2019

Relationship Between Perceived Usefulness, Ease of Use, and Acceptance of Business Intelligence Systems

Christina Ndiwa Sandema-Sombe
Walden University

Walden University

College of Management and Technology

This is to certify that the doctoral study by

Christina Ndiwa Sandema-Sombe

has been found to be complete and satisfactory in all respects,
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the review committee have been made.

Review Committee
Dr. Brandon Simmons, Committee Chairperson, Doctor of Business Administration Faculty

Dr. Jamiel Vadell, Committee Member, Doctor of Business Administration Faculty

Dr. Jaime Klein, University Reviewer, Doctor of Business Administration Faculty

The Office of the Provost

Walden University
2019

Abstract

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by

Christina Ndiwa Sandema-Sombe

MM, University of Phoenix, 2016

BA, Agnes Scott College, 2006

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Business Administration

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October 2019

Abstract

In retail, the explosion of data sources and data has provided incentive to invest in information systems (IS), which enable leaders to understand the market and make timely decisions to improve performance. Given that users' perceptions of IS affects their use of IS, understanding the factors influencing user acceptance is critical to acquiring an effective business intelligence system (BIS) for an organization. Grounded in the technology acceptance model theory, the purpose of this correlational study was to examine the relationship between perceived usefulness (PU), perceived ease of use (PEOU), and user acceptance of business intelligence systems (BIS) in retail organizations. A 9-question survey was used to collect data from end-users of BIS in strategic managerial positions from retail organizations in the eastern United States who reported using BIS within the past 5 years. A total of 106 complete survey responses were collected and analyzed using multiple linear regression and Pearson's product-moment correlation. The results of the multiple linear regression indicated the model's ability to predict user acceptance, $F(2,103) = 21.903$, $p < .000$, $R^2 = 0.298$. In addition, PU was a statistically significant predictor of user acceptance ($t = -3.947$, $p = .000$), which decreased with time as shown by the results from Pearson's product-moment correlation, $r = -.540$, $n = 106$, $p < .01$. The implications of this study for positive social change include the potential for business leaders to leverage BIS in addressing the underlying causes of social and economic challenges in the communities they serve.

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Dedication

I want to dedicate this work to my husband, life-long partner, love of my life and best friend, Clive Sombe. Thank you for the support, encouragement, and unwavering commitment to helping me achieve my goals and reach my potential. To Killian and Tea, our children, who have been so patient throughout this challenging journey, cheerleading their mummy through and through. And to my parents Killian and Eunice for praying for me constantly, checking on me and encouraging me and teaching me to be the kind of person that has the grit to persevere through enormous obstacles. You breathed into me a love for education and are a constant reminder in my subconscious to reach the heights of Kilimanjaro. For that, I love you, and thank you. To my brother Edgar and Jan Sandema for helping me get started with my university education. You gave me the opportunity of a lifetime, and I'm forever grateful. To my baby sister Janet who has heard more about this study than she probably wanted to know, and just loved me through the process, I thank you. And finally to the uncles and aunts that have prayed for me and hoped for this achievement; aunty Patricia Madekurozwa, uncle Mukwenda Sandema, uncle Mfungula Sandema, and auntie Rose Lubasi. Your prayers have been the wind at my back, pushing me towards success. Thank you for always being in my corner. Ndiwa.

Acknowledgments

I would first like to thank my chair, Dr. Brandon Simmons, for his guidance and support through this journey. Your support and encouragement have kept me focused on the result. I would also like to thank my committee member Dr. Jamiel Vadell and my university research reviewer Dr. Jaime Klein for their valuable input and expertise.

I would also like to thank the following people who have been supportive throughout this journey. James Sombe, Esther Nkaambi, Ella Vakhidova, Stuart Rosenberg, Benjamin Johnson, Vandana Mysore, Sara Matthews, and Louise Notley. I thank you all for being such supportive friends and family to me during this extremely challenging journey.

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Section 1: Foundation of the Study

During the past few decades, business leaders have made significant investments in implementing complex information systems (IS) to achieve a competitive advantage (Bischoff, Aier, Haki, & Winter, 2015). Simultaneously, a significant number of organizations exhibit a contradictory relationship between technology investments and firm performance, also known as a *productivity paradox* (Venkatesh & Bala, 2008). According to Venkatesh and Bala (2008), low adoption and underutilization are key reasons for the productivity paradox, further exacerbated by a lack of understanding about why end-users accept or reject IS. To benefit from IS investments, it is essential to understand why end-users accept IS. Business leaders can then purposefully evaluate IS solutions, considering the intended end-users before procurement.

Using Davis's (1989) technology acceptance model framework in this quantitative correlational study, I examined the relationship between (a) perceived usefulness (PU), (b) perceived ease of use (PEOU), and (c) user acceptance of business intelligence systems (BIS) in retail organizations. My objective in this study was to help business leaders understand the factors influencing user acceptance of BIS. Business leaders armed with the diagnostic tools to predict user acceptance of BIS can then identify appropriate technology to enhance firm performance or facilitate design changes before end-users have experience with the system (Taylor & Todd, 1995). To achieve these objectives, I used an online survey to collect data from end-users of BIS and

analyzed the data using multiple linear regression and Pearson's product-moment correlation.

Background of the Problem

Strategic management researchers emphasize the concept of business intelligence (BI) as an essential competitive tool necessary for organizational sustainability and success. As a result, BI has become one of the prerequisites for competitive advantage in the marketplace (Abzaltynova & Williams, 2013). Business leaders invest in BIS to take advantage of the structured and unstructured data available to support, improve, and accelerate decision making (Eybers & Giannakopoulos, 2015). Despite significant investments in BIS, unsuccessful implementation and suboptimal performance are common (Boyton, Ayscough, Kaveri, & Chiong, 2015; Eybers & Giannakopoulos, 2015; Guarda et al., 2016). Low adoption and underutilization are significant barriers to successful implementation because end-users transmit their technology beliefs through the organization, influencing more end-users to resist the technology and thereby impacting user acceptance of the technology. Business leaders need to understand end-users' perceptions about a BIS before selecting, procuring and implementing BIS to avoid underutilization resulting from a lack of user acceptance (Escobar-Rodríguez & Romero-Alonso, 2014; Venkatesh & Bala, 2008). The technology acceptance model (TAM) is the theoretical framework applied in this study to provide the means to understand end-users' beliefs about technology. The results of this study may enable

business leaders to understand the factors to consider in the selection of BIS to encourage acceptance and ultimately accelerate management decision-making processes.

Problem Statement

Organizational leaders are generally unenthusiastic about publicizing outright failures or suboptimal BIS (Guarda et al., 2016). Approximately 50% to 70% of BI implementations do not meet stakeholder expectations and do not deliver any real business value (Boyton et al., 2015). The general business problem was that a lack of user acceptance of BIS undermines efforts to accelerate decision-making processes within an organization. The specific business problem for this study was that some business leaders in the retail industry lack knowledge about the relationship between (a) PU, (b) PEOU, and (c) user acceptance of BIS.

Purpose Statement

The purpose of this quantitative correlation study was to examine the relationship between (a) PU, (b) PEOU, and (c) user acceptance of BIS in the retail industry. The independent variables were (a) PU and (b) PEOU, and the dependent variable was (c) user acceptance. The target population comprised of end-users of BIS from retail businesses in the eastern United States. The implications for social change could include the use of BIS in the decision-making processes involving corporate contribution to positive social change using evidence-based insights to identify the most impactful investments for a community.

Nature of the Study

For this study, I evaluated the appropriateness of quantitative, qualitative, and mixed-method research methods to examine the relationship between (a) PU, (b) PEOU, and (c) user acceptance of BIS. The quantitative methodology was appropriate because each of the variables in this study was measurable ordinal, interval, or ratio data. Also, quantitative methods are appropriate for research containing one or more hypotheses and where the intent is to use the data to examine variables' relationships or differences (Lach, 2014). Although researchers often use qualitative and mixed-methods methodologies in technology user acceptance studies, both were inappropriate for this study because of the intent of qualitative research. Researchers use qualitative research methodology to explore behaviors, social processes, and individual experiences (Bailey, 2014; Riazi & Candlin, 2014). My focus in this study was to examine the relationships among the identified variables.

Within quantitative research, researchers can choose from multiple designs, including correlational, quasi-experimental, and experimental research designs. Quantitative correlational design was the appropriate approach for this study because my intent was to examine how multiple variables relate to one another. Bala, Brown, and Venkatesh (2013) described quasi-experimental and experimental designs as designsresearchers use when cause and effect are the focus of the study. In this study, I did not include examinations of cause and effect relationships. Specifically, my focus in

this research was to examine the extent to which there is a relationship between the variables of interest.

Research Question

I used the following research question in this study: What is the relationship between (a) PU, (b) PEOU, and (c) user acceptance of BIS?

Hypotheses

Null Hypothesis (H_0): There is no statistically significant relationship between (a) PU, (b) PEOU, and (c) user acceptance of BIS

Alternative Hypothesis (H_1): There is a statistically significant relationship between (a) PU, (b) PEOU, and (c) user acceptance of BIS

Theoretical Framework

The TAM provided the framework for this study. Developed by Davis in 1986, the TAM model is the most widely applied model of users' acceptance and use of technology (Venkatesh, 2000). The TAM framework provides IS researchers with a model and theory for studying all types of IS usage and user acceptance situations and the means to formulate, approach, and solve research problems (Silva, 2007). Specifically, the TAM model provides a framework to assess how and when an individual user will use new technology. For this reason, the TAM framework was appropriate for this study.

The TAM theory posits two variables, PU and PEOU, are determinants of individual adoption and use of information technology (IT) (Davis, 1989). As illustrated in Figure 1, these two determinants serve as the basis for attitude towards systems use,

thereby generating the actual usage behavior (Salman, Abdullah, Aziz, Ahmad, & Kee, 2014). PU and PEOU are the independent variables used in this study. My goal was to measure the extent and nature of the relationship between the independent variables, PU and PEOU, and the dependent variable user acceptance of BIS.

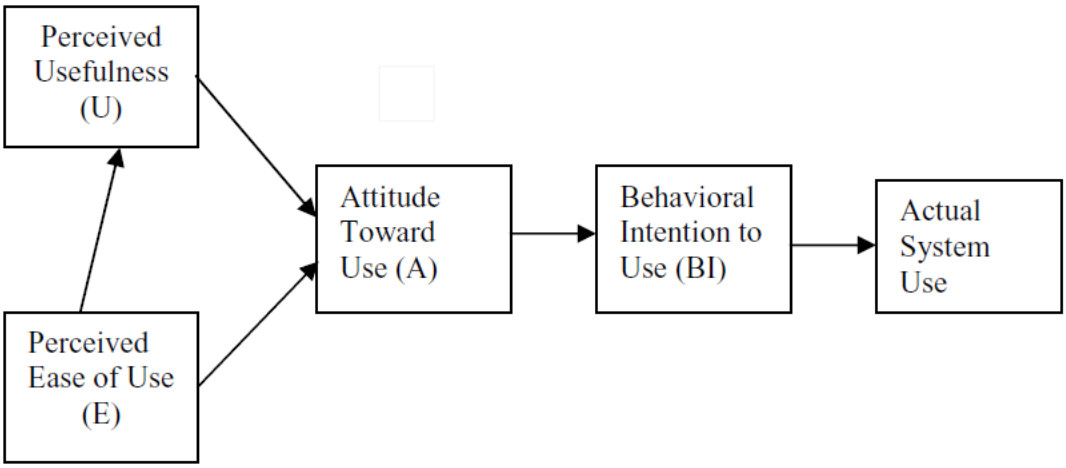

Figure 1. Technology acceptance model adapted from "User acceptance of computer technology: a comparison of two theoretical models" by F. Davis, R. Bagozzi and P. Warshaw, 1989, *Management Science*, *35*, p. 985.

Operational Definitions

Several terms used in this study could have different interpretations. Therefore, to aid in comprehension, I have provided operational definitions to promote a consistent interpretation of my findings. The definitions provided reflect the use of these terms in this doctoral study and are intended to assist the reader.

Business intelligence (BI): BI is the ability to apprehend the interrelationships of presented facts in such a way as to guide action toward a desired goal (Luhn, 1958). Furthermore, BI as the ability of an organization or business to reason, plan, predict,

solve problems, think abstractly, comprehend, innovate and learn in ways which increase organizational knowledge, inform decision processes, enable effective actions, and help to establish and achieve business goals (Wells, 2008).

Business intelligence systems or BI implementations (*BIS*): BIS are most commonly identified as technological solutions holding quality information in well-designed data stores, connected with business-friendly tools which provide users—incumbents of executives, managers, business analysts and other roles within a firm using BIS-enabled information for analytical decision making—with timely access to as well as effective analysis and insightful presentation of the information generated by enterprise-wide applications, enabling them to make the right decisions or take the right actions (Popovič, Hackney, Coelho, & Jaklič, 2014). BIS describes the technical artifacts which provide BI functionality to users. (Fink, Yogev, & Even, 2017)

End-user(*s*) or *user*(*s*): I use *end-user(s)* and *user(s)* interchangeably throughout this study and are defined as all employees who are not information technology experts, but who use a BIS to perform their duties at work (Costabile, Fogli, Mussio, & Piccinno, 2007).

Perceived ease of use (*PEOU*): PEOU is the extent of the belief that using a specific information system will be effortless (Davis, 1989)

Perceived usefulness (*PU*): PU is the extent of the belief that using a specific information system will improve job performance and provide rewards or benefits to the user (Davis, 1989).

Technology acceptance model (*TAM*): The TAM is an information-technology-specific theory that hypothesizes PEOU and PU are the predominant traits relevant to the behavior of users toward technology acceptance (Davis, 1989).

User acceptance: User acceptance is the noticeable willingness to use information technology in accordance with the purpose and functions of the technology to accomplish tasks on the job (Yucel & Gulbahar, 2013).

Assumptions, Limitations, and Delimitations

Research bias and threats to internal and external validity are unavoidable in any research study. All research undertaken by a researcher is influenced by the researcher's assumptions, which constitute their beliefs or presumptions of truth (Kirkwood & Price, 2013). In addition, all research has limitations and delimitations. Limitations constitute threats to the internal validity or the weaknesses of the study (Brutus, Aguinis, & Wassmer, 2012). Delimitations are researcher-imposed constraints on the scope of the study, which affect the external validity or generalizability of the results of the study (Kromidha & Kristo, 2014). Therefore, to aid in clarity and comprehension, promote a common understanding of this research study and enable others to objectively evaluate the methods, conclusions, and findings and reduce variability, the researcher is responsible for explicitly documenting and disclosing their assumptions, limitations, and delimitations of their research interpretation (Arghode, 2012; Ellis & Levy, 2009; Kirkwood & Price, 2013).

Assumptions

The assumption reality is objective and controlled by cause and effect relationships primarily drove my decision to pursue a quantitative correlational research design (Arghode, 2012). Also, my decision to use a self-reported questionnaire reflects my assumption that all participants shared a common understanding of what constitutes a BIS and which individuals or employees constituted end-users of BIS. And finally, I assumed all the survey respondents would answer honestly and objectively because their participation is voluntary and anonymous.

Limitations

Following recommendations from Brutus et al. (2012) regarding reporting limitations, I am providing a detailed explanation of the material limitations and severity of each of the limitations. First, as a new researcher, my lack of experience in primary data collection coupled with the lack of user acceptance studies on BIS in retail organizations during the past 5 years could have impacted the formulation of the research objectives, the quality of the data collection method and therefore the outcomes I obtained. Second, participants' PU and PEOU of BIS depend on their experiences in their current business environment. Using an online survey to collect data anonymously from participants could have limited the ability to observe significant heterogeneity across the targeted groups.

Delimitations

I used SurveyMonkey's American audience (2015a) to simplify access to a purposive sample delimited to end-users of BIS in retail companies located in the eastern United States. In addition, I targeted users who had used a BIS within the past 5 years . Considering published research on the adoption of BIS began long before 2014, an extended window of observation may have yielded different trends. Second, the reliance on participants from the retail industry represented selective coverage of user acceptance of BIS. In conjunction with the strong regional focus on the eastern United States, the influence of this study may be limited to retailers in the United States. A less restrictive sample frame could have impacted the extent of variations. Future researchers can validate the strength of the study by using different study participants and timeframes. Generalizations regarding BIS software was not warranted because specific BIS software used by participants was not my focus in this study.

Significance of the Study

Contribution to Business Practice

A business leader's purpose is to find ways to meet or exceed business goals and objectives. The decision to invest in BI technologies to augment or transform the decision-making processes in an organization is undertaken to improve organizational performance by improving management decision-making. In the decision support technology literature, BI technologies are purported to provide unprecedented capacity to accrue, analyze and synthesize vast amounts of information from multiple sources into

competitive intelligence or insights, which are used to inform and accelerate operational and strategic decision-making processes in real-time (Bischoff et al., 2015; Boyton et al., 2015). The findings from this study could be significant in providing business leaders insights, from the end-user perspective, regarding the PEOU and the PU of BIS. Leaders armed with a better understanding of their end-users' requirements can then invest in appropriate solutions which are more likely to be used for the acceleration of management decision-making processes.

Implications for Social Change

Business leaders face challenges determining the most effective ways to make social investments which have an enduring positive influence. In response, prioritization of corporate social responsibility (CSR) as normal business practice is becoming common practice. Social responsibility investments promote the brand or reputation of an organization and generate positive reactions from current and future customers (Hilderbrand et al., 2017). As a result, often, customer perceptions rather than evidence-based insights drive business strategy regarding social investments (Hilderbrand, Demotta, Sen, & Valenzuela, 2017; Kilton & Purdy, 2014). Potentially, BIS could provide the means to support leader's decision-making processes regarding what social issues to support, how much to contribute, and in what ways (e.g., cash, products, company know-how, employee volunteerism) (Hilderbrand et al., 2017). The findings from this study could lead to positive social change as acceptance of BIS increases, improving and broadening managers decision-making processes to include social

investment planning and execution. For example, leaders using BIS to identify environmental interventions to invest in might discover an increase in employee training on environmental management would have a greater effect than sponsoring a local recycling event (Hung, Ramasamy, & Lee, 2010). A business leader could then refocus resources on employee training resulting in more efficacious environmental outcomes for the community.

A Review of the Professional and Academic Literature

Introduction

This review of the literature published during the past 5 years provides an overview of research focused on user acceptance of BIS in the retail industry. BIS has gained importance across industries as a tool necessary to support and improve the decision-making processes of the greatest number of managers in an organization given one of the main functions of management is decision-making (Arnott, Lizama, & Song, 2017; Hanifi & Taleei, 2015). Understanding the reasons end-users of BIS accept or reject BIS is critical to successful planning, implementation, and execution of BIS as well as the design of interventions to encourage usage of BIS. The literature provides a foundation to better understand the relationship between PU, PEOU, and user acceptance of BIS.

The literature review includes descriptions of the research topic, the theoretical framework, as well as literature published on BIS and user acceptance of BIS and comparable technologies in the retail industry. I culled and synthesized the ideas and

concepts about the relationship between PU, PEOU, and user acceptance of BIS in the retail industry published during the past 5 years for this study from peer-reviewed journal articles and refereed conference papers using the Walden University online library. I used a range of business and management databases, including Business Source Complete, IEEE Xplore Digital Library, Emerald Management, ScienceDirect, EBSCOhost, ABI/Inform Complete, and ProQuest. I also used Google Scholar to find free full-text items, not in the library and to ensure my search for scholarly literature beyond the Walden Library was comprehensive. Search strings such as *business intelligence, BI, big data, retail and business intelligence, retail and BI, retail and big data, decision-support systems and competitive advantage, retail and data analytic, retail technology and user acceptance, technology acceptance model, TAM perceived usefulness, perceived ease of use, user acceptance, adoption, technology acceptance, technology usage, user acceptance of business intelligence systems, business intelligence systems*, and *acceptance of complex systems* (and substrings of these terms); using "all fields" to avoid limiting the search to the title or keywords. I also limited results to full-text, scholarly journals, and conference papers in English.

