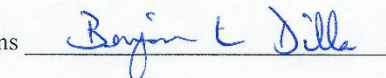# SIRI, ALEXA, AND OTHER DIGITAL ASSISTANTS:

A STUDY OF CUSTOMER SATISFACTION WITH ARTIFICIAL

INTELLIGENCE APPLICATIONS

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SIRI, ALEXA, AND OTHER DIGITAL ASSISTANTS:

A STUDY OF CUSTOMER SATISFACTION WITH ARTIFICIAL INTELLIGENCE

APPLICATIONS

by

THOMAS M. BRILL

Presented to the Faculty of

The University of Dallas in Partial Fulfillment

of the Requirements

for the Degree of

DOCTOR OF BUSINESS ADMINISTRATION

THE UNIVERSITY OF DALLAS

February, 2018

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ACKNOWLEDGEMENTS

I have received tremendous support throughout this journey. Words cannot fully express my eternal gratitude to those who have inspired, assisted and supported me during this time. I can only hope to pay it forward by providing some degree of similar support to others who may seek my involvement.

First and foremost, I would like to thank my wife Linda. The completion of this endeavor would not have been accomplished without your enduring love, support and patience throughout this process. This effort would not have been possible without your sacrifices and willingness to adapt. I also want to acknowledge the support of my sons (Eric, Kyle and Adam as well as the angelic support of Jason).

It is impossible to express adequate thanks to my committee of Dr. Laura Munoz (chair) and Dr. Rich Miller. Their leadership, attention, and mentorship were key enablers for me being able to successfully complete this dissertation. I am very appreciative to have been taught and lead by such dedicated scholars. I also want to thank the Gupta DBA faculty and staff for your contributions towards developing my academic competencies.

For my cohort peers, we have shared a unique journey together and created history as the inaugural Gupta DBA cohort. Your friendship and support helped me to overcome periods of self-doubt while also inspiring me to complete this effort. Not to be overlooked are your unique perspectives, experiences, and personalities which contributed to making our time together to be both enjoyable and rewarding. I look forward to keeping up with each of you in the years to come.

DEDICATION

This dissertation effort is dedicated to my parents, Marlene and Roger Brill. They were influential in the formulation of my beliefs on the value of intellectual curiosity. While always putting family needs before their own, they demonstrated that it is never too late to pursue higher education. For it wasn't until I had completed my undergraduate studies, that they completed their own, even though some of my siblings were still at home.

I was blessed to have supportive parents who provided unwavering support for my ambitions and goals and they reaffirmed my ability to 'conquer the world'. They were role models in developing a strong work ethic while balancing those needs with equally strong family values. As parents, they proved that these sometimes-opposing forces can successfully coexist. While they are no longer physically present, I still feel their angelic support in everything that I do. I thank you both for the love and support that you provided me and feel comfort in knowing that you both are still watching over me.

ABSTRACT

SIRI, ALEXA, AND OTHER DIGITAL ASSISTANTS:

A STUDY OF CUSTOMER SATISFACTION WITH ARTIFICIAL INTELLIGENCE

APPLICATIONS

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The University of Dallas, 2018

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Siri, Alexa, and other digital assistants are rapidly becoming embraced by consumers and are projected to grow from 390 million to 1.8 billion for the period of 2015 to 2021. While offering benefits to consumers, digital assistants are proving to be a disruptive technology for businesses as well. Coupling digital assistants with other artificial intelligence technologies offers the potential to transform companies by creating more efficient business processes, automating complex tasks, and improving the customer service experience. Businesses have begun integrating this technology into their operations with the expectation of achieving significant productivity gains. Yet, there is little empirical evidence of customer satisfaction with digital assistants. This study used PLS-SEM to analyze 244 survey responses obtained from a cross-section of consumers. Using the Expectations Confirmation Theory as its foundation, the study

results identified that this model substantially explained customer satisfaction with digital

assistants. Using analysis of the relative importance of model constructs, the study provides

guidance which allows firms to prioritize marketing and managerial activities. These priorities

identify areas of high importance for customer satisfaction, but which require performance

improvements.

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CHAPTER 1

INTRODUCTION

Artificial intelligence (AI) technologies are emerging as disruptive change agents, challenging many established marketing strategies and processes (V. Kumar, A. Dixit, R. G. Javalgi, & M. Dass, 2016). Businesses must now quickly understand and respond to the changes in attitudes facilitated by customer exposure to AI technologies (V. Kumar et al., 2016). In doing so, companies need to evaluate the experience at each point of customer interaction (Lemon & Verhoef, 2016), as well as their overall marketing engagement model (Piotrowicz & Cuthbertson, 2014). As such, context-specific recognition must be given to the cognitive, emotional, and behavioral components of the engagement (Calder, Malthouse, & Maslowska, 2016). One study relays that "firms already acknowledge the importance of understanding and managing customer experience and engagement levels" (Grewal, Roggeveen, & Nordfält, 2017, p. 3). Accordingly, firms must transform their customer preference and behavioral information into actionable knowledge. Knowledge is a fundamental source of competitive advantage. Firms that meet this challenge are afforded significant opportunities for competitive advantage and growth (V. Kumar et al., 2016).

There is a large and growing array of advanced AI technologies and applications; digital assistants represent one of many categories of integrated AI applications (Milhorat et al., 2014). Digital assistants and AI technology offer the potential to transform companies by creating more

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efficient business processes, automating complex tasks (Koehler, 2016), and improving the customer service experience (Parise, Guinan, & Kafka, 2016). Canbek and Mutlu (2016) have identified that consumers are rapidly embracing personal digital assistants, including those offered by the current market leaders (e.g., Apple's Siri, Amazon's Alexa, Google's Google Home, Samsung's Bixby and Microsoft's Cortana). Similarly, this technology is rapidly being adopted within the business markets. Digital assistants are viewed as dynamic systems possessing the ability to learn customer preferences (V. Kumar et al., 2016).

For the period of 2015 to 2021, worldwide consumer users of digital assistants are projected to grow from 390 million to 1.8 billion. Business users are forecasted to expand from 150 million to 843 million during the same period. The corresponding worldwide annual revenue for digital assistant technology is expected to increase from $1.6 billion to $15.8 billion (Tractica, 2016, August 25). These statistics suggest that the integration of digital assistants and other AI-based technology has launched a disruptive transformation in the interaction experience between customers and businesses (V. Kumar et al., 2016).

For consumers, digital assistants help users research topics and perform day-to-day tasks. In doing so, the technology offers users an opportunity to simplify how they become informed and how they act (Grand View Research, 2016). The internet offers users a plethora of information about their topic of choice, but the volume of information can sometimes become overwhelming. Digital assistants (through their linkage to other AI technologies) are enabling users to more quickly sort through options to make better decisions, access more relevant and beneficial offers, and obtain faster service (Grewal et al., 2017).

Recent research has offered insights into the impacts of prior generations of intelligent technologies on customer relationships and interactions. While on different technology platforms

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that have fewer technical and user capabilities, insights have been garnered about customer relationships with online recommendation agents (e.g., Li & Karahanna, 2015; Shen, 2014; Wang, Qiu, Kim, & Benbasat, 2016; Zhang, Guo, & Chen, 2016), how firms need to consider the consequences of customer satisfaction (Alqahtani & Farraj, 2016; Coelho & Henseler, 2012; Zhang et al., 2016), and how firms must embrace the importance of user trust (Dabholkar & Sheng, 2012; Fang et al., 2014; Lankton, McKnight, & Thatcher, 2014; Wang et al., 2016; Zhang et al., 2016). These insights provide a foundation for comparison against user expectations and experiences associated with the new generation of AI technology.

Recommendation systems are widely used in e-commerce, online and mobile advertisements, and other major areas that involve personal transactions and communications (Li & Karahanna, 2015). These systems capture user preferences and behaviors for use in extending personalized recommendations for selected products and services (Shen, 2014). Many times, the systems utilize rational appeal features (i.e., fact-based communications and rule-based arguments) to engage and persuade users to purchase items (Wang et al., 2016). This approach has been successful as time- and energy-starved users value these recommendations to filter through a seemingly overwhelming amount of information and options (Zhang et al., 2016). These studies provide many insights that are likely transferable to digital assistants and associated AI technologies.

As online retailing continues to grow and be adopted by more industry participants, competition continues to challenge the status quo and intensify the need to migrate away from generic solutions. Given the potential threat to profitability, firms must increasingly consider the consequences of satisfaction associated with customer intentions to continue use and/or be loyal

(Bhattacherjee & Lin, 2015). In service marketing, consumers evaluate not only the quality of the service, but also the quality of the service experience. This evaluation not only impacts the satisfaction judgment, but also influences the consumer's likelihood to continue using the service (Zhang et al., 2016). Other studies have examined factors that drive satisfaction and build a sense of loyalty in the customer mindset (Alqahtani & Farraj, 2016; Coelho & Henseler, 2012). While these studies are not specific to new technologies, they highlight the growing importance of personalization and their insights call attention to the capability benefits linked to digital assistants and associated AI technologies.

While prior research has highlighted consumer preference for self-service approaches (Scherer, Wünderlich, & von Wangenheim, 2015), the ongoing success of these platforms (i.e., online, e-commerce, service or retail) depends on the user's perception of trust (Hoffmann, Lutz, & Meckel, 2014). These systems capture significant volumes of personal and behavioral information. Thus, user trust in the system is among the critical enablers influencing users to continue using the system (e.g., Dabholkar & Sheng, 2012; Fang et al., 2014; Lankton et al., 2014; Wang et al., 2016; Zhang et al., 2016). Given the importance of trust in these studies, it is appropriate to assume that user perceptions of trust are also important to digital assistants and associated AI technologies.

This study advances our understanding of the theoretical foundations for customer satisfaction as related to a new AI technology platform. Given the relative infancy of current AI application adoption and utilization, there is limited empirical work directly related to the consumer experience and customer satisfaction. Instead, most of the recent literature has focused on either customer relationships with online recommendation agents (e.g., Li & Karahanna, 2015; Shen, 2014; Wang et al., 2016; Zhang et al., 2016) or how firms must consider the

consequences of customer satisfaction (Alqahtani & Farraj, 2016; Coelho & Henseler, 2012; Zhang et al., 2016). These studies tend to focus on the user experience within a controlled environment (e.g., website or online system), which generally requires focused and deliberate user actions. This type of environment contrasts with the more casual voice activated (i.e., no computer screen needed) atmosphere afforded to digital assistant users. Given their ability to support interactivity through voice, touch and vision input methods, digital assistants support a more fluid and dynamic interaction capability not available in traditional website design (Kiseleva et al., 2016). This interactivity also allows for the systematic capture of user data enabling machine learning and deep learning capabilities to identify personal preferences and routines (Milhorat et al., 2014).

Customer satisfaction has long been a focal point of extant marketing literature. In the past, this focus has been conveyed to the introduction of new technologies. Research, however, has yet to explore this focal point for AI technologies due to the relative infancy of AI-supported digital assistants. Considering the significant investment firms are making in digital assistant technology and the re-design of core production and customer service processes, confirmation is needed that customers are indeed satisfied with this technology. Therefore, it is imperative to study the degree to which there is alignment of digital assistant user expectations with the perceptions of the technology performance towards customer satisfaction. The dearth of research on this topic opens opportunities to provide clarity and insights to firms as they pursue ongoing programs involving digital assistants. To address this question, this study draws on the expectations confirmation theory (ECT) as the core theory to better understand how user satisfaction judgments are formed (Oliver, 1980, 1981). Its structure emulates the dynamic

process of expectation formation, technology use, and confirmation towards a satisfaction judgment.

Recent advancements in machine learning and deep learning capabilities allow for data-driven discoveries involving previously hidden patterns, correlations, and other revealing personal insights (Alpaydin, 2014). From a positive perspective, these resultant discoveries may offer desired benefits to the user in the form of enhanced personalization (Rust & Huang, 2014). However, for some users, concern exists that the digital data may be misused or abused (Miltgen, Popovič, & Oliveira, 2013). Frequent news reports and publication of studies associated with cyber-crime, data breaches, and employee mistakes (Ponemon Institute, 2016a, 2016b) tend to reinforce technology-related information privacy issues. This concern is among the topics included in the United States Government review of artificial intelligence (White House, 2014a). The collective impact of negative reports can challenge consumer confidence as to how their personal information is being secured and utilized. As such, the negative ramifications of misused or abused data can be significant (Miltgen et al., 2013). No study has focused specifically on these emerging influences of information privacy and trust implications within the context of digital assistants. While the technological benefits to consumers are suggested to be many, businesses face substantial risk of abandoned investment or brand injury if consumers lack trust in either the firm or the technology. Additional risk exists if firms cannot protect the privacy of personal information obtained using this technology. Thus, it is imperative to study to what extent the cognitive considerations associated with information privacy concerns and perceived trust offer a moderating influence on the ECT relationships. To address this question, this study draws on important elements of the social cognitive theory (SCT) and the protection motivation theory (PMT). SCT offers explanation as to how individuals acquire knowledge and

become aware of how they can control their own behavior to emulate the desired result or satisfy a personal need (Bandura, 1977, 1986). This knowledge acquisition approach underlies how individuals form perceptions, gain knowledge, and use digital assistants and AI technologies. PMT explains the cognitive processes used by individuals in response to fears associated with a threat (Rogers, 1975, 1983). Within the context of this study, SCT and PMT support the moderating effects of user perceptions associated with personal information privacy and trust on the customer satisfaction relationship with digital assistants and associated AI technologies.

This survey-supported study delivers three important contributions to the marketing and service management literature. First, it provides empirical support for the integration of the socio-cognitive foundations of the study theories (i.e., ECT, SCT, and PMT) towards explaining customer satisfaction. Second, it advances our understanding of the theoretical foundations for customer satisfaction as related to a new AI technology platform. Finally, the insights gathered in this study contribute practical implications, which can guide marketing strategies and practices and user experience as businesses transform their firm by incorporating new AI technology.

The rest of the study is arranged as follows. In Chapter 2, a literature review and hypotheses are presented in support of the conceptual model constructs impacting customer satisfaction. In addition to customer satisfaction, the chapter reviews topics such as customer expectations, perceived performance, expectations confirmation, perceived trust and perceived privacy. Chapter 3 provides an overview of the research methodology, the development of the survey instrument, the data analysis approach, and the justification for this analysis. Chapter 4 includes the data analysis and results of the study. Lastly, Chapter 5 summarizes the implications of these findings, limitations and suggestions for future research.

CHAPTER 2

LITERATURE REVIEW

This chapter presents the technology background, the foundational strategy, and the theoretical framework for this research. The first section provides an overview of the respective AI technologies pertinent to this study. The second section provides a review of the study's primary theories of ECT, SCT, and PMT. The third section provides an overview of customer satisfaction and the other constructs used in the study. The last section identifies the constructs and provides the rationale for the hypothesized relationship

2.1 Artificial Intelligence

2.1.1 Overview of artificial intelligence. AI is a multi-disciplinary field of research and concepts that covers a wide variety of content, technologies, and different applications involving cognitive science, robotics, and natural interfaces (Borana, 2016). Even though there are multiple taxonomies of AI, there is no all-inclusive, universally accepted definition (The Office of Science and Technology Policy, 2016, October). However, AI is making advancements towards "embracing the scientific goal of constructing an information-processing theory of intelligence" (Nilsson, 2014, p. 2). Consistent with that goal, this study adopts a recent definition of AI as being a collection of technologies which sense, learn, and act (Stone et al., 2016). While the AI approach to these outcomes may not mirror those of human beings, such outcomes are intended

to mimic and possibly out-perform human beings (Borana, 2016). This study will focus on specific AI applications involving machine learning, natural language processing, and digital assistants.

      2.1.2 Machine learning. Machine learning is a subset of AI. It serves as the technical basis for solving problems, uncovering insights or producing a behavior (Witten, Frank, Hall, & Pal, 2016). It does so by analyzing large sets of structured (i.e., traditional machine learning) and unstructured data (i.e., deep learning) to find useful information (Najafabadi et al., 2015). This information can be important for predicting, explaining, and understanding a phenomenon (Witten et al., 2016). Its goal is to develop cognitive learning algorithms that can be programmed to solve new problems using applied learning from previous examples rather than directly programming algorithms to solve those new problems as they arise (Marsland, 2015). This learning is achieved through supervised, unsupervised, and reinforcement learning. Feedback data from prior analysis efforts enable the machine learning algorithms to train and learn without the need for manual intervention involving additional program code (Marsland, 2015). These algorithms assist systems to adapt, make predictions, and reach conclusions not previously available (Najafabadi et al., 2015).

      The explosion of big data has enabled companies to collect a vast variety and volume of information from customers at unprecedented speed for use in advanced analytics (Christensen, Hall, Dillon, & Duncan, 2016). The advanced analytic insights offered by using big data within machine learning algorithms provide an important differentiating factor to firms (Davenport & Kim, 2013). Businesses in every industry are using advanced machine learning approaches to gain a competitive advantage and generate new revenue by delivering intelligent products and services that are more personalized, efficient, and adaptive (Moorthy et al., 2015). For instance,

gains have been observed in health care, manufacturing, education, financial modeling, policing, and marketing (Alpaydin, 2014). Machine learning represents a major component of the influence of AI technologies within the evolution of businesses to Industry 4.0 (Zawadzki & Żywicki, 2016).

For marketers, machine learning allows a company to analyze more thoroughly what their customers are doing and feeling, who they are, and what their preferences are (Moorthy et al., 2015). These insights can enable a firm to focus resources and offers personalized to the needs of the customer (Davenport & Kim, 2013). These insights also enable new offers and benefits to be presented to customers through tailored experiences in the user's preferred application, channel, or communication device (Moorthy et al., 2015). Often, these experiences are powered by insights extracted from recent analytic advancements in the areas of visual object recognition, sentiment analysis, question answering, and speech recognition (LeCun, Bengio, & Hinton, 2015).

2.1.3 Natural language processing. Natural language processing (NLP) "tries to understand speech and text as human beings would do" (Osman & Zalhan, 2016, p. 44). It is part of the computational linguistics branch of computer science focused on enabling computers to learn, understand, and produce human language content (Hirschberg & Manning, 2015). NLP is often paired with advanced speech recognition, web-scraping techniques, and other capabilities to enable human learning and machine reasoning (Stone et al., 2016). It uses computational methods to analyze and produce conceptual models of the linguistic data (Canbek & Mutlu, 2016). To prepare the model inputs, NLP verifies the linguistic content of the inputs, which are usually received through advanced speech recognition capabilities. Among the preliminary activities performed by NLP are correcting spelling errors, forming syntactic sentence structures,

providing semantic relationships, and combining the syntactic sentence structure and semantic

relationships for the appropriate response (Canbek & Mutlu, 2016).

In this era of big data, NLP is the primary application used for accessing and analyzing

human language content, whether spoken or written (Stone et al., 2016). It can process spoken

content or read written content displayed on web pages and social media (Hirschberg &

Manning, 2015). NLP serves as the technology bridge enabling machine language to ultimately

be transformed to human communications and vice versa (Davis & Marcus, 2015). By itself,

NLP understands speech and text by manipulating individual words, short phrases, or even an

individual sentence (Canbek & Mutlu, 2016). However, it lacks the ability to provide a deeper

and more contextually relevant understanding of this content. It also lacks the ability to perform

expanded image matching and interpretation abilities (Davis & Marcus, 2015). Fortunately,

technology advancements have enabled the integration of machine learning and NLP. The

resulting insights have enabled new knowledge to be discovered. The integration has also

expanded capabilities associated with image matching, recognition, and interpretation (Hauswald

et al., 2015). As a result, these new abilities and capabilities have created the ability to include

temporal reasoning and qualitative reasoning previously missing from the technology content

analysis (Davis & Marcus, 2015). These technologies also offer opportunities to assimilate a vast

amount of information while completing analytic activities with greater speed, efficiency, and

accuracy (V. Kumar et al., 2016).

Firms are now able to identify and monitor trending topics as well as emerging opinions,

beliefs, and sentiment. Marketers can match these items with demographic information to

identify customer needs, behaviors, and attitudes; product and pricing reviews; and advertising

effectiveness (Hirschberg & Manning, 2015). Subsequently, these insights can enable a

competitive advantage for a responsive firm by focusing specific resources and extending timely personalized offers to the customer (Moorthy et al., 2015). This actionable knowledge is increasingly important due to the dynamics of the competitive market (V. Kumar et al., 2016).

      2.1.4 Digital assistants. Digital assistants are speech-enabled integrated AI technologies (generally referenced as conversation-enabled applications) resident within various mobile platforms. They are viewed as dynamic systems possessing the ability to learn customer preferences (V. Kumar et al., 2016). These systems "use inputs such as the user's voice, vision (images), and contextual information to provide assistance to users by answering a question in natural language, making recommendations, and performing actions" (Hauswald et al., 2015, p. 223). The captured information is compressed and streamed to cloud-based data centers where speech recognition and semantic extraction programs associated with NLP convert the content into machine-readable text (Brown, 2016). Subsequently, this text is incorporated into other integrated AI applications that perform reasoning, predictive intelligence, and machine learning activities. These activities are designed to understand the question and return a personalized response to the user through the digital assistant (Canbek & Mutlu, 2016).

