084	.639	1.564
	HT	-.018	.067	-.018	-.270	.788	-.151	.115	.203	4.917
	FC*BI*Age	.007	.002	.234	4.111	.000	.004	.010	.271	3.693
	HM*BI*Age	.003	.003	.096	1.169	.245	-.002	.008	.129	7.763
	PV*BI*Age	-.002	.001	-.069	-1.629	.107	-.005	.000	.492	2.031
	HT*BI*Age	-.011	.003	-.330	-4.187	.000	-.016	-.006	.141	7.069
	HM*BI*Gdr	-.469	.102	-.322	-4.615	.000	-.671	-.267	.180	5.554
	FC*BI*Gdr	.001	.065	.001	.013	.989	-.128	.130	.356	2.806
	PV*BI*Gdr	.020	.065	.014	.313	.755	-.109	.150	.451	2.215
	HT*BI*Gdr	.321	.103	.203	3.113	.002	.116	.526	.206	4.848

Note. PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitating conditions, HM = hedonic motivation, PV = price value, BI = behavioral intention, HT = habit, and Gdr = gender.

Appendix D: Permission to Use UTAUT2 Survey Instrument

MIS Quarterly

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

September 23, 2016

Alain Ouattara
Walden University

Permission to use material from
MIS Quarterly in Dissertation Research

Permission is hereby granted for Alain Ouattara to use material from "Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology," V. Venkatesh, J. Y. Thong, and X. Xu, *MIS Quarterly* (36:1), March 2012, pp. 157-178, specifically the constructs and the measurement scales and additional reference material as needed, in his doctoral dissertation tentatively titled "Information Technology (IT) Consumerization: Antecedents of Employees' Consumerization Behavioral Intentions," being completed at Walden University.

In addition to the citation information for the work, the legend for the material should include

Copyright © 2012, Regents of the University of Minnesota. Used with permission.

Permission to use this material extends to electronic distribution of the original dissertation through the ProQuest Information and Learning in electronic format, and to any academic journal articles resulting from the dissertation. Any other use may require payment of a fee and separate permission must be obtained.

Janice
DeGross

Janice I. DeGross
Manager