Despite carefully formulating the search strings, I may have excluded potentially relevant articles which did not explicitly use any of these term. For example, the search criteria did not include articles involving strategies for user acceptance of business intelligence. I completed the search on October 25, 2018. I retrieved 88 sources of which 77 (88%) were published between 2014 and 2018.

Table 1

Source Properties

Total	Peer-reviewed	Non-peer-reviewed	<5 years	≥6 years
88	74 (95%)	4 (5%)	67 (86%)	11 (14%)

BIS Introduction

The importance of accurate and timely decision-making is of critical importance for longevity and sustainability of any business. Business leaders covet BIS because they simplify the storage, identification, and analysis of information (Fink et al., 2017). BIS also enables business leaders to have a comprehensive view of their entire organization, enabling an analysis of business activities from multiple perspectives and improving decision-making processes (Fink et al., 2017). Using information from a variety of sources culled and transformed into knowledge, business leaders can make informed decisions to advance their organization's competitive advantage and improve firm performance. As a result, there is burgeoning interest in research and practice for knowledge which enables the successful implementation of BIS.

BIS in Retail Organizations

In the retail industry, there is an increasing need for business leaders to improve their decision-making processes. The retail industry contributes some of the largest numbers of businesses and employees in the world, exists in every country, and is therefore critical to the stability of the world economy (Zamba et al., 2018). The

emergence and tremendous growth of economies have unleashed powerful forces which are reshaping the retail industry at an unprecedented rate (Zamba et al., 2018; Jayakrishnan, Mohamad, Azmi, & Abdullah, 2018). The growing interest in BIS in academia and management practice is indicative of the importance placed on BIS as a solution to coping with the tremendous growth of economies and the resulting increase in data, especially in the retail industry. Synthesizing the literature to determine is already know, what still needs to be known, and how to minimize the gaps is important to advancing the research agenda in BIS. More important, research which contributes to the successful implementation of BIS in practice is warranted to provide business leaders with the information they need to take actions to maintain the viability of their organizations.

Past and Present

To fully appreciate the importance of BI in retail, one must first understand the history and evolution of BI in the retail industry. Historically, BI emerged as a hot topic in retail management with the advent of the point of sale (POS) cash registers (Chroneos-Krasavac, Soldic-Aleksic, & Petkovic, 2016). The data generated from the POS cash registers were the basis for segmentation, determination of the beginning of a promotion, the variety of items on price promotion and many other important marketing decisions (Chroneos-Krasavac et al., 2016). The success contributed to the increase in desire for more information from the marketplace to inform decision-making in other areas in retail business management.

The adoption of technological advances to deliver new experiences and streamline processes for customers in retail organizations is not uncommon. For example, retailers use information from social media, mobile devices, internet-enabled television IETVs, video cameras, digital product configuration, and 3D body scanners creating new opportunities and challenges for retail organizations (Lewis & Loker, 2014; Renko & Druzijanic, 2014). The data from these new sources can be structured or unstructured, and, if aggregated and analyzed, can provide powerful insights about the market. Business leaders desire to leverage these information sources; however, they provide no value to the organization without a means to cull, analyze, and create new actionable knowledge about the market.

Fundamentally, new information needs emerge because of the need to understand the market a retailer operates in. Currently, the number of information sources available in retail extends beyond the point of sale. For example, retailers collect vast amounts of data daily about products, competitors, suppliers, distributors orders, inventory, accounts payable, point of sale transactions, and of course, customers (Banerjee & Mishra, 2017; Langlois & Chauvel, 2017). The number of data sources and the challenges understanding the market and the consumer will continue to grow, but retail organizations with successful BIS implementations will have the ability to cull, synthesize, and provide the means to derive actionable insights from structured and unstructured information sources.

Information Explosion

Although retailers already have access to high volumes of data, based on evidenced trends, their information needs continue to grow. To put the volume of data in context, in 2016, it was estimated exabytes, or 10^{18}, of new data, were being generated every day (Chroneos-Krasavac et al., 2016). Ittmann (2015) provided the following additional examples of data being generated daily from individual sources, which today retailers hope to leverage in understanding consumers better:

- Each day, Facebook handles more than 250 million photo uploads and the interactions of 800 million active users, with more than 900 million objects (pages, groups, etc.).
- More than 5 billion people are calling, texting, tweeting and browsing on mobile phones worldwide

As the number of potential sources is multiplied, it becomes obvious how varied and voluminous the data available to retailers has become.

Undoubtedly, the volume of data in retail is increasing at an unprecedented rate. Chroneos-Krasavac et al. (2016) stated that the consequence of increasing the number of data sources causes a slowdown in the ability to process information. Optimized BIS could be the means to cope with the increasing volume of information, speed up the processing of information in varied formats, from varied sources, and relate information across disparate sources into new actionable knowledge.

The Influence of the Internet

The increasing diversity of information sources in retail has been made possible primarily because of the internet. Retail businesses are more accessible to new markets as retailers retreat from only conducting business from brick and mortar establishments. For example, online wine sales grew by 57% from 2003 to 2012 and as much as 30% growth since 2012 (Bonn, Kim, Kang, & Cho, 2016). In addition, Wagner, Schramm-Klein, and Steinmann (2017) reported an increase in IETV use as a point of sale for online purchases. As a result, the importance of maintaining an online presence for retailers cannot be understated.

Consequently, as more retailers establish or migrate their physical businesses online, more data sources are created about customers and competitors. Ittmann (2015) provides the following real examples of information accumulated by the minute:

- Wal-Mart handles more than a million customer transactions each hour and imports those into databases estimated to contain more than 2.5 petabytes of data.
- Radio frequency identification systems used by retailers and others can generate from 100 to 1000 times the data of conventional barcode systems.

Ittman's examples do not encompass the magnitude of data available from every data source available to a retailer. These examples demonstrate the magnitude of challenge retail leaders face in gaining insight into the markets they compete in.

Adoption of Novel Technology

Novel technology adoption is not uncommon in retail. Retailers often embrace new technologies to improve management through cost reduction, improved consumer service and increased sales volume (Renko, & Druzijanic, 2014). Often, business leaders experience trepidation investing in new technologies because of the uncertainty of whether users will accept the technology and yield expected returns on investment (ROI) (Renko & Druzijanic, 2014). As a result, adoption of BIS in retail organizations is inconsistent despite a general belief BI and BIS are the solutions to understanding, planning for, and reacting to disruptions which affect progress and performance (Gauzelin & Bentz, 2017; Han, Shen, & Farn, 2016). Investment in research which provides business leaders the knowledge to identify the right BIS for their end-users is a critical step towards user acceptance and potential improvements in the organization decision-making processes.

Legacy Systems

Technological transition does not occur instantaneously. In addition to new sources of information, retailers are constantly overwhelmed with vast and diverse information from enterprise and legacy systems making it challenging to distinguish important from unimportant information (Zamba et al., 2018). Solutions which enable old and new information to connect so business leaders have a holistic view of the markets they operate in. Without BIS to connect new and legacy information, business leaders cannot make sense of the retail environment and react appropriately to market needs.

Changes in Consumer Behavior

The shift to internet-enabled retail business models is in-part driven by consumer behavior. Statistical evidence shows as much as 80% of purchases are now made online (Chroneos-Krasavac et al., 2016). These changes in consumer purchasing behavior are possible because of the increased connectivity among people, things, places, and processes through social networks, the transfer of social and economic activities to the web, global positioning systems (GPS), radio frequency identification (RFID) technology, the internet of things (IoT), and the internet of everything (IoE) (Chroneos-Krasavac et al., 2016). Business leaders must contend with and find solutions to operating in the internet-enabled environment as consumer behavior is not likely to reverse course. In addition, there is a significant amount of information on the internet business leaders need to take advantage of to understand the market better.

BIS Technologies

Business leaders are often overwhelmed by the number of technological solutions available to serve their BIS needs. Implementing optimal solutions for BIS end-users who usually cannot tell what their information needs are before they experience the system is extremely challenging (Boyton et al., 2015; Popovič et al., 2014; Venter & Goede, 2017;). In addition, a single system might not fulfill all BI needs of an organization, such as reporting, analysis, monitoring, or prediction (Gauzelin & Bentz, 2017). Choosing a solution based solely on the popularity of the product or producer may not result in a

successful implementation. These issues present challenges in identifying the right solution for an organization.

End-Users and BIS

Although the implementation of BIS is a significant investment toward improving the decision-making processes in an organization, the people who use the systems are equally important. Implementation of BIS by itself does not solve business problems and does not guarantee user acceptance, especially in voluntary environments (Grublješič & Jaklič, 2015b). Often, user acceptance of technology solutions like BIS is many times lower than the expectations before the implementation of the BIS (Grublješič & Jaklič, 2015b). BIS is effective when end-users use the systems as part of their everyday activities to achieve strategic impact (Popovič et al., 2014). The value extracted from BIS is less about possessing the technology and more about people's ability to use the information for decision-making. The end-user must perceive the value of the technology to them and its ease of use.

BIS Research Landscape

In the past 5 years, BI and BIS studies have been conducted using a variety of theories, research lenses, and empirical approaches. The popularity of BIS in financial institutions, entertainment, healthcare, retail, and other contexts continues to fuel academic and practice interest in the development of BIS research (Caya & Bourdon, 2016). The diversity of topics and approaches in BIS research has created an assorted view of the BIS landscape and contributed to the lack of an integrated view of BIS

research (Trieu, 2017). Much of the research published on BIS contributes to the fragmented understanding of BIS by segregating or only addressing parts of BIS such as data mining and OLAP. More important, the chaotic approach to research on BIS has resulted in significant gaps in the literature and limited information on critical topics such as user acceptance of BIS. This study is warranted because it can provide business leaders in the retail industry knowledge regarding the relationship between the PEOU, PU, and user acceptance of BIS systems.

Often, the lack of knowledge causes business leaders to underestimate the complexity of implementing a BIS before acquiring a technology solution. Implementation is often costly, complex, and can take time to yield correct analysis making it impossible for many organizations to realize the full benefits of BIS (Caesarius & Hohenthal, 2018; Gauzelin & Bentz, 2017; Langlois & Chauvel, 2017). Also, the specific competencies required to derive meaningful, accurate insights can take time to develop in the end-user population (Gauzelin & Bentz, 2017). Business leaders who do not plan to address these issues are more likely to experience failure or suboptimal BIS.

Despite a lack of knowledge regarding how to implement BIS successfully, many leaders across industries continue to prioritize and allocate significant resources towards BIS implementation. The literature contains emerging and contradictory points of view on how to achieve BIS success. For example, some researchers contend successful adoption of BIS requires the culture of the organization to transform to a fact-based decision-making environment to evolve how business activities and decision-making

processes are performed (Fink et al., 2017). While some researchers proclaim the future of BIS is cognitive solutions which can analyze data and eliminate the need to train and retain talent who can correctly analyze information (Sato & Huang, 2015). Both these arguments have significant implications on a business leader's considerations and the decisions made regarding the approach for implementation of BIS in their organization.

Research Frameworks in BIS User Acceptance Research

There are several frameworks user acceptance researchers have used to understand user acceptance of innovative technologies like cloud computing and BI (Ramzan et al., 2018). Intention models are the most popular in the information technology literature as it relates to user acceptance and usage (Butler Lamar, Samms-Brown, & Brown III, 2016). In the retail context, the most popular approach to investigating the acceptance of innovative technologies has been specific to consumers' acceptance of specific technologies, such as self-service technologies (Pantano, 2014). Unfortunately, none of this research adequately addresses user acceptance of BIS in a retail organization.

In the BIS context user acceptance in retail research falls into two categories:

- Studies focused on user acceptance of segments of BIS such as data mining, and online analytical processing (OLAP) (Pejić Bach, Zoroja, & Čeljo, 2017; Šebjan, Bobek, & Tominc, 2017).
- Comparative studies which compare user acceptance frameworks in retail BIS.

The first category of studies, while valuable, do not provide a business leader a holistic view of BIS. Rather, they provide a greater understanding of the parts of a BIS system and are often misleading to business leaders trying to implement BIS in segments. Siloed implementations of BIS are quite common and have been shown to limit the ability to derive insights from disconnected information sources (Caesarius & Hohenthal, 2018). The second category of studies is most suitable for researchers to identify appropriate frameworks useful in researching BIS. For example, Hou (2014), conducted a study in 330 Taiwanese electronic industry firms using structural equation modeling to determine which of three intention models (TAM, the theory of planned behavior (TPB) or decomposed theory of planned behavior (DTPB)) best explained users' intentions to adopt BIS in Taiwan's electronics industry. The results from Hou (2015) indicated the DTPB model was the most parsimonious and had greater explanatory power.In terms of the ability to explain BI usage behavior, the TAM, TPB, and DTPB models were found to be comparable, and the findings from this study were limited to a single industry (Hou, 2015). Although both categories of research are valuable in the BIS research landscape, more categories of research are needed to provide business leaders with the knowledge to successfully implement and utilize BIS.

As a researcher, comparative studies provide useful information to evaluate the application, benefits, and limitations of multiple research frameworks. The TAM, for example, is a popular user acceptance framework which is frequently used to understand user acceptance of retail technologies. For example, in retail, there are many studies

focused on the user intent and attitudes of consumers of in-store technologies and social networking (Lewis & Loker, 2014; Renko & Druzijanic, 2014). Although I did not find any studies where the TAM was used to understand the factors affecting user acceptance of BIS across retailer types, the TAM has been applied successfully in several retail contexts to understand user acceptance of novel technology. Combined with the findings from other user acceptance researchers, I have confidence in the appropriateness of the TAM framework for this study.

Future of BIS in Retail

In conclusion, BIS literature does not provide business leaders a roadmap to success. Although the consistent doubling of information every 2 to 3 years pressures leaders to invest in BI capabilities, systems, and competencies, the lack of information on how to implement BIS successfully hinders successful implementation (Gauzelin & Bentz, 2017; Grublješič & Jaklič, 2015a; Langlois & Chauvel, 2017; Popovič et al., 2014). Often, leader's choose their organization's BIS implementation approach without substantial literature or documented experiences to support the approach. For example, some leaders have transformed their organizational structures, processes, and resources despite the lack of coherent guidance, while others invest in developing competencies of their people to make sense of the vast amounts of data available (Caya & Bourdon, 2016; Gauzelin & Bentz, 2017). The frequency of failure is both unsurprising and confirmation of the need for research which enables leaders to invest in the right solutions for their end-users.

Despite the challenges of implementing and deriving the benefits of a BIS, inaction is not an option in the retail sector. Retailers' performance is affected by all the stakeholders, including their suppliers and distributors (Venuturumilli, Peyyala, & Alamuri, 2017). All retail stakeholders are users of several modern technologies which collect information such as the point of sale, barcoding, and scanning, electronic data interchange, radio frequency identification, data warehousing and data mining (Sato & Huang, 2015; Venuturumilli et al., 2017). Competitive retailers will have the ability to leverage all the available information to their advantage. Therefore, learning from organizations which have successful BIS implementations can create a clearer roadmap to success.

In addition, organizations which have successfully implemented BIS are providing tangible evidence of the return on investment from BIS. Chroneos-Krasavac et al., (2016) cited Intel's 2014 study as an example of the benefits retailers have already derived from successful BIS implementations. Mainly, business decisions based on data analysis have already realized a 60% increase in trading margins, are 5% more productive and 6% more profitable than their competitors (Chroneos-Krasavac et al., 2016). The interconnectedness of disparate information sources proving the performance improvements organizations can achieve from integrated BIS systems (Hou, 2014; Zamba et al., 2018). These improvements in the competitive position of retailers using BIS demonstrates the value added to management decision-making processes (Qushem, Zeki, Abubakar, & Akleylek, 2017). These results should also increase the confidence of

business leaders on the merits of BIS and increase their appetite to learn about the factors which negatively impact successful BIS implementation.

Gaps in the research.

A review of the literature revealed BI research from the past 5 years has mostly focused on the application of the knowledge gained from research on IT business value. The main limitation of previous research is the segregation of topics inter-related in BI. Fink et al., (2017) categorizes the research in BI into 3 categories:

Category 1: Studies focused on differentiating BI capabilities (BI software and hardware versus human knowledge and skills).

Category 2: Studies which distinguish operational versus strategic (efficiency, improvement, process optimization, time, and cost reduction versus improvements in effectiveness, profitability, market share, customer satisfaction).

Category 3: Studies focused on the importance of learning and innovation as drivers for the business value of BI resources.

The majority of BIS user acceptance studies focus on user acceptance in very specific contexts. For example, Caya and Bourdon (2016) research user acceptance of BIS in sports organizations or sports analytics to develop a new conceptual framework of value creation from BI and analytics (BI&A) in competitive sports. In addition, there is a lack of user acceptance studies involving new technology innovations. Ramzan et al., (2018) found a lack of user acceptance studies on cloud computing in the telecom

industry. Like user acceptance of cloud computing technology, user acceptance of BIS is an under-researched area because it is newer technology advancement.

Pejić Bach et al., (2017), identified two streams of user acceptance research involving the TAM framework and two BI technologies which have generated a significant amount of the research about user acceptance of BIS.

Stream 1: Researchers investigating user acceptance of OLAP

Stream 2: Researchers investigating user acceptance of data mining

Research on BIS implementation and post-acceptance use behavior are warranted because this is an under-researched area (Grublješič & Jaklič, 2015b). The partial views of BI and user acceptance of BIS create challenges for understanding BI and user acceptance holistically.

Notwithstanding the above, the literature review also confirmed the lack of studies addressing factors contributing to user acceptance or resistance to BIS. While several researchers address very specific research questions relating to how BI creates business value, no comprehensive research agenda has been developed to understand the process of organizations obtaining business value from BI (Trieu, 2017). Current literature lends attention to the conditions for improved organizational performance, i.e., investments, assets, and impacts; but does not sufficiently research the probabilistic processes linking these conditions together (Trieu, 2017) such as user acceptance. Despite the general acceptance of the value creation of BI, there is a lack of measurement methods and resources to justify BI value (Hou, 2014).

Equally important is the overall number of studies evaluating user acceptance of BI irrespective of the size of business. There is a significant gap in the BI adoption literature of studies which include small to medium companies as part of the target population. Generally, small to medium-sized businesses (SMEs) are considered laggards in the implementation of BIS and are likely to be excluded from research because it is assumed they are incapable of keeping pace with their larger competitors (Qushem et al., 2017; Gudfinnsson & Strand, 2017). And yet, small businesses are the backbone of the global economy (Gudfinnsson & Strand, 2017; Puklavec, Oliveira, & Popovič, 2014; Zamba et al., 2018). Given the importance of SMEs, in the world economy and the business opportunities, BI could uncover to improve the competitive advantage of SMEs, adoption of BIS is of critical importance (Gudfinnsson & Strand, 2017; Puklavec et al., 2014). Therefore, studies which include SMEs as part of the target population are warranted.

Contribution to the existing body of knowledge.