Many of the market leaders (particularly Amazon and Google) for digital assistants, have succeeded in promoting applications which are affordable, fun, and relevant to the public as well as simple, flexible, and easy to use (Milhorat et al., 2014). The simplicity of the voice-controlled interface significantly alters how users search the internet. The depth and breadth of available stored information, combined with the speed of technical response, facilitates a dialogue-style interaction which is important to the time-pressed or self-reliant consumer (Hofmann, Li, & Radlinski, 2016). Thus, digital assistants are becoming more widely adopted by consumers. These applications meet customer demand for contextually-relevant and highly-personalized

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content that is delivered to the user on a real-time basis, with a high degree of reliability and convenience (Wise, VanBoskirk, & Liu, 2016).

History has demonstrated that people can become emotionally dependent on technology (Karapanos, 2013). Therefore, as more solutions use digital assistants, the emotional bond or comfort-level between user and technology will become even stronger (Hutson, 2017). This positive relationship can then establish an enhanced framework of customer expectations intended for nearly all companies with which they interact (Straker & Wrigley, 2016).

The recent advancements in AI technologies have enhanced the user experience with linguistic prowess and cognition capabilities for digital assistants (Canbek & Mutlu, 2016). As users demand scales for this technology, a growing stream of literature (as shown in Table 1) identifying applications involving digital assistants is beginning to emerge. Most of the studies are focused on the technology applications and recommendations for different applications involving digital assistants. Still other research concentrated on marketing strategy, user experiences, user enjoyment, and customer commitment topics involving digital assistants. Two studies focused on user behavior-based model enhancements for user satisfaction involving digital assistants. However, neither of these studies involved theory-based model constructs. No other study focuses on theory-based construct assessments of customer/user satisfaction involving digital assistants.

Table 1

Recent Literature Involving Digital Assistants

Category	Context	Finding	Authors
Technology applications	Usefulness in recording patient information or diagnosis decision support	Personal digital assistants appear to have potential in improving some processes and outcomes of clinical care, but the evidence is limited, and reliable conclusions on whether they help, in what circumstances, and how they should be used are not possible.	(Divall, Camosso-Stefinovic, & Baker, 2013)
	Usefulness in survey administration of youthful students	Personal digital assistants are a viable alternative to paper and pencil versions of surveys for participants in a range of in-school and out-of-school settings and should be investigated by others for use in youth development research.	(Abo-Zena, Warren, Issac, Du, Phelps, Lerner, & Roeser, 2016)
	Using digital assistants for operational data collection	For collecting experience sampling studies, participants using a personal digital assistant had a higher response rate than participants using a cell phone involving an IVR condition.	(Burgin, Silvia, Eddington, & Kwapil, 2013)
	Intelligent personal assistants use is learning programs	Both personal digital assistants and intelligent personal assistants were found to be beneficial for second language learning within Natural Language Processing.	(Canbek & Mutlu, 2016)
	Dynamic electricity trading intelligent agents	Efforts to predict sustainable electricity smart markets using community-developed competitive simulation platforms proved to be inconclusive yet, offered insights into future studies.	(Ketter, Peters, Collins, & Gupta, 2016)
	Using digital assistants for data collection on plant samples	Personal digital assistants proved to be a well-structured, but flexible mobile tool for collecting on-site measurements for efficient evaluation and shared use of data.	(Köhl & Gremmels, 2015)
Technology enhancements	Improvements needed for digital assistants	Proposed technology changes for personal digital assistants aimed at making a constrained human-machine dialogue more flexible and adaptable to the user's requirements.	(Milhorat, Schlogl, Chollet, Boudy, Esposito, & Pelosi, 2014)
	Technology architecture for intelligent personal assistants	Proposed an alternate technology design for intelligent personal assistants which yield improvements in performance, power, and cost implications.	(Hauswald, Laurenzanon, Yunqi, Hailong, Yiping, Cheng, Rovinski, Khurana,

Category	Context	Finding	Authors
			Dreslinski, Mudge, Petrucci, Tang & Mars, 2016)
	Technology improvements needed for digital assistants	Proposed technology changes for personal digital assistants which would reduce user dissatisfaction used by the system's inability to service queries correctly.	(Sarikaya, Crook, Marin, Jeong, Robichaud, Celikyilmaz, Kim, Rochette, Khan, Liu, Anastasakos, Feizollahi, Ramesh, Suzuki, Holenstein, Krawczyk, Radostev, & Boies, 2016)
Marketing strategy	Research framework and taxonomy for intelligent agent technologies	Proposed a marketing-centric definition and a systematic taxonomy and integrated conceptual framework with several propositions regarding IAT adoption.	(Kumar, Dixit, Javalgi, & Dass, 2016)
User experience	Research observations for omnichannel customer experience	Provided recommendations for optimizing the user experience when firms are deploying a digital assistant supported customer service platform.	(Parise, Guinan, & Kafka, 2016)
User enjoyment	Digital assistants in computer games	Developers of digital assistants must exercise caution when introducing humanlike assistants within products and service platforms.	(Sara, Rocky Peng, & Ke, 2016)
User satisfaction	Predictive model for user satisfaction with intelligent assistants based on user interaction patterns	Successfully tested a task-independent approach to evaluate user behavior-based evaluations (i.e., satisfaction) of intelligent personal assistants.	(Jiang, Awadallah, Jones, Ozertem, Zitouni, Kulkarni & Khan, 2015)
	Predictive model for user satisfaction with intelligent assistants based on interaction signals	Created an intelligent learning process which predicts user satisfaction with various types of interaction queries involving intelligent personal assistants.	(Kiseleva, Williams, Hassan Awadallah, Crook, Zitouni, & Anastasakos, 2016)

2.2 Theoretical Framework

This study advances our understanding of the theoretical foundations for customer satisfaction as related to a new AI technology platform. Given this focus, the theoretical underpinnings of the ECT (also called expectation disconfirmation theory) will be leveraged. However, supplemental explanatory power will be added to the discussion using cognitive elements of the SCT and PMT. By integrating these three theories within the constructs, the study can leverage the cognitive dimensions resident within the three theories of ECT, SCT, and PMT as shown in Figure 1.
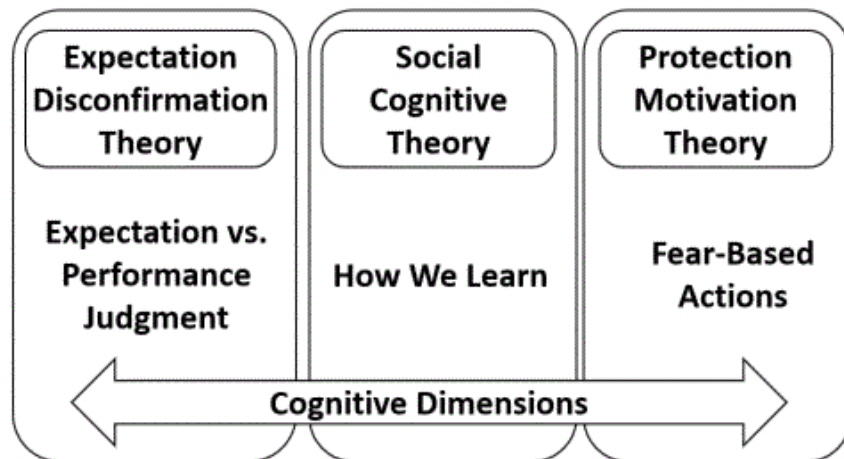
Figure 1. Illustration of cognitive dimensions within the adopted theories of expectations confirmation theory, social cognitive theory, and protection motivation theory.

2.2.1 Expectations confirmation theory. Satisfaction is both a central concept and a topic of extensive research interest throughout the fields of psychology, marketing, management, and information systems (e.g., Anderson, 1973; Oliver, 1977, 1980; Yi, 1990). From a marketing perspective, a large and growing stream of literature posits that customer satisfaction is an important goal for establishing and retaining customer relationships as well as generating profits

for the firm (c.f., Aksoy, Cooil, Groening, Keiningham, & Yalçin, 2008; Fornell, Mithas, Morgeson III, & Krishnan, 2006; Fornell, Morgeson, & Hult, 2016; Hult, Morgeson, Morgan, Mithas, & Fornell, 2017). Despite the many definitions of customer satisfaction in extant literature, ECT continues to be a primary theoretical lens used for defining customer satisfaction (e.g., Anderson & Sullivan, 1993; Caruana, La Rocca, & Snehota, 2016; Oliver & Swan, 1989; Park, Cho, & Rao, 2012; Valvi & West, 2013; Yi, 1990).

In describing ECT, Morgeson (2013) suggested that "satisfaction judgments are formed through a cognitive process relating prior expectations to perceived performance and the confirmation or disconfirmation of expectations relative to performance" (p. 1). Fan and Suh (2014) identified that "ECT encapsulates the cognitive process through which dissonance between expectations and performance shapes consumers' attitudes" (p. 4). Both descriptions align with assertions that the ECT framework evaluates satisfaction through two processes: the creation of expectations, and the confirmation or disconfirmation of those expectations. The confirmation or disconfirmation results from the assessment of the perceived performance through the comparison process (Oliver, Balakrishnan, & Barry, 1994). Thus, this theory advances its position that satisfaction is the rational post-adoption/post-consumption behavior resulting from expectations and perceived performance. This rational behavior is mediated through the positive or negative confirmation between expectations and perceived performance (Bhattacherjee, 2001; Fan & Suh, 2014). These relationships are reflected in the generic ECT model displayed in Figure 2 below. The model reflects the three core antecedent constructs for customer satisfaction: expectations, perceived performance, and confirmation of expectations.
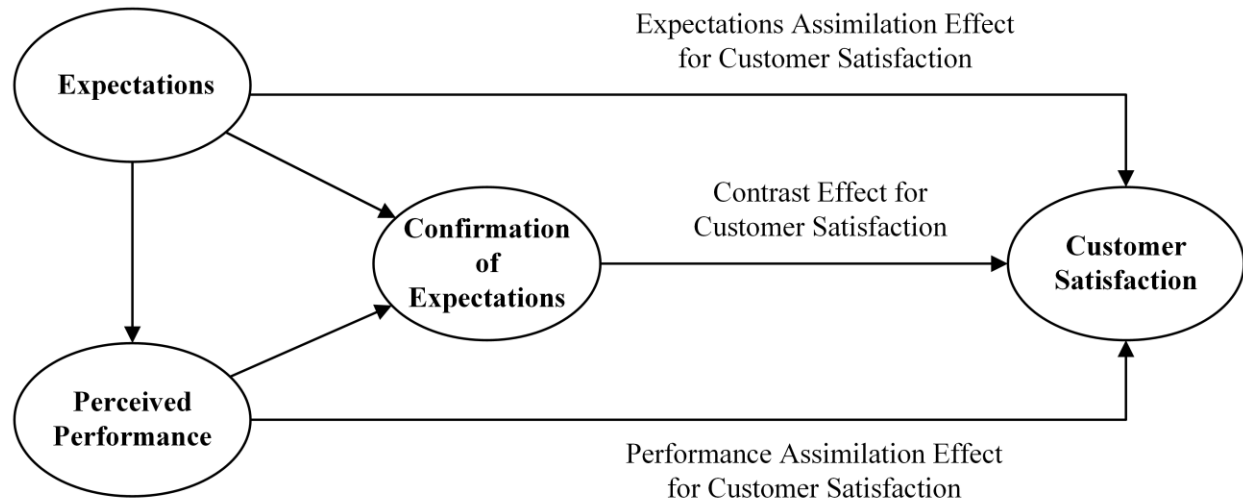
Figure 2. Generic expectations-confirmation model. This figure illustrates the primary construct relationships resident in the expectations confirmation theory.

Note. The expectations assimilation effect for customer satisfaction, the contrast effect for customer satisfaction and the performance assimilation effect for customer satisfaction have been added as identified in *Satisfaction: A Behavioral Perspective on the Consumer* by R.L. Oliver, 2014. New York, NY: Routledge.

In addition to its applicability to customer satisfaction, ECT was used in studies involving customer satisfaction consequences associated with post-purchase/post-consumption behaviors (e.g., repurchase intention and loyalty marketing) and service marketing (e.g., Chou, Kiser, & Rodriguez, 2012; Hossain, Dwivedi, & Naseem, 2015; Kim, 2012; Park et al., 2012; Tan, Benbasat, & Cenfetelli, 2016; Valvi & West, 2013). These consequences reflected the maturation of the customer relationship. Currently, while businesses continue to emphasize satisfaction, they increasingly have established key performance indicators focused on the outcome elements of customer loyalty and retention (Oliver, 2014).

ECT has also been widely used to examine expectations and various key satisfaction consequence topics of interest for information systems. Besides satisfaction, one of the key consequences studied was user system continuation intention (e.g., Bhattacherjee & Barfar,

2011; Fleischmann, Amirpur, Grupp, Benlian, & Hess, 2016; Lankton et al., 2014; Lu, Liu, &

Wei, 2017; Shiau & Luo, 2013; Shin, Biocca, & Choo, 2013).

   2.2.2 Social cognitive theory. SCT is an approach to understanding human cognition,

action, motivation, and emotion as each of these elements influence how individuals function. It

assumes that people are active agents in their personal motivation, and capable of self-reflection

and self-regulation. Further, SCT shows that people also actively shape their environments rather

than simply react to them (Bandura, 1986; 1989a). This theory excels in explaining human

psychosocial functioning through the simultaneous and dynamic interplay of personal factors,

behavior, and the external environment (Bandura, 1986). The relative impact of each of these

three elements is controlled by the individual. As a result, an individual's behavior is not always

consistent and may not be the same as in a similar situation even though the same set of stimuli

is involved (Jones, 1989).

   This study focuses on the SCT's contributions related to personal factors, which

themselves are related to knowledge and skill acquisition. Personal factors consist of cognitive,

vicarious, self-regulatory, and self-reflective processes (Bandura, 1986). SCT excels in

explaining knowledge acquisition through five core cognitive processing capabilities:

symbolizing, forethought, vicarious learning, self-regulation, and self-reflection (Stajkovic &

Luthans, 1979). While recognizing the contributions of experiential learning (i.e., learning

through the "self-efficacy of doing"), SCT also focuses on learning through observation. It filters

observed behavior through the three primary determinants of personal, behavioral, and

environmental interactions (Bandura, 1977, 1986).

   SCT states that observational learning can be achieved through the visual, verbal, or

published artifacts acquired in the observation of human models such as close associates or

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casual acquaintances (Bandura, 1986). Historically, human models have been cited for their influence (positive or negative) on individuals. As individuals observe these models, their knowledge is acquired through the attention given to the model; the retention of behavioral outcomes generated through the model; the ability of the individual to produce the model's behavior; and the motivation for the individual to replicate the model's behavior (Bandura, 1988, 2002). Individuals learn the general rules and strategies for dealing with diverse situations from these models. The greatest probability of learning occurs when there is close identification between the observer and the model, and when the observer also has sufficient self-efficacy (Bandura, 1988, 1989).

Advertising and product promotions can serve as knowledge sources for users. Bandura (2011) notes that the electronic media functions as a growing and influential source of social learning. This observation reinforces his earlier framework (Bandura, 2001), which links SCT to mass communications. This framework is still valid and assists in explaining why viewers pay attention to television commercials, YouTube videos, and other promotional material involving digital assistants can develop a higher level of self-efficacy and learn from these media sources.

At present, no marketing or information technology study has been published involving the linkage of SCT to digital assistants or AI technologies. Yet, SCT continues to be a regularly cited theoretical component of other studies involving marketing, information technology, and various other disciplines. From a marketing perspective, SCT continues to be used in selected studies to reinforce how customer behavior is influenced. C. K. Yim, K. W Chan, and S. S. Lam (2012) utilized SCT's relational efficacy beliefs to assist in the confirmation that customers derive enjoyment from active participation in the financial advisory process. This enjoyment, however, was positively moderated by the alignment of the customer's self-efficacy and the

efficacy of the financial advisor. Jin, Li, Zhong, and Zhai (2015) leveraged the positive outcome expectation element associated with SCT's self-efficacy as a significant explanatory factor as to why users continuously contribute knowledge to online social question and answer communities. Among the findings was that absent financial incentives or rewards, this behavior was stimulated by the contributor's desire to receive attention. Johnstone and Hooper (2016) examined how consumers' green consumption behaviors were influenced by the social sustainability environment. Utilizing the underlying observational learning elements of SCT, they confirmed that consumers' green consumption behaviors were significantly influenced by the observed behavior of other individuals. These three studies have logical extensions and applicability to digital assistants. Self-efficacy and observational learning are among the critical enablers for customers to perceive high performance of digital assistants.

SCT also continues to contribute to studies involving information technology. Wan, Compeau, and Haggerty (2012) studied employee social learning strategies within a firm's e-learning environment. Using SCT's self-regulation feature, they found that learners adopted different self-regulated learning strategies resulting in different e-learning outcomes. This finding can influence training support for digital assistants. Baker, Thatcher, Gundlach, and McKnight (2014) examined various antecedents to information technology use. Leveraging the vicarious experience and social persuasion elements of SCT, they found that social aversion (i.e., a predisposition to feel anxiety when interacting with social actors) positively influenced a user's computer self-efficacy beliefs and subsequent likelihood to use the information technology. It is logical to assume that this finding similarly applies to digital assistants. Keith, Babb, Lowry, Furner, and Abdullat (2015) similarly explored the impact of mobile-computer self-efficacy through vicarious learning. They found that users tended to place greater trust in mobile app

providers and perceived less risk in the actual app itself, even when the intentions of the app providers could not be verified. This finding has direct implications on many perception-influenced subjects including technology adoption (likely including digital assistants), trust, and privacy.

The studies cited above provide evidence that SCT is still relevant to the consumer experiences of today. By coupling observational learning with experiential learning, SCT offers explanatory power in how individuals both acquire knowledge and become aware of how they can emulate the use of a product or service to achieve a desired result or satisfy a personal need. Thus, it is appropriate to assume that SCT is similarly relevant to digital assistants and AI technology. However, future studies are needed to confirm this assumption.

2.2.3 Protection motivation theory. PMT explains the cognitive processes used by individuals when faced with fear associated with threats (Rogers, 1975, 1983). Fear occurs once a danger or threat is perceived by the individual. While the symptoms are unique per individual, they typically are depicted as dread, negative arousal, concern or worry, discomfort, or a general negative mood (Leventhal, 1970; Rogers, 1983; Witte, 1992). Subsequently, how individuals react is based on the perceived severity of a threatening event, the perceived probability of the occurrence or vulnerability, the recommended preventive behavior efficacy, and the level of perceived self-efficacy (Rogers, 1975, 1983). These reactions are represented in how individuals gather information and formulate their intention to cope with a potential threat (i.e., protection motivation) as well as their coping behaviors (i.e., coping mode) (Rogers, 1975, 1983).

Rogers (1975, 1983) states that coping intentions are based on two assessments. The first assessment involves the maladaptive response to the threat appraisal. The individual assesses if the intrinsic and extrinsic rewards derived from engaging in protection motivation exceed the

degree of harm expected from the threat, and the probability that the threat will even occur. Essentially, the individual judges if he or she is motivated enough to seek protection. The second assessment involves the adaptive response. The individual subjectively assesses if the recommended threat remedy behavior is appropriate and able to be fulfilled. The remedy judgement assessment is then compared to the expected cost of fulfilling the adaptive behavior. This non-mathematical comparison significantly influenced the subsequent behavior and actions of the individual (Fry & Prentice-Dunn, 2005; McMath & Prentice-Dunn, 2005). In effect, the individual judges if the threat is deemed personally relevant and sufficiently important enough to act.

This theory originated within the field of preventive medicine and was used to explain an individual's protection response after receiving news of a health threat (Rogers, 1975; Rogers, Prentice-Dunn, & Gochman, 1997). The theory has been expanded over time to include the element of self-efficacy (Maddux & Rogers, 1983) and confirmed its relevance to other fields of interest (Posey, Roberts, & Lowry, 2015). Examples of applicable studies in other fields included organizational development, wildlife management, construction and design, and food consumption and management. The expanded coverage of PMT allows it to be considered a general theory of motivation which can be used to explain an individual's actions involving any threat (Posey et al., 2015).

Like SCT, no marketing or information technology study has been published involving the linkage of PMT to digital assistants or AI technologies. From a marketing perspective, there has been only limited linkage of PMT to marketing communication studies involving risk management (e.g., Cismaru, Lavack, & Markewich, 2008; Nelson, Cismaru, Cismaru, & Ono, 2011; Pechmann, Zhao, Goldberg, & Reibling, 2003), and the marketing of products to mitigate

risk (Bolton, Cohen, & Bloom, 2006). PMT has been widely accepted in studies involving

intentions and beliefs associated with information privacy and security as well as proper system

utilization (Boss, 2015). Examples of such studies include Herath and Rao (2009); Johnston and

Warkentin (2010a); Lee and Larsen (2009); and Tu, Turel, Yuan, and Archer (2015). Given this

linkage, it is appropriate to conclude that PMT has similar applicability to digital assistants and

AI technologies.

This theory offers insights that are critical in shaping the cognition, attitudes, and

protection behavior intentions of individuals in response to the fear appeals associated with

threats against their personal information security (Boss, 2015; Posey, Roberts, Lowry, &

Hightower, 2014). It also addresses the significant influence of information sources on which

threat and coping appraisals are developed (Tu et al., 2015). Given these linkages, it is important

to understand and communicate the actions they take to preserve the privacy and protection of an

individual's personal information. Therefore, PMT offers added explanatory power in what

decisions and actions individuals may undertake if they feel that their personal information is at

risk following use of a digital assistant.