The in-depth analysis of literature created in the past 5 years, revealed a limited number of studies conducted to explore and measure user acceptance of BIS retail organizations. As a result, the literature falls short in providing empirical evidence depicting the relationship between PU and PEOU of the end-users and their value perceptions of BIS in retail organizations**.** Given the gaps above in the literature, the goal of this study is to provide a holistic view of end-user acceptance of BI technologies in

retail organizations irrespective of the size of the organization in the eastern United States using the TAM framework.

TAM

As previously stated, the TAM is a popular user acceptance research framework. Developed by Fred Davis (1989), the TAM was specifically developed to explain user acceptance of IS or information technology (IT) (Hou, 2014). The TAM is based on two models originating from the social psychological theory of predicting behavioral intentions and actual behavior. Specifically, Fishbein and Ajzen's theory of reasoned action (TRA) (Fishbein & Ajzen, 1975) and the theory of planned behavior (TPB) (Ajzen, 1985). The TAM proposes two distinctive behavioral beliefs, namely PU and PEOU which together provides the individual's behavioral intention to use technology, and the actual use is determined by behavioral intention (Davis et al., 1989). Correspondingly, PU, PEOU, and attitude have been shown to provide significant contributions to behavioral intention to adopt new technologies (Ayele & Birhanie, 2018). Although the TAM does not have any external variables it has been sufficient to aid managers understanding the drivers and determinants of user acceptance, and in developing strategies to improve user acceptance of new systems (Emaeilzadeh, 2016; Verma & Sinha, 2016). The TAM has been used successfully in a variety of studies to examine the factors affecting user acceptance of technologies such as assistive technologies for people with disabilities, electronic banking, knowledge conversion, online auctions, e-learning, internet use and others (Yoon, 2016; Nasser Al-Suqri, 2014).

Thus, demonstrating TAMs broad applicability to novel technologies and beyond theory to practice.

User acceptance is required to exploit technology investments. Specifically, businesses can reap envisioned productivity improvements when employees use technology (Venkatesh et al., 2003). Several factors influence the end user's decision to use new technology (Lala, 2014). Fred Davis' TAM hypothesizes the attitude of the end-user towards a system is a major factor influencing the acceptance or rejection of a system (Lala, 2014). TAM also posits end-user attitudes are a combination of the end user's beliefs in the PU and PEOU of the technology (Lala, 2014). As such, the TAM model is an appropriate model to understand end-user attitudes toward new technologies.

Applicability of the TAM Framework in BIS User Acceptance Research

Despite the broad applicability of TAM to user acceptance research, researchers must still justify using the TAM framework instead of one of several competing models available in information technology acceptance research. As demonstrated in the literature, the TAM model has been used vastly to study innovation adoption behavior. Kaushik and Rahman (2015) summarized the types of studies already conducted using TAM. Namely:

- Empirical examinations of the relationships among PU, PEOU, attitude, and intention toward adoption
- Conceptual support for central constructs (PU and PEOU) of TAM
- Extension of TAM

- Comparison of TAM with other adoption theories/models

Thus, the usage of the TAM model for this study aligns with the model's application in previous similar studies, i.e., empirical examinations of the relationships between TAM variables; and it is a reliable model researchers use to explain the variance in individual or organizational intention to use technology.

The popularity of the TAM model among IS researchers contributes to my confidence in the framework. In fact, despite the availability of alternative user acceptance models, the TAM is still the most popular among user acceptance researchers (Pejić Bach et al., 2017; Emaeilzadeh, 2016). The simplicity of the TAM and its ability to explain the cause and effect relationships makes it extremely attractive (Yasa, Ratnaningrum, & Sukaatmadja, 2014). Second, the TAM is popular in technology adoption research as it allows for quick and low-cost data collection (VanDeventer, 2018). And finally, the TAM is validated as being adequate, easily comprehensible and applicable to various technologies (Butler Lamar et al., 2016; Garavand, Samadbeik, Kafashi, & Abhari, 2017; Magotra, Sharma, & Sharma, 2017; VanDeventer, 2018). Indeed, a review of the literature demonstrates TAM's ability to explain the correlation between an individual's attitudes of acceptance and actual usage of technology. Similarly, the purpose of this quantitative correlation study is to examine the relationship between (a) PU (b) PEOU, and (c) user acceptance of BIS and the TAM model is an appropriate framework for this purpose.

Arguments Against the TAM Framework

In as much as the academic literature shows vast support for the TAM, researchers have also explored other factors relevant to the adoption and usage of technology. The literature shows researchers often explore whether there are external variables which are mediators of the TAM's belief variables and if so, which external variables are important. Several studies extend the TAM to account for additional variables. However, because there were no previously published research studies investigating the user acceptance of BIS in retail organizations using the TAM framework to my knowledge; the inclusion of additional variables was unwarranted. In short, TAM increases opportunities to understand the peculiarities of user interactions with technology in contemporary technology-mediated environments (Lim, 2018). Nevertheless, a discussion of the core tenets of TAM and comparison to rival theories is warranted to confirm the appropriateness of the TAM for this study.

The Core Tenets of TAM

Perceived Usefulness, Perceived Ease of Use (PEOU), and User Acceptance.

Acceptance is the psychological process users go through when they decide to use new technology (Grublješi̇č & Jaklič, 2015a). User acceptance is the noticeable willingness to use information technology in accordance with the purpose and functions of the technology to accomplish tasks on the job (Yucel et & Gulbahar, 2013). I will use the TAM in this study to predict user acceptance using two factors, PU and PEOU (Nasser Al-Suqri, 2014; Zhao, Fang, & Jin, 2018). PU is the extent of the belief that

using a specific information system will improve job performance and provide rewards or benefits to the user (Davis, 1989). For example, if an information system can help people do their jobs better, it is perceived to be useful (Zhao et al., 2018). While PEOU is the extent of the belief that using a specific IS will be effortless (Davis, 1989); or IS, which are easy to use are perceived to be easy to use (Zhao et al., 2018). PU and PEOU have a significant influence on user acceptance (Zhao et al., 2018) because they are relevant to user's feelings of ownership and buy-in to a technology (Yim, Moses, & Azalea, 2018). As a result, the literature highlights them both as robust technology attributes for analyzing technology adoption (Magotra et al., 2017). It is worthwhile to examine the literature further to understand how these two key factors of the TAM are key to user acceptance research.

Perceived usefulness (PU).

PU appears in several studies in the past 5 years, highlighting its continued importance in understanding user acceptance. Literature stemming from the fields of management science, operational research, and informatics (Comer, Gibson, Zou, Rosenman, & Dixon, 2018) use PU to understand end-user perceptions of the usefulness of IS. For example, Moslehpour, Pham, Wong, and Bilgiçli (2018) found the advantages of online shopping versus traditional in-store shopping to users contributed to the users PU of online shopping. According to Davis (1989), PU has an impact on the intention to use a system. Prior research confirms the positive association between PU and an individual's intention to use information technology (Tallaha, Shukor, & Abu Hassan,

2014). PU can change over time as evidenced in studies like Nasser Al-Suqri (2014) who researched e-book acceptance in a non-western population. The author could not confirm PU as an antecedent of usage behavior in a population comprising of faculty who reported already having experience using e-books (Nasser Al-Suqri, 2014). Despite these findings, the author still contended the TAM variables are a good predictor of user acceptance regardless of culture or geography.

Perceived ease of use (PEOU).

Like PU, PEOU is also prominently featured in user acceptance literature. Researchers consistently agree that PEOU is an important factor in examining and assessing user acceptance of novel technologies (Ameri Shahrabi et al., 2014). Moslehpour et al., (2018) explained PEOU in terms of a user finding a technology more favorable than another for use, making it more likely to be approved by the user. Therefore, the less complicated a technological application is perceived to be, the more likely (Moslehpour et al., 2018) users will use it. Thus, ease of use and simplicity are key ingredients in IT acceptance (Sanitnarathorn, & Prajaknate, 2018). Experience plays a major role in determining the ease of use of the system. Nasser Al-Suqri's (2014) findings regarding e-book acceptance in a university in the Middle East demonstrated how more experienced users could negate the impact of PEOU on user acceptance. Beginners or novice users are more likely to encounter difficulties interacting with new technology and are more likely to report it (Caffaro, Bisaglia, Cutini, Cremasco, &

Cavallo, 2018). Therefore, an effective research design takes into account the impact experience can have on the homogeneity of the sample population.

Rival Theories/Opponents of the TAM

Rival theories to the TAM have emerged because of persistent criticisms of the TAM as being too general. User acceptance researchers have argued the determinants of intention to use technology, PU and PEOU are insufficient to accommodate contextual peculiarities (Lim, 2018). For example, Susanto and Aljoza (2015) researched the user acceptance of e-government services in Indonesia. The researchers found in addition to PU and PEOU, trust and social factors have significant influence on an individual's intention to use an e-government service. Also, their analysis of the target population highlighted specific peculiarities specific to users of government technology and uncommon in adoption studies. The role of the users expands beyond technology users to include citizen and customer roles. Thus, IT adoption behavior is impacted by the unique characteristics of its users (Emaeilzadeh, 2016), and the TAM model is not always the appropriate model to understand user acceptance. In some contexts, the TAM is too generic and trivializes self-regulatory and social aspects of user behavior, changes in the socio-economic environment, technological proliferation and therefore lacks practical value (Lim, 2018). The TAM is further criticized for being dependent on self-reported data, omitting crucial attitude variables, and having a questionable theoretical foundation (Nasser Al-Suqri, 2014). As a result, the TAM has been extended several times to include additional variables. These extensions have had the dual effect of increasing the

robustness of the model and extending it to cover non-technology ideas, broadening the use of the TAM and enabling researchers to study user acceptance ideas outside of the TAM (Hsiao & Tang, 2014; Pierce, Willy, Roncace, & Bischoff, 2014). The most popular extensions, in chronological order of development, being the TAM2, unified theory of acceptance and use of technology (UTAUT), and the TAM3. I will discuss these models in subsequent sections in greater detail.

Consequently, the majority of user acceptance studies in the past five years show an increase in the number of research studies proposing an extension to the TAM. For example, Ayele and Birhanie (2018) extended the TAM model with the additional variable's user training, incentives and, support and commitment of management study to conduct a user acceptance study of e-learning technology in Ethiopian Universities. In the BI user acceptance literature, Pejić Bach et al., (2017) investigated the adoption of BIS using the TAM framework while considering the concepts of technology-driven strategy, information quality, and project management in companies. Grublješič and Jaklič (2015a) proposed a new user acceptance model, the BI acceptance model (BIAM), which included organizational factors as determinants to modifying an individual's behavioral beliefs and improving the user acceptance of BIS. Kaushik and Rahman (2015) extended the technology acceptance model by analyzing the impact of trust and subjective norm on consumers' attitude and behavioral intention toward adopting self-service technologies in offline retail environments. Nasser Al-Suqri (2014) proposed an extension to the TAM which included the effects of language and personal characteristics (gender, age, and field

of study) on the PU, PEOU of e-books for academic work in a university setting in the middle east. Thus, demonstrating the vastness of proposed extensions available.

Some researchers have conducted research to compare the predictive and explanatory power of user acceptance models. For example, Hsiao and Tang (2014) assessed five theoretical models of user acceptance (TAM, TPB, DTPB, the UTAUT, and the combined TAM and TPB theory of acceptance (C-TAM-TPB)) to determine which model exhibited the greatest explanatory power of behavioral intention to use e-textbooks in Taiwan. While, Hou (2014) compared the TAM, the TPB, and the DTPB to determine which best explained user intentions to adopt BIS in the Taiwanese electronics industry. The researchers for these two studies found the TAM was adequate for predicting user's intentions to use BIS but recommended the UTAUT and DTPB respectively as exhibiting greater explanatory power (Hou, 2014; Hsiao & Tang, 2014). Due to the varied approaches of Hsiao and Tang (2014) and Hou (2014) when conducting the comparisons of user acceptance theoretical models, the results of their studies are insufficient to make generalizations about the appropriate acceptance model for BIS user acceptance research.

Other researchers have combined the TAM with established theoretical frameworks to study user acceptance. For example, Khan and Mir (2016) studied user acceptance using determinants of TAM, diffusion innovation theory framework, and internal and external factors to investigate user acceptance and diffusion of mobile banking. While Bhattacharya (2015) conducted research using the stage model to identify positive influencers of RFID adoption. Bhattacharya (2015) stated knowledge,

persuasion, design, decision, and implementation stages (using Rogers diffusion of innovation model) affect RFID adoption. Although these approaches provide interesting, points of view, these studies contribute to the proliferation of acceptance models and the ensuing chaos of user acceptance literature detracts from our ability progress coherently with consistent approaches to understanding user acceptance.

Despite the concerns some researchers have expressed regarding the generality of the TAM, the literature demonstrates its continued application and relevance in IS research. While augmentations of TAM and other established acceptance models are prevalent, the TAM predictors of user intention, PU and PEOU, are consistently used and believed to be critical to understanding user acceptance. The TAM is a widely accepted and cited model which has been used successfully to predict system use and its continued popularity in IS research evidences its overall explanatory power and measurement validity in various empirical environments (Pierce et al., 2014). It would be remiss to proceed with this research study without evaluating the established rival frameworks. Specifically, we will discuss in greater detail, the TRA, the TPB, the TAM2, UTAUT, the TAM3, task-technology fit (TTF), technology-organization-environment (TOE), and the diffusion of innovation (DOI) theory.

TRA

The TRA is the first theoretical perspective to gain widespread acceptance in technology acceptance research (Samaradiwakar & Gunawardena, 2014) and has been influential in the development of subsequent models like the TAM and the TPB (Hou,

2014; Liu & Yang, 2018). Proposed by Fishbein and Ajzen, (1975), the TRA posits the main determinants to accept and use new technologies is the individual's behavioral intent (Ayele & Birhanie, 2018) as shown in Figure 2. Moreover, the strength of a person's intent determines the actual performance of the expected behavior (Ayele & Birhanie, 2018). Despite the influence and commonalities between the TRA and TAM, some differences make the TAM a more appropriate model for this study.

Similar to the TAM, the TRA was developed to predict and comprehend human behavior and attitudes, and it has been used successfully to predict how individuals will behave based on their pre-existing behavioral intentions (Liu & Yang, 2018). The TRA is a general model, not designed for a specific behavior or technology (Rondan-Cataluña, Arenas-Gaitán, & Ramírez-Correa, 2015). Advocates of the TAM contend the strength of the model is its broad applicability and consistent ability to predict user acceptance of information technology (Rondan-Cataluña et al., 2015). And therefore, the TAM is the preferred model to understand user acceptance of information technology.

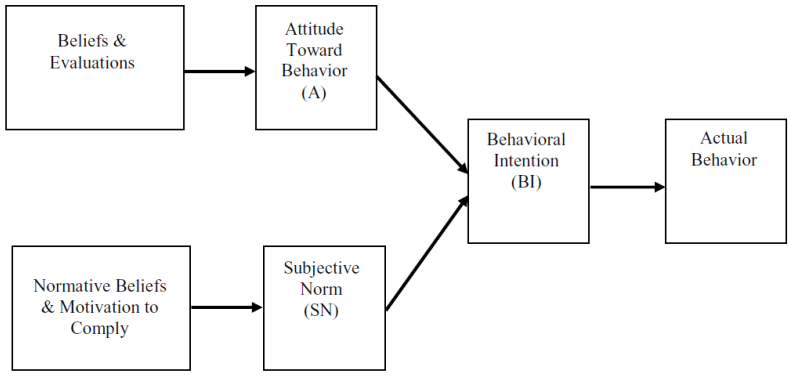

Figure 2. Theory of reasoned action (TRA) model from "User acceptance of computer technology: a comparison of two theoretical models" by F. Davis, R. Bagozzi and P. Warshaw, 1989, *Management Science*, *35*, p. 984.

TPB

A second rival theory, the TPB, is also an extension of the TRA (Hou, 2014). Developed by Icek Ajzen (1985), the TPB extends the TRA with the additional construct of perceived behavioral control (Hou, 2014). Ajzen theorized intention to be the best predictor of individual behavior (Butler Lamar et al., 2016; Yoon & Kim, 2017) and attitude, subjective norms, and perceived behavioral control are the influencers of behavioral intention (Hou, 2014). Proponents of the TPB continue to use the TPB in user acceptance research to explain how behavioral intention precedes adoption behavior (Yoon & Kim, 2017). Like the TRA, the TPB has limitations which make the TAM the more appropriate framework for this study.

Although the attitude factor in TAM was derived from the TPB (Butler Lamar et al., 2016), there are significant differences between the two frameworks. Specifically, attitudes, subjective norms and behavioral factors (Yoon & Kim, 2017), which are determined by the availability of skills, resources, and opportunities to achieve outcomes (Samaradiwakar & Gunawardena, 2014), influence individual behavior. The TAM is the first model to mention psychological factors affecting technology acceptance (Samaradiwakar & Gunawardena, 2014) and is intended for performing user acceptance research IS. TAM also provides a more accurate explanation of the determinants of computer acceptance and is more capable of explaining user behavior across a broad range of end-user computing technologies and user populations, while at the same time

being both parsimonious and theoretically justified (Davis et al., 1989). Therefore, the TAM was deemed to be the appropriate framework for this study.

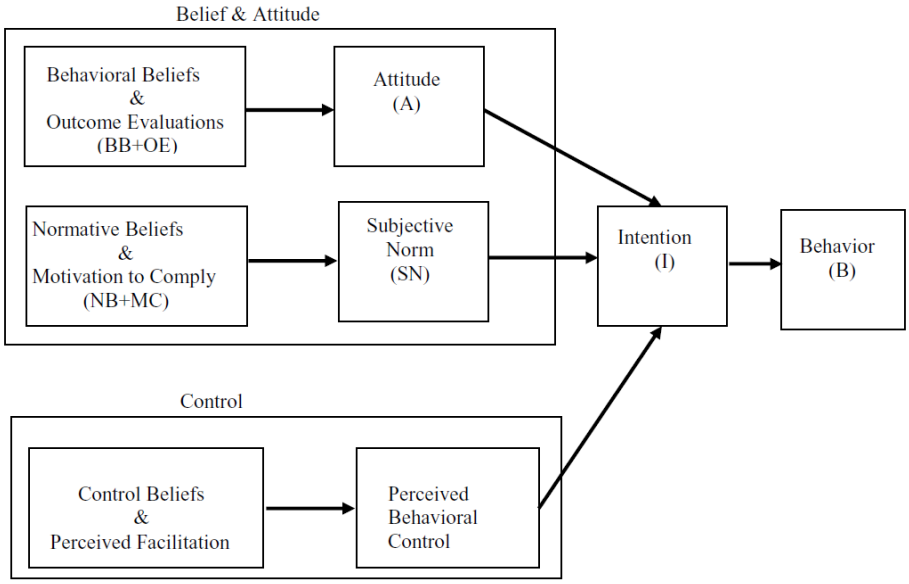

Figure 3. Theory of planned behavior model adapted from "Predicting user intentions: Comparing the technology acceptance model with the theory of planned behavior" by K. Mathieson, 1991, *Information Systems Research*, *2*(3), p.175.

Extended Technology Acceptance Models (TAM2, UTAUT, and TAM3)

Several rival models have been developed as extensions of the TAM by researchers to improve the predictive power of the TAM. The majority of these extensions are ad hoc models, which mix concepts of various theories or use only those favorable to their objectives without considering the contributions of others (Rondan-Cataluña et al., 2015). There are three extensions of the TAM which are well established and frequently used in user acceptance research. The TAM2, UTAUT, and TAM3 each include additional variables which allow researchers to explain technology behavior and pinpoint specific reasons technology may not be adopted (Abdullah, Ward, & Ahmed,

2016). Thus, the value of these extensions to researchers and practitioners is the insights derived from their application are often used to pursue appropriate corrective steps.