2.3 Constructs

2.3.1 Customer satisfaction. Extant marketing literature provides multiple definitions of

customer satisfaction reflecting widely diverse dimensions and applications (e.g., offering value,

quality, and loyalty to customers). Further, marketers advertise various types of satisfaction

guarantees (e.g., money-back guarantee, pricing guarantee, replacement guarantee, etc.) to

induce consumer response (Meyer, Gremler, & Hogreve, 2014; Oliver, 2014). Yet, there is no

all-inclusive, universally accepted definition of customer satisfaction (e.g., Giese, 2000;

Szymanski & Henard, 2001). Oliver, Rust, and Varki (1997) addressed this standard definitional void by noting that "everyone knows what [satisfaction] is until asked to give a definition. Then it seems, nobody knows" (p. 13). Zhao, Lu, Zhang, and Chau (2012) posited that the definitional differences can be attributed to the dynamic, complex, and context-specific nature of the construct. Most marketing researchers have used discrepant terms, somewhat interchangeably, in attempts to define the satisfaction/customer satisfaction relationship. Within the context of this study, both satisfaction and customer satisfaction are considered as an equal substitute for the other term.

Even though described differently, the definitions of customer satisfaction in extant literature generally shared three common components (Giese, 2000). Ha and Park (2013, p. 678) identified these components as: response (emotional or cognitive); focus (e.g., expectations, product, consumption experience); and time (e.g., post-consumption, post-choice) based on accumulated experience. As shown in Table 2, many of the studies utilized some form of evaluative judgment for the response, and most reflected a post-consumption or post-choice timeframe. These common elements are consistent with the definition adopted for this study which is espoused by Oliver et al. (1997, p. 13): "satisfaction is the consumer's fulfillment response. It is a judgment that a product/service feature, or the product or service itself, provided (or is providing) a pleasurable level of consumption-related fulfillment, including levels of under- or overfulfillment". Similarly, if the level of fulfillment was judged by the consumer to be unpleasant, then the individual would be dissatisfied. This definition represents a consumer's summary or overall fulfillment judgment and is not a transactional fulfillment judgment.

Pleasurable fulfillment response implies that pleasure is either increased or the amount of pain is reduced. However, there is no assertion that this increase in pleasurable response matches

the need of the individual. Overfulfillment represents a measure of unexpected pleasurable

response as compared to a standard or norm. However, overfulfillment is not always pleasurable.

If the overfulfillment is deemed to be an unpleasant response, then the outcome would be

dissatisfaction. Dissatisfaction represents a negative satisfaction state. Underfulfillment

represents a measure of unexpected unpleasurable response as compared to a standard or norm.

This outcome would also be dissatisfaction (Oliver, 2010, 2014; Oliver et al., 1997).

Satisfaction is a broadly used term with implications across a wide variety of levels (i.e., at the

individual consumer level, the firm level, the industry level, and the political structure level).

Viewing satisfaction from the consumer perspective is the dominant approach used in recent

literature as shown in Table 3. This approach reflected the individual's pursuit of a pleasurable

achievement or experience through the consumption of a product or utilization of a service

(Oliver, 2014). The firm level view of satisfaction focused on the critical need to stimulate

consumer repeat purchasing to maintain ongoing profitability (Oliver, 2014). While only a

limited number of studies are presented, the primary approach of assessing firm-level satisfaction

is through a dyadic study of employees to their customers. The industry level view of satisfaction

was facilitated through the establishment of the American Customer Satisfaction Index (ACSI),

which enables comparison across industries (Fornell et al., 2016; Sorescu & Sorescu, 2016) and

across nations (Morgeson et al., 2015). The societal (i.e., political structure) perspective of

satisfaction is reflected in studies involving "better life outcomes". Examples of these positive

outcomes included health, social and mental adjustments, or finances (Oliver, 2014). However,

no societal perspective study was included in the analysis of recent satisfaction literature.

Table 2

Definition of Satisfaction/Customer Satisfaction in Recent Customer Satisfaction Literature

Author(s)	Definition	Response	Focus	Time	Finding
(Bhattacherjee & Lin, 2015)	The overall emotive state resulting from users' disconfirmation of expectations from prior IT usage experiences (Bhattacherjee, 2001).	Affective (Emotional response)	Consumer experience with prior usage	Post consumption (accumulated experience)	Organizational managers and vendors should not only educate their user base of the benefits of IT usage, but also ensure that they are satisfied with their IT usage experience.
(Coelho & Henseler, 2012)	The feeling or attitude of a customer after receiving relevant customized treatment (p. 334).	Affective (attitudinal response)	Customer experience with front-line employees	Post consumption (post treatment)	Customization increases perceived service quality, customer satisfaction, customer trust, and ultimately customer loyalty toward a service provider.
(Dabholkar & Sheng, 2012)	The evaluative response to the current consumption event (p.1434).	Affective (attitudinal response)	Degree of consumer involvement in using the recommendation agent on the website	During consumption	Greater customer participation in using a recommendation agent leads to more satisfaction, greater trust, and higher purchase intentions.
(Fang, Qureshi, Sun, McCole, Ramsey, & Lim, 2014)	An evaluative outcome based on past exchanges with the trustee, with the evaluation based on past similar experiences being the most influential (Holmes 1991).	Affective (attitudinal response)	Expectations of user experience compared to prior experiences	Post consumption (accumulated experience)	Vendors should allocate their trust-building resources according to the level of existing e-commerce institutional mechanisms (e.g., the maturity level of online credit card guarantees, escrow services, and privacy protection services).
(Ha & Park, 2013)	The customers' accumulated impressions for the product or service (p. 679).	Combined (both affective and cognitive)	Customer perceptions of utilitarian and hedonic benefits derived through purchases of products/services	Post consumption (accumulated experience)	To attract and retain customers, a company should offer (1) utilitarian benefit such as greater performance, greater stable quality, and greater reliability, and (2) hedonic benefit by improving entertainment or communication with friends and family, anytime and anywhere.

Author(s)	Definition	Response	Focus	Time	Finding
(Helena & Sampaio, 2012)	The consumer's assessment of the product or service providing a pleasurable fulfillment, including levels of under- or over-fulfillment (Oliver, 1997, p. 13).	Affective (attitudinal response)	Product or service performance during the consumption experience	Post consumption (accumulated experience)	Demographic and relational variables are important in explaining the customer satisfaction-customer loyalty relationship. Repurchase behavior is preferred to repurchase intention when evaluating and explaining customer loyalty.
(Hult, Morgeson, Morgan, Mithas, & Fornell, 2017)	American Customer Satisfaction Index (ACSI) (p. 4).	Combined (both affective and cognitive)	Experience was at least as good as it was supposed to be	Post consumption (accumulated experience)	Managers overestimate the levels of customer satisfaction and attitudinal loyalty. Manager understanding of the drivers of customer satisfaction and loyalty are disconnected from those of their actual customers.
(Kim, 2012)	The consumer's attitudinal assessment of the supplier's pleasurable performance fulfillment.	Affective (attitudinal response)	Supplier performance during the consumption experience	Post consumption (accumulated experience)	The more consumers trust the seller, the greater the likelihood that they will be satisfied. In turn, consumer satisfaction affects consumers' post-expectation and their future behavioral intention such as repurchase intention.
(Koufteros, Droge, Heim, Massad, & Vickery, 2014)	Encounter satisfaction is the consumer response to current order fulfillment service quality.	Affective (attitudinal response)	Recent quality of the retailer order fulfillment service (not full consumption experience)	Transactional consumption	Policies that create highly positive events for consumers can thus supersede past negative experiences.
(Lankton, McKnight, & Thatcher, 2014)	The subjective evaluation of any outcome or experience associated with consuming a product or service (Oliver, 2010).	Combined (both affective and cognitive)	Technology performance during the consumption experience	Post consumption (accumulated experience)	Lowering expectations is not a strategy for increasing disconfirmation and other technology-related outcomes.
(Matzler, Strobl, Thurner, & Füller, 2015)	Prior experience influences the focal product or service expectations and performance norms (p. 119).	Affective (attitudinal response)	Product performance expectations vs norm.	Post consumption (accumulated experience)	In saturated markets, the customers that can be most easily acquired may be those that are the most difficult to retain because customers experienced in switching are difficult to satisfy – and low satisfaction means lower perceived

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Author(s)	Definition	Response	Focus	Time	Finding
					financial and relational switching costs and, in turn, lower loyalty.
(Morgeson III, Sharma, & Hult, 2015)	American Customer Satisfaction Index (ACSI) (p. 3)	Combined (both affective and cognitive)	Nationality-based perceptions of product performance during the consumption experience	Post choice	Satisfaction will have a greater impact on future customer behaviors in some markets (developed markets) than in others (emerging markets). Investments in satisfaction may "pay off" less in emerging markets, where customers are more sensitive to other factors such as price and relative income instability.
(Stock & Bednarek, 2014)	The feeling or attitude of a customer after interacting with the frontline employees (p. 404).	Affective (attitudinal response)	Customer experience with front-line employees	Post consumption (post treatment)	Customer demands impede frontline employees' customer-oriented attitudes and customer satisfaction through frontline employees' emotional exhaustion, whereas customer resources indirectly increase customer satisfaction.
(Yoon, Hostler, Guo, & Guimaraes, 2013)	The consumer perception that the product recommendation is appropriate and meaningful (p.886).	Cognitive (Evaluative judgment)	Customer perceived value of a brand product during the consumption experience	Post consumption (accumulated experience)	Using recommendation agents to support consumers accessing e-commerce websites means these systems must be designed with a greater understanding of the needs and interests of individual users or user groups, and user shopping experience and interests.
(Zhao, Lu, Zhang, & Chau, 2012)	Satisfaction is "an effective state representing an emotional response" to the service encounter (McKinney et al., 2002, p. 297).	Cognitive (Affective state resulting from cognitive evaluation process)	Service quality during the consumption experience	Post consumption (Both transactional and accumulated experience)	Both cumulative satisfaction and transaction-specific satisfaction exert a significant positive effect on continuance intention. Transaction-specific satisfaction is a good predictor of cumulative satisfaction.

Customer satisfaction continues to be a primary focus for marketing practitioners and academics (Kumar, 2016). It represents a core construct in marketing exploration of consumer behavior, marketing strategy, and theoretical and empirical modeling research streams (Rego, Morgan, & Fornell, 2013). Customer satisfaction has repeatedly been validated in extant literature as a key contributor to the success of firms in terms of acquiring and retaining customers, positive word-of-mouth communications, premium pricing, and increased customer value (e.g., Anderson, 1998; Bearden & Teel, 1983; Cronin Jr & Taylor, 1992; Reinartz & Kumar, 2003). While not necessarily solely responsible, superior customer service has been confirmed as a substantial contributor to achieving superior stock performance (e.g., Anderson, Fornell, & Mazvancheryl, 2004; Fornell et al., 2016; Sorescu & Sorescu, 2016). Thus, firms continue to be incentivized to invest in customer satisfaction programs associated with increasing product quality, developing product innovations, or improving customer interactions (Stock & Bednarek, 2014). Investments in AI technologies represent a portion of these programs (Makridakis, 2017).

2.3.2 Expectations. Expectations represent an individual's prediction or anticipatory judgment about what they should or will receive through the performance of a product or service (e.g., Bhattacherjee, 2001; Kim, 2012; Lankton et al., 2014; Oliver, 1980, 1981). This judgment is prior to the comparison of performance (e.g., LaTour & Peat, 1980; Oliver & DeSarbo, 1988; Yi, 1990). Oliver (2014) defined expectations as the "anticipatory judgment of an outcome based on its facilitation or frustration of the consumer's goal, usually in the form of a valanced reaction such as good or bad performance" (p. 22). These expectations represent the probability of occurrence (i.e., reflective of the individual's desires and needs) and the evaluation of the occurrence (e.g., desirable or undesirable, good or bad, etc.) Thus, expectations established a

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Table 3

Level of Analysis for Satisfaction/Customer Satisfaction in Recent Literature

Authors	Level of Analysis	Sample	Finding
(Agnihotri, Dingus, Hu, & Krush, 2016)	Individual	Large group of sales professionals involved in B2B industrial selling.	Social media plays an important role in communicating information to customers, but as an antecedent enhancing salesperson behavior to increase customer satisfaction rather than a direct factor.
(Alqahtani & Farraj, 2016)	Individual	Mobile phone service users living in Saudi Arabia.	Overall customer satisfaction is comparatively low among customers.
(Bhattacherjee & Lin, 2015)	Individual	Insurance agents at a large life insurance company in Taiwan.	Organizational managers and vendors should not only educate their user base of the benefits of IT usage, but also ensure that they are satisfied with their IT usage experience.
(Coelho & Henseler, 2012)	Individual	Banking and cable TV customers in a Western European country.	Customization increases perceived service quality, customer satisfaction, customer trust, and ultimately customer loyalty toward a service provider.
(Dabholkar & Sheng, 2012)	Individual	Undergraduate college students from a southeastern US university.	Greater customer participation in using a recommendation agent leads to more satisfaction, greater trust, and higher purchase intentions.
(Fang, Qureshi, Sun, McCole, Ramsey, & Lim, 2014)	Individual	Sample of university personnel.	Vendors should allocate their trust-building resources according to the level of existing e-commerce institutional mechanisms (e.g., the maturity level of online credit card guarantees, escrow services, and privacy protection services).
(Fornell, Morgeson III, & Hult, 2016)	Industry	Customer satisfaction data for approximately 300 of the largest companies, across 45 distinct industries, in the U.S. consumer market.	Companies that treat their customers well tend to produce better returns to their investors.
(Ha & Park, 2013)	Individual	Survey of 449 users having either a smartphone or netbook.	To attract and retain customers, a company should offer (1) utilitarian benefit such as greater performance, greater stable quality, and greater reliability, and (2) hedonic benefit by

Authors	Level of Analysis	Sample	Finding
			improving entertainment or communication with friends and family, anytime and anywhere.
(Helena & Sampaio, 2012)	Individual	Active private clients of a Portuguese credit card company, in possession of their card for more than one year with at least one transaction per year.	Demographic and relational variables are important in explaining the customer satisfaction-customer loyalty relationship. Customer relationship strategies have positive results. Repurchase behavior is preferred to repurchase intention when evaluating and explaining customer loyalty.
(Hult, Morgeson, Morgan, Mithas, & Fornell, 2017)	Individual & Firm	Dyad sample of customers and their managers across a range of industries.	Managers overestimate the levels of customer satisfaction and attitudinal loyalty. Manager understanding of the drivers of customer satisfaction and loyalty are disconnected from those of their actual customers.
(Kim, Xu, & Gupta, 2012)	Individual	Web-based survey of students enrolled in two universities in Korea.	The more consumers trust the seller, the more they are likely to be satisfied. In turn, consumer satisfaction affects consumers' post-expectation and their future behavioral intention such as repurchase intention.
(Koufteros, Droge, Heim, Massad, & Vickery, 2014)	Individual	Survey of undergraduate business students.	Policies that create highly positive events for consumers can thus supersede past negative experiences.
(Lankton, McKnight, & Thatcher, 2014)	Individual	Business undergraduates enrolled in an IS course in the Midwest U.S.	Lowering expectations is not a strategy for increasing disconfirmation and other technology-related outcomes.
(Matzler, Strobl, Thurner, & Füller, 2015)	Individual	Small business owners who are clients of an information and communications technology company.	In saturated markets, the customers that can be most easily acquired may be those that are the most difficult to retain because customers experienced in switching are difficult to satisfy – and low satisfaction means lower perceived financial and relational switching costs and, in turn, lower loyalty.
(Morgeson III, Sharma, & Hult, 2015)	Industry	Cross-national (5 countries) survey of wireless service (telephone) customers in Barbados.	Satisfaction will have a greater impact on future customer behaviors in some markets (developed markets) than in others (emerging markets). Investments in satisfaction may "pay off" less in emerging markets, where customers are more sensitive to other factors such as price and relative income instability.
(Rego, Morgan, & Fornell, 2013)	Firm	Data from 200 companies for the period of 1994 – 2006.	A firm's customer satisfaction can predict its future market share when it is benchmarked against that of its nearest rival and customer switching costs are low.

Authors	Level of Analysis	Sample	Finding
(Sorescu & Sorescu, 2016)	Industry	Customer satisfaction data for 296 of the largest companies, across diverse and distinct industries, in the U.S. consumer market.	Results are like those of Fornell, Morgeson III, & Hult (2016) except for three caveats: 1) results are critically dependent on the way the industry is defined; 2) authors are unable to distinguish prior study attribution to satisfaction vs. characteristics of trading strategy; and 3) some of prior study performance might be driven by sample characteristics unrelated to customer satisfaction.
(Stock & Bednarek, 2014)	Individual & Firm	Dyadic data from frontline employees and their customers in different business-to-consumer industries.	Customer demands impede frontline employees' customer-oriented attitudes and customer satisfaction through frontline employees' emotional exhaustion, whereas customer resources indirectly increase customer satisfaction.
(Yoon, Hostler, Guo, & Guimaraes, 2013)	Individual	Lab experiment involving 251 undergraduate business students at a mid-Atlantic private liberal arts college.	Using recommendation agents to support consumers accessing e-commerce websites means these systems must be designed with a greater understanding of the needs and interests of individual users or user groups, and user shopping experience and interests.
(Zhao, Lu, Zhang, & Chau, 2012)	Individual	Survey of both undergraduate and graduate level students in a major university in China.	Both cumulative satisfaction and transaction-specific satisfaction exert a significant positive effect on continuance intention. Transaction-specific satisfaction is a good predictor of cumulative satisfaction.

point of reference against which performance judgments can be made (Lankton et al., 2014).

Extant literature offers no clear agreement as to a conceptual definition of the expectations

construct (Kim, Ferrin, & Rao, 2009). Expectations are context-specific and inherently contain a

level of abstraction. Some individuals focus on what they expect to receive in the form of

attribute performance; others are more concerned about receiving macro performance outcomes

such as value and quality. Both scenarios involve predicted outcomes and anticipated

satisfaction. Yet, the differences in anticipated satisfaction highlighted the challenges with

defining expectations (Oliver, 2014). If the studies are limited to product or service attributes,

then the researcher risks omitting the intensity of consumer's level of desire. Prior literature

acknowledged that consumers have different levels of desire through the establishment of

expectation zones (e.g., Oliver, 1980; Parasuraman, Berry, & Zeithaml, 1991; Zeithaml, Berry,

& Parasuraman, 1993). These zones reflect the inherent level of desire associated with the

expectations as shown in Figure 3.

Expectation Zone	Level of Expectation
"Too Good to be True" (Ceiling effect)	Positive Disconfirmation

Zone of Tolerance:
Ideal	High
Desired	
Needed	Confirmation
Adequate	
Minimum Tolerance	Low

"Unacceptable" (Floor effect)	Negative Disconfirmation
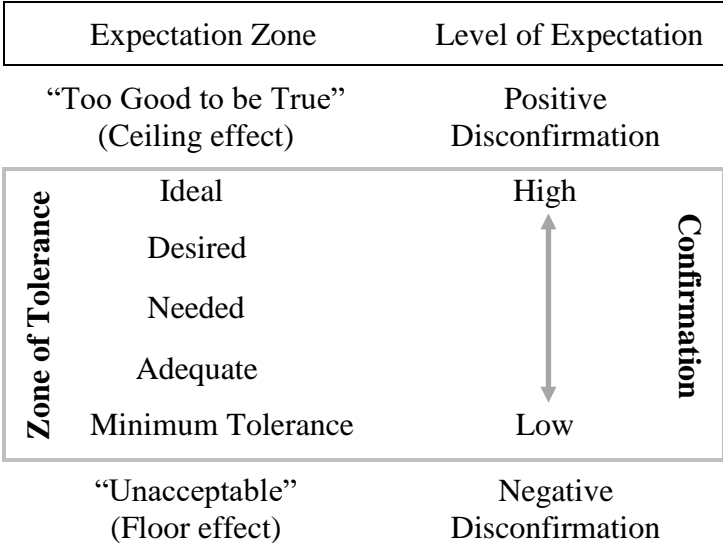
Figure 3. Association of expectation zone to level of expectation. This figure illustrates the mapping of expectations to the confirmation or disconfirmation category.

Collectively, this desired range of expectations is referred to as the zone of tolerance. It is bounded at the upper end by "ideal" and at the lower end by "minimally acceptable" level of expectations (Teas & DeCarlo, 2004; Yap & Sweeney, 2007; Zeithaml et al., 1993; Zeithaml, Berry, & Parasuraman, 1996). In general, the upper boundary is associated with excellence or superiority (Oliver, 2010). Caution is noted, though, for extreme levels of expectations. If expectation levels are established too high, then the probability of performance being less than the floor of the zone of tolerance is high. Such a scenario is likely to result in negative disconfirmation. Similarly, if the levels of expectation are established too low, then the probability of performance being greater than the ceiling of the zone of tolerance is high. Such a scenario is likely to result in positive disconfirmation (Teas, 1993).

Expectations are generally not static but represent of a dynamic compilation of experience, knowledge, and desires. Initial expectations can be updated during consumption as a component of a transactional event. Further updates can occur post-consumption after completion of comparison judgments against performance. This updated expectation then becomes the reference point for the next evaluative judgment (Oliver, 2014).