The first extended model developed by Venkatesh and Davis (2000) is called the TAM2. TAM2 extends the TAM to three variables which are believed to influence a user's decision to adopt technology. These variables are PU, PEOU, and subjective norm (Butler Lamar et al., 2016). In the TAM2, the antecedents of PU and usage intentions are explained in terms of social influence (compliance, internalization and identification) and cognitive instrumental processes (job relevance, output quality, result demonstrability, and PEOU) (Nasser Al-Suqri, 2014; Rondan-Cataluña et al., 2015; Salman et al., 2014) as shown in Figure 4. The TAM2 has been used successfully in voluntary and mandatory work settings. Subjective norm was found to not affect voluntary settings (Venkatesh & Davis, 2000). The effect of subjective norm on PU and behavioral intention diminishes over time as users gain more experience with a system (Venkatesh & Bala, 2008). Given I planned to conduct the study in a voluntary setting in a condensed period of time, the additional variable, subjective norm, does not add any value to this study, and therefore, the TAM2 is inappropriate for this study.

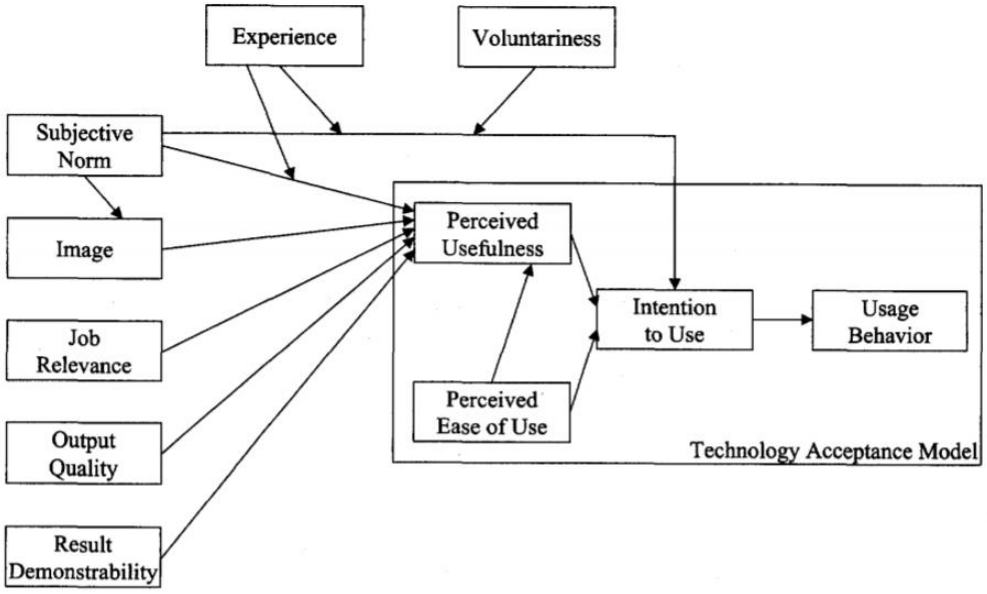

Figure 4. TAM2 from "A theoretical extension of the technology acceptance model: Four longitudinal field studies" by V. Venkatesh and F. D. Davis, 2000, *Management Science, 46*, p. 188.

The second extended model, named the UTAUT, was developed by Venkatesh, Morris, Davis, and Davis (2003). Venkatesh et al., (2003) reviewed and consolidated the TRA, TAM, motivational model, the TPB, a model combining the TAM and TPB, the model of PC utilization, the innovation diffusion theory, and the social cognitive theory to expand and refine the range of influences on behavioral intentions and use, and synthesize a unified view of user acceptance called the UTAUT. Through the consolidation of these models, the authors identified four main influencing factors of intention to use technology as follows:

- performance expectancy
- effort expectancy

- social influence
- facilitating conditions

Performance expectancy replaced the PU dimension of the original TAM, while effort expectancy replaced PEOU (Nasser Al-Suqri, 2014; Mohammadi, 2015). The model also identified several intervening or moderating influences, including gender, age, experience, and voluntariness of use, as shown in Figure 5. Thus, the UTAUT advanced cumulative theory while retaining a parsimonious structure (Rondan-Cataluña et al., 2015). The social influence factors are irrelevant to this study, and therefore, the UTAUT was deemed inappropriate for this study.

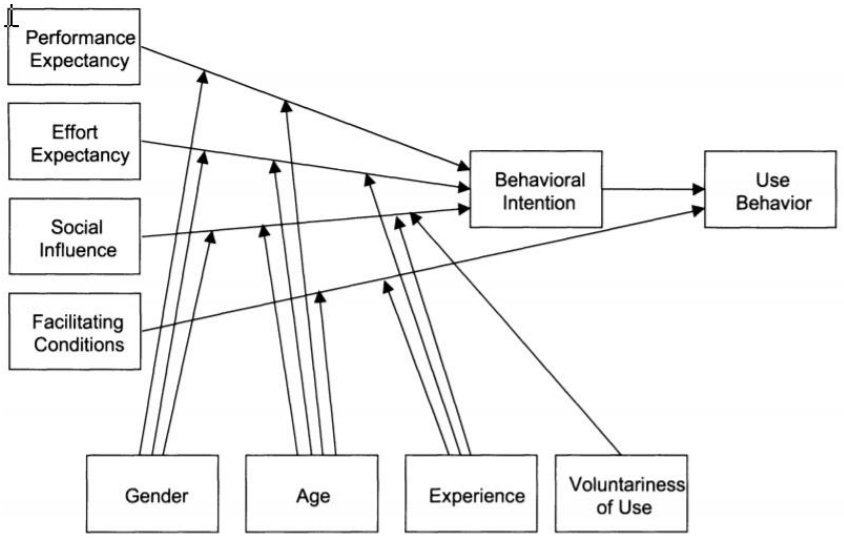

Figure 5. UTAUT adapted from "User acceptance of information technology: Toward a unified view" by V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, 2003, *MIS Quarterly, 23*(3), p. 447

The third popular extended model is the TAM3. Developed by Venkatesh and Bala (2008), the authors combined the TAM2 and the determinants of PEOU, to develop

an integrated model of technology acceptance. Venkatesh and Bala (2008) expanded the TAM2 to create the TAM3 by adding the determinants PEOU, computer self-efficacy, computer anxiety, computer playfulness, perceptions of external control, perceived enjoyment and objective usability of human decision making (Rondan-Cataluña et al., 2015) as shown in Figure 6. Like the UTAUT, the social influence factors are irrelevant to this study, and therefore, the TAM3 was also deemed inappropriate for this study.

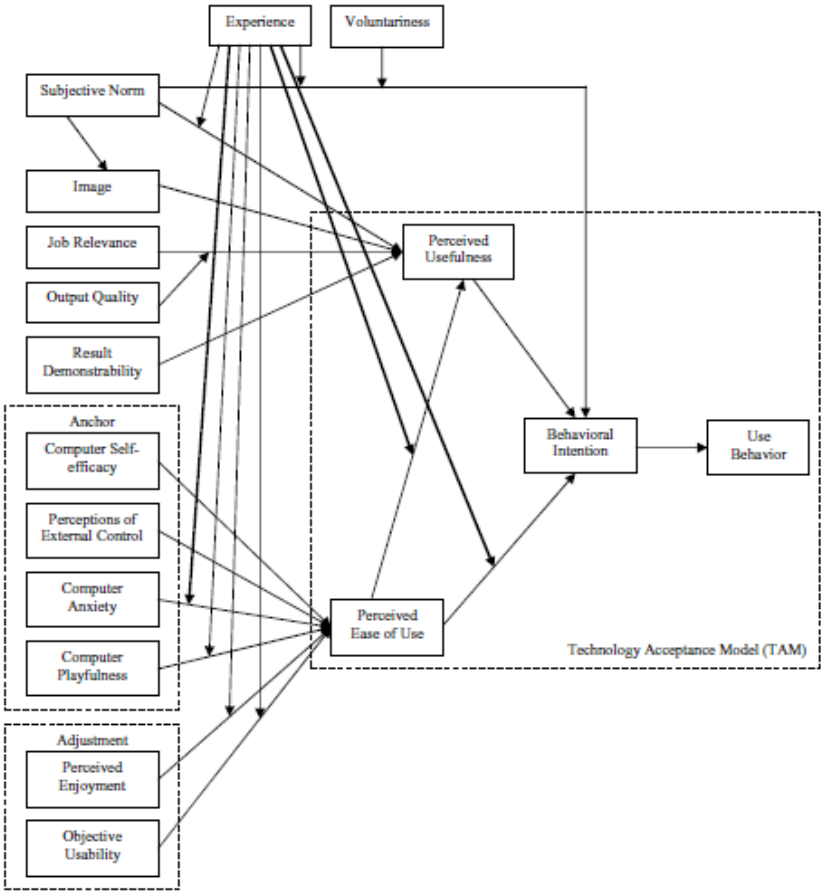

Figure 6. TAM3 adapted from "Technology acceptance model 3 and a research agenda on interventions" by V. Venkatesh and H. Bala, 2008, *Decision Sciences, 39*(2), p. 280.

Task-Technology Fit

TTF is an established rival theory developed independently of the TRA and TAM constructs. Developed by Goodhue and Thompson (1995), the TTF model is used to measure the fit between characteristics of tasks and characteristics of technology, which can further lead to technology utilization by a user. Thus, TTF posits increased compatibility between the user and technology will result in higher individual performance and decreased compatibility between the user and technology will have the opposite effect (Khidzir, Diyana, Ghani, Guan, & Ismail, 2017; Liu, 2014; Samaradiwakar & Gunawardena, 2014). The TTF consists of five major constructs; task characteristics, technology characteristics, task-technology fit, performance impacts, and utilization (Goodhue & Thompson, 1995) as shown in Figure 7.

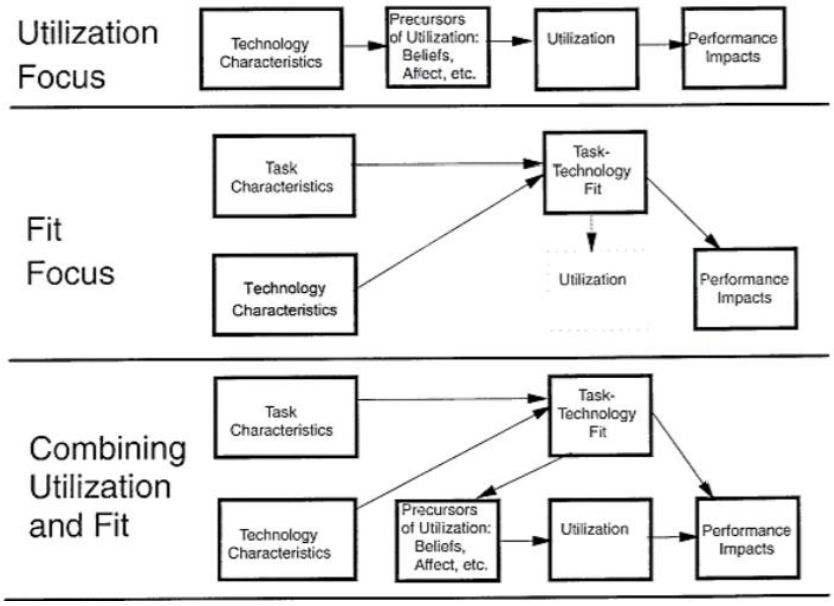

Figure 7. TTF adapted from "Task-technology fit and individual performance," by D. L. Goodhue and R. L. Thompson, 1995, *MIS Quarterly, 19*, p.215

The TTF is a frequently applied adoption intention and usage framework. Proponents of the TTF consistently support the validity of TTF as an influential model to determine the user's level of intention or utilization for a specific technology (Khidzir et al., 2017). Most literature focuses on measuring the strength of relationships between task-technology fit, individual performance, and system effectiveness (Goodhue & Thompson, 1995). For example, Liu (2014) used TTF to guide the development of novel and effective access-control mechanisms while Khidzir et al., (2017) researched the intention to adopt cloud-based m-retail applications (CBMA) among textile cyberpreneurs by examining the relationships between textile cyberpreneurs' task characteristics, CBMA characteristics, task-technology fit and intention to adopt. TTF researchers consistently maintain the TTF plays a significant role in influencing intention to adopt (Khidzir et al., 2017; Liu, 2014; Ozturk, Bilgihan, Nusair, & Okumus, 2016). Despite the success using the TTF on a diverse range of information system studies, it was deemed inappropriate for this study. Although TTF is effective in assessing the efficacy of a new system in helping users perform work-related tasks, it did not address the interactions between the PU and PEOU of technology to the end-user and was therefore inappropriate for this study.

Rogers' Diffusion of Innovation

Rogers theory of innovation diffusion or diffusion innovation theory (DOI) is one of the most widely applied theories in the prediction of organizational level technology

adoption (Puklavec, Oliveira, & Popovič, 2018). Developed by Everett Rogers in 1962, Rogers (2003) defined diffusion as the process by which an innovation is communicated through certain channels over time among the members of a social system. Rogers (2003) defines the five main characteristics of DOI theory as:

- The relative advantage which is the degree to which an innovation is seen as better than the idea, program, or product it supersedes
- Compatibility which is the degree to which the innovation is perceived as consistent with the existing values, past experiences, and needs of a potential adopter
- Trialability which is the degree to which an innovation can be experimented with on a limited basis
- Observability which is the degree to which the results of an innovation are visible to potential adopters
- Complexity which is the degree to which an innovation is perceived as relatively difficult to understand and use

Simply stated, Lai (2017) describes the diffusion of innovation as the process by which the members of a social system communicate an innovation through certain channels over time.

DOI theory is used by some researchers to explain the importance of science and technology innovation in society involving individuals, formal groups, or organizations (Ismail, 2016). An example of the diffusion innovation process is a business launching a

new product or service involving new technology (Khan & Mir, 2016). The diffusion process is used to predict the acceptability of the technology and explains the speed at which users adopt the technology (Khan & Mir, 2016) over time, as shown in Figure 8.

DOI studies and TAM extensions containing the DOI are common. For example, Ismail (2016), in his study regarding the intention to use smartphones by testing the influence of perceived compatibility, PU, PEOU, and intention to use a smartphone, recommended the TAM framework could be more comprehensive by extending it to include variables from the TPB and DOI theories. The DOI is used in firm-level acceptance studies, which this study is not. DOI theory posits adoption occurs gradually through a population over time (Mohammadi, 2015), and this study will conclude before sufficient time has passed to monitor the diffusion process, the DOI and all TAM extensions which include the DOI are not appropriate for this study.

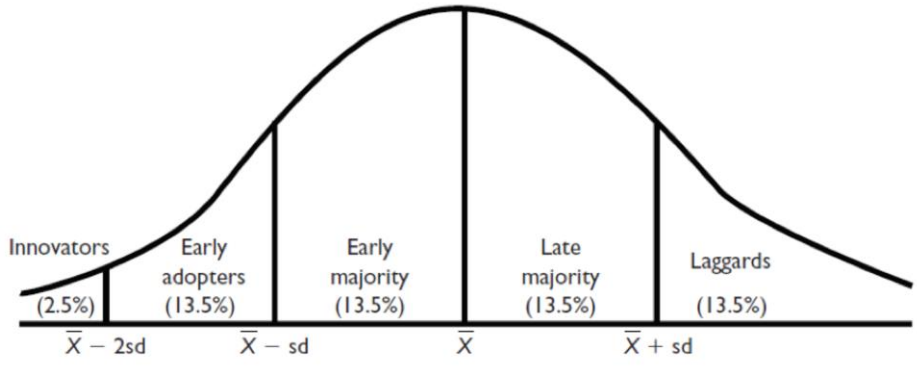

Figure 8. Diffusion of innovation adapted from "Diffusion of innovations" by E. M. Rogers, 2003, 5th ed. New York: Free Press, p. 281.

Technology-Organization-Environment framework

The TOE framework is another established acceptance model which is widely applied in the prediction of organizational level technology adoption (Puklavec et al., 2018). Developed by DePiettro, Wiarda, and Fleischer (1990), TOE posits technology, organization, and environment are the three contexts influencing a firm's adoption of innovation (Feldman, Shah, Chapman, & Amini, 2016). As shown in Figure 9., DePierto et al., (1990) and Aboelmaged (2014) describes the three contexts as follows:

- The environmental context reflects the firm surrounded by multiple stakeholders such as competitors, suppliers, customers, the government, the community, etc. who determine the need for innovation, ability to acquire resources for pursuing innovation, and capability for deploying it (DePierto et al., 1990, pp.154).
- The organizational context manifests common organizational attributes which may facilitate or constrain innovation adoption. Such attributes may consist of scope, firm size, characteristics of the managerial structure, quality of human resource; decision making, and communication mechanisms (Aboelmaged, 2014).
- The technological context focuses on how technological practices and structure can influence the adoption process (Aboelmaged, 2014).

Several researchers have articulated several weaknesses of the TOE framework. Specifically,

- The TOE aligns with other explanations of innovation adoption rather than offering a competing explanation to them. For example, some researchers note the consistency of the TOE framework with the DOI theory (Puklavec et al., 2018).
- The TOE framework does not offer a concrete set of factors which affect technology adoption; rather it categorizes factors within their respective context where the adoption process takes place (Aboelmaged, 2014; Aboelmaged & Hashem, 2018) and therefore, specific determinants identified within the three contexts may vary across different studies

Despite the purported weaknesses, the TOE framework provides a good starting point when analyzing and considering suitable factors for understanding the innovation-adoption decision, because it has consistent empirical support. My study focuses on the individual rather than firm-level acceptance of the technology. Thus, the TOE was deemed inappropriate for this study.