Consumers become aware of product or service information through a variety of external and internal referent sources. One of the roles of marketing is to influence consumer perceptions of a given product or service to stimulate sales, generate usage, or create a sense of pleasure or satisfaction (Shiv, Carmon, & Ariely, 2005). External sources of information include a variety of company promotional claims (e.g., company product and service claims), word of mouth recommendations (e.g., social media), third-party reviews and recommendations (e.g., CNET, Consumer Reports and search engines), as well as specific product cues (e.g.,

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price, scarcity, brand name, store image, and advertising). Internal sources of information include the consumer's experience with the product or service (and those of its competitors), ease of recall, and vividness of recall. Experience plays an important and sometimes pivotal role in information sourcing (Oliver, 2014). However, the low involvement products (i.e., products which are unimportant to the individual) tend to hinder the individual from recalling the product or service prior to the performance experience. In these instances, individuals generally limit the amount of cognitive effort they will devote to recalling the product. Conversely, users tend to keep the prior performance experience for high involvement products (i.e., products which are important to the individual) at the forefront of their memory. Users are more apt to expend the cognitive effort needed to recall this product (Oliver, 2014). Negative past experiences also tend to be more vividly recalled than positive experience. However, unique or distinctive positive experiences tend to also be recalled more vividly (Oliver, 2014).

2.3.3 Perceived performance. Performance has been demonstrated through two types: objective performance and perceived performance (e.g., Venkatesh, Morris, Davis, & Davis, 2003; Yi, 1990). Objective performance represents the actual performance level of the product or service. Because this performance level is a constant for a product or service, it is easier to measure (e.g., Venkatesh et al., 2003; Yi, 1990). On the other hand, perceived performance represents a subjective assessment. It refers to the individual's cognitive perceptions about the performance of a product's attributes, levels of attributes, or outcomes (Spreng & Olshavsky, 1992). Perceived performance has generally been used as a reference point against which expectation is compared in validation of satisfaction models. While not included in all studies, many studies have demonstrated that a strong relationship between perceived performance and satisfaction exists when perceived performance is included in the model (Spreng & Olshavsky,

1992). Given the differences in individual perceptions, this performance type is harder to measure (Yi, 1990).

Often, objective performance information may not be available to the individual, or the individual is unwilling to access the performance information (Oliver, 2010, 2014). For this reason, most performance assessments utilize perceived performance within the comparison of performance. Given that most individuals do not have access to objective performance information for digital assistants, this study is based on perceived performance. As such, this study will adopt the Spreng and Olshavsky (1992) definition that performance is an individual's cognitive perception about the performance of a product's attributes, levels of attributes, or outcomes. Typically, this outcome judgment is reported using an objective scale bounded by valanced reaction such as good or bad performance.

2.3.4 Confirmation of expectations. As previously noted, the ECT framework evaluates satisfaction through two processes: the creation of expectations and the confirmation of those expectations by assessing the perceived performance through the comparison process (Oliver et al., 1994). Like many other constructs in this study, there is no standard definition and measurement of "confirmation" (Yi, 1990). However, there is general consensus that it represents a mental comparison of performance with an anticipated probability (Oliver, 1981). For this study, the terms confirmation and confirmation of expectations will be used interchangeably and carry the same meaning.

There are two types of confirmation: objective confirmation and subjective confirmation. Objective confirmation represents the discrepancy between expectations and objective performance (e.g., Cardozo, 1965; Cohen & Goldberg, 1970; Olshavsky & Miller, 1972; Weaver & Brickman, 1974). Subjective confirmation represents the discrepancy between

expectations and perceived performance (Yi, 1990). This study will use perceived instead of objective performance, as the objective performance results for digital assistants are not readily available to most users. Consistent with this direction, this study adopts the definition offered by Jiang and Klein (2009) that confirmation of expectations is the "difference between a perceived outcome, usually a collection of events or activities, as compared to an established expectation" (p. 400).

Dissecting this definition reveals three separate elements for confirmation: the event, the probability of occurrence, and the desirability or undesirability of the performance event (Oliver, 2014). (Table 4 presents these elements in an illustrative experiential example.) Confirmation of expectations occurs when low and high probability performance standards do or do not occur, as expected. Positive disconfirmation occurs when low probability desirable "high performance" occurs and/or high probability undesirable "low performance" does not occur. Negative disconfirmation occurs when high probability desirable "high performance" does not occur and/or low probability undesirable "low performance" occurs (Oliver, 2010, 2014).

Some researchers have proposed eliminating confirmation of expectations as a unique construct by arguing that the magnitude of the confirmation experience resulted from higher expectations or lower performance (Churchill Jr. & Surprenant, 1982). Oliver (1977) challenged this approach, arguing that confirmation of expectations should maintain its status as a unique and important construct as it offers additional explanatory power for the effects on satisfaction.

Table 4

Experiential Descriptions of Categories of Confirmation of Expectations

Experience parameter	Expectations experience	State of confirmation
Low probability desirable event occurs and/or high probability event does not occur.	A struggling athletic team, largely manned by 1st year players, defeats the dominant athletic team to win the championship.	Positive Disconfirmation (Low probability desirable event occurs)
Low and high probability events do or do not occur, as expected.	The last place athletic team receives the 1st selection in the next new player selection draft.	Confirmation[1] (High probability event occurs as expected)
High probability desirable events do not occur, and/or low probability undesirable events occur.	The dominant athletic team expects to win the championship but instead fails to qualify for the playoff tournament.	Negative Disconfirmation (Low probability undesirable event occurs)

[1] Extant literature sometimes references this state as Zero Disconfirmation.

Table concept adapted from Oliver, 2014, p. 100.

This distinction reflects the reality that many individuals will not perform the actual numerical calculation of the discrepancy gap between expectations and performance (Churchill Jr. & Surprenant, 1982; Oliver, 1977). Instead, these individuals rely on a subjective evaluation where expectations and performance are implicitly incorporated into the confirmation judgment. Subjective confirmation is more commonly used in literature than objective confirmation (Oliver, 2014) as it tends to offer greater explanatory power (Oliver, 1981, 2010, 2014; Tse & Wilton, 1988).

2.3.5 Perceived trust. Trust has been conceptualized in many ways and widely studied across a multitude of disciplines (Gefen, Karahanna, & Straub, 2003). Yet, it continues to evolve and to elude a singular, all-inclusive definition due to its context-specific dimensions (McKnight, Choudhury, & Kacmar, 2002). Within marketing contexts, it has been used in a

wide variety of studies from relationship marketing (e.g., Garbarino & Johnson, 1999; Grayson, Johnson, & Chen, 2008), to broad marketplace trust (Xie & Kronrod, 2012), and brand trust (Chaudhuri & Holbrook, 2001; Delgado-Ballester & Luis Munuera-Alemán, 2005; Giesler, 2012), to name a few. It can involve either offline or online interactions. However, in these environments, the underlying concept of trust involve intentions to be vulnerable in anticipation of certain outcomes (Kim et al., 2012).

More specific to studies involving online technology, vendors and applications are perceived as either trustworthy (e.g., expected to process and support online transactions in an honest manner) or not (Kim, Tao, Shin, & Kim, 2010). Perceived trust enables individuals to have confidence to overcome perceptions of uncertainty and risk in order to engage in "trust-related behaviors" with web-enabled technologies (McKnight et al., 2002). This concept has been widely used in extant literature (e.g., Bhattacherjee, 2002; Dinev, 2006; Gefen et al., 2003; Kim & Benbasat, 2006; McKnight et al., 2002; Pavlou & Fygenson, 2006). Perceived trust has been posited to be more important in the virtual environment of web-based interactions than in offline commerce due to the elimination of many prominent social cues (Cho, de Zuniga, Shah, & McLeod, 2006; Gefen, 2002; Reichheld & Aspinall, 1994). While these studies are not specific to AI technologies or digital assistants, it is logical to conclude that they are equally as relevant.

Perceived trust is constructed as a dynamic process (Kim, 2012). Like expectations in ECT, the trust building process is constantly updated through new experiences, knowledge, or observations (Gefen et al., 2003; Li, Hess, & Valacich, 2008; Zucker, 1986). For every new trustee, there is an initial trust assessment by the trustor. The perception from this initial trust

assessment can be temporary. As updates become available, the initial trust evolves into a summary perception of ongoing trust (Kim, 2012).

Perceived trust assumes that other people will respond in a predictable way (Luhmann & Schorr, 1979) as described in the trust building process. Recent definitions have focused on "beliefs …" or "willingness …" to begin describing the cognitive judgments. These judgments reflect a customer's perceptions of a specific vendor or product attributes such as competence, benevolence, and integrity (Komiak & Benbasat, 2006). The dominant outcome of these studies is either "continuation intention" or "purchase intention". Both are considered outcome behaviors associated with customer satisfaction. Thus, perceived trust is relevant to this research. This study will adopt a definition of perceived trust based on the customer's subjective trust beliefs established in the trust building process. It is focused on the customer's perceptions of a specific vendor or product attributes such as competence, benevolence, and integrity (Komiak & Benbasat, 2006).

Competence is centered around the belief in the trustee's ability to do what the trustor expects (Venkatesh, Thong, Chan, Hu, & Brown, 2011). Within the context of AI technologies and digital assistants, the trustee is expected to fulfill the trustor's needs for reliable and personalized information content on a real-time basis. Further, the trustee has the appropriate infrastructure, controls, and experience to sustain this product or service. The trustee's product or service should operate safely and be consistent with the public good.

Benevolence reflects the belief that the trustee will act in the trustor's interests rather than making such interests subservient to those of the trustee (Venkatesh et al., 2011). For AI technologies and digital assistants, the trustee is expected to be accountable to the trustor. While

providing new knowledge and innovation, care should be exercised to guard against unnecessary biases due to inconsistent or incomplete data.

Integrity focuses on the belief that the trustee will be honest and keep its promise (Venkatesh et al., 2011). Within the context of AI technologies and digital assistants, the trustee is expected to appropriately secure any personal information of the trustor and only use this information in a manner consistent with the agreed-on terms of service. Further, the trustee will follow ethically sound principles and will allow users to also have control over decisions involving their information unless the user defers to the decisions offered though machine intelligence.

Should a trustor determine that the AI technologies or digital assistant fail to uphold the trustor's expectations of competence, benevolence and integrity, then the trustor must decide which impacts should be trusted for this situation. Consistent with PMT, the trustor must assess both the cost of exiting the relationship and the probable costs of retribution mitigation. If the costs of exiting the relationship are higher than the short-term advantages of maintaining the status quo, then the relationship would be discontinued (Lewicki, Tomlinson, & Gillespie, 2006). Similarly, if a breach of confidence should occur, then the trustor must consider the costs of retribution mitigation. If the costs of retribution mitigation are higher than the short-term advantages of maintaining the status quo, then the relationship would be discontinued (Lewicki et al., 2006).

2.3.6 Information privacy concerns. While the potential is promising, the road to adoption of AI technologies and digital assistants is not without challenge. It must be recognized that this technology creates a rich digital data footprint which contains a plethora of personal and behavioral data as users integrate digital assistants into their everyday life

(Belanger & Xu, 2015). Recent advancements in machine learning allow for data-driven discoveries of previously hidden patterns, correlations, and other revealing personal insights (Belanger & Xu, 2015). From a positive perspective, these resultant discoveries may offer desired benefits to the user in the form of enhanced personalization (Rust & Huang, 2014). For some users, however, concern exists that the digital data may be misused or abused (Miltgen et al., 2013). These concerns reflect an individual's reservations about the collection, the errors, the secondary use, and the unauthorized access to personal information (Smith, Milberg, & Burke, 1996). Frequent news reports and publication of studies associated with cyber-crime, data breaches and employee mistakes (Ponemon Institute, 2016a, 2016b) tend to reinforce technology-related information privacy issues. These reports and publications can challenge consumer confidence as to how their personal information is being secured and utilized.

The awareness and concern for these negative ramifications are widely held (Belanger & Xu, 2015). Even though there are many existing privacy protection and data security laws (e.g., Health Insurance Portability and Accountability Act of 1996 (HIPAA), Children's Online Privacy Protection Act of 1998 (COPPA), Fair and Accurate Credit Transactions Act of 2003 (FACTA), Privacy Act 1974, and Computer Matching and Privacy Act 1988), it is unknown if these laws provide sufficient protection as AI technology continues to evolve (V. Kumar et al., 2016). The enormous scope of this issue is reflected in the attention given to it by the federal government. The White House and the President's Council of Advisors on Science and Technology published a report encouraging research on the implications of AI and big data on privacy. While the promise of AI technology is acknowledged, so too are the many and varied risks. In the report, caution was urged, and regulation strongly recommended until business, government, and academicians can craft an appropriate framework of policies, laws, and

regulations which protect individuals while also stimulating innovation. It is recommended that this framework ensures justice, fairness, safety, and accountability while also limiting unintended consequences (White House, 2014a, 2014b).

While the risk of government regulation and intervention can introduce costs to the business, firms also cannot overlook individual perceptions associated with information privacy concerns. Consistent with the cognitive principles of SCT, user information privacy and trust perceptions may be influenced by pre-existing attitudes, or dispositional tendencies, and differing levels of knowledge or insights (Kehr, Kowatsch, Wentzel, & Fleisch, 2015). Because of this, companies must provide sufficient transparency and confidence with how personal and private information is being used and secured. By doing so, companies can instill a trusting mindset (a necessary influence for customer satisfaction) in both customers and agents who influence future customers towards digital assistants and other AI applications. Schoeman (1984) identified that perceived information privacy represents an individual's self-assessed cognitive state in which external parties have limited access to information about that individual. Consistent with the fear-based cognitive dimensions of PMT, this study defines information privacy concern as an individual's concerns about the collection, errors, secondary use, and unauthorized access to information (Malhotra, Kim, & Agarwal, 2004).

Across all technology-dependent business sectors, customers are increasingly concerned about the vulnerability of their personal data and the possibility of it being compromised or misused. Individuals are increasingly challenged with managing the complex trade-offs of technology innovation with risks of information privacy concerns (A. Acquisti, L Brandimarte, & G. Loewenstein, 2015). AI technologies and digital assistants are not immune from these concerns (Belanger & Xu, 2015). These concerns have been directly linked to cognitive

decision-making by customers in terms of vendor selection and technology usage (Zimmer, Arsal, Al-Marzouq, & Grover, 2010). Therefore, consumers with higher privacy concerns will perceive greater risks associated with their personal information being compromised or misused. In the following section, a set of hypotheses is presented suggesting relationships between the constructs previously mentioned above. Arguments are developed which will allow for the assessments of the research questions.

2.4 Hypotheses

The research model as shown in Figure 4, illustrates the study's hypotheses directly associated with the constructs of expectations, perceived performance, confirmation of expectations, and customer satisfaction from the ECT model. Additional constructs were added for perceived trust and perceived information privacy.
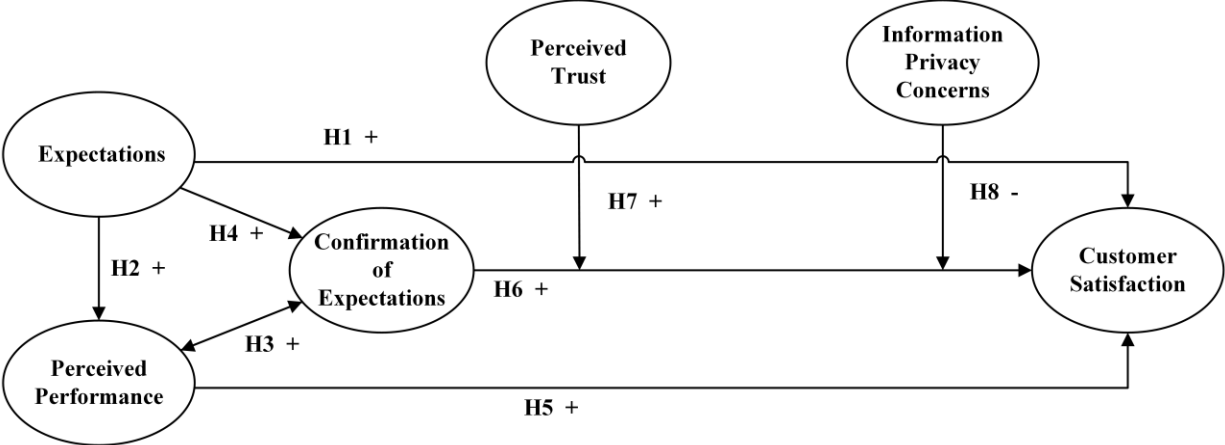
Figure 4. Research model.

2.4.1 Expectations and customer satisfaction. The ECT framework evaluates satisfaction through two processes: the creation of expectations and the confirmation of those expectations by assessing the performance through the comparison process (Oliver et al., 1994).

Satisfaction is the response to the individual's judgment that the product or service performed as expected (Oliver et al., 1997). Expectations represent an individual's prediction or anticipatory judgment about what they should or will receive through the performance of a product or service (e.g., Bhattacherjee, 2001; Lankton et al., 2014; Oliver, 1980, 1981). ECT depicts the expectations construct as positively predicting customer satisfaction (Oliver et al., 1997) through an assimilation effect. This effect occurs if the individual views that there is a disparity between performance and expectations for a product or service. If this disparity is small, then the individual's perceptions of performance may be assimilated toward one's expectations to reduce dissonance (Anderson, 1973; Lankton et al., 2014; Olshavsky & Miller, 1972). This assimilation effect, as shown above in Figure 2, is more likely to occur when expectations are stronger and more salient than performance information (Einhorn & Hogarth, 1978). For more established products and services with which users have an extensive experience history, the expectations should increase in both accuracy and confidence. Thus, expectations are based on a strong and stable knowledge base which generally is consistent with the product's perceived performance (Johnson, 1991).

Consistent with recent IT system research using this theory (e.g., Bhattacherjee, 2001; Kim, 2012; Kim et al., 2009; Lankton & McKnight, 2012; Lankton et al., 2014), and within the context of this study, satisfaction is the user's cumulative feeling about the level of pleasure provided by using the digital assistant. Expectations represent the user's prediction about how digital assistants can assist them with their goal (e.g., Bhattacherjee, 2001; Kim, 2012; Lankton et al., 2014; Oliver, 1980, 1981). As such, the following hypothesis is offered:

H1. Expectations will be positively related to customer satisfaction.

2.4.2 Expectations and perceived performance. Expectations and perceived performance are among the core constructs of the ECT (Oliver et al., 1994). Expectations represent an individual's prediction or anticipatory judgment about what he or she should or will receive through the performance of a product or service (Kim, 2012; Lankton et al., 2014; Oliver, 1980, 1981). Perceived performance represents an individual's subjective assessment about the performance of a product's attributes, levels of attributes, or outcomes (Spreng & Olshavsky, 1992). The ECT model establishes a positive relationship between these constructs as expectations establish a point of reference or norm against which performance judgments can be made (e.g., Guo, Barnes, & Le-Nguyen, 2015; Lankton & McKnight, 2012; Lankton et al., 2014; Oliver, 2010, 2014). As such, the following hypothesis is offered:

H2. Expectations will be positively related to perceived performance.

2.4.3 Perceived performance and confirmation of expectations. The ECT framework posits that expectations and perceived performance are antecedents to confirmation (Spreng & Page, 2003). Perceived performance represents an individual's subjective assessment about the performance of a product's attributes, levels of attributes, or outcomes (Spreng & Olshavsky, 1992). Confirmation is the consumer's judgment of the performance relative to a pre-consumption or pre-experience comparison to expectations (Jiang & Klein, 2009). When performance exceeds expectations, it offers a positive effect on confirmation. Conversely, when performance is worse than expectations, it offers a negative effect on confirmation (e.g., Anderson & Sullivan, 1993; Bhattacherjee, 2001; Oliver, 1980, 1993).

Recent ECT-based studies have reconfirmed this relationship (e.g., Hsu, Hsu, Wang, & Chang, 2016; Kim, 2012; Morgeson, 2013). Unexpected positive or negative perceptions of performance can occur. Provided that the levels of performance are within the zone of tolerance,

positive confirmation occurs. Similarly, technology focused studies have also confirmed this relationship (e.g., Jin, Zhou, Lee, & Cheung, 2013; Lankton et al., 2014). This relationship is appropriately assumed to apply to digital assistants as well. As such, the following hypothesis is offered:

H3. Perceived performance will be positively related to confirmation of expectations.

2.4.4 Expectations and confirmation of expectations. Per the ECT framework, expectations influence confirmation through the confirmation judgment (Oliver et al., 1994). This influence reflects a positive relationship between expectations and confirmation (e.g., Lankton & McKnight, 2012; Oliver, 2010, 2014; Venkatesh et al., 2011) and is referred to as the halo effect. The halo effect occurs when users "see what they want to see". With it, users with high expectations will only see high outcomes, which are also better than expected outcomes. Users with low expectations will only see low outcomes, which are also worse than expected outcomes, thus creating a positive relationship between expectations and confirmation of expectations (Oliver, 1997).

If there is no halo effect and expectations are high, then negative disconfirmation will occur if performance fails to meet or exceed these high expectations. This scenario reflects the ceiling effect for expectation levels (Oliver, 2010, 2014; Oliver et al., 1997). Similarly, if there is no halo effect and expectations are low, then positive disconfirmation will occur if performance fails to be less than the low expectations. This scenario illustrates the floor effect for expectation levels (Oliver, 2010, 2014; Oliver et al., 1997). As such, the following hypothesis is offered:

H4. Expectations will be positively related to confirmation of expectations.

2.4.5 Perceived performance and customer satisfaction. The ECT framework

posits that perceived performance is among the antecedents of customer satisfaction and

is a component of the confirmation of expectations comparison (Spreng & Page, 2003).

However, a positive direct link between perceived performance and customer

satisfaction has also been identified (e.g., Anderson & Sullivan, 1993; Churchill Jr &

Surprenant, 1982; Tse & Wilton, 1988). This direct linkage reflects the performance

assimilation effect (LaTour & Peat, 1979). Since perceived performance involves the

evaluation created either during or post-consumption, users may be inclined to modify

their expectation anchor rather than the performance perception (Tse & Wilton, 1988).

Thus, perceived performance is adopted as the standard of expectations. This approach

is generally pursued as a dissonance reduction strategy (Festinger, 1957; Holloway,

1967).

When viewed through the lens of a new product experience, this performance

assimilation effect may be reflective of new learnings or insights gained following use of the

product (Tse & Wilton, 1988). Many times, users do not have an extended prior performance

history on which expectations can be based. In these situations, high performing new products

are likely to yield higher customer satisfaction judgments. This higher satisfaction level is not

dependent on the pre-experience comparison of standard and confirmation of expectations.

Instead, the perceived performance is adopted as the updated standard of expectations (Tse &

Wilton, 1988).

Based on the insights discussed above, the location of the product on the life-cycle curve

is not the influential variable for the evaluation of this hypothesis. Rather, it is the user

evaluation of the appropriateness of the expectations anchor which drives this evaluation (Tse &

Wilton, 1988). Recent ECT technology-based studies have reconfirmed this relationship (e.g.,

Lankton & McKnight, 2012; Lankton et al., 2014; Morgeson, 2013; Park et al., 2012).

Therefore, this relationship is appropriately assumed to apply to digital assistants as well. As

such, the following hypothesis is offered:

H5. Perceived performance will be positively related to customer satisfaction.

2.4.6 Confirmation of expectations and customer satisfaction. As previously

mentioned, the ECT framework evaluates satisfaction through two processes: the creation of

expectations and the confirmation of those expectations by assessing the performance through

the comparison process (Oliver et al., 1994). Satisfaction derived from confirmation represents

a cognitive comparison on the part of the individual (Jiang, Klein, & Saunders, 2012).

Confirmation's influence on satisfaction is evaluated through the contrast effect (Oliver, 1980).

The contrast effect (as shown above in Figure 2) is the converse of the assimilation effect

(Anderson, 1973), reflects a dissonance reduction action. The contrast effect was originally

identified in social psychology and states that people tend to exaggerate the positive

disconfirmation or negative disconfirmation judgment (Tse & Wilton, 1988). Thus, it reveals an

individual's perception of whether an outcome succeeds in meeting an established expectation

or whether it fails to do so (Bhattacherjee, 2001).

As applied in satisfaction literature, performance above expectations will be judged

more favorably than objectively justified (Tse & Wilton, 1988). For positive discrepancies (i.e.,

performance is better than expected), individuals experience more pleasurable fulfillment. Thus,

confirmation will have a positive effect on satisfaction (Oliver & DeSarbo, 1988; Oliver et al.,

1997; Yi, 1990). Similarly, performance below expectations will be judged more harshly than it

really is (Tse & Wilton, 1988). For negative discrepancies (i.e., performance is worse than

expected), individuals experience unpleasurable fulfillment. Thus, confirmation will have a negative effect on satisfaction (Oliver & DeSarbo, 1988; Oliver et al., 1997; Yi, 1990). Recent ECT-based studies have reconfirmed this relationship (e.g., Bhattacherjee & Lin, 2015; Kim, 2012). In addition, technology-focused studies have also confirmed this association (e.g., Jin et al., 2013; Lankton et al., 2014; Liao, Palvia, & Chen, 2009). This connection is appropriately assumed to apply to digital assistants as well. As such, the following hypothesis is offered:

H6. Confirmation of expectations will be positively related to customer

satisfaction.

2.4.7 Moderating effect of perceived trust. Individual beliefs provide the foundation for a customer's perception of trust. Because this foundation is not based on hard facts, trust can be fragile and subjective (Yannopoulou, Koronis, & Elliott, 2011). Within the context of this study, trust reflects the customer's perceptions of a specific vendor or product attributes such as competence, benevolence, and integrity (Komiak & Benbasat, 2006). This trust enables individuals to overcome perceptions of uncertainty and risk and engage in "trust-related behaviors" with web-enabled technologies (McKnight et al., 2002). Further, Dabholkar (2006) identified that trust is a critical decision influencer in consumer use of recommendation agents. Hengstler, Enkel, and Duelli (2016) also posited a linkage between trust and AI technology adoption. If users perceive a high level of trust, then the associated risk perceptions would be reduced (Kim et al., 2010; Kim et al., 2012). Thus, it is appropriate to suggest that trust would similarly apply to digital assistants.

Recent studies have focused on the impacts of trust as an independent variable in its relationship with satisfaction and its consequences. Among these studies, trust and satisfaction have been posited to involve cognitive and emotional dimensions which influence individual

behavior outcomes involving IT systems (e.g., Chan et al., 2011; Dabholkar & Sheng, 2012; Fang et al., 2014; Kim, 2012; Lankton et al., 2014). The statistical significance of this relationship was confirmed within each study.

Earlier studies utilized trust as a moderating variable in technology-focused studies. Among other items, Cockrill, Goode, and Beetles (2009) posited trust to be a moderating variable in a study on satisfaction with automated teller machines. Trust was confirmed to be significant for moderating relationship between usability and satisfaction. Chang and Wong (2010) incorporated trust as a moderator in their study of e-procurement executives. In that study, trust was confirmed to be significant as a moderator of the relationship between e-procurement adoption and e-marketplace participation. Therefore, it is reasonable to expect that perceived trust will have a moderating relationship within the customer satisfaction framework given the relative importance of trust within the disciplines of IT systems, online behaviors, and new technology. As such, the following hypothesis is offered:

> *H7. Perceived trust will positively moderate the relationship between*
>
> *confirmation of expectation and customer satisfaction.*

2.4.8 Moderating effect of information privacy concerns. Across all technology-dependent business sectors, customers are increasingly concerned about the vulnerability of their personal data and the possibility of it being compromised or misused. These concerns are reflective of the definition of information privacy concerns. Smith et al. (1996) cite this definition as being an individual's concerns about the collection, the errors, the secondary use, and the unauthorized access to personal information.

Individuals are increasingly challenged with managing the complex trade-offs of technology innovation with the risks of information privacy concerns (A. Acquisti et al., 2015). People are becoming so dependent on the growing proliferation of digital applications to help manage their active lifestyles that their privacy concerns are sometimes moved to a lower priority in their decision-making criteria. A. Acquisti et al. (2015) cite that "people are often unaware of the information they are sharing, unaware of how it can be used, and even in the rare situations when they have full knowledge of the consequences of sharing, uncertain about their own preferences" (p. 513).

Various theories and information privacy topics are routinely cited in nearly all recent marketing research involving user behaviors of technology, social media and/or web-based applications. Yun, Han, and Lee (2013) explored the moderating effects of privacy concerns involving smartphones. In this study, the moderating influence of information privacy concerns was found to be significant for the relationships involving continuous usage intentions, performance expectancy, and effort expectancy. While in different contexts, the moderating effects of information privacy concerns were confirmed in studies by Nepomuceno, Laroche, and Richard (2014) and Mothersbaugh, Foxx, Beatty, and Wang (2012) Therefore, it is reasonable to expect that information privacy concerns will have a moderating relationship within the customer satisfaction framework given the relative importance of information privacy within the disciplines of IT systems, online behaviors, and new technology. As such, the following hypothesis is offered:

> *H8. Information privacy concerns will negatively moderate the relationship*
>
> *between confirmation of expectation and customer satisfaction.*

CHAPTER 3

METHODOLOGY

Chapter 3 is divided into five sections which identify the methodological choices used to test the hypothesized relationships in this study. The first section provides an overview of the expected research design. The second section discusses the sample of participants and how the data was collected. The third section details how the constructs were operationalized and a summary of the items that were adapted for the questionnaire. The fourth section explains the analytical approach used. Lastly, the fifth section discusses the common method variance associated with this approach and the applicable remedies.

3.1 Research Design

This study used a cross-sectional, quantitative survey design as its methodological approach. This design used online methods to collect self-reported respondent information which was used to assess the relationship of the primary ECT antecedent constructs and customer satisfaction. In addition, the moderating influences of perceived trust and information privacy concerns on the customer satisfaction relationship were assessed. Given the subjective nature of the constructs, empirical research commonly uses surveys as a method to investigate customer satisfaction (Oliver, 2006). This approach is consistent with recommendations from the marketing and information systems literature, as summarized in Chapter 2.

3.2 Data Collection

 3.2.1. Data sample source. A sample of adults (i.e., age 18 and older) in the United

States who have used a digital assistant was solicited through email and social media platforms

(e.g., Facebook and LinkedIn). This approach allowed for snowball sampling effects to occur.

Respondents were provided an overview of the research topic, eligibility for a drawing, and a

link to the Qualtrics-based survey (www.qualtrics.com). All respondents were volunteer

participants for the survey. Participants who completed the fifteen-minute survey and provided

a valid contact email address were entered in a drawing for a prepaid VISA® gift card.

Participants were advised that no sales solicitation contact would result from providing their

email address. The email address was removed from the response data and maintained in a

separate password protected file that only the researcher had access to. This action is necessary

to preserve the anonymity of the individual responses. All responses were secured in password

protected files and preserved by the researcher on both a computer hard drive, and two different

cloud-based repositories. Any summary participation results and/or findings were aggregated

prior to publication. The design was approved by the University of Dallas Institutional Review

Board.

 Since digital assistants operate through an internet-based infrastructure, users have at

least some experience with an online environment. Therefore, soliciting participants through

email and social media platforms was consistent with the intent of this study. Recent examples

of marketing research involving online samples include online communications and buying

behavior (Groeger & Buttle, 2014; Kumar, Bezawada, Rishika, Janakiraman, & Kannan, 2016;

Toder-Alon, Brunel, & Fournier, 2014), brand loyalty (Laroche, Habibi, & Richard, 2013),

social media sentiment analysis (Schweidel & Moe, 2014), youth exposure to alcohol marketing (Jernigan & Rushman, 2014), microblog marketing (Jin, Tang, & Zhou, 2017), and social media advertising and marketing (Lawlor et al., 2016; Schivinski, Christodoulides, & Dabrowski, 2016; Thies, Wessel, & Benlian, 2014).

3.2.2 Data analysis method selection. Partial least squares structural equation modeling (PLS-SEM) allows for analyzing latent variable models with multiple constructs and indicators. It is used to extend theories in exploratory research and explain target constructs (E. E. Rigdon, 2012) while becoming the dominant approach used in recent marketing studies (Hair, Hult, Ringle, & Sarstedt, 2013). PLS-SEM represents the study constructs using proxies. These proxies reflect weighted composites of indicator variables associated with a particular construct (Hair, Hult, Ringle, & Sarstedt, 2017). Some of the appeal for using PLS-SEM is that it excels in maximizing the explained variance of dependent latent constructs in a causal model. PLS-SEM is highly functional with non-normally distributed data, a wide range of sample sizes, and complex models (Cassel, Hackl, & Westlund, 1999). It is also widely used when the research objectives are focused on exploratory goals (Hair, Ringle, & Sarstedt, 2011).

PLS-SEM is a variance-based analytical methodology and has fewer restrictions compared to covariance-based structural equation modeling (CB-SEM) approaches in terms of sample size, measurement scales and residual distributions. Unlike CB-SEM, PLS-SEM does not require data normality and can provide reliable analysis even with the smaller sample size estimated for this study. Further, when compared to CB-SEM, it can also handle larger and more complex models with many constructs and indicators (Hair et al., 2017), which again aligned with those components in this study.

Based on the method choice rules offered by (Hair et al., 2017), PLS-SEM was selected based on these factors: the research goal focuses on predicting the key target construct of customer satisfaction; the study used a formative model (i.e., even though reflective constructs are also included); the structural model is complex; the data is non-normally distributed (i.e., reflecting the finding of Fornell (1992) that virtually all research involving the satisfaction construct is highly skewed); and it involves latent variable scores. Therefore, PLS-SEM was an appropriate choice as the data analysis method.

3.2.3 Sample size requirements. The minimum sample size for PLS-SEM should be the larger of either: ten times the greatest number of formative indicators measuring one construct, or ten times the greatest number of structural paths heading for a particular latent construct in the structural model (Barclay, Higgins, & Thompson, 1995; Hair, Sarstedt, Ringle, & Mena, 2012). However, sample size computations should also consider the power analysis associated with the section of the model with the largest number of predictors (Hair et al., 2017). Accordingly, the estimated sample size calculated using G*Power 3.1.9.2 (Faul, Erdfelder, Buchner, & Lang, 2009) is 82 participants. This estimate reflects the parameters of an alpha error probability of 5%, two tailed, and a medium effect size of 0.30. While this estimate is the minimum sample size, a larger sample was targeted for collection.

3.3 Measures

This study followed the guidelines of D. Straub, M. C. Boudreau, and D. Gefen (2004) in the construction of the survey questionnaire to ensure the maximum content validity of the instrument. All instruments were measured using multi-item scales. The measurement items were adapted from previous research and modified to fit the context of this research. As

recommended by Anderson and Gerbing (1984) and Bentler and Chou (1987), each construct was measured by at least three observable indicators. The items were written in the form of statements or questions. Most measurements used a 7-point Likert rating scale system with end points such as strongly disagree/strongly agree. Customer satisfaction and confirmation of expectations had alternative end points. A summary of the measurements and scales is presented in Table 5. Each individual scale is described below and summarized in Appendix A.

3.3.1 Customer satisfaction. Customer satisfaction represents the individual's summary judgment that the product, service, or experience provided a pleasurable level of consumption or experiential fulfillment (Oliver et al., 1997). Within the context of this study, customer satisfaction reflects the user's perception of their overall satisfaction with the digital assistant. This construct was measured using the four item semantic differential overall satisfaction scale from Spreng, MacKenzie, and Olshavsky (1996). Oliver and DeSarbo (1989) emphasized that intensity and valence are necessary dimensions to measure. As adapted, this scale captured the significance of participants' high- and low-intensity satisfaction responses towards a digital assistant along seven-point scales anchored between four semantic differential adjective pairs: "very dissatisfied/very satisfied", "very displeased/very pleased", "very frustrated/very contented", and "absolutely terrible/absolutely delighted". Since semantic scales capture the connotative meaning of things, they are believed to be the most effective approach for capturing the connotative meaning of this construct (Bhattacherjee & Lin, 2015). Similar scales were used in other recent studies involving IT system continuance (Bhattacherjee & Lin, 2015; Hong, Thong, Chasalow, & Dhillon, 2011; Lankton et al., 2014), social network continuance (Lin, Featherman, & Sarker, 2017), online re-purchase intentions (Kim, 2012), e-government system

continuance (Venkatesh, Chan, & Thong, 2012), and mobile service continuance (Zhao et al., 2012).

3.3.2 Expectations. Expectations represent the individual's anticipated performance outcome based on that outcome meeting the consumer's goal (Oliver, 2014). When viewed in terms of technology-based intentions, Davis (1989) depicted expectations as being reflected in a user's perceptions of receiving benefits in the form of technology usefulness. This depiction is consistent with the definition of perceived usefulness. It is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, p. 320). Within the context of this study, expectations represented the individual's judgment of a digital assistant's ability to perform and deliver benefits which meet their need or goal. By doing so, the user is establishing an anchor of usefulness for which the digital assistant is expected to contribute. Therefore, expectations was measured using six items adapted from the perceived usefulness scale (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989). The items were rated on seven-point Likert-type scales, with 1 = "Strongly Disagree" and 7 = "Strongly Agree". Similar scales were used in other recent studies involving IT system continuance (Brown, Venkatesh, & Goyal, 2014; Guo et al., 2015; and Venkatesh & Goyal, 2010), software adoption (Lankton & McKnight, 2012), and online re-purchase intention (Park et al., 2012).

3.3.3 Perceived performance. Perceived performance represents an individual's perception of the performance outcome realized from the product, service, or experience (Oliver, 2014). Within the context of this study, it represented an individual's perception of the performance of a digital assistant. Consistent with the evaluation lens used in expectations, perceived performance was measured using six items adapted from the perceived usefulness scale (Davis, 1989; Davis et al., 1989). The items were rated on seven-point Likert-type scales,

with 1 = "Strongly Disagree" and 7 = "Strongly Agree". As with measuring expectations, similar scales were used in other recent studies involving IT system continuance (Bhattacherjee & Lin, 2015; Guo et al., 2015; Lankton et al., 2014; Venkatesh & Goyal, 2010), software adoption (Lankton & McKnight, 2012), e-government system continuance (Venkatesh et al., 2012), online re-purchase intention (Kim, 2012; Park et al., 2012) and social network continuance (Lin et al., 2017).

       3.3.4 Confirmation of expectations. Confirmation of expectations represents the difference between an individual's perceived outcome and that individual's established expectations (Jiang & Klein, 2009). Within the context of this study, it represented the individual's usability experience being aligned within the zone of tolerance for expectations of his or her digital assistant. Consistent with the evaluation lenses used in expectations and perceived performance, confirmation of expectations was measured using six items adapted from the perceived usefulness scale (Davis, 1989; Davis et al., 1989). The items were rated on seven-point Likert-type scales, with 1 = "Much worse than expected" and 7 = "Much better than expected". As previously described, similar scales were used in recent IT studies involving system continuance (Bhattacherjee & Lin, 2015; Guo et al., 2015; Lankton et al., 2014; Venkatesh & Goyal, 2010), software adoption (Lankton & McKnight, 2012), e-government system continuance (Venkatesh et al., 2012), online re-purchase intention (Kim, 2012; Park et al., 2012), mobile service continuance (Zhao et al., 2012), and social network continuance (Lin et al., 2017).

       3.3.5 Perceived trust. Perceived trust is a moderating variable for this study. It focused on the customer's subjective trust beliefs established in the trust building process (Benbasat & Wang, 2005). Within this study, it represented the user's perception of trust beliefs in both the

application and the artificial intelligence infrastructure supporting the digital assistant. In alignment with the recommendation of McKnight et al. (2002), Benbasat and Wang (2005) presented perceived trust as a reflective second order construct. It was comprised of the three reflective indicator variables of competence, benevolence, and integrity. Similar scales (i.e., either partially or totally) were used in other recent studies involving IT system continuance (Lankton et al., 2014; Venkatesh et al., 2011), online recommendation agents (Dabholkar & Sheng, 2012), online re-purchase intentions (Kim et al., 2012), and brand relationships (Veloutsou, 2015).

3.3.5.1 Competence. Competence measured perceptions of how well the trustee performed in terms of expertise, aptitude, and proficiency (Xiao & Benbasat, 2002). For this study, it reflected user's trust beliefs in the competence of the network provider(s) involved with transporting the inquiry and content as well as the firm(s) supporting the host application and the artificial intelligence infrastructure supporting the digital assistant. The five items appropriate for this study were adapted from the cognitive and emotional trust scale (Xiao & Benbasat, 2002) and rated on seven-point Likert-type scales, with 1 = "Strongly Disagree" and 7 = "Strongly Agree".

3.3.5.2 Benevolence. Benevolence focused on the trustee acting in the individual's best interest, trying to help, and being genuinely concerned (Xiao & Benbasat, 2002). For this study, it reflected a user's trust beliefs in the benevolence of the network provider(s) involved with transporting the inquiry and content as well as the firm(s) supporting the host application and the artificial intelligence infrastructure for the digital assistant. The four items appropriate for this study were adapted from the cognitive and emotional trust scale (Xiao & Benbasat, 2002)

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and rated on seven-point Likert-type scales, with 1 = "Strongly Disagree" and 7 = "Strongly Agree".

  3.3.5.3 Integrity. Integrity captures the perceptions that the trustee adheres to a set of principles which are acceptable to the trustor (Xiao & Benbasat, 2002). These principles are centered around the trustee's honesty, truthfulness, sincerity, and promise keeping (i.e., as viewed from a reliability or dependability perspective). These principles are reflected in the user's collective belief about the integrity of the network provider(s), the host application, and the artificial intelligence infrastructure for the digital assistant. The four items appropriate for this study were adapted from the cognitive and emotional trust scale (Xiao & Benbasat, 2002) and rated on seven-point Likert-type scales, with 1 = "Strongly Disagree" and 7 = "Strongly Agree".

  3.3.6 Information privacy concerns. Information privacy concerns is a moderating variable for this study. It represents an individual's concerns about the beliefs, attitudes, and perceptions toward information privacy (Smith, Dinev, & Xu, 2011). Malhotra et al. (2004) presented information privacy concerns as a reflective second order construct. Within the context of this study, it was measured through the two reflective indicator variables of general privacy concerns and perceived privacy protection associated with digital assistants. Other studies using this scale (i.e., either partially or totally) include IT system continuation (Li & Liu, 2014; Miltgen et al., 2013), online transactions (Bansal, Zahedi, & Gefen, 2016; Kehr et al., 2015; Li & Liu, 2014; Li, Sarathy, & Xu, 2011; Smith et al., 2011), mobile services (Keith et al., 2015; Limpf & Voorveld, 2015; Yun et al., 2013), and social network continuance (Choi & Land, 2016).