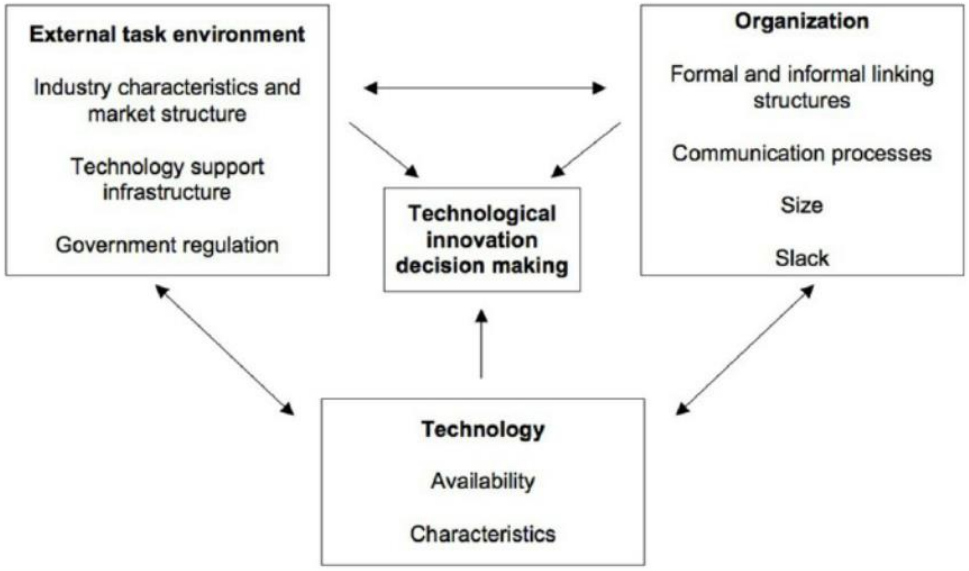

Figure 9. Technology-organization-environment (TOE) framework adapted from "The context for change: Organization, Technology, and Environment" by DePietro, R., Wiarda, E., and Fleischer M. in "The processes of technological innovation" by L. G. Tornatzky and M. Fleischer, 1990, pp. 153. Lexington, MA: Lexington Books

Summary

The TAM framework continues to be a relevant and accommodative framework to study user acceptance in a rapidly evolving technology landscape. The tenets of TAM have been continually validated in acceptance research as relevant and applicable to a broad range of technology environments. But most importantly, the literature demonstrates the applicability of TAM to business practice and the positive outcomes of using the insights gleaned from its usage. For example, Tella, Oyewole, and Tella (2017) studied user adoption of google scholar by post-graduate students of the University of Ilorin, Nigeria. The result of the study were recommendations regarding changes to the user interface of Google Scholar to improve users PEOU. Overall, the literature review confirmed the TAMs continued popularity and relevance in understanding user

acceptance and adoption behavior. Ma, Gam, & Banning (2017) argue the use of the TAM framework with and without modifications demonstrates the value of the TAM across a wide range of empirical studies intended to predict and explain user acceptance. User acceptance studies continue to confirm the appropriateness of the TAM framework to predict the corrective steps to encourage the use of IS in any organization efficiently (Jardali, Abdallah, & Barbar, 2015). Thus, confirming the relevance of the TAM framework generally and to this study.

The literature review also surfaced user acceptance studies in which the researcher extended the TAM or leveraged a competing model. Most commonly, researchers opting to extend or leverage a rival theory argued the core tenets of TAM, PU, and PEOU, are insufficiently clear and only partially explain the effects on behavioral intentions (Liu & Yang, 2018). For example, Liu (2014) used PEOU and perceived privacy benefit to assess the acceptance of password-protected control of articles in blog environments. These assertions do not make the TAM an irrelevant framework for studies of user interactions with technologies. Instead, researchers should consider the TAM as a basic model which offers the benefit and flexibility of integrating extended and contextualized motivational influences and user behaviors based on emerging realities in contemporary technology-mediated environments. (Lim, 2018). And in fact, these deficiencies represent opportunities for future research and confirm the feasibility of the current study.

Transition

In section 1, I introduced my study. The purpose of the quantitative correlation study was to examine whether a relationship exists between the independent variables (a) PU (b) PEOU, and (c) user acceptance of BIS. Included in the section are the (a) foundation of the study, (b) background of the problem, (c) problem statement, (d) purpose statement, (e) nature of the study, (f) research question, (g) hypotheses, (h) definitions of terms, (i) the theoretical framework,(j) significance of the study, (k) definition of terms, (l) assumptions, limitations and delimitations, and (m) the literature review.

In section 2, I detail the (a) research purpose, (b) role of the researcher, (c) method and design of the study, (d) population and sampling size, (e) data collection and analysis. I also (f) detail the strategies I used to ensure reliability and validity of the study, including data collection instruments, data collection techniques, data tracking method, and data security.

Finally, in section 3, I present the results of the study and discuss how the research findings support or reject the null hypothesis. This section also includes detailed information on the (a) research findings, (b) implications for social change, (c) recommendations for future research, and (d) reflections about my journey completing this study.

Section 2: The Project

Purpose Statement

The purpose of this quantitative correlation study was to examine the relationship between (a) PU, (b) PEOU, and (c) user acceptance of BIS in the retail industry. The independent variables were (a) PU and (b) PEOU, and the dependent variable was (c) user acceptance. The target population comprised of end-users of BIS from retail businesses in the eastern United States. The implications for social change could include the use of BIS in the decision-making processes involving corporate contribution to positive social change using evidence-based insights to identify the most impactful investments for a community.

Role of the Researcher

To appreciate my role and interest in this study requires an appreciation of my professional background and impetus for researching issues affecting the successful adoption of BIS. I have worked in multiple knowledge management roles for the past 10 years in global nonprofit and for-profit organizations. My experience spans multiple projects related to organizational performance, impact measurement, collaboration, taxonomy, and currently master data quality and governance. My attraction to the BI arena is motivated by the similarity of the objectives of these practice areas. Like knowledge management, BI provides information to the right person at the right time in the right format and enables decision-makers to take appropriate actions to advance a goal (Hammond, 2001; Nedelcu, 2013).The adoption of knowledge management systems

in my experience is low. Without strategies to promote adoption, knowledge management systems do not yield the expected return on investment. Given the similarities in the overarching goals of knowledge management and BI and the cross-industry interest, leadership sponsorship and significant financial investment leaders are making in BIS; my curiosity was peaked to investigate whether a lack of user acceptance similarly affects BIS.

Interest in BI and BIS in the business and academic communities has surged in recent years. Although at times BI is debated within knowledge management literature, it is more often discussed separately from knowledge management. BI has emerged as a separate discipline demonstrated by the vast amounts of information available in white papers, academic research, vendor marketing, as well as an increase in academic offerings in the growing field of BI. Bijakšić, Markić, and Bevanda (2018) contended the difference between knowledge management and BI is BI uses appropriate tools to provide decision-makers with correct, timely, and concise information necessary for decision making. Knowledge management involves the creation, dissemination, and use of knowledge by resources in an organizational system (Bijakšić et al., 2018).

As an organizational priority, BI ranks among the top priorities for chief information officers across industries (Arnott et al., 2017; Wieder & Ossimitz, 2015). Practitioner-oriented publications and academic research contend organizations frequently fail to realize the promise of BI because of a lack of alignment between BI capabilities, the problem space or the decision environment of the organization (Işık,

Jones, & Sidorova, 2013). BI implementations often fail to meet the expectations of stakeholders and are considered suboptimal for several reasons including ROI, project management measures, user satisfaction and nonconcrete measures such as increased brand recognition and sales leads (Boyton et al., 2015). Nevertheless, the scope of potential issues is too broad and diverse for this study. In this study, I focused only on the relationship between PU, PEOU, and user acceptance of BIS in companies with successful implementations of BIS.

A quantitative correlational research study furthered my goals to contribute to academia and practice, as well as the influence of user perceptions and attitudes toward using BIS. Per my responsibilities as a researcher, I (a) ensured the appropriateness of the research instrument and (b) the accessibility of the survey to participants, and I (c) contacted the participants and (d) ensured there were no violations of the participants' rights in accordance with the Belmont Report (U.S. Department of Health, Education, and Welfare, 1979); furthermore, I (e) encouraged participation. I maintained the highest ethical standards while compiling, organizing, analyzing, and interpreting the data collected to test the hypotheses and answer the research question and verified the reliability and validity of the survey instrument.

Participants

The target population for this study was end-users of BIS in retail organizations headquartered in the eastern United States. Users who had used a BIS for less than 5 years were the target participants for this study although my sample included users with

more than 5 years of experience. Within a purposive sample of end-users of BIS employee, I selected strategic and tactical managerial positions from middle and upper management who reported using BIS in their roles. This population included executive managers and senior and middle managers. Technology experts of BIS were excluded from this study because of their experience with BIS to avoid inflating the study sample with experienced or advanced users of BIS. Data collection only commenced after obtaining ethics clearance from the Walden University Institutional Review Board (IRB).

To enable participant recruitment of a purposive sample, I relied on SurveyMonkey American Audience. SurveyMonkey American Audience has access to millions of members who voluntarily participate and benefit from participating through charitable incentives, sweepstakes, and the receipt of credits which participants can apply toward rewards such as gift cards. In addition to SurveyMonkey's demographic filters, I provided demographic filters to aid in the identification of a purposive sample for my study.

Research Method and Design

Research Method

In this section, I will focus on explaining the differences among and the rationale for choosing the quantitative research method instead of qualitative or mixed methods for this study. The difference between quantative and qualitative research methods research is how reality is viewed (ontological) and how knowledge and truth are viewed (epistemological) (Mengshoel, 2012). Quantitative studies rely on a

positivist/postpositivist paradigm (Mengshoel, 2012). Specifically, quantitative studies take on a confirmatory approach used to confirm (or disconfirm) hypotheses (Taguchi, 2018). Researchers can study reality by determining variables and examining probable relationships between variables such as those identified for this study (relationships between the variables PU, PEOU, and user acceptance of BIS). Qualitative studies are often predicated on a constructivist or interpretivist paradigm (Mengshoel, 2012). The qualitative approach is by nature exploratory, whereas mixed methods research combines quantitative and qualitative research methods systematically reinforcing results and interpretations (Taguchi, 2018). My study was not exploratory. I did not study people's experiences or social influence factors in this study. Therefore, qualitative and mixed methods research methods are inappropriate because of the intent and purpose of qualitative research methods.

Research Design

I used a descriptive and explanatory design for this study. Specifically, I used correlation design and multiple linear regression to examine the probable relationships between PU, PEOU, and user acceptance of BIS. Correlational design was suitable for this quantitative study because the objective of this study is to examine the relationships between variables from data collected online using a slightly modified Davis (1989) TAM survey to suit the BI context. According to Curtis, Comiskey, and Dempsey (2016), the purpose of correlational research is to investigate the extent to which differences in one characteristic or variable are related to the difference in one or more other

characteristics of variables' characteristics. I used Pearson's product-moment correlation to quantify the strength of the linear relationship between PU, PEOU, and user acceptance of BIS and multiple linear regression to predict user acceptance of BIS based on the independent variables PU and PEOU.

Experimental design was inappropriate for this study because the nature of this study and the research question identified did not warrant experimentation. According to Stürmer, Wyss, Glynn, and Brookhart (2014), researchers use experimental designs in research to understand phenomena by affecting the behavior of research participants. For example, experimental design is suitable for comparisons among variables and cause and effect relationships, which was not the intention of this study. I collected data which was easily coded into numerical data to examine the probable relationships between PU, PEOU, and user acceptance of BIS and infer the results to a larger population.

Population and Sampling

Population

The targeted population for this study comprised of end-users of BIS. I collected a purposive sample of end-users of BIS from retailers headquartered in the eastern United States using SurveyMonkey American audience. The TAM survey instrument with minor modifications for the BI context was administered online to end-users of BIS who identified themselves as employees in strategic managerial positions, upper and middle management (excluding technology experts) roles, who are the end-users of BIS in retail

organizations in the eastern United States using SurveyMonkey's cloud-based platform. In addition, I targeted end-users with 5 or less years of experience with BIS.

Sampling

Random sampling is the preferred method when ease of access to participants is not a concern. The ease of access to BI professionals in retail organizations with 5 or less years of experience was a concern because:

- An end-user can be a new user to current technology but have more than 5 years of experience as an end-user of BIS technologies.
- The variety of tools available for BIS and differences in their capabilities is vast and may affect perceptions of BIS (e.g., open-source, vendor solutions, etc.)

Nonprobability sampling methods are preferred for the recruitment of participants from hard-to-reach populations (Valerio, M. A. et al., 2016). Within nonprobability sampling methods, are two methods both evaluated for their appropriateness for this study. According to Valerio et al. (2016), snowball sampling is a chain-referral method where initial participants recruit others from their social network and

- Enables a researcher to reach participants with the same characteristics.
- Is often used in community engagement research studies, and mixed methods approaches.
- Is based on networks and relationship which may lend credibility to the research.

Although purposive sampling, also known as judgmental, selective, or subjective sampling, it does the following:

- Allows for selection of a sampling frame most affected by the specific issue.
- Aims to maintain rigor and identify a sampling frame based on specific study driven variables or characteristics.

Based on the descriptions and strengths of snowball versus purposive sampling, I determined purposive sampling met the objectives of this study and snowball sampling did not.

Recruitment Method.

I used SurveyMonkey American audience (2015a) to identify a purposive sample for this study. The steps to launching my survey and collect my data were as follows:

- Created the survey and included my invitation to participate and the consent form with my approved IRB number in the consent form.
- Selected the following options from SurveyMonkey's demographic choices
    - Company size: 2-5, 11-25, 51-100, 101-250, 501-1000, 1001-5000, Greater than 5000, 6-10, 26-50, 251-500
    - Country: United_States
    - Age: 18 - 99+
    - Primary role in organization: Owner or Partner, President/CEO/Chairperson, Middle Management, Chief Financial Officer (CFO), Senior Management, Project Management, Chief Technical Officer (CTO), C-level executive, Director, HR manager

  - Location: Northeast, South
  - Age Balancing: 25-64: 80%, 65-99: 20%
  - Gender Balancing: None
  - Incidence rate: 50-74%

- Launched the survey to SurveyMonkey's American audience.

Additional questions in the demographic section of the survey were intended to screen the audience further (See Appendix E). Once the survey launched, it joined other open surveys assigned to respondents via email invitations. SurveyMonkey American audience survey panelists donate their time to complete surveys (SurveyMonkey American audience, 2015a).:

- SurveyMonkey American audience Contribute panelists take surveys for charity and a chance to win sweepstakes prizes
- SurveyMonkey American audience Rewards panelists earn credits for completing surveys which they can redeem for gift cards or donate to charity

The relevance of the population rested in the diversity of the retailer types and the varying size of retail businesses participating in this study.

Sample Size

A priori power analysis using G*Power 3.1.9.2 software was conducted to determine the adequate sample size for this research study and eliminate type 1 errors (Buchner, Erdfelder, Faul, & Lang, 2014). Following Cohen's (1989) suggestions for

calculating sample size when there are no specific expectations, I calculated sample size using (a) *f* of 0.15, (b) power of 1 – β = .80 and, (c) alpha (α = .05) or 95% confidence rather than risk associations due to chance. Results from the analysis showed the minimum sample size for this study is 68 participants (See Figure 10).

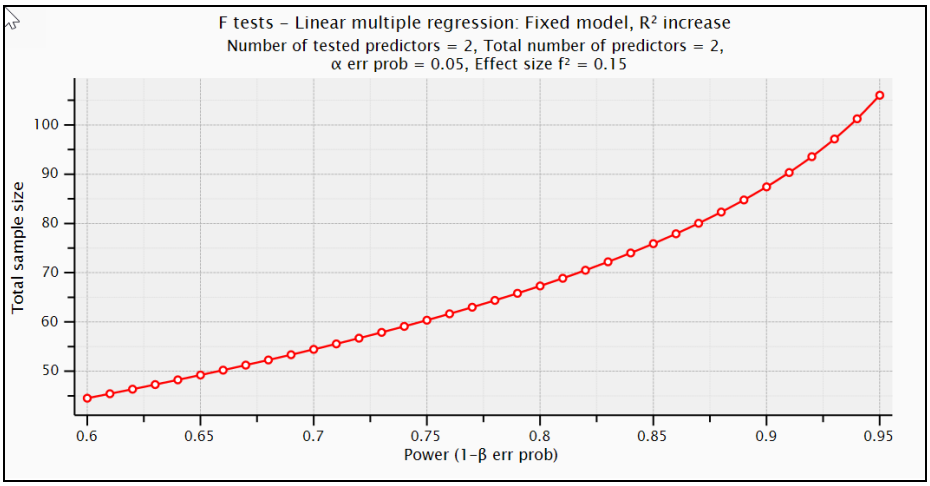

Figure 10. G*Power Analysis.

Ethical Research

Ethical standards, as well as the ethical conduct and decision-making processes of the researcher, are paramount to protecting the interests of human participants. A history of abused participants in research provided the impetus for the creation of the 1947 Nuremberg Code, 1964 Declaration of Helsinki, the 1974 National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research, and the resulting 1979 Belmont Report (Ferdowsian, 2011). The benefit of the Belmont report is it provides a detailed ethical framework to resolve ambiguity in research involving human subjects. Specifically, the Belmont Report contains a set of principles researchers can use

to examine and resolve ethical conflicts as they relate to human subjects' research (Corbie-Smith et al., 2018). In traditional research contexts, researcher-initiated research requires review by an institutional review board (IRB) (Corbie-Smith et al., 2018). Therefore, I sought guidance from Walden University IRB to ensure my research study was conducted following the highest ethical standards, including the protection of respondents and their associated information. In addition, I completed the human subjects' protection training course offered by the CITI Program and received certificate record number 29844213.

I used SurveyMonkey to host my online survey and SurveyMonkey American audience to recruit participants. An invitation to participate (Appendix B) and consent form (Appendix C) displayed on the first two pages of the online form before any data collection began to ensure all participants provided their informed consent to participate in this study before completing any survey questions. Information in the consent form included:

- Invitation and background information about the purpose of the study, criteria to participate, how the participant was selected and the researcher's name
- Procedures including instructions to complete the survey, sample questions, the amount of time the survey would take to complete, and the goal date to collect all survey responses.
- Any risks and benefits of participating in the study

- The voluntary nature of participation and choice to accept or turn down the invitation to participate without repercussion
- An explicit statement stating there was no additional compensation for participation in this study beyond the incentives provided by Survey Monkey to members of their panelist groups
- A statement on privacy standards guaranteeing the confidentiality of all participant's information and responses to the survey to ensure no harm befalls a participant.
- My contact information, and the contact information for the research participant advocate at Walden University.

I did not collect any personally identifiable information (PII). During and post data collection, I adhered to the IRB ethical guidelines. In addition, all records will remain stored on a password-protected external hard drive in a fire and waterproof safe using my biometric credentials at a secured location to which only I have access for 5 years from the end of the study. After 5 years, I will destroy all data using KillDisk, an industrial-grade disk sanitation hardware solution for the consumer market which can destroy all data on hard disks, solid-state disks (SSD), USB disks and memory cards (LSoft Technologies Inc, 2018). The IRB approval number is 06-20-19-0140074.

Data Collection Instruments

The data collection instrument I used was the TAM survey questionnaire (Davis, 1989). The TAM survey has been used to measure the behavior of users toward

technology acceptance based on the users PEOU and PU of a technology. Davis (1989) used the definitions for PU and PEOU to develop scale items pretested for content validity and then tested for reliability and construct validity in two studies and four application programs (Abdolmaleki, & Mohamadi, 2013; Ameri Shahrabi et al., 2014). In addition, the Davis (1989) TAM survey instrument has been used successfully across a broad range of IS acceptance situations and environments. As a result, researchers can rely on the validity of this survey instrument based on its successful application in prior studies (Carter et al., 2011; Cheng et al., 2011; Fillion et al., 2012; Holden & Rada, 2011; Suki et al., 2011). I also conducted an internal consistency reliability check of the TAM survey instrument against my sample in SPSS using Cronbach's alpha reliability coefficient, detailed in Section 3, Table 6. The reliability check enabled a comparison of how closely the reported reliability coefficient and my calculated reliability coefficient were. Finally, I enhanced the reliability and validity of the instrument by examining the first 70 surveys returned as a strategy to address threats to validity and internal consistency. The first 70 surveys did not count towards the minimum sample size and were used to verify the responses met the objectives of this study.

Using SurveyMonkey, I published an online survey which included the invitation to participate (Appendix B), consent form (Appendix C), a demographic section and the TAM survey questionnaire with minor modifications to ensure the scales reflected the BIS context (Appendix E). In the demographic section, respondents completed questions to confirm the responses received were a representative sample of the target population.