3.3.6.1 General privacy concerns. General privacy concerns reflected an individual's general tendency to worry about the privacy of his or her personal information (Malhotra et al., 2004). Within the study context, it represented similar concerns associated with the network provider(s) involved with transporting the inquiry, the firm(s) supporting the host application, and the artificial intelligence infrastructure. This variable was measured by using the five higher-level components of the global information privacy concerns scale (Malhotra et al., 2004; Smith et al., 1996). Consistent with the focus of this study and the approach used by Li et al. (2011), the detailed sub-dimensions of scale were not included. The five items appropriate for this study were rated on seven-point Likert-type scales, with 1 = "Strongly Disagree" and 7 = "Strongly Agree".

3.3.6.2 Perceived privacy protection. Perceived privacy protection refers to the "consumer's perception of the likelihood that the Internet vendor will try to protect the consumer's confidential information collected during electronic transactions from unauthorized use of disclosure" (Kim, Ferrin, & Rao, 2008, p. 550). In the context of this study, it referred to the user's perception of the likelihood that the personal information collected by the digital assistant will be protected from unauthorized use or disclosure. This perception spans multiple firms. It includes the network provider(s) involved with transporting the inquiry, the firm(s) supporting the host application, and the artificial intelligence infrastructure. To measure the variable, six items were adapted from the perceived privacy protection scale (Chen, Han, & Yu, 1996); Kim et al. (2008). All items were rated using seven-point Likert-type scales, with 1 = "Strongly Disagree" and 7 = "Strongly Agree".

Table 5

Summary of Measurements and Scales

Construct	Indicator Variables	# of Items	Scale	Measurement
Customer satisfaction		4	Overall satisfaction (Spreng et al., 1996)	7-point semantic differential
Expectations		6	Perceived usefulness (Davis, 1989; Davis et al., 1989)	7- point Likert-type
Perceived performance		6	Perceived usefulness (Davis, 1989; Davis et al., 1989)	7- point Likert-type
Confirmation of expectations		6	Perceived usefulness (Davis, 1989; Davis et al., 1989)	7- point Likert-type
Perceived trust[1]				
	Competence	5	Cognitive & emotional trust (Xiao & Benbasat, 2002)	7- point Likert-type
	Benevolence	4	Cognitive & emotional trust (Xiao & Benbasat, 2002)	7- point Likert-type
	Integrity	4	Cognitive & emotional trust (Xiao & Benbasat, 2002)	7- point Likert-type
Information privacy concerns[2]				
	General privacy concerns	5	Global information privacy concerns (Malhotra et al., 2004; Smith et al., 1996)	7- point Likert-type
	Perceived privacy protection	6	Perceived privacy protection (Chen et al., 1996; Kim et al., 2008)	7- point Likert-type

[1] Perceived trust is measured through the three reflective indicator variables of competence, benevolence, and integrity.

[2] Information privacy concerns is measured through the two reflective indicator variables of general privacy concerns and perceived privacy protection.

3.3.7 Control variables. Given its relative early lifecycle, little information is available

identifying the impact of control variables in customer satisfaction studies involving a digital

assistant. It is logical to assume, however, that certain control variables used in website research would be similarly relevant to this study. The categorical variables of gender, age, education, income and experience have previously been shown to influence relationships in ECT and other acceptance research (e.g., Bhattacherjee & Premkumar, 2004; Lankton et al., 2014; Venkatesh et al., 2003; Venkatesh et al., 2011).

3.4 Data Analysis

The PLS-SEM methodology distinguishes two components of model building: the measurement model and the structural model. Although both models are evaluated simultaneously by the PLS-SEM software, the measurement model analysis results are typically examined before the structural model analysis results. The analysis of the measurement model is conducted to evaluate the quality of the data through the measurement model characteristics (Hair et al., 2012). This analysis reports on the indicator loadings for their respective constructs and cross-loadings for other constructs. These findings can be used to assess convergent and discriminant validity among the construct measures. Anderson and Gerbing (1982) identified that this step is "necessary before meaning can be assigned to the analysis of the structural model" (p. 453).

The structural model analysis reports the path coefficient measures along with latent variable R-squares; together, these reflect the explanatory power of independent variables (Fornell & Larcker, 1981). This analysis will be examined and validated with structural equation modeling resident within the SmartPLS software (C. M. Ringle, S. Wende, & J. M. Becker, 2015). The software package SmartPLS 3.2.6 was used in this study.

3.5 Common Method Variance

Common method variance (CMV) is a potential problem in behavior research. While there are many potential sources of CMV, method biases represent one of the main sources of measurement error (P. M. Podsakoff, S. B. MacKenzie, J. Y. Lee, & N. P. Podsakoff, 2003). CMV can occur when data from both exogenous and endogenous constructs are collected from the same respondent at the same time (Podsakoff & Organ, 1986). When CMV is too high, the result can be common methods bias (CMB). To reduce the likelihood of CMV, survey question presentation in this study were randomized (Podsakoff, MacKenzie, & Podsakoff, 2012). To further reduce the likelihood of CMB, the scale points and anchor labels of scales were varied between constructs in the design of the questionnaire (P. M. Podsakoff et al., 2003). While these actions may not fully protect the study from CMV, they minimized the likelihood of a significant CMB impact on the study results (D. Straub et al., 2004).

This chapter reviewed the methods of the study, including research design, questionnaire, population and sample, data collection, and data analysis. In addition, the likelihood of common method variance was reviewed, as well as applicable remedies. All constructs used existing measures. Measurement items for each construct in the model were based on a 7-point Likert type scale except for customer satisfaction (which used a 7-point semantical differential scale). All items were adapted from the extant literature to maximize the validity and reliability of the measurement model.

CHAPTER 4

RESULTS

Chapter 4 describes the analytical framework used and methods applied in the study along with the results of the analysis. This chapter includes four sections. First, the measurement model properties were evaluated. Second, the relationship between the indicators and the constructs within the measurement model were examined. Third, the hypothesized relationships reflected in the structural model were examined. Lastly, the research results were assessed and reported in the fourth section.

4.1 Measurement Model Properties

Survey measures are commonly used in research to capture responses to options along a scale or from pre-established categories. Researchers hope that respondents complete the survey as directed by the instructions (Huang, Liu, & Bowling, 2015). However, it is generally known that not all participants are similarly motivated to respond to questions in a thoughtful and meaningful manner (DeSimone, Harms, & DeSimone, 2015). Thus, researchers must exercise proper scrutiny to ensure that the response data was properly reviewed and carefully screened for suspicious response patterns and nonsensical outliers. By doing so, the researcher minimizes random measurement error associated with increasing Type I error rates (Huang et al., 2015). Any impacted response must be identified and analyzed prior to running PLS-SEM (Hair, Black, Babin, & Anderson, 2010).

4.1.1 Case screening. After the survey responses were collected, the data were reviewed and carefully screened for suspicious response patterns and nonsensical outliers. A total of 260 responses were received. However, 16 cases did not complete all survey items and were omitted. The remaining cases were also scrutinized for suspicious response patterns using standard deviation calculations and visual inspection. Nonsensical outliers were analyzed using boxplots to identify unusually large or small values compared to the other values of the same variable (Aguinis, Gottfredson, & Joo, 2013). The results of this collective review identified no additional cases appropriate for exclusion from the study. Thus, 244 complete responses were included in this study.

4.1.2 Variable screening. Even though PLS-SEM does not require normally distributed variables, normality analysis and review involving skewness and kurtosis should still be conducted. "Skewness assesses the extent to which a variable's distribution is symmetrical. If the distribution of responses for a variable stretches toward the right or left tail of the distribution, then the distribution is referred to as skewed." "Kurtosis is a measure of whether the distribution is too peaked (a very narrow distribution with most of the responses in the center)" (Hair et al., 2017, p. 61). The normal acceptable range of skewness and kurtosis is bounded by values of +/- 1.0. In this study, three of the variables had mild degrees of skewness (< -1.280) and one variable had mild nonnormal kurtosis ($< +1.250$). While these values represent nonnormal data, these values are less than the "high skew" scenario presented by Goodhue, Lewis, and Thompson (2012, p. A13) and are thus acceptable in SmartPLS (Hair, Hult, Ringle, & Sarstedt, 2014; Sarstedt, Ringle, & Hair, 2017).

4.1.3 Study characteristics. The study sample was collected through responses to email and social media invites (e.g., Facebook and LinkedIn) during a six-week period. Emails were

distributed only once but recipients were encouraged to refer other participants to also complete the survey. In addition, twice per week informational and reinforcement postings were shared on social media to stimulate response awareness. Many of the social media postings targeted individuals who also received the emails. Respondents were redirected to a Qualtrics website to complete the survey. Participation was voluntary but completed responses were eligible for a drawing for a prepaid VISA® gift card.

The sample contains the responses of 244 participants of which 49% (121) were men and 51% (123) were women. Ethnicities were represented as follows: 81% (197) Caucasian, 8% (20) Hispanic, 5% (12) African American, 6% (15) Other. For age, the largest groups of respondents were between the ages of 50 – 59 years old, 32% (79). The remaining age groups were 18 – 29, 21% (51); 40 – 49, 20% (49); 60 and older, 16% (38); and 30 – 39, 11% (27). For experience with digital assistants, 1 – 2 years, 25% (62); 3 – 4 years, 27% (65); 1 – 12 months, 25% (60); 5 years or more, 15% (36); and never used, 8% (21). The sample demographic profile is depicted in Table 6.

Table 6

Sample Characteristics (n = 244)

Gender			Age			Experience		
Description	Count	Pct.	Description	Count	Pct.	Description	Count	Pct.
Male	121	49%	18 - 29	51	21%	1 – 12 months	60	25%
Female	123	51%	30 - 39	27	11%	1 – 2 years	62	25%
			40 - 49	49	20%	3 – 4 years	65	27%
			50 - 59	79	32%	5 or more years	36	15%
			60 or over	38	16%	Never used	21	8%

Ethnicity			Income			Education		
Description	Count	Pct.	Description	Count	Pct.	Description	Count	Pct.
African American	12	5%	$30k or less	47	19%	Some high school/diploma	4	2%
Caucasian	197	81%	$30k - $70k	33	14%	Some college	40	16%
Hispanic	20	8%	$70k - $100k	28	11%	Undergraduate degree	107	44%
Other	15	6%	$100k - $150k	75	31%	Master's degree or higher	93	38%
			$150k or above	61	25%			

4.2 Measurement Model Evaluation

As with most studies using this approach, the initial focus of PLS-SEM analysis is on the evaluation of the quality of the data through the measurement model characteristics (Hair, Ringle, & Sarstedt, 2011). By first evaluating the outer model, insights were gathered confirming the validity of the constructs. This validity establishes a foundation for the basis of assessment of the inner model relationships. This study includes both reflective and formative measures. Thus, a confirmatory factor analysis (CFA) was used to examine and validate the measurement model as well as examine the convergent and discriminant validity on each of the model's constructs (D. Straub, M.-C. Boudreau, & D. Gefen, 2004).

The model estimation used the default algorithm settings (i.e., path weighting scheme, a maximum of 300 iterations, factor weighting scheme, a stop criterion of 0.0000001 (or 1×10^{-7}), and equal indicator weights) recommended (Dijkstra & Henseler, 2015; Henseler, Hubona, & Ray, 2016; Lohmöller, 1989, 2013). It required eight iterations of the algorithm, far less than the maximum number of 300 iterations (Ringle, Wende, & Will, 2005). All 244 cases within the current survey data were sourced to draw 5000 random subsamples (Hair et al., 2011) for the consistent PLS bootstrapping analysis.

4.2.1 Internal consistency reliability for reflective constructs. Internal consistency reliability was assessed to evaluate the extent to which a group of items measure the same construct, as evidenced by how well the items vary together, or intercorrelate. A high degree of internal consistency reliability enables the researcher to interpret the composite score as a measure of the construct (MacKenzie, Podsakoff, & Podsakoff, 2011). Since the model includes both reflective and formative constructs, indicator analysis was evaluated separately for the

reflective and formative constructs. This section focused upon the reflective indicators associated with the latent variables. (The evaluation of the formative constructs is discussed in Section 4.2.4).

The scores for the reflective constructs are displayed in Table 7. With the exception of Integrity (.631, .626), the Cronbach's alpha and the composite reliability scores were all above the recommended score of .70 (Bagozzi & Yi, 1988; Chin, 1998; Nunnally & Bernstein, 1994) and lower than the upper limit of .95 (Diamantopoulos, Sarstedt, Fuchs, Wilczynski, & Kaiser, 2012; Hair et al., 2017). While Integrity does not met the ideal threshold, it is an acceptable score since it exceeds .60 (Hair et al., 2017).

4.2.2 Convergent validity for reflective constructs. Convergent validity was assessed to evaluate the extent to which each measure correlates positively with alternative measures of the same construct. This validity is useful in establishing the strength of the relationship between two different measures as well as demonstrating the legitimacy of measurement for the construct (Anderson & Gerbing, 1988; Fornell & Larcker, 1981). This assessment involved three different tests, which are displayed in Table 7.

The first test involved identifying the indicator reliability. The results show that 21 of the 26 reflective indicators have outer loadings above the threshold level of .70 (Hulland, 1999; Nunnally, 1978; Nunnally & Bernstein, 1994). Each of the remaining 5 indicators were lower than the .70 threshold but they were sufficiently large enough for continued use as their removal would not have increased composite reliability (Hair et al., 2011). The second test involved confirmation of each indicator's statistical significance (Fornell & Larcker, 1981; Henseler et al., 2016). For this study, each indicator was confirmed to be statistically significant ($p < .001$).

Table 7

Results Summary for Reflective Measurements

Latent Variable[a]	Indicators[b]	Convergent Validity				Internal Consistency Reliability	
		Loadings	Indicator Reliability	*t* Statistic[c]	AVE	Composite Reliability	Cronbach's Alpha
Confirmation of Expectations (Confirm)	CU1	.885	.854	29.438	.788	.918	.917
	CU4	.938	.891	33.085			
	CU6	0924	.918	38.041			
Customer Satisfaction (Sat)	S1	.922	.903	39.392	.812	.945	.945
	S2	.935	.892	40.907			
	S3	.913	.895	31.243			
	S4	.936	.913	32.125			
Expectations (Expect)	EU1	.847	.757	16.674	.763	.928	.926
	EU2	.927	.913	34.727			
	EU3	.928	.905	28.540			
	EU5	.917	.909	29.320			
Benevolence (Ben)	TB1	.827	.680	11.331	.473	.729	.724
	TB2	.870	.731	14.599			
	TB3	.710	.649	8.737			
Competence (Comp)	TC1	.788	.721	18.026	.567	.797	.795
	TC2	.886	.798	27.657			
	TC5	.851	.739	18.678			
Integrity (Int)	TI1	.751	.486	6.894	.365	.627	.631
	TI2	.795	.713	16.002			
	TI3	.726	.591	9.152			
General Privacy Concerns (GenPv)	PC1	.826	.702	13.424	.562	.792	.791
	PC2	.832	.693	10.575			
	PC3	.860	.844	21.923			
Perceived Privacy (PercPv)	PT1	.874	.764	17.467	.709	.879	.878
	PT2	.908	.844	29.057			
	PT6	.908	.912	39.117			

Notes: [a] Perceived performance was removed as a construct due to factor cross-loading issues. See the discussion of discriminant validity for additional details.

[b] CU2, CU3, CU5, EU4, EU6, TB4, TC3, TC4, TI4, PT3, PT4, & PT5 were removed to improve reliability, validity, and multicollinearity estimates.

[c] The *p* value for each indicator was < .001.

The third test involved computing the average variance extracted (AVE) (e.g., Fornell & Larcker, 1981; Henseler et al., 2016; Mallin & Munoz, 2013). Each of the constructs had AVE scores equal to or greater than the .50 threshold (Bagozzi & Yi, 1988; Hair et al., 2012), with the exception of benevolence (.472) and integrity (.364). However, AVE is a very conservative estimate. Since the composite reliability for both of these variables is acceptable, then it is appropriate to include these constructs in the study (Gaskin, 2017). Given the scores for these three tests, each of the reflective first-order constructs has been determined to have adequate convergent validity for this study.

4.2.3 Discriminant validity for reflective constructs. Discriminant validity supports construct validation by establishing that the measure is empirically unique. It evaluates whether all the indicators related to a latent variable are different from other indicators that are measuring other latent variables (Hair et al., 2010). Failure to establish this validity exposes risks to the research findings. Lacking this validation, "constructs [have] an influence on the variation of more than just the observed variables to which they are theoretically related" and, consequently, "researchers cannot be certain results confirming hypothesized structural paths are real or whether they are a result of statistical discrepancies" (Farrell, 2010, p. 324). In the past, marketing researchers routinely relied on the Fornell-Larcker criterion and cross-loadings (Hair et al., 2012) to determine discriminant validity. However, in recent years, scholars challenged this approach (Henseler et al., 2014; Rönkkö & Evermann, 2013). Henseler, Ringle, and Sarstedt (2015) and Voorhees, Brady, Calantone, and Ramirez (2016) recommended that the primary criterion be the confidence interval of the heterotrait-monotrait ratio of correlations (HTMT) statistic.

For this study, each of the three test criteria were assessed for insights but HTMT was used as the sole criteria for determining discriminant validity. The first test involved an examination of the cross-loadings (Table 8). It examined the indicator outer loading to identify any significant cross loadings onto other constructs (Chin, 1998; Grégoire & Fisher, 2006; Henseler et al., 2016). This examination identified the existence of significant cross-loadings between expectations and perceived performance. This development is not surprising given the cognitive dimensions of each of the original constructs.

The second test utilized the Fornell and Larcker (1981) criterion and the construct correlation matrix to assess discriminant validity. This test requires that the square root of the AVE value for each construct be higher than the construct's respective correlation with all other constructs displayed in Table 9. Both the cross-loading report and the construct correlation matrix provided insights that supported removal of the perceived performance construct.

The third test involved the HTMT statistic. This test determined that all reflective constructs (except for perceived performance) had HTMT values which were significantly less than conservative threshold value of .85 (Dijkstra & Henseler, 2015; Henseler et al., 2016). Additionally, a review of the lower and upper bounds of the 95% confidence interval similarly confirmed that no score exceeded 1.00. Thus, the results presented in Table 10 provide evidence of adequate discriminant validity. Efforts to remedy the significant cross-loadings between expectations and perceived performance were unsuccessful and were reflected in perceived performance's HTMT score being above the acceptable HTMT boundary. Thus, perceived performance was removed from the study. As a result, hypotheses 2, 3, and 5 could not be tested and were also removed from the study.

Table 8

Reflective Variable Cross-Loadings

Latent Variable	Indicator	Confirm	Sat	Expect	Ben	Comp	Int	GenPv	PercPv
Confirmation of Expectations (Confirm)	CU1	**0.854**	0.688	0.699	0.413	0.670	0.570	0.155	0.016
	CU4	**0.891**	0.767	0.734	0.409	0.716	0.510	0.063	-0.025
	CU6	**0.918**	0.768	0.771	0.437	0.721	0.558	0.014	-0.069
Customer Satisfaction (Sat)	S1	0.741	**0.903**	0.762	0.458	0.764	0.572	0.017	-0.080
	S2	0.754	**0.892**	0.728	0.481	0.728	0.580	-0.046	-0.152
	S3	0.758	**0.895**	0.721	0.479	0.728	0.599	-0.071	-0.145
	S4	0.756	**0.913**	0.773	0.453	0.757	0.585	-0.066	-0.157
Expectations (Expect)	EU1	0.613	0.616	**0.757**	0.305	0.583	0.529	0.065	-0.010
	EU2	0.751	0.753	**0.913**	0.442	0.714	0.570	0.023	-0.054
	EU3	0.784	0.765	**0.905**	0.433	0.666	0.530	-0.002	-0.080
	EU5	0.735	0.750	**0.909**	0.465	0.706	0.548	-0.074	-0.109
Benevolence (Ben)	TB1	0.304	0.311	0.288	**0.680**	0.507	0.682	0.048	-0.043
	TB2	0.358	0.398	0.381	**0.731**	0.554	0.601	0.104	-0.038
	TB3	0.311	0.361	0.307	**0.649**	0.586	0.436	0.138	0.129
Competence (Comp)	TC1	0.577	0.595	0.536	0.464	**0.721**	0.707	0.060	-0.076
	TC2	0.628	0.640	0.614	0.730	**0.798**	0.593	0.059	-0.047
	TC5	0.582	0.632	0.578	0.595	**0.739**	0.563	0.076	0.056
Integrity (Int)	TI1	0.249	0.310	0.292	0.343	0.388	**0.486**	-0.108	-0.257
	TI2	0.445	0.505	0.486	0.515	0.591	**0.713**	-0.187	-0.300
	TI3	0.396	0.335	0.325	0.645	0.488	**0.591**	0.032	-0.066
General Privacy Concerns (GenPv)	PC1	0.065	-0.081	-0.019	0.067	-0.026	-0.100	**0.702**	0.603
	PC2	0.169	0.078	0.076	0.261	0.237	0.013	**0.693**	0.544
	PC3	-0.022	-0.089	-0.046	0.009	-0.001	-0.231	**0.844**	0.756
Perceived Privacy (PercPv)	PT1	0.050	-0.073	-0.019	0.047	-0.008	-0.244	0.641	**0.764**
	PT2	-0.004	-0.122	-0.044	0.055	0.003	-0.288	0.713	**0.844**
	PT6	-0.109	-0.171	-0.118	-0.047	-0.067	-0.335	0.794	**0.912**

Note: Perceived performance was removed as a construct due to factor cross-loading issues with Expectations.