Data collected in this section provided the following self-reported data about the participants:

- The size of the company the participant works for based on the number of employees (small, medium, or large)
- Confirmation the company, the participant represents, uses a BIS in is a retail organization. The SurveyMonkey American Audience screening choices limit retail to a single industry. This question was intended to broaden the participant pool by including all industries and refining retailers by a company's business model. Any organization conducting business with consumers (e.g., bookstores, airlines, digital subscription services) was part of the target population (Berry, Bolton, Bridges, Meyer, Parasuraman & Seiders, 2010).
- The participant's position in their organization to confirm the sample comprises of managerial level respondents
- Confirmation of BIS usage (i.e., they are an end-user of BIS and how they use their company's BIS in their position)
- Confirmation of the length of experience the participant has with their BIS (more or less than 5 years)
- The measure of usage behavior of BIS (frequency of use of BIS)

In the second section, the participant completed the TAM survey questionnaire, which had made minor modifications to reflect the BI context. The TAM survey is a validated instrument which uses a summated rating scale which follows a 7-point

metric ranging from 1 = *extremely unlikely* to 7 = *extremely likely*. The TAM survey instrument adheres to the criteria for summated rating scales elaborated by Vaske et al., (2017). Specifically, the TAM survey questionnaire:

- has multiple survey questions which the researcher combines using averaging,
- each item in the scale reflects the concept being measured,
- there are no right or wrong answers, and
- each item in the scale is a statement and respondents rate each statement.

Respondents indicated their level of agreement to the statements regarding the research constructs.

The PU scale in the TAM survey is a 6-item questionnaire which respondents provide ratings from 1 = extremely unlikely to 7 = extremely likely (Davis et al., 1989). The PU scale assesses one's perceptions with regards to the usefulness of a given entity. The survey questions were all positively worded. For example, "Using the BIS would improve my job performance." High scores on this instrument are indicative of high levels of PU. Similarly, the PEOU scale is also a 6-item measure which respondents provided ratings from 1 = extremely unlikely to 7 = extremely likely (Davis et al., 1989). The PEOU scale assesses one's perceptions with regards to the ease of use of a given entity.

Data Collection Technique

Once I obtained IRB approval, I collected data from human participants using SurveyMonkey. I delivered the TAM Survey Instrument (Appendix E) online. I relied on the SurveyMonkey American audience (2015a) capability to identify in conjunction with questions I included in the demographic section of the survey to screen participants for this study. I also used the SurveyMonkey option to assign high priority to the survey to ensure participants prioritized responses to my survey to speed up the data collection process. The recruitment and data collection occurred from June 20, 2019, to July 3, 2019, for a total of 13 days. Table 2 is populated with the number of responses received per day. The percent response rate was 32.6%.

When the participants of a study are sensitive or exhibit misgivings about exposing their identities and associated information, online surveying gives the most flexibility to participants, enabling anonymity and resulting in more reliable data collection (Kilinç & Fırat, 2017). Prior research on BIS reveals business leaders are unlikely to report sub-optimal or failed BIS implementations (Boyton et al., 2015; Eybers & Giannakopoulos, 2015; Guarda et al., 2016). Voluntary involvement in this study will decrease the likelihood of collecting misleading answers. The right survey technique can promote voluntary involvement in a survey (Kilinç & Fırat, 2017). Therefore, to encourage voluntary participation, the online TAM survey provided participants anonymity, and participants could choose to terminate their participation at any point.

Table 2

Number of Survey Responses Received by Date

Date response received	Number of responses
June 20, 2019	53
July 1, 2019	76
July 3, 2019	196
Total # of responses	325

Data Analysis

The purpose of this quantitative correlational study was to examine the relationship between (a) PU, (b) PEOU, and (c) user acceptance of BIS. The central research question guiding this study was: What is the relationship between (a) PU, (b) PEOU, and (c) user acceptance of BIS? And the following null and alternative hypotheses relate to the research question:

Null Hypothesis (H_0): There is no statistically significant relationship between (a) PU, (b) PEOU, and (c) user acceptance of BIS

Alternative Hypothesis (H_1): There is a statistically significant relationship between (a) PU, (b) PEOU, and (c) user acceptance of BIS.

In the subsequent sections, I provide the data analysis plan used to answer the research question and accept or reject the null hypotheses.

Data Analysis Plan

Test of Assumptions

I confirmed my assumptions about the data. Specifically,

- the variables are normally distributed (Green & Salkind, 2017).
- the responses represented a random sample from the population (Green & Salkind, 2017).
- the responses were independent of one another (Green & Salkind, 2017).

I collected data using Davis (1989) TAM survey instrument after making minor adjustments to the survey by modifying the questions in the survey to ensure the questions relate to the context of BI systems usage.

Correlation

Often researchers conflate correlation and causation, especially in contexts involving human behavior resulting in incorrect application or interpretation of correlational design (Bleske-Rechek, Morrison, & Heidtke, 2015). To enable a consistent understanding of the findings from this study:

- A correlational coefficient greater than 0 but less than 1 is a positive correlation meaning the variables seem to be closely related (Dziak, 2016).
- A correlational coefficient less than 0 but greater than -1 is a negative correlation which signifies an increase in one variable decreases the other (Dziak, 2016)

- A correlational coefficient of 0 or close to 0 suggests the variables are probably not related at all. The results are plotted on graphs and used to make scientific predictions (Dziak, 2016).

Multiple Linear Regression

Post data collection, I conducted a correlational analysis and used multiple linear regression analysis to analyze the survey responses because:

- the data collected through the survey was ordinal
- the purpose of correlational research is to investigate the extent to which differences in one characteristic or variable are related to the difference in one or more other characteristics of variables' (Curtis et al., 2016).
- multiple linear regression is useful when there are two or more independent variables, and the objective of the research is to look for predictive relationships with the dependent variable (Kayri, Kayri, & Gencoglu, 2017).

There are several correlational analysis options available to analyze ordinal data. I used Pearson's product-moment correlation coefficient to analyze the variables in this study because it is easy to calculate, interpret, and extend to further analyses (Choi, Peters, & Mueller,2010).

Software

Several software tools are available for analyzing data including Statistical Product and Service Solution (SPSS) (Ozgur, Kleckner, & Li., 2015), SAS System, and R (Ozgur et al., 2015). SPSS is a robust statistical program which offers student packages

for college attendees (Ozgur et al., 2015). SPSS is arguably the leading statistical analysis software package for the social sciences (Ozgur et al., 2015; IBM, 2014). SPSS is comprehensive, flexible, and is used with almost any type of data file to generate tabulated reports, charts, and plots of distributions and trends, as well as generate descriptive statistics such as means, medians, modes and frequencies in addition to more complex statistical analyses like regression models (Crossman, 2014). For the above reasons, I chose to use SPSS v. 25 for statistical analysis.

Interpretation of Inferential Results

The bootstrapping method is used to counter assumption violations and validate assumptions about the data (Ahad, Abdullah, Lai Choo, & Ali, 2012). I used a bootstrap of 95% confidence where appropriate. In addition, SPSS outputs yielded various statistics, including descriptive statistics, which I used to add supporting detail and provide information about representative scores, the amount of variation in the data, and normality detail. The research specific parameters to interpret are (a) R^2, (b) *F*, (c) *B*, (d) *SE B*, (e) β, (f) *Sig.* or *(p)*, and (g) *t* which are defined as follows:R^2 overall measure of the strength of association and does not reflect the extent to which any particular independent variable is associated with the dependent variable.

- *F-statistic* is the mean square (regression) divided by the Mean Square (residual)
- *B* are the values for the regression equation for predicting the dependent variable from the independent variable

- *SE B*: is the standard error (i.e., the square root of the estimated variance) weight associated with the regression equation (Green & Salkind, 2014).
- β are the standardized coefficients. These are the coefficients which you would obtain if you standardized all the variables in the regression, including the dependent and all of the independent variables, and ran the regression. By standardizing the variables before running the regression, you have put all of the variables on the same scale, and you can compare the magnitude of the coefficients to see which one has more of an effect
- Sig. (p): The p-value is compared to some alpha level in testing the null hypothesis where all of the model coefficients are 0.
- *t-statistic* is the ratio of the departure of the estimated value of a parameter from its hypothesized value to its standard error

Study Validity

The goal of all research is to produce reliable knowledge. Theory and practice advance as reliable knowledge is developed (Cor, 2016). Therefore, researchers must address threats to internal and external validity. In the subsequent sections, I describe the threats to statistical conclusion validity, how I address those threats, and explain my procedures. I also discuss the generalizability of research finders to larger populations and settings.

Internal Validity

It is important to understand the difference between internal validity and external validity and their impact on one's research study. Internal validity is relevant to establish a causal relationship and is used to determine whether a particular practice makes a difference while external validity asks whether a particular practice is generalizable to other populations, settings, or treatments (Schalock, Gomez, Verdugo, & Claes, 2017; Aguinis & Edwards, 2014; Neall & Tuckey, 2014; Pirog, 2014). External validity refers to the ability of a researcher to make reliable inferences about a topic beyond its current context (Lancsar & Swait, 2014). For this study, internal validity is not a concern because it is a non-experimental design (correlational), and threats to internal validity are not applicable.

External Validity

Data assumptions can affect the validity of the study. For example, there could be significant heterogeneity in the data across the targeted groups which are not observable in online data collection. Therefore, the findings could contain biased estimates, leading to Type 1(rejecting the null hypothesis when it is true) and Type 2 (accepting the null hypothesis when it is false) errors, and result in invalid conclusions. I screened the first 30 responses to overcome external validity issues. The target population analyzed contained 106 responses using multiple linear regression analysis to determine whether a relationship between the variables exists (Elzamly & Hussin, 2014).

Threats to Statistical Conclusion Validity

Threats to statistical conclusion validity refer to questions which may arise regarding the reasonableness of the conclusions made about the relationship between the variables in a research study (Gibbs & Weightman, 2014). Specifically, conditions which inflate Type 1 error rates and Type 2 error rates. The three conditions which can inflate Type 1 or Type 2 errors are the reliability of the instrument, the data assumptions, and the sample size.

Generalizability

Finally, end-users of BIS in retail organizations in the eastern United States will have similar characteristics to other end-users of BIS in retail organizations in the United States. Thus, future researchers will have the ability to replicate this study. Also, the findings from this study could apply to other retailers in the United States. However, the results should not be generalized to non-US retailers.

Transition and Summary

The purpose of this quantitative correlation study is to examine the relationship between (a) PU (b) PEOU, and (c) user acceptance of BIS. In section 2, I detailed (a) the purpose statement, (b) role of the researcher, (c) description of the participants in the study, (d) the research method and design, (e) the population and sampling, (f) ethical research, (g) the data collection instrument, (f) the data analysis, and (g) an explanation of the of the validity of the study. All sections align with the overall research question of the study and the research hypotheses. To conclude this study, section 3 includes the (a)

overview of-of study, (b) a presentation of the findings of the data analysis, (c) provides suggestions on how the study affects the professional community, (d) includes the implications for social change, (e) shares recommendations for action (f) shares recommendations for further study, (f) provides my reflections, (g) conclusions.

Section 3: Application to Professional Practice and Implications for Change

Introduction

The purpose of this quantitative correlation study was to examine the relationship between (a) PU (b) PEOU, and (c) user acceptance of BIS in the retail industry. The independent variables were PEOU and PU. The dependent variable was user acceptance of BIS. I used a nine-item survey instrument to collect research data for this study. The null hypothesis was rejected. There is a statistically significant relationship between (a) PU, (b) PEOU, and (c) user acceptance of BIS. The model was significantly able to predict user acceptance of BIS in retail organizations, $F(2,103) = 21.903$, $p < .000$, $R^2 = .298$. The R^2 (.298) value indicated approximately 29.8% of variations in user acceptance of BIS were accounted for by combined predictor variables. PU was statistically significant predictor ($t = -3.947$, $p = .000$), however, PEOU was not a statistically significant predictor ($t = -.977$, $p = .331$).

Presentation of the Findings

In this subsection, I will discuss testing of the assumptions, present descriptive statistics, present inferential statistic results, provide a theoretical conversation pertaining to the findings, and conclude with a concise summary. I employed Bootstrapping, using 1,000 samples, to address the possible influence of assumption violations. Thus, bootstrapping 95% confidence intervals are presented where appropriate.

Descriptive Statistics

A sample size of 68 participants was required to achieve at least 80% confidence in the results from this study. In total, I received 325 survey responses. After cleansing the data, 219 records were eliminated due to the following:

- My review of the first 70 responses to confirm the responses met the objectives of my study.
- Missing data necessary to perform the analysis for this study (e.g., independent and dependent variables questions).
- Responses whichindicated the respondent was not part of the targeted population (e.g., job levels freelancer, consultant, individual contributor).

After data cleansing, a total of 106 records remained for the analysis.

Once the data was cleansed, I began to analyze the characteristics of the sample population. Several insights regarding the population were discovered as follows:

- The majority of participants reported they had used BIS for more than 5 years.
- Participants who reported having used BIS for less than 5 years reported being employed by companies with less than 999 employees.
- Based on participant responses, the number of users of BIS in retail companies with more than 999 employees was consistent regardless of retail business model.
- Based on participant responses, the number of users of BIS in retail companies with less than 100 employees was consistent regardless of retail business model.

- Based on participant responses, the number of users of BIS in retail companies with more than 100 employees and less than 999 employees had the highest number of BIS users in e-commerce and online and brick and mortar retail business models.
- The majority of participants in this study reported their job-level as manager.
- Participants reported using BIS for prediction the least.

The population characteristics were as follows:

- Figure 11 depicts a stacked bar chart which breaks down the sample population characteristics by the respondent's length of experience with BIS, employee job level, and company size.
- Figure 12 depicts a 2D plot graph which breaks down survey responses by retail business model and company size.
- Figure 13 depicts a 2D plot graph which breaks down survey responses by retail business model and job-level.
- Figure 14 depicts a bar chart which displays the survey respondent’s usage of BIS in their organization.

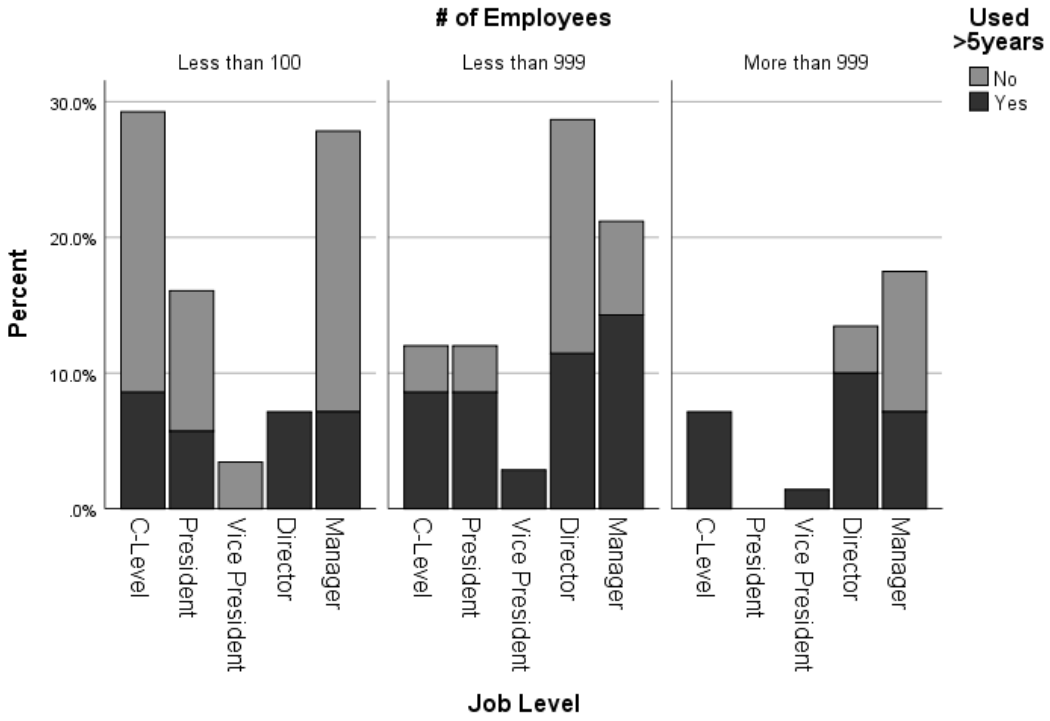

Figure 11. Stacked bar chart filtered by reported experience with BIS (less or more than 5 years), company size (denoted by the number of employees) and the employee level in the company. Employees with 5 or less years of experience with BIS are associated with retail companies with 999 employees or less.

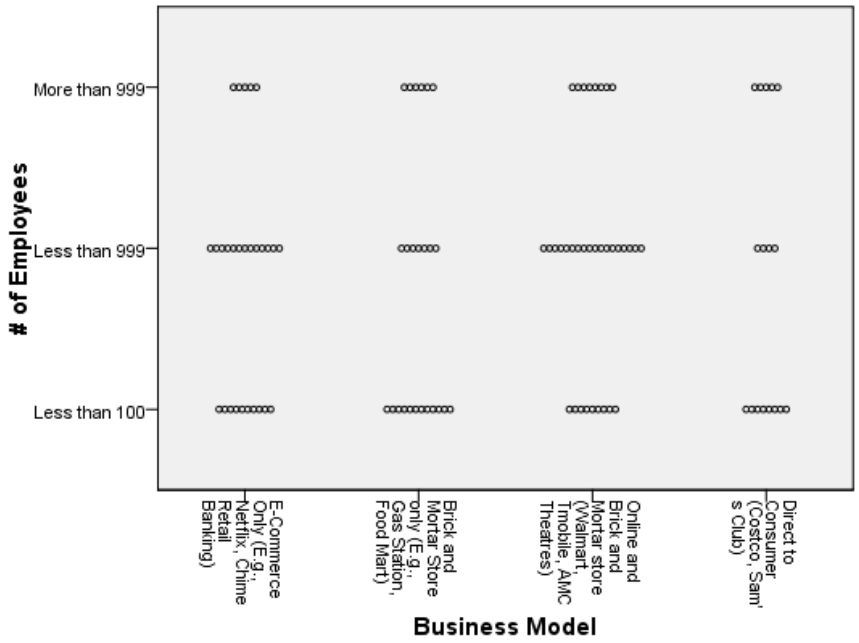

Figure 12. The 2D dot plot depicts respondents categorizing the retail business model by company size. The majority of analyzed responses were from companies with less than 999 employees.

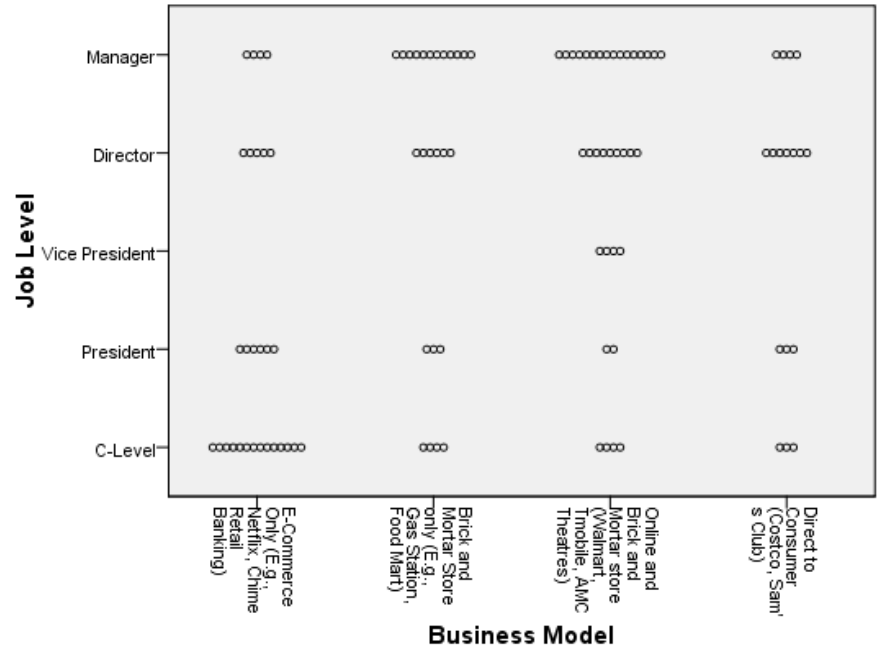

Figure 13. The 2D dot plot depicts responses categorizing the retail business model by job-level of the respondent. Across retail job levels, BIS usage is lowest in the job level president and vice president in the sample population.

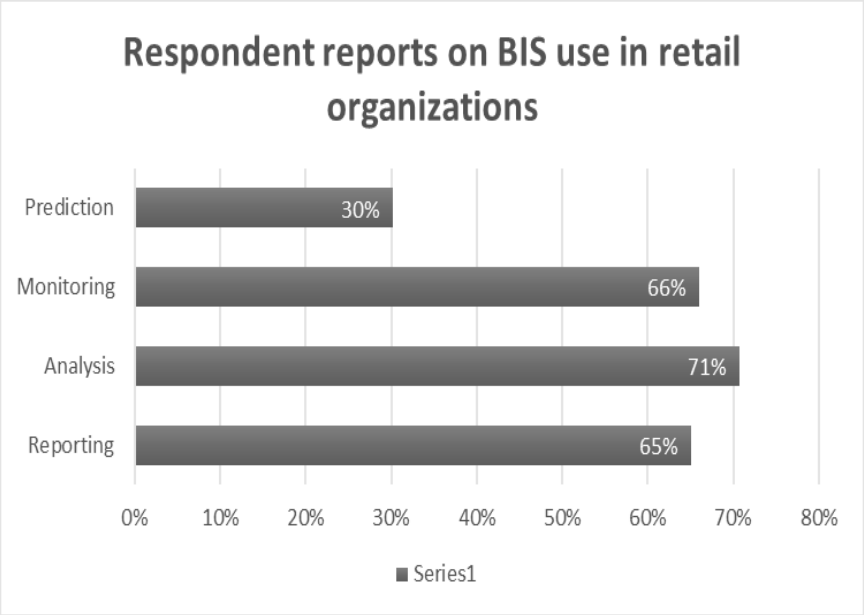

Figure 14. The bar chart depicts respondents self-report usage of BIS systems. Most common use indicated were analysis, monitoring, and reporting, while only 30% of respondents indicated prediction as to the use of BIS.

The descriptive statistics of the variables are reported as follows:

- Table 3 contains descriptive statistics of the PU scale.
- Table 4 contains descriptive statistics of the PEOU scale.
- Table 5 contains descriptive statistics of the study variables.

Table 3

Descriptive Statistics for the Individual PU Items Sorted by Highest Mean

Survey item	*M*	*SD*
Q1. Using the business intelligence system in my job would enable me to accomplish tasks more quickly	6.11	.979
Q3. Using the business intelligence system in my job would increase my productivity	5.90	1.050
Q4. Using the business intelligence system would enhance my effectiveness on the job	5.95	1.124
Q5. Using the business intelligence system would make it easier to do my job	5.91	1.151
Q6. I would find the business intelligence system useful in my job	5.92	1.255
Q2. Using the business intelligence system would improve my job performance	5.78	1.287

Note: *N* = 106. Items based on a 7-point Likert scale ranged from 1 = *extremely unlikely* to 7 = *extremely likely*.

Descriptive Statistics for PU. Descriptive statistics for the six individual PU survey items sorted by the highest mean are in Table 6. The basis for Q1-Q6 was a 7-point Likert scale ranging from 1 = E*xtremely Unlikely* to 7 = *Extremely Likely*. Q1, "Using the business intelligence system in my job would enable me to accomplish tasks more quickly," had the highest mean (M = 6.11), and Q2, "Using the business intelligence system would improve my job performance" had the lowest mean (M = 5.78).

Table 4

Descriptive Statistics for the Individual PEOU Items Sorted by Highest Mean

Survey item	*M*	*SD*
Q5. It would be easy for me to become skillful at using the business intelligence system	5.84	1.088
Q1. Learning to operate the business intelligence system would be easy for me	5.80	1.125
Q6. I would find the business intelligence system easy to use	5.70	1.140
Q2. I would find it easy to get the business intelligence system to do what I want it to do	5.67	1.248
Q3. My interaction with the business intelligence system would be clear and understandable	5.63	1.290
Q4. I would find the business intelligence system to be flexible to interact with	5.52	1.340

Note: N = 106. Items based on a 7-point Likert scale ranged from 1 = *extremely unlikely* to 7 = *extremely likely*.

Descriptive Statistics for PU

Descriptive statistics for the six individual PEOU items sorted by the highest mean are in Table 6. The basis for Q1-Q6 was a 7-point Likert scale ranging from 1 = E*xtremely Unlikely* to 7 = *Extremely Likely*. Q4, "It would be easy for me to become skillful at using the business intelligence system," had the highest mean (M = 5.84), and Q2, "I would find the business intelligence system to be flexible to interact with" had the lowest mean (M = 5.52).

Table 5

Means and Standard Deviations for Quantitative Study Variables

Variable	*M*	*SD*
PU	5.9292	.90617
PEOU	5.6934	.96859
User acceptance	2.0189	1.17093

Note. $N = 106$.

Reliability of the Variables

I used Cronbach's alpha to measure the internal consistency of my survey. The Cronbach's alpha value for the constructs PU and PEOU were >.7 suggesting both items had relatively high internal consistency (Table 6).

Table 6

Reliability Statistics for Study Constructs

Variables	Cronbach's alpha
PU	.880
PEOU	.889

Note: $N = 106$.

Tests of Assumptions

The assumptions of multicollinearity, outliers, normality, linearity, homoscedasticity, and independence of residuals were evaluated. Bootstrapping, using 1,000 samples, enabled combating the influence of assumption violations.

Multicollinearity

Multicollinearity was evaluated by viewing the correlation coefficients

among the predictor variables. All bivariate correlations were small to medium (Table 7); therefore, the violation of the assumption of multicollinearity was not evident. The following table contains the correlation coefficients.

Table 7

Correlation Coefficients Among Study Predictor Variables

Variable	PEOU	PU
PEOU	1.00	-.706
PU	-.706	1.00

Note. $N = 106$.

Outliers, normality, linearity, homoscedasticity, and independence of residuals.

Outliers, normality, linearity, homoscedasticity, and independence of residuals were evaluated by examining the Normal Probability Plot (P-P) of the Regression Standardized Residual (Figure 15), the scatterplot of the standardized residuals (Figure 16), and the histogram of the regression standardized residuals (Figure 17). The examinations indicated there were no major violations of these assumptions. The tendency of the points to lie in a reasonably straight line (Figure 15), diagonal from the bottom left to the top right, provides supportive evidence the assumption of normality has not been grossly violated (Pallant, 2010). The lack of a clear or systematic pattern in the scatterplot of the standardized residuals (Figure 16) supports the tenability of the assumptions being met. In addition, 1,000 bootstrapping samples were computed to combat any possible influence of assumption violations and 95% confidence intervals based upon the bootstrap samples are reported where appropriate.

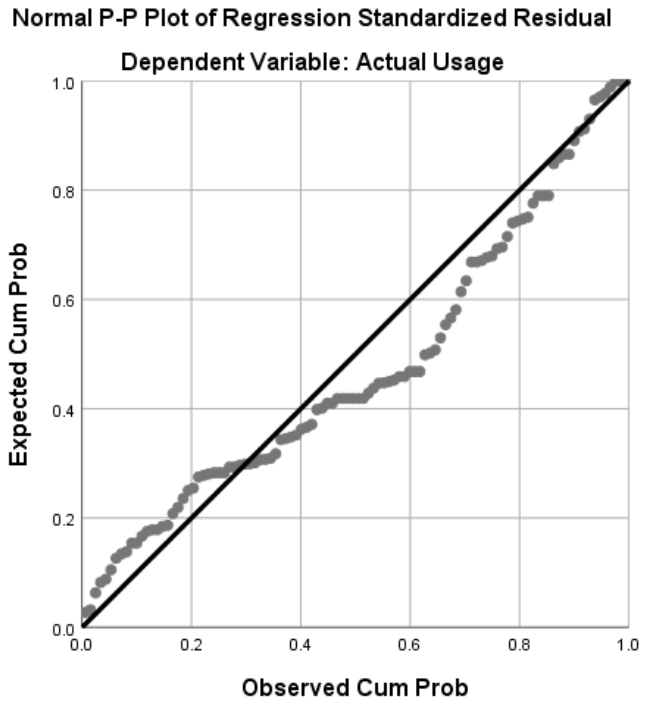

Figure 15. Normal probability plot (P-P) of the regression standardized residuals

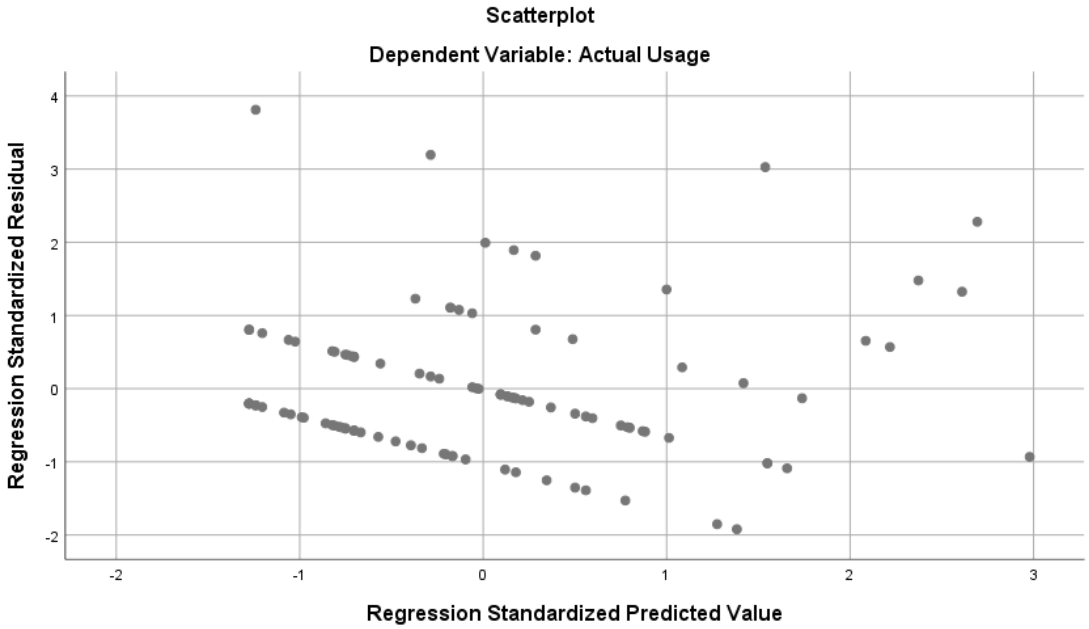

Figure 16. Scatterplot of the standardized residuals.

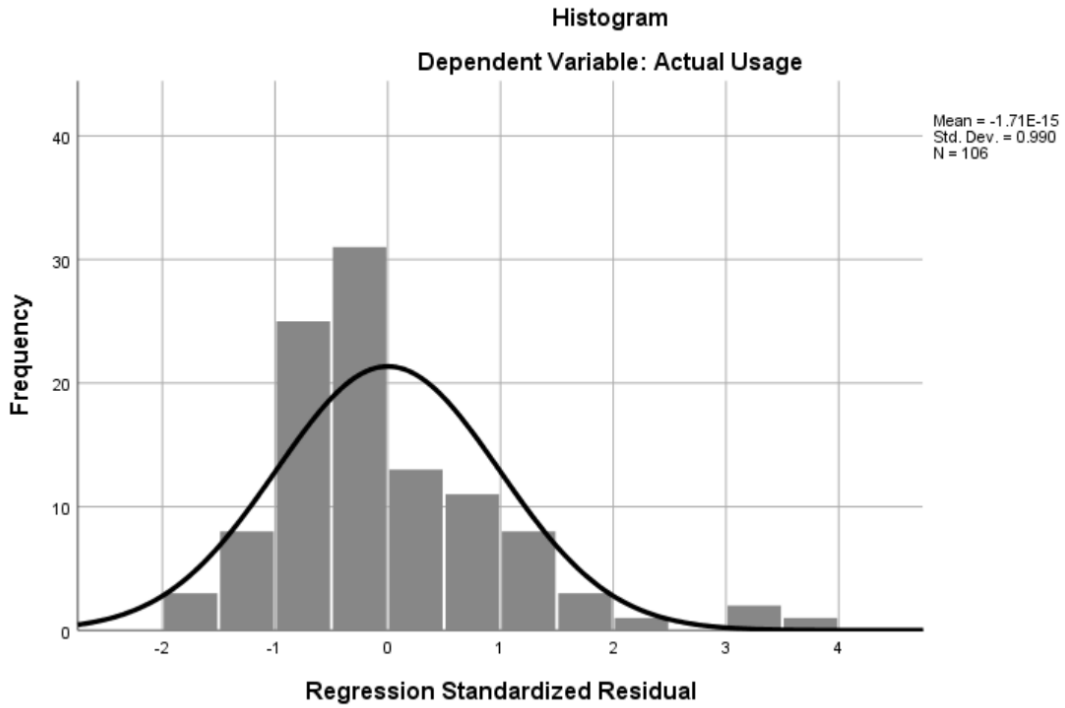

Figure 17. Regression standardized residuals.

Inferential Results

Pearson's Product Moment Correlation

A Pearson Product-Moment correlation test (two-tailed), a = .05, was conducted to assess whether there is a statistically significant relationship between PU, PEOU, and user acceptance of BIS. Table 6 depicts Pearson correlations for all the variables.

Table 8

Pearson Correlations

Variable	PEOU	PU	Actual Usage
PU	.706	1.00	-.540
PEOU	1.00	.706	-.439
User Acceptance of BIS	-.439	-.540	1.00

The results were as follows:

- strong positive correlation between PU and PEOU, $r = .706$, $n = 106$, $p < .01$, with high PU associated with high PEOU
- strong negative correlation between PU and actual usage of BIS, $r = -.540$, $n = 106$, $p < .01$, as PU decreases user acceptance of BIS increases
- moderate negative correlation between actual BIS usage and PEOU, $r = -.439$, $n = 106$, $p < .01$, as PEOU decreases user acceptance of BIS increases

Multiple Linear Regression

Standard multiple linear regression, $\alpha = .05$ (two-tailed), was used to examine the relationship between PU, PEOU, and user acceptance of BIS. The independent variables were PU and PEOU. The dependent variable was user acceptance of BIS. The null hypothesis was there is no statistically significant relationship between (a) PU, (b) PEOU, and (c) user acceptance of BIS. The alternative hypothesis was there is a statistically significant relationship between

(a) PU, (b) PEOU, and (c) user acceptance of BIS. Preliminary analyses were conducted to assess whether the assumptions of multicollinearity, outliers, normality, linearity, homoscedasticity, and independence of residuals were met; no serious violations were noted. The model as a whole was able to significantly predict user acceptance, $F(2, 103) = 21.903$, $p < .000$, $R^2 = 0.298$. The R^2 (.298) value indicated approximately 29.8% of variations in user acceptance is accounted for by the linear combination of the predictor variables (PU and PEOU). In the final model, PU and PEOU were statistically significant with PU ($t=-3.947$, $p = .000$, $\beta = -.460$) accounting for a higher contribution to the model than PEOU ($t = -.977$, $p = .000$, $\beta = -.114$). The final predictive equation was:

User Acceptance = 6.326 -.460(PU) -.114(PEOU)

PU. The negative slope for PU (-.594) as a predictor of user acceptance of BIS indicated there was about a .594 decrease in user acceptance of BIS for each one-point increase in PU. In other words, user acceptance of BIS tends to decrease as PU increases. The squared semi-partial coefficient (sr^2) estimated how much variance in user acceptance was uniquely predictable from PU was .13, indicating 13% of the variance in user acceptance is uniquely accounted for by PU when PEOU is controlled.

PEOU. The negative slope for PEOU (-.138) as a predictor of user acceptance of BIS indicated there was a .138 decrease in user acceptance for each additional one-unit increase in PEOU, controlling for PU. In other words, PEOU

decreases as user acceptance increases. The squared semi-partial coefficient (sr^2) estimated how much variance in user acceptance of BIS was uniquely predictable from PEOU was .01, indicating 1% of the variance in user acceptance of BIS is uniquely accounted for by PEOU when PU is controlled. Table 9 depicts the regression summary table.

Table 9

Regression Analysis Summary for Predictor Variables

Variable	*B*	*SE B*	*β*	*t*	*p*	*B* 95% Bootstrap CI
PU	-.594	.151	-.460	-3.947	.000	[-.893, -.296]
PEOU	-.138	.141	-.114	-.977	.331	[-.417, .142]

Note. *N*= 106.

Analysis summary

The purpose of this study was to examine the relationship between PU, PEOU, and user acceptance of BIS in retail organizations. I used standard multiple linear regression to examine the ability of PU and PEOU to predict user acceptance of BIS in retail organizations. Assumptions surrounding multiple regression were assessed with no serious violations noted. The model as a whole was able to significantly predict user acceptance of BIS, $F(2, 103) = 21.903$, $p < .000$, $R^2 = .298$. PU provided useful predictive information about user acceptance. The conclusion from this analysis is that PU significantly associated with user acceptance.

Theoretical conversation on findings

The factors affecting user acceptance of a novel technology can be challenging to identify because they can be unique to the environment where the usage is occurring. Emaeilzadeh (2016) articulated this simply by stating that IT adoption behavior is impacted by the unique characteristics of its users. Despite these challenges, the TAM model was able to provide a partial explanation of the factors affecting user acceptance of BIS in retail organizations. Specifically, PU was found to be the only variable with a statistically significant relationship with user acceptance. These findings are consistent with research that demonstrated:

- TAM partially explains behavioral intentions (Liu & Yang, 2018)
- PU is consistently a more powerful predictor than PEOU (Amin, Rezaei, and Abolghasemi, 2014).

In addition, the majority of participants in this study had more than 5 years of experience with BIS. The negative slopes for PU (-.594) and PEOU (-.138) demonstrates PU and PEOU subside over time. This finding concurs with research findings which showed PU and PEOU effect on user acceptance declines as users become more experienced (Butler Lamar, 2016; Moslehpour et al., 2018; Nasser Al-Suqri, 2014). These findings suggest experienced users are less likely to encounter difficulties interacting with new technology and therefore, more likely to use them (Caffaro, Bisaglia, Cutini, Cremasco, & Cavallo, 2018).

Applications to Professional Practice

The results of my regression analysis indicated PU was the only statistically significant contributor to user acceptance of BIS in retail and subsided over time. To enhance PU, leaders should realize BIS should make users' work and life easier, acquire the information they need easily and, be perceived as useful (Amin et al., 2014). Strategic and tactical leaders of retail organizations can increase user acceptance of BIS by end-users by ensuring adoption strategies factor in PU to the end-user. It may also be helpful to promote the importance or benefits of using BIS; explaining to users how using information technology can improve their productivity and reduce error and redundancy. Administrators, practitioners, and instructors could also implement a variety of methods to ensure information technology usage.