Table 9

Correlation Matrix (Fornell-Larcker Criterion)

	Confirm (1)	Sat (2)	Expect (3)	Ben (4)	Comp (5)	Int (6)	GenPv (7)	PercPv (8)	Privacy (9)	Trust (10)
Confirmation of Expectations (Confirm)	0.888									
Customer Satisfaction (Sat)	0.835	0.901								
Expectations (Expect)	0.828	0.828	0.874							
Benevolence (Ben)	0.473	0.519	0.475	0.688						
Competency (Comp)	0.791	0.826	0.766	0.797	0.753					
Integrity (Int)	0.614	0.648	0.622	0.837	0.822	0.604				
General Privacy Concerns (GenPv)	0.085	-0.046	0.000	0.140	0.086	-0.152	0.750			
Perceived Privacy (PercPv)	-0.030	-0.148	-0.075	0.019	-0.030	-0.345	0.853	0.842		
Information Privacy Concerns (Privacy)	0.023	-0.107	-0.043	0.076	0.022	-0.271	1.078	1.054	0.761	
Perceived Trust (Trust)	0.695	0.736	0.686	1.056	1.072	1.097	0.042	-0.107	-0.042	0.635
Age	0.053	0.125	0.134	0.108	0.111	0.089	0.216	0.064	0.137	0.113
Education	-0.063	-0.012	-0.033	-0.033	-0.041	-0.065	0.081	0.183	0.144	-0.048
Ethnicity	-0.051	-0.031	-0.042	-0.021	-0.025	-0.060	0.020	0.141	0.091	-0.035
Experience	-0.042	-0.032	-0.021	0.012	-0.008	-0.041	0.014	0.019	0.018	-0.011
Gender	-0.087	-0.047	-0.037	-0.054	-0.003	0.054	-0.153	-0.126	-0.145	-0.003
Income	0.069	0.178	0.183	0.100	0.125	0.132	0.079	0.026	0.052	0.128
Composite Reliability (CR)	0.918	0.945	0.928	0.729	0.797	0.627	0.792	0.879	0.891	0.856
Average Variance Extracted (AVE)	0.788	0.812	0.763	0.473	0.567	0.365	0.562	0.709	N/A	N/A
Mean	0.917	0.945	0.927	0.728	0.796	0.626	0.792	0.879	0.891	0.856
Standard Deviation (SD)	0.012	0.007	0.009	0.037	0.025	0.046	0.028	0.018	0.013	0.016

Notes:

1. Square roots (AVEs) are on diagonal, and construct correlations are below the diagonal
2. AVEs of formative indicators are not applicable.

Table 10. Discriminant Validity

Discriminant Validity (Heterotrait-Monotrait Ratio of Correlations)

	Confirm (1)	Sat (2)	Expect (3)	Ben (4)	Comp (5)	Int (6)	GenPv (7)	PercPv (8)
1. Confirmation of Expectations (Confirm)								
2. Customer Satisfaction (Sat)	0.835 [0.769, 0.890]							
3. Expectations (Expect)	0.827 [0.769, 0.879]	0.828 [0.753, 0.884]						
4. Benevolence (Ben)	0.475 [0.309, 0.619]	0.522 [0.372, 0.662]	0.473 [0.334, 0.602]					
5. Competency (Comp)	0.793 [0.703, 0.870]	0.829 [0.745, 0.898]	0.767 [0.663, 0.850]	0.801 [0.683, 0.904]				
6. Integrity (Int)	0.604 [0.442, 0.742]	0.637 [0.482, 0.768]	0.613 [0.451, 0.757]	0.834 [0.683, 0.972]	0.818 [0.670, 0.950]			
7. General Privacy Concerns (GenPv)	0.129 [0.065, 0.173]	0.110 [0.053, 0.172]	0.073 [0.029, 0.090]	0.182 [0.091, 0.258]	0.136 [0.074, 0.163]	0.208 [0.104, 0.282]		
8. Perceived Privacy (PercPv)	0.070 [0.020, 0.091]	0.146 [0.060, 0.257]	0.074 [0.024, 0.117]	0.110 [0.028, 0.154]	0.083 [0.036, 0.111]	0.343 [0.202, 0.463]	0.848 [0.751, 0.924]	
Mean	0.917	0.945	0.927	0.728	0.796	0.626	0.792	0.879
Standard Deviation (SD)	0.012	0.007	0.009	0.037	0.025	0.046	0.028	0.018
t Statistic	74.458	141.551	100.152	19.555	32.065	13.777	27.921	49.723

Note: The values in the brackets represent the lower and the upper bounds of the 95% confidence interval; $p < .05$

4.2.4 Construct validity of formative indicators. While the composite reliability of the first-order reflective variables examines the internally correlated latent variables, this assessment approach is not appropriate for formative constructs (e.g., Diamantopoulos & Winklhofer, 2001; Petter, Straub, & Rai, 2007; Detmar Straub et al., 2004). Formative indicators can have positive, negative, or no correlations among each other. Outer loadings, composite reliability, and the square root of AVE are meaningless for a latent variable made up of uncorrelated measures. Thus, formatively measured constructs are evaluated through significance and relevance of indicator weights, convergent validity, and collinearity (Sarstedt, Ringle, Smith, Reams, & Hair, 2014). This analysis utilized the repeated indicator approach (Hair et al., 2013; Lowry & Gaskin, 2014; Wold, 1982). All results are displayed in Table 11.

4.2.4.1 Statistical significance and relevance. This assessment was facilitated using the bootstrapping algorithm and settings within PLS-SEM and followed the recommendations of Hair et al. (2011). Similar to prior descriptions, all 244 cases within the current survey data were sourced to draw 5,000 random subsamples for analysis. The model was then estimated for each of the subsamples, yielding a high number of estimates for each model parameter. These estimates included the outer weights for the second-order formative constructs of perceived privacy and information privacy concerns. For formative constructs, the indicators should be approximately equal while also having significant t-statistics (Ringle, Sarstedt, & Straub, 2012). The assessment results confirmed that the formative indicator weights' were approximately equal, had statistical significance at the $\alpha = .05$ level, and were substantially above zero indicating an acceptable construct relationship (Hair et al., 2017).

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4.2.4.2 Convergent validity. The assessment of convergent validity for the second-order formative construct involves testing if the construct is highly correlated with the measures from the associated first-order reflective constructs (Ringle et al., 2012). The assessment results confirmed that each of the formative indicators shown in the outer weights column of Table 11 were roughly equal and have significant t-statistics. Thus, convergent validity was appropriately inferred.

Table 11

Results Summary for Formative Measurements

Construct	Formative Indicator	Outer Weights	(Outer Loadings)	t Statistic	95% BCa Confidence Interval	Outer VIF
Perceived Trust (Trust)	TB1	0.410	(0.680)	13.533*	[0.352, 0.471]	1.679
	TB2	0.441	(0.731)	16.674*	[0.393, 0.496]	1.844
	TB3	0.391	(0.649)	9.263*	[0.303, 0.473]	1.242
	TC1	0.379	(0.721)	22.085*	[0.347, 0.414]	1.463
	TC2	0.419	(0.798)	28.317*	[0.393, 0.451]	2.057
	TC5	0.388	(0.739)	24.730*	[0.358, 0.420]	1.888
	TI1	0.357	(0.486)	9.143*	[0.268, 0.424]	1.351
	TI2	0.524	(0.713)	15.753*	[0.467, 0.600]	1.322
	TI3	0.434	(0.591)	9.933*	[0.344, 0.517]	1.151
Information Privacy Concerns (Privacy)	PC1	0.373	0.702	15.675*	[0.321, 0.417]	1.616
	PC2	0.368	0.693	12.517*	[0.304, 0.421]	1.698
	PC3	0.448	0.844	17.957*	[0.407, 0.509]	1.697
	PT1	0.338	0.764	25.678*	[0.308, 0.360]	2.156
	PT2	0.373	0.844	30.993*	[0.351, 0.399]	2.650
	PT6	0.403	0.912	29.644*	[0.383, 0.440]	2.562

Note: *$p < .001$

4.2.4.3 Collinearity assessment. Given the constructs in this study, multicollinearity poses a greater risk for formative indicators than for reflective indicators. To assess this risk and

to confirm formative construct validity, multicollinearity testing among the indicators must be assessed using regression. The assessment results were confirmed to be less than the 5.0 threshold suggested by Kock (2015b); Kock and Gaskins (2014). Since all formative indicator variance inflation factors (VIFs) were below the threshold, sufficient construct validity for the formative indicators was inferred.

4.3 Structural Model Evaluation

Like the measurement model, the predictive power of the structural model capabilities also requires validation. Thus, the key metrics associated with the structural model are coefficients of determination (R^2, i.e., explained variance), predictive relevance (Q^2, i.e., external validity), effect sizes (f^2 and q^2), and the size and statistical significance of the path coefficients. Since this model includes moderators, their respective effects were also analyzed. However, common method variance (CMV) should be assessed prior to examining the explanatory power of the model. SmartPLS 3 software (C. M. Ringle, S. Wende, & J.-M. Becker, 2015) was used to examine these relationships.

4.3.1 Common method variance. CMV can result from either the measurement method used in a study or the social desirability considerations influencing an individual's response to a question. It is not an impact driven by the interplay of causes and effects among the latent variables in the model (Kock, 2015a). CMV suggests an external component is influencing the item response. This variance can have potentially serious effects on research findings due to its

contribution to measurement error (P. M. Podsakoff, S. B. MacKenzie, J.-Y. Lee, & N. P. Podsakoff, 2003).

Survey respondents completed the questionnaire and answered questions related to both endogenous and exogenous variables. However, the study proactively used various procedural remedies including methodological, temporal separation, and evaluation apprehension reduction techniques to reduce the impact of CMV as suggested by Philip M Podsakoff et al. (2003). Methodological design techniques included the use of semantical differential scales for the outcome variable while Likert-type scales were used for the other predictor variables. The temporal separation technique used randomized question presentation order to allow previously recalled information to leave short-term memory. Evaluation apprehension reduction techniques included allowing respondent answers to be anonymous as well as communicating to participants that there is no right or wrong answer.

The effectiveness of these procedural remedies was tested using the full collinearity testing approach within PLS-SEM. This testing addressed both vertical and lateral collinearity (Kock & Gaskins, 2014; Kock & Lynn, 2012). VIFs were calculated for all latent variables in the measurement model and confirmed to be less than the 5.0 threshold suggested by Kock (2015b); Kock and Gaskins (2014). Thus, CMV was not determined to be significant for this study.

4.3.2 Goodness-of-fit. Traditional SEM studies typically include a goodness-of-fit (GoF) analysis. However, there are differences of opinion among scholars as to the appropriateness of measured fit (within a factor-based SEM context) as being a relevant concept for PLS-SEM (Hair et al., 2017; Lohmöller, 1989; Edward E Rigdon, 2012). PLS-SEM does not estimate the

divergence between the empirical covariance matrix and the model-implied covariance matrix. Rather, PLS-SEM utilizes a predictive modeling approach, which maximizes the amount of explained variance of the endogenous latent variables. Thus, substantive conceptual differences exist between explanation and prediction approaches (Sarstedt, Ringle, Henseler, & Hair, 2014).

However, in recognition that some scholars may still find value in assessing GoF, this study included such an analysis. Currently, the recommended best PLS-SEM approximation of GoF is to utilize the standardized root mean square residual (SRMR) (Hu & Bentler, 1998; Hu & Bentler, 1999). Unfortunately, scholars have not aligned on an appropriate PLS threshold level. Byrne (2008, 2013) identified that an SRMR value less than .05 infers an acceptable model fit while a value of 0 suggests a perfect fit. Henseler et al. (2016) and Hu and Bentler (1999) suggest that a threshold value of .08 is more appropriate for PLS path models. For this study, the bootstrapped SMRM value of .033 was well under the most conservative threshold. As such, this score infers an adequate model fit for this study.

4.3.3 Overall model predictive power (R2). Given that the path model fit has been tested, the predictive power of the model must be assessed. This assessment used bootstrapping to assess the model's ability to explain variances in the dependent value of customer satisfaction through a high R^2 as well as substantial and significant structural paths (Chin, 1998). The R^2 value indicates the variance explained in the endogenous construct by the exogenous constructs. For marketing studies, an R^2 value of .75, .50, and .25 respectively is considered to be substantial, moderate, or weak respectively (Hair et al., 2011; Henseler, Ringle, & Sinkovics,

2009). Given these thresholds, the R^2 value (Table 12) of customer satisfaction (0.797) was

assessed as being substantial in predictive power and is statistically significant.

Table 12

Predictive Power of the Model

Endogenous Construct	R^2	$R^2_{Adjusted}$	t Statistics	p Values	95% Confidence Intervals
Customer satisfaction	.797	.787	21.250*	.000	[.699, .854]

Note: *$p < .001$

4.3.4 Effect size (f^2). Since the R^2 value has been evaluated as being substantial in

predictive power, it is also important to evaluate the size of the effect resulting from the removal

of a construct from predictive model relationship. The effect size was computed as the increase

in R^2 relative to the proportion of variance that remains unexplained in the endogenous latent

variable. The significance of this evaluation (Table 13) was assessed by comparing the effect size

results against the f^2 guidelines of 0.35 for large effect, 0.15 for medium effect, and 0.02 for

small effect (Cohen, 1988) for exogenous latent variables. Effect size values of less than 0.02

indicate that there was no effect. Given these guidelines, expectations → confirmation of

expectations (2.177) was assessed as a large and significant effect. Confirmation of expectations

→ customer satisfaction (0.276) was assessed as a medium but non-significant effect. Whereas,

expectations → customer satisfaction (0.110), direct effect of perceived trust → customer

satisfaction (0.091), direct effect of information privacy concerns → customer satisfaction

(0.058), and moderating effect of information privacy concerns on confirmation of expectations

→ customer satisfaction (0.024) were all deemed to be small and non-significant effects. Lastly,

the moderating effect of perceived trust on confirmation of expectations → customer satisfaction

(0.010) was assessed as having no effect.

Table 13

Effect Size (f ^{2}) of the Predictor Variables

Predictor Relationships	f^2	t Statistics	p Values	95% Confidence Intervals
Confirmation of Expectations → Customer Satisfaction	0.276	1.743	.081	[-.014, .299]
Expectations → Confirmation of Expectations	2.177	4.315*	.000	[.724, .724]
Expectations → Customer Satisfaction	0.110	1.066	.286	[-.194, .138]
Direct Effect of Perceived Trust → Customer Satisfaction	0.091	1.627	.104	[-.009, .087]
Moderating Effect of Perceived Trust on Confirmation of Expectations → Customer Satisfaction	0.010	0.574	.566	[-.089, .040]
Direct Effect of Information Privacy Concerns → Customer Satisfaction	0.058	1.291	.197	[-.245, -.245]
Moderating Effect of Information Privacy Concerns on Confirmation of Expectations → Customer Satisfaction	0.024	0.875	.381	[.051, .037]

t-Statistic Significance: *p < .001

It is important to note that three paths were not assessed due to the removal of perceived performance from the study. This action resulted in expectations → perceived performance, perceived performance → confirmation of expectations, and perceived performance → customer satisfaction no longer being included in the study. Thus, the effect size could not be calculated for those paths.

4.3.5 Predictive relevance (Q^2). After evaluating the effect size (f^2) on the R^2 value, it is prudent to also examine the predictive relevance (i.e., external validity) using Stone-Geisser's Q^2 value (Geisser, 1975; Stone, 1974). This assessment used the Q^2 values calculated through the non-parametric blindfolding option within SmartPLS 3, with an omission distance of seven and the path weighting scheme (Hair et al., 2017). Values larger than zero for a specific reflective endogenous latent variable infer the strength of predictive relevance of a dependent construct. Conversely, a value of zero or below indicates a lack of predictive relevance. Using the cross-validated redundancy approach for calculating the values of both confirmation of expectations (.476) and customer satisfaction (.584), the study results demonstrated Q^2 values which support the model's acceptable predictive relevance.

4.3.6 Effect size (q^2). Given the strong predictive relevance (Q^2) findings described above, the relative impact of the predictive relevance was assessed through the q^2 effect size. The significance of this evaluation was determined by comparing the effect size results against the q^2 guidelines of .35, .15, .02 for strong, moderate, or weak degree of predictive relevance (Chin, 1998; Henseler et al., 2009). Any q^2 value below .02 is deemed to be negligible. The q^2 results displayed in Table 9 identified a strong predictive relevance for expectations → confirmation of

expectations (.908). Whereas confirmation of expectations → customer satisfaction (.100), expectations → customer satisfaction (.069), direct effect of perceived trust → customer satisfaction (.053), and direct effect of information privacy concerns → customer satisfaction (.017) were identified as having a weak predictive relevance. Lastly, the predictive relevance of the moderating effect of information privacy concerns on confirmation of expectations → customer satisfaction (.000) and the moderating effect of perceived trust on confirmation of expectations → customer satisfaction (.000) were assessed as being negligible.

4.4 Results Reporting

This model successfully explains 79.7% of the variance (i.e., $R^2 = .797$) for customer satisfaction. The assessment of the specific hypothesis path relationships in the model involved the calculation of the path coefficient estimates. These estimates, as well as the relevant effect size values are displayed in Table 14. Figure 5 depicts the respective paths and the associated statistics.

Table 14

Significance Testing Results of the Structural Path Coefficients

Hypotheses	Structural Path	Path Coefficients β	t Statistics	p Values	95% Confidence Intervals	f^2 Effect Size	q^2 Effect Size	Hypothesis Results
H1	Expectation → Customer Satisfaction	.291	2.665	.008**	[.067, .494]	0.110	.069	Supported
H4	Expectation → Confirmation of Expectations	.828	29.800	.000*	[.770, .879]	2.177	.908	Supported
H6	Confirmation of Expectations → Customer Satisfaction	.454	4.223	.000*	[.248, .668]	0.276	.100	Supported
Post Hoc Analysis	Direct Effect of Perceived Trust → Customer Satisfaction	.193	3.645	.000*	[-.194, -.037]	0.091	.053	--
H7	Moderating Effect of Perceived Trust on Confirmation of Expectations → Customer Satisfaction	.049	1.368	.171	[-.021, .122]	0.010	.000	Not Supported
Post Hoc Analysis	Direct Effect of Information Privacy Concerns → Customer Satisfaction	-.114	2.827	.005**	[-.215, -.035]	0.058	.017	--
H8	Moderating Effect of Information Privacy Concerns on Confirmation of Expectations → Customer Satisfaction	-.056	1.934	.053	[-.118, -.004]	0.024	.000	Not Supported

Note: *$p < .001$; ** $p < .05$
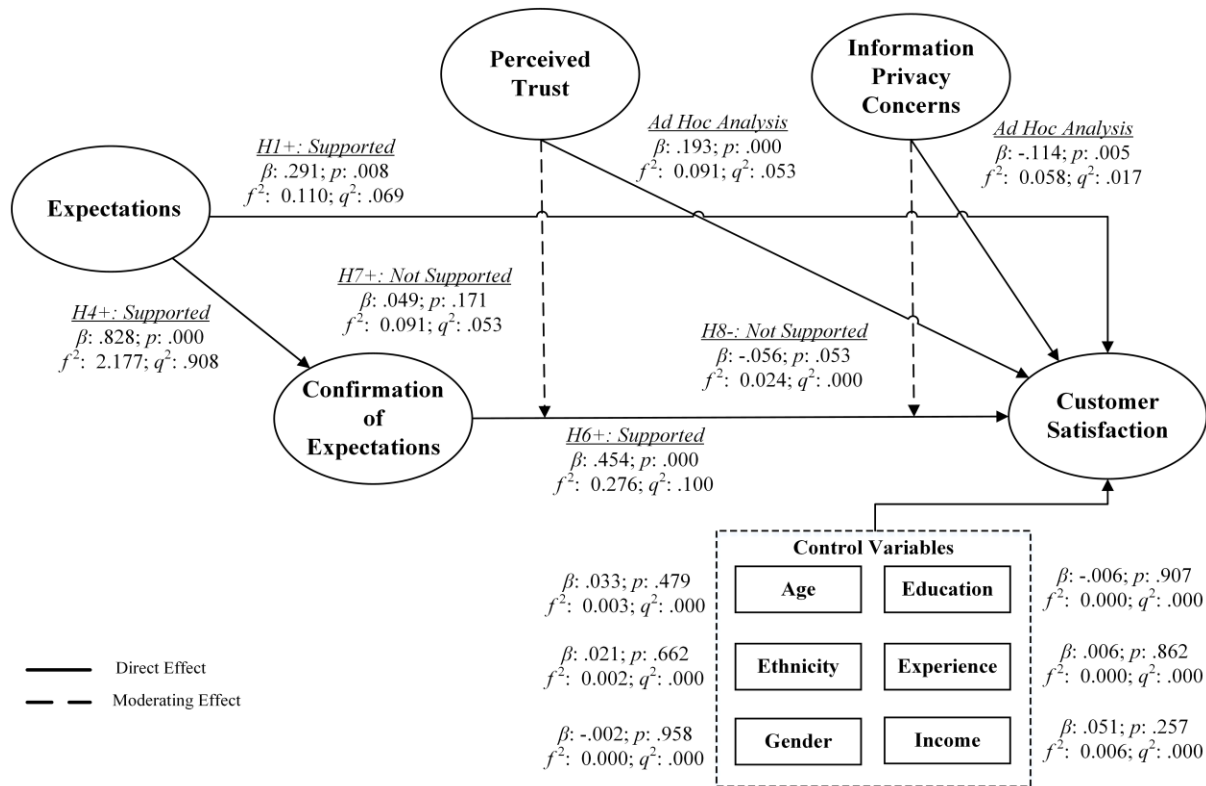
Figure 5. Structural model results.