Implications for Social Change

The potential implications for positive social change could be impactful locally and globally. Retail businesses affect every economy in the world (Zamba et al., 2018), and their failure would significantly impact the availability of employment globally. According to Bernabè and Krstić (2008), growth is widely perceived as an important channel in reducing poverty. A lack of employment opportunities contributes to an increase in poverty and encourages corruption, anti-social activities like drugs, smuggling, and prostitution. Therefore, the success of retail organizations can positively impact the growth of employment opportunities and by extension, contribute to the reduction of poverty locally and globally.

A second positive outcome resulting from user acceptance of BIS could be the use of BIS beyond organizational decision-making processes to social investment decision-making processes. According to Petrini and Pozzebon (2009), BI methods and tools can help organizations implement and monitor sustainable and socially responsible business practices. Further Petrini and Pozzebon (2009) state the role of BI is to create an informational environment in which operational data gathered from transactional systems and external sources can be analyzed, to reveal ‘‘strategic” business dimensions (Petrini & Pozzebon, 2009). Data on social and economic issues could be collected and analyzed to understand opportunities to address social and economic issues as part of organizational goals and strategy. Usage of BIS by end-users is therefore required to acquire the evidence-based insights necessary to identify opportunities for corporate intervention in solving social and economic problems.

Recommendations for Action

Often business leaders invest in IS solutions expecting the implementation to solve business problems and the users to automatically accept and use the new technology. Often, this is not the case, especially in voluntary use environments (Grublješič, & Jaklič, 2015a). The findings from this study have practical implications for retail business leaders and user acceptance of BIS researchers. Specifically, leaders should pay attention to the significance of PU in promoting user acceptance. PU subsides over time, suggesting it is a critical factor post-implementation. Business leaders can benefit from evaluating BIS solution in the selection phase of BIS for their organization.

Furthermore, business leaders can employ additional strategies to incentivize user acceptance through user training, promotion, financial benefits, as well as workload and time reduction. In addition, communicating the benefits of BIS, such as improved productivity, error, and redundancy reduction may also help promote user acceptance (Ayele, 2018; Butler Lamar, 2016).

The results from this study will be available through the ProQuest dissertation and thesis database for review by students, scholars, practitioners, and librarians. I will also make a summary of my findings available to research participants interested in reviewing my study results. I plan to pursue publication in academic journals referencing my doctoral study as well as presenting my study outcomes at practitioner conferences and professional organization meetings.

Recommendations for Further Research

A limitation of this study was my inexperience in research. As previously stated, my inexperience may have impacted the formulation of the research objectives, the quality of the data collection method, and therefore, the outcomes I obtained. Therefore, my recommendation for future research to address this limitation would include:

- Potentially repeating the study using the same criteria
- Potentially repeating the study focusing on different geographies
- Reducing the number of years of experience end-users have had with BIS
- Focusing on specific BIS solutions which were created within the past 1-3 years

A second limitation of this study was the commonality of participants experiences in varied business environments. This limitation could be addressed by conducting future research, including:

- Potentially performing mixed or qualitative study with the same population
- Focusing on a narrower definition of retailers
- Focusing on a specific retail business model
- Focusing on companies with less than 999 employees to identify novice users

A final recommendation for further research is using one or a combination of rival user acceptance theories.

Given PU accounted for a higher contribution to the model, future research could advance our understanding of additional factors which may have a statistically significant relationship with user acceptance of BIS in retail organizations. For example, Lim (2018) argued the TAM model limits discovery of other factors affecting user acceptance such as self-regulatory and social aspects of user behavior, changes in the socio-economic environment or technological proliferation. Identifying additional factors affecting user acceptance of BIS in retail would provide leaders additional information to consider prior to investing in BIS.

Reflections

The greatest challenge I faced during my doctoral study was organizing my time around work, family, and school. I learned to manage my work in big bursts of effort, to complete a section and then break to recover in other areas of my life. At one point

during the proposal phase, I chose to manage the bare minimum requirements as my work life was in a peak period. I felt the risk of leaving the program was greater if I took time off and chose to maintain minimum engagement. My decision to continue on rather than take a temporary leave of absence resulted in additional financial cost and the continued challenge of juggling work, life, and school.

Despite the challenges of time management and prioritization, the process was valuable on several fronts. First, learning how to accept and incorporate feedback which serves me well both in my personal and professional life. Second, the development of concise writing skills will be valuable to me as I pursue opportunities to author original works. And finally, the value of multiple points of view in the iteration process. I am certain my final study is the best it could be as a result of the rigor applied in the topic refinement, proposal development, and the reporting of my findings. I feel extremely optimistic about my future and my career post-doctorate.

Conclusion

Using BIS in retail organizations is a valuable offensive strategy to gain a competitive advantage in the market. BIS has the potential to improve firm performance, but only to the extent end-users of BIS use these systems. This study provided insights into the factors influencing user acceptance of BIS in retail organizations in the eastern United States. Grounded in technology acceptance theory (TAM), the purpose of this quantitative correlational study was to examine the factors influencing user acceptance of BIS in retail organizations. Responses from 106 participants, who were representative of

the target population, were used in the final analysis. The findings were consistent with the results of similar studies of novel technology where the TAM theoretical framework was used. The results showed the TAM models ability to predict user acceptance of BIS in retail organizations; and the combined predictor variables, PU and PEOU, accounted for approximately 29.8% of variations in user acceptance of BIS. Although both independent variables subsided over time, demonstrating PU and PEOU effects on user acceptance of BIS decrease as user acceptance increases, PU accounted for a higher contribution to the model and is, therefore, a critical factor to consider. Therefore, business leaders can use the results of this study to assess appropriate BIS prior to purchasing and implementing as well as develop strategies to improve user acceptance post-launch of a BIS.

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Appendix A: Permission to Conduct Research Using SurveyMonkey

SurveyMonkey Inc.
www. surveymonkey.com

For questions, visit our Help Center
help.survemonkey.com

Re: Permission to Conduct Research Using SurveyMonkey

To Whom It May Concern:

This letter is being produced in response to a request by a student at your institution who wishes to conduct a survey using SurveyMonkey in order to support their research. The student has indicated that they require a letter from SurveyMonkey granting them permission to do this. Please accept this letter as evidence of such permission. Students are permitted to conduct research via the SurveyMonkey platform provided that they abide by our Terms of Use at https://www.surveymonkey.com/mp/legal/terms-of-use/.

SurveyMonkey is a self-serve survey platform on which our users can, by themselves, create, deploy and analyze surveys through an online interface. We have users in many different industries who use surveys for many different purposes. One of our most common use cases is students and other types of researchers using our online tools to conduct academic research.

If you have any questions about this letter, please contact us through our Help Center at help.surveymonkey.com.

Sincerely,

SurveyMonkey Inc.

Appendix B: Invitation to Participate in Study

You are invited to participate in a research study conducted by Christina Sandema-Sombe in the Walden University Doctor of Business Administration program on the factors that affect usage of business intelligence systems in retail organizations in the eastern United States. The findings from this research may help business leaders identify the right business intelligence solutions for their organizations by providing insights regarding the factors that affect end-users use of business intelligence systems.

The researcher is inviting:

- participants over the age of 18
- employees in strategic managerial positions, middle management (excluding technology experts) and have been end-users of business intelligence systems for less than 5 years
- in retail companies/organizations in the eastern United States

You can only complete the survey once, and it should take no more than 10 minutes to complete. Your responses are anonymous.

If you have any questions about the survey, please contact Christina Ndiwa Sandema-Sombe at christina.sandema@waldenu.edu

Appendix C: Consent Form

Consent Form

You are invited to take part in a research study titled "Relationship between perceived usefulness, perceived ease of use and user acceptance of business intelligence systems." The researcher is inviting participants to be in the study who are:

- over the age of 18
- employees in strategic managerial positions, middle management (excluding technology experts) who have been end-users of business intelligence systems for less than 5 years
- work in retail companies/organizations in the eastern United States

You were randomly chosen for this study from the SurveyMonkey American Audience population. This form is part of a process called "informed consent" to allow you to understand this study before deciding whether to take part.

This study is being conducted by a researcher named Christina Ndiwa Sandema-Sombe, who is a doctoral student at Walden University.

Background Information:
The purpose of this study is to examine whether there is a relationship between perceived usefulness, perceived ease of use and user acceptance of business intelligence systems.

Definitions that will aid in providing a common understanding of the survey are as follows:

- **End-user:** is defined as all employees who are not information technology experts, but who use a business intelligence system to perform their duties at work
- **Retailers:** Are any organizations that conduct business with consumers (e.g., bookstores, airlines, digital subscription services)
- **Business intelligence systems:** are technological solutions holding quality information in well-designed data stores, connected with business-friendly tools that the provide users – incumbents of executives, managers, business analysts and other roles within a firm utilizing BIS-enabled information for analytical decision making – with timely access to as well as effective analysis and insightful presentation of the information generated by enterprise-wide applications, enabling them to make the right decisions or take the right actions. In addition, business intelligence system is used to describe the technical artifacts that provide business intelligence functionality to users

Procedures:
If you agree to be in this study, you will be asked to:

- Complete a survey consisting of 9 questions divided into 3 sections
- Only complete the survey once.

The entire survey should take under 10 minutes to complete. Here are some sample questions:

- What position do you hold at your company?
- Do you use a business intelligence system in your role?
- Have you used a business intelligence system for more than 2 years?
- Using the business intelligence system in my job would enable me to accomplish tasks more quickly?

Voluntary Nature of the Study:
This study is voluntary. You are free to accept or turn down the invitation. You will not be treated differently if you decide not to be in the study. If you decide to be in the study now, you can still change your mind later. You may stop at any time.

Risks and Benefits of Being in the Study:
There are no personal risks as a result of your decision to participate in this study, and there are no direct benefits to you as an individual participant. Participants in this type of study may experience minor discomforts that can be encountered in daily life. If participation produces greater stresses than daily life, please contact the crisis hotline at (888) 724-7240 for assistance. Your participation may benefit executives by providing leaders insight into the perceived ease of use and perceived usefulness of business intelligence systems for the end-users of business intelligence systems before making financial investments.

Payment:
SurveyMonkey American Audience contribute panelists take surveys for charity and a chance to win sweepstakes prize. SurveyMonkey American Audience rewards panelists earn credits for completing surveys which they can redeem for gift cards or donate to charity. There is no separate or additional compensation for participation in this study.

Privacy:
All responses provided by you are anonymous. Reports coming out of this study will not share the identities of individual participants. Details that might identify participants, such as the location of the study, also will not be shared. Even the researcher will not know who you are. Your information is not linked to your employment, and your employer will not be aware of your participation or answers. The researcher will not use your personal information for any purpose outside of this research project. Data will be kept secure by Christina Sandema-Sombe in a secure location which only the researcher has access to. Data security measures will include biometric password protection. Data will be kept for at least 5 years, as required by the university.

Contacts and Questions:
You may ask any questions you have now. Or if you have questions later, you may contact the researcher via email at christina.sandema@waldenu.edu or by phone at 404.216.7852. My doctoral study chairperson is Dr. Brandon Simmons. You can contact Dr. Simmons via email at brandon.simmons@mail.waldenu.edu. If you want to talk privately about your rights as a participant, you can call the Research Participant Advocate at my university at 1-800-925-3368 ext. 312-1210 from within the USA, 001-612-312-1210 from outside the USA, or email address irb@waldenu.edu. After completion of the study, the researcher will post a summary of the results at https://www.researchgate.net/project/Relationship-between-perceived-usefulnessperceived-ease-of-use-and-user-acceptance-of-business-intelligence-systems. Walden University's approval number for this study is **06-20-19-0140074** and it expires on **June 19, 2020.**

Obtaining Your Consent
To help keep personally identifiable information separate from this study no signature is required. By proceeding with the survey, you are providing your implied consent to participate. Recall that you may stop participation and exit at any time. Incomplete surveys will be discarded and will not be included in the results. I have read the information in this form and consent to participate in this study. My continuation in this study demonstrates my agreement with the statements and information in this informed consent document. Please print a copy of this consent form for your records.

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Appendix D: Permission to Use UTAUT and TTF Figures, and Adapt TAM Survey

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January 7, 2019

Christina Sandema-Sombe
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Walden University
School of Management
Doctoral Candidate/DBA

This letter replaces the Copyright Permission Letter Dated January 4, 2019

Permission to use material from
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Permission is hereby granted to Christina Sandema-Sombe to reprint the information outlined in detail below – UTAUT (Figure 3); Appendix Final Measurement Scales for Perceived Usefulness and Perceived Ease of Use; and Task-Technology Fit (Figure 4); (and supporting material as necessary).

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Title: User acceptance of information technology: Toward a unified view
Authors: V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, 2003,
Publish Date: September 2003
Journal: MIS Quarterly,
Content requesting permission for: UTAUT (Figure 3)
Journal volume: 23
Issue: 3
Page: 447

Appendix Final Measurement Scales for Perceived Usefulness and Perceived Ease of Use
Title: Perceived usefulness, perceived ease of use, and user acceptance of information technology
Author: Davis, F;
Publish Date: September 1989,
Journal: MIS Quarterly
Content requesting permission for: Appendix Final Measurement Scales for Perceived Usefulness and Perceived Ease of Use
Journal Volume: 13
Journal Issue: 3
Journal Page: 340

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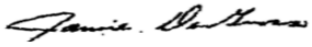

Janice I. DeGross
Manager, MIS Quarterly

Appendix E: Survey

Screening Questions

1. Do you use a business intelligence system in your role?

- Yes
- No

2. Have you used a business intelligence system for more than 5 years?

- Yes
- No

Demographics

3. How many employees work at your company?

- Less than 100
- Less than 999
- More than 999

4. What is your company's business model?

- E-Commerce Only (E.g., Netflix, Chime Retail Banking)
- Brick and Mortar Store only (E.g., Gas Station, Food Mart)
- Online and Brick and Mortar store (Walmart, Tmobile, AMC Theatres)
- Direct to Consumer (Costco, Sam's Club)
- Other (please specify)

5. What position do you hold at your company?

- C-level
- President
- Vice President
- Director
- Manager
- Consultant/Contractor/Freelancer
- Individual Contributor
- Other (please specify)

6. What activities do you use your BI system for? (You can select multiple answers)

- [ ] Reporting
- [ ] Analysis
- [ ] Monitoring
- [ ] Prediction
- [ ] Other (please specify)

7. How frequently do you use the BI system?

- ○ Daily
- ○ Weekly
- ○ Bi-Weekly
- ○ Monthly
- ○ Quarterly
- ○ Semi-annually
- ○ Annually
- ○ Never

8. Perceived Usefulness of Business Intelligence Systems							
	Extremely Likely	Likely	Somewhat Likely	Neither Likely/Unlikely	Somewhat Unlikely	Unlikely	Extremely Unlikely
Using the business intelligence system in my job would enable me to accomplish tasks more quickly.							
Using the business intelligence system would improve my job performance.							
Using the business intelligence system in my job would increase my productivity							
Using the business intelligence system would enhance my effectiveness on the job.							
Using the business intelligence system would make it easier to do my job.							
I would find the business intelligence system useful in my job.							

9. Perceived Ease of Use of Business Intelligence Systems							
	Extremely Likely	Likely	Somewhat Likely	Neither Likely/Unlikely	Somewhat Unlikely	Unlikely	Extremely Unlikely
Using the business intelligence system in my job would enable me to accomplish tasks more quickly.							
Using the business intelligence system would improve my job performance.							
Using the business intelligence system in my job would increase my productivity							
Using the business intelligence system would enhance my effectiveness on the job.							
Using the business intelligence system would make it easier to do my job.							
I would find the business intelligence system useful in my job.							

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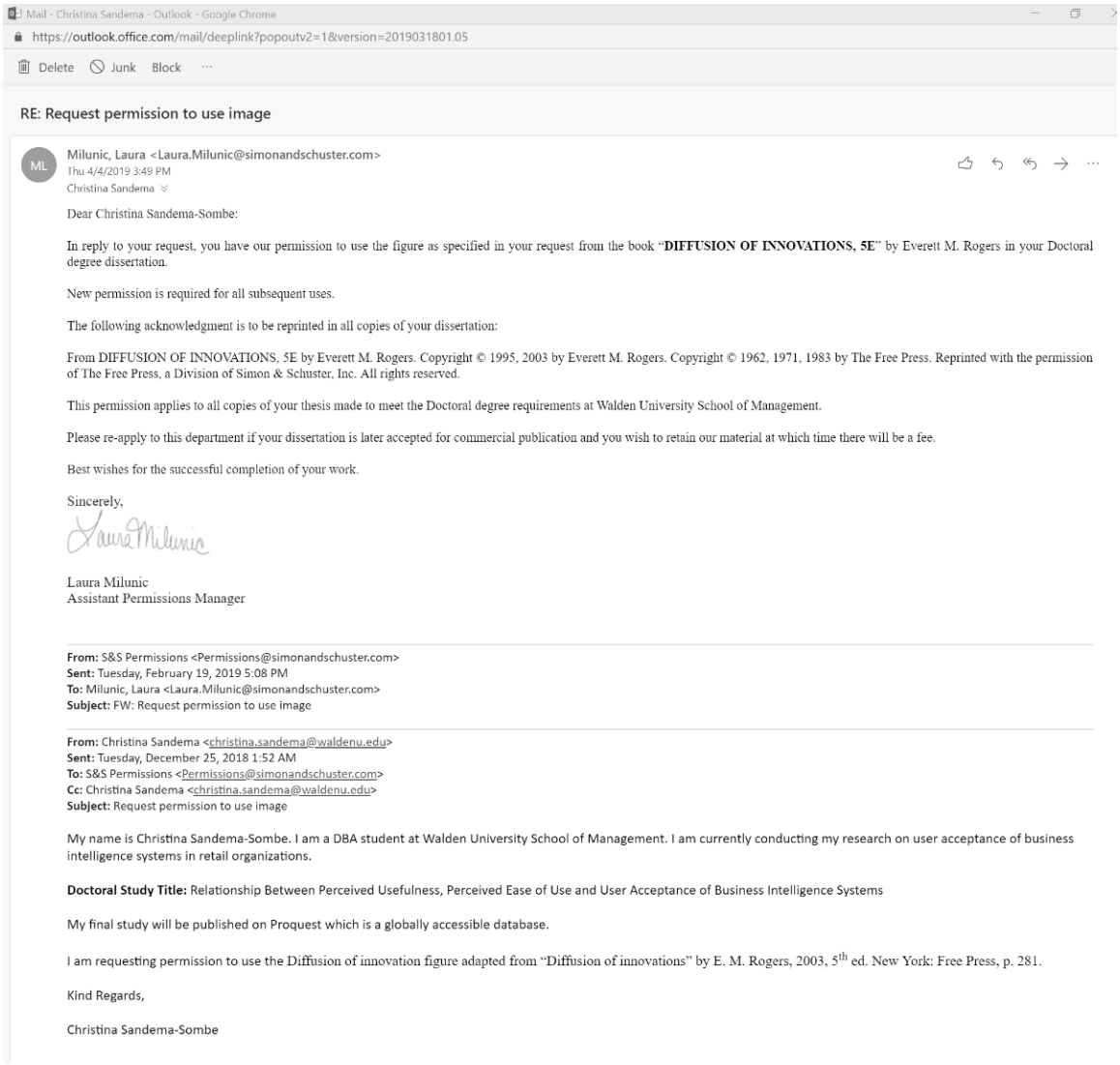

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