4.4.1 Estimates for expectations, confirmation of expectations and customer satisfaction. Expectations had a positive and significant effect on customer satisfaction (β = .291, p = .008) in support of H1. However, this path relationship only demonstrated a small f^2 effect size (0.110) and was considered to have a weak predictive relevance (q^2 = .069). Expectations had a positive and significant effect on confirmation of expectations (β = .828, p = .000) in support of H4. This path relationship demonstrated a large f^2 effect size (2.177) with strong predictive relevance (q^2 = .908). Confirmation of expectations had a positive and significant effect on customer satisfaction (β = .454, p = .000) in support of H6. This path

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relationship demonstrated a medium f^2 effect size (0.276) with weak predictive relevance ($q^2 =$ .100).

4.4.2 Moderation effect of perceived trust. The primary objective of this interaction test was to identify and disclose the significance of a moderating effect of the formative construct. The two-stage calculation method was used for the moderation calculation. H7 proposed that the relationship between confirmation of expectations and customer satisfaction was positively moderated by perceived trust. In other words, the higher a respondent's perceived trust, the stronger the relationship between confirmation of expectations and customer satisfaction.

The analysis results were calculated separately for the direct effect and the moderating effect. The direct effect of perceived trust on customer satisfaction was deemed to be a positive and significant effect ($\beta = .193$, $p = .000$). This path relationship demonstrated a small f^2 effect size (0.091) with weak predictive relevance ($q^2 = .053$). The moderating effect of perceived trust on the relationship between confirmation of expectations and customer satisfaction was deemed to be a positive but non-significant effect ($\beta = .049$, $p = .171$). The f^2 effect size (0.091) was determined to be small with negligible predictive relevance ($q^2 = .053$). Thus, the moderating effect results indicate that H7 was not supported.

Since perceived trust is a continuous variable, the moderating effect is measured through a slope of regression line as depicted in Figure 6. The positive slope of the regression line is different at each value of the interaction effect. The upper line represents a higher level of perceived trust. It has a slightly flatter slope as compared to the mean line. The difference

represents the increase in customer satisfaction (.503) as determined by the interaction effect (confirmation of expectations → customer satisfaction (.454) plus the simple effect of perceived trust on confirmation of expectations → customer satisfaction (.049). The lower line represents a lower level of perceived trust. It has a slightly steeper slope as compared to the mean line and slope. The difference represents the decrease in customer satisfaction (.405) as determined by the interaction effect (confirmation of expectations → customer satisfaction (.454) less the simple effect of perceived trust on confirmation of expectations → customer satisfaction (.049).
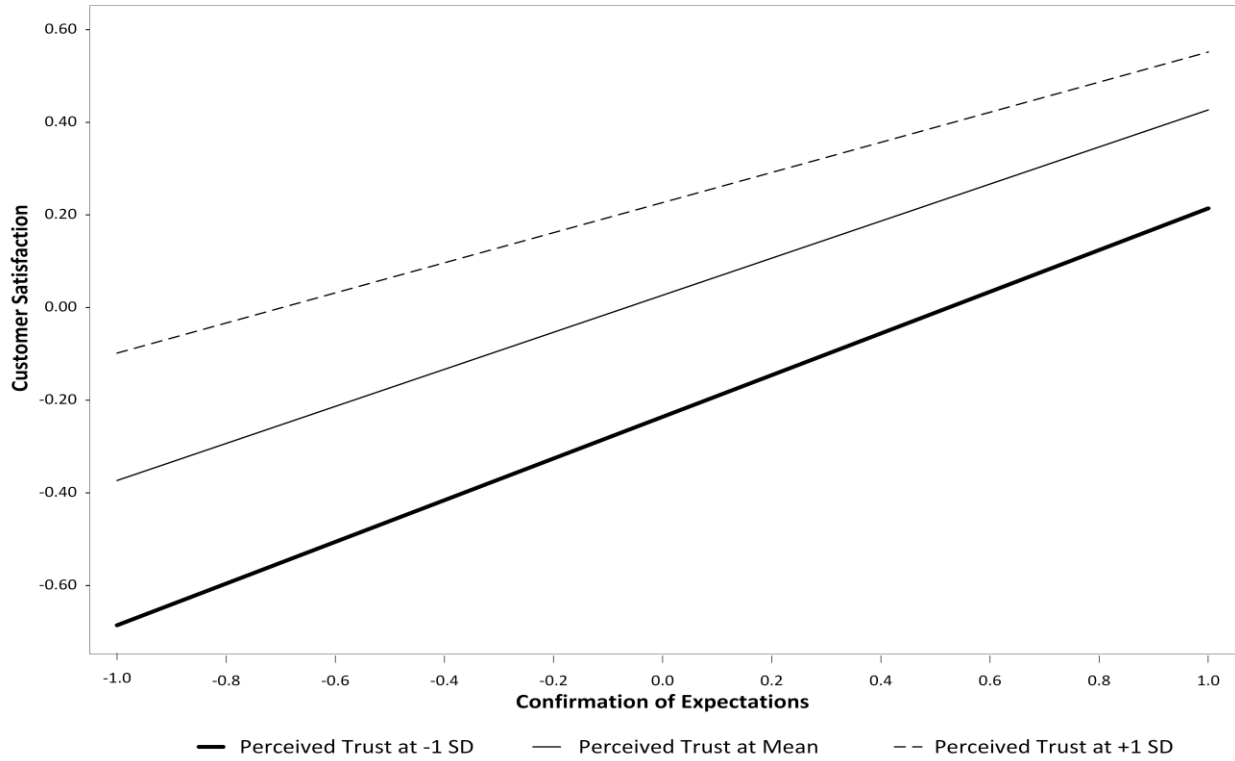

Figure 6. Simple slope analysis of the interaction effect of perceived trust.

4.4.3 Moderation effect of information privacy concerns. Like H7, the interaction term for moderation relationships involving information privacy concerns was statistically tested using the two-stage calculation method. H8 proposed that the relationship between confirmation of expectations and customer satisfaction was negatively moderated by information privacy concerns. In other words, the higher a respondent's information privacy concerns, the weaker the relationship between confirmation of expectations and customer satisfaction.

The analysis results were calculated separately for the direct effect and the moderating effect. The direct effect of information privacy concerns on customer satisfaction was deemed to be a negative and a significant effect ($\beta = -.114$, $p = .005$). This path relationship demonstrated a small f^2 effect size (0.058) with weak predictive relevance ($q^2 = .017$). The moderating effect of information privacy concerns on the relationship between confirmation of expectations and customer satisfaction was deemed to be a negative and non-significant effect ($\beta = -.056$, $p = .053$). The f^2 effect size (0.024) was determined to be small with negligible predictive relevance ($q^2 = .000$). Thus, the moderating effect results indicate that H8 was not supported.

Since information privacy concerns is a continuous variable, the moderating effect is measured through a slope of regression line as depicted in Figure 7. The negative slope of the regression line is different at each value of the interaction effect. The upper line represents a higher level of information privacy concerns. It has a slightly flatter slope as compared to the mean line. The difference represents the decrease in customer satisfaction (.447) as determined

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by the interaction effect (confirmation of expectations → customer satisfaction (.454) plus the

simple effect of perceived trust on confirmation of expectations → customer satisfaction

(-.056). The lower line represents a lower level of information privacy concerns. It has a slightly

steeper slope as compared to the mean line and slope. The difference represents the decrease in

customer satisfaction (.461) as determined by the interaction effect (confirmation of expectations

→ customer satisfaction (.454) less the simple effect of perceived trust on confirmation of

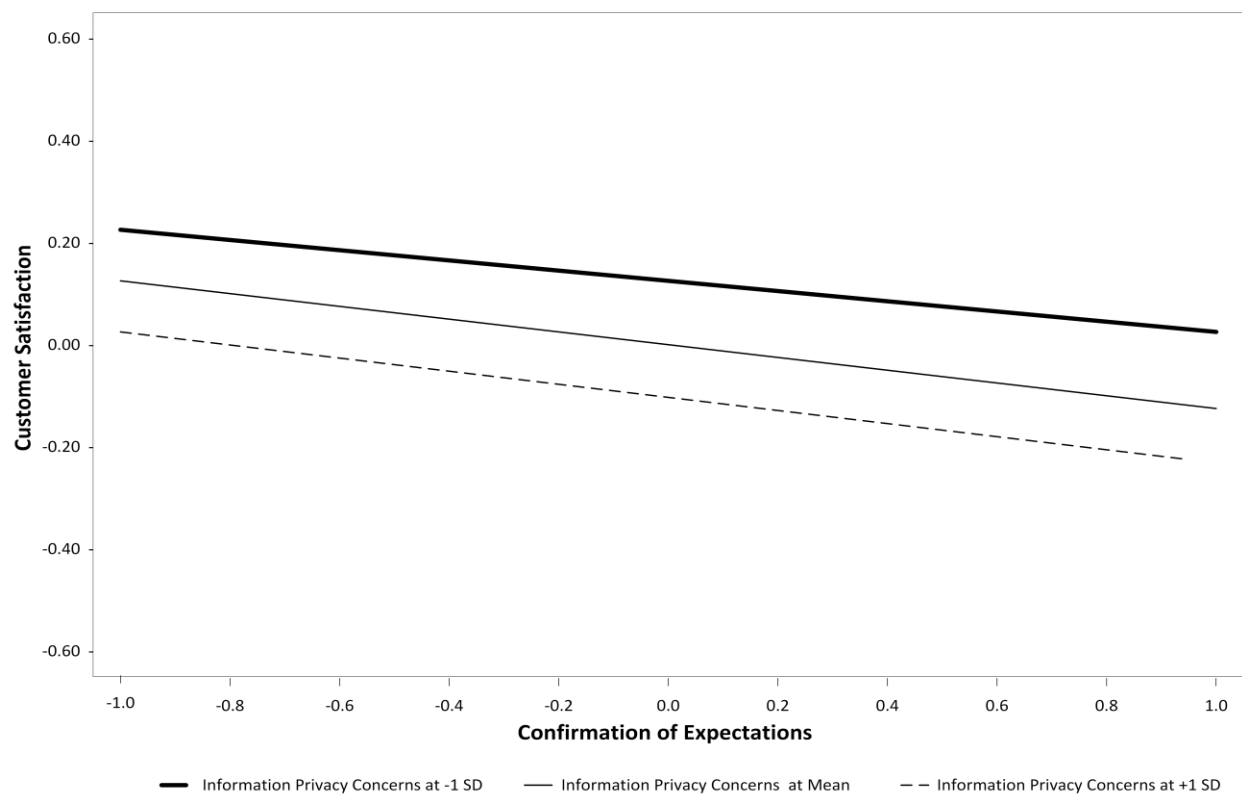expectations → customer satisfaction (-.056).

Figure 7. Simple slope analysis of the interaction effect of information privacy concerns

4.4.4 Path coefficient multigroup analysis. As previously identified in the

sample characteristics discussion (see 4.1.3), the sample is comprised of a diverse group of

respondents with differing characteristics and experiences. While many respondents may have

similar perceptions and observations, assumptions of homogeneity are unrealistic. Instead,

individuals are likely to be heterogeneous in their perceptions and evaluations (Sarstedt,

Henseler, & Ringle, 2011). The multigroup analysis (MGA) functionality within SmartPLS 3

was used to analyze the differences offered through the control variables. The MGA calculations

utilized the default PLS settings, complete bootstrapping with a 5,000 subsample, percentile

bootstrap confidence interval method, and the omnibus test of group differences (OTG) based

upon absolute values. The path coefficient difference results are displayed in Table 15. No

subgroup difference was found to be statistically significant at $p < 0.05$.

4.4.5 Importance-performance analysis. The importance-performance matrix analysis

(IPMA) within SmartPLS 3 identifies the relative importance of constructs in explaining other

constructs in the structural model. These analysis results identify the determinants with a

relatively high importance and relatively low performance for a particular endogenous construct

(Hock, Ringle, & Sarstedt, 2010; Ringle, Ringle, Sarstedt, & Sarstedt, 2016). The importance

score reflects the unstandardized total effects (i.e., direct and indirect effect) for each predictor

variable (Slack, 1994). The performance score was calculated using the latent variable scores for

the unstandardized outer weights for each construct. These scores were then rescaled on a 0 - 100

performance score for that construct (Hock et al., 2010; Ringle et al., 2016).

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Table 15.

Path Coefficient Multigroup Analysis

| | | Age | | | | | Education | | | | |
		Gen Z + Millennials	Gen X or older	β Difference	t Statistic	p Value	Bachelor or less	Advanced	β Difference	t Statistic	p Value
	n =	88	156				151	93			
Confirmation → Satisfaction		.433	.334	.080	0.566	.572	.391	.412	.025	0.184	.854
Expectation → Satisfaction		.219	.398	.166	1.085	.279	.319	.219	.010	0.071	.944

| | | Ethnicity | | | | | Experience | | | | |
		Caucasian	Other	β Difference	t Statistic	p Value	2 Years or less	> 2 Years	β Difference	t Statistic	p Value
	n =	197	47				143	101			
Confirmation → Satisfaction		.356	.380	.026	0.157	.875	.340	.437	.091	0.638	.524
Expectation → Satisfaction		.382	.158	.248	1.533	.127	.390	.265	.117	0.807	.421

| | | Gender | | | | | Income | | | | |
		Male	Female	β Difference	t Statistic	p Value	Low/Middle (< $80k)	High (> $80k)	β Difference	t Statistic	p Value
	n =	121	123				87	157			
Confirmation → Satisfaction		.406	.335	.057	0.422	.674	.334	.400	.070	0.473	.636
Expectation → Satisfaction		.318	.334	.004	0.026	.980	.253	.319	.055	0.347	.729

| | | Digital Assistant | | | | |
		Siri	Other	β Difference	t Statistic	p Value
	n =	175	69			
Confirmation → Satisfaction		.391	.317	.083	0.551	.582
Expectation → Satisfaction		.335	.397	.065	0.426	.670

No path coefficient absolute difference is significant at $p < .05$ or less. Confirmation = Confirmation of Expectations; Satisfaction = Customer Satisfaction

The importance and performance scores are more easily interpreted once displayed on a scatter plot (Figure 8). Lines representing the mean importance score and the mean performance score for all constructs were also displayed to create a four-quadrant grid. Generally, constructs in the lower right area (i.e. above average importance and below average performance) are of highest interest to achieve improvement, followed by the higher right, lower left and, finally, the higher left areas. As a result, the importance-performance visualization map provides guidance for the prioritization of marketing and managerial activities of high importance for customer satisfaction, but which require performance improvements. The results also indicate the total effect impact of increasing the performance score by one unit.
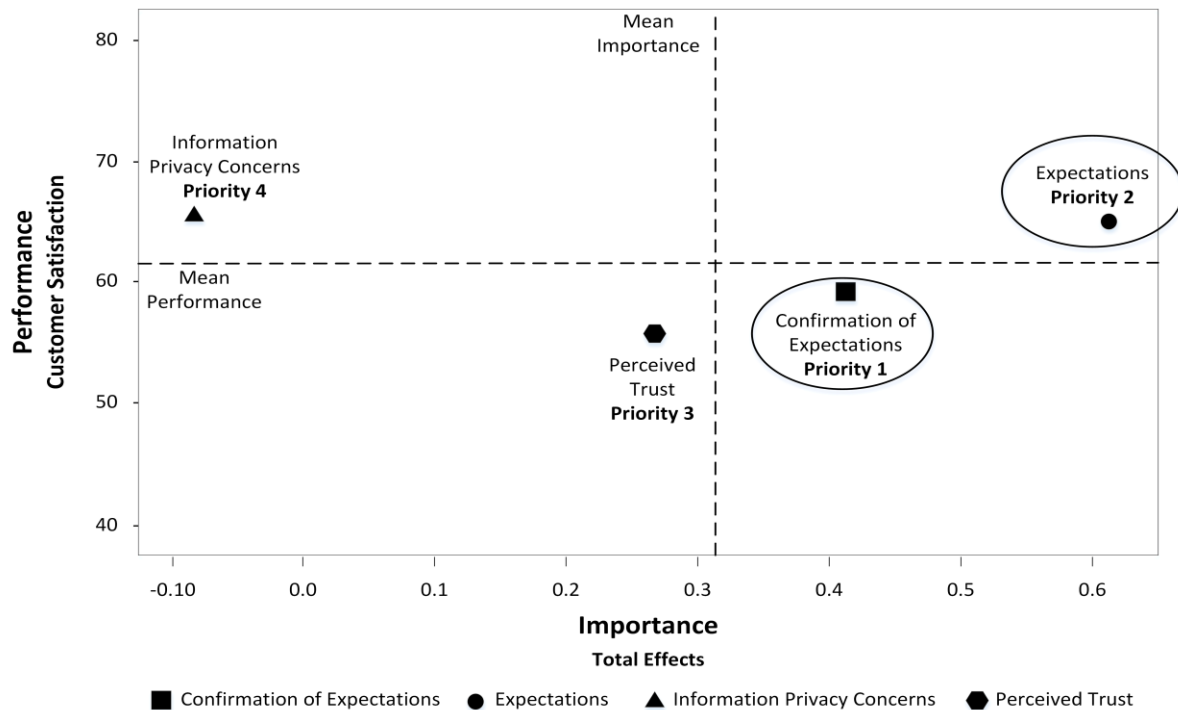

Figure 8. Importance-performance map for customer satisfaction

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Based upon the grid quadrant prioritization approach, confirmation of expectations is the top priority for action. It has an above average importance (0.413) and a below average performance score (59.053). Thus, there is significant room for improving its performance. The second priority is expectations. It has an above average importance score (0.650) and an above average performance score (61.823). Perceived trust is the third priority. It has both a below average importance score (0.266) and a below average performance score (55.699). Thus, there is significant room for improvement but the lower total effect score limits its contribution to improving the performance score. Information privacy concerns are the lowest priority. It has a below average importance score (-0.081) and an above average performance score (66.572). It has the highest performance score among all constructs as well as the lowest importance score. Given the low total effects, it offers little contribution to improving the performance score.

When the IPMA sub-group results were analyzed using a similar grid quadrant prioritization approach, each sub-group identified confirmation of expectations as its top priority except for 'Non-Siri Digital Assistants'. Expectations was identified as its top priority for that sub-group. Similarly, each sub-group identified expectations as its second priority except for 'Females' and 'Non-Siri Digital Assistants'. 'Females' identified perceive trust as its second priority. 'Non-Siri Digital Assistants' identified confirmation of expectations as its second priority.

In addition to identifying priorities, the analysis also identified some major

discrepancy gaps for performance scores between peer groups. 'Gen Z + Millennials' has a 9.7%

discrepancy gap for expectations performance as compared to its peer group. 'Experience ≤ 2

Years' also has an 11.4% underperformance gap for expectations performance against its peer

group. 'Low/Middle Income (< $ 80k)' has a 15% underperformance gap for both confirmation of

expectations and expectations when compared against its peer group. The identification of these

performance gaps provide additional guidance to assist management in prioritizing sub-group

activities for high importance activities impacting customer satisfaction.

4.5 Summary of Results

The model assessment substantiated the reliability and validity of the PLS path modeling

results. The empirical analysis provided support for most of the hypothesized cause-effect

relationships depicted in the model. The presented theoretical concept explained 79.7% of user

satisfaction with digital assistants. Analysis of path coefficients identified that there are

differences between subgroups but that the differences were not statistically different.

Examination of the pertinent latent variables identified that expectations was the most important

area of influence for customer satisfaction. In a similar manner, constructs of somewhat lesser

areas of influence were confirmation of expectations and perceived trust. Surprisingly,

information privacy concerns exerted a comparatively low importance impact on customer

satisfaction.

Table 16

Importance-Performance Matrix for Customer Satisfaction

Latent Variable	Total Effect	Performance	Total Effect	Performance	Total Effect	Performance	Total Effect	Performance
	Gen Z + Millennials (n = 88)		Bachelor's Degree or less (n = 151)		Caucasian (n = 197)		Experience ≤ 2 Years (n = 143)	
Confirm	**0.472**	**57.768**	**0.424**	**59.752**	**0.387**	**59.107**	**0.373**	**57.639**
Expect	**0.470**	**58.219**	**0.662**	**62.493**	**0.662**	**61.526**	**0.613**	**59.035**
Privacy	-0.177	63.642	-0.118	64.206	-0.129	63.998	-0.065	66.364
Sat	0.000	56.846	0.000	60.879	0.000	61.073	0.000	59.614
Trust	0.306	55.391	0.237	59.537	0.220	58.827	0.210	58.203
	Gen X and older (n = 156)		Advanced Degree (n = 93)		Non-Caucasian (n = 47)		Experience > 2 Years (n = 101)	
Confirm	**0.357**	**59.763**	**0.463**	**57.910**	**0.436**	**58.811**	**0.469**	**61.056**
Expect	**0.716**	**63.840**	**0.555**	**60.821**	**0.415**	**63.252**	**0.690**	**65.774**
Privacy	-0.086	66.428	-0.127	67.400	0.014	71.398	-0.180	64.091
Sat	0.000	63.484	0.000	61.354	0.000	61.043	0.000	63.127
Trust	0.195	61.065	0.316	58.176	0.387	59.820	0.254	60.172
	Males (n = 121)		Low/Middle Income (< $ 80k) (n = 87)		Siri Digital Assistant (n = 175)		Constructs (n = 244)	
Confirm	**0.440**	**60.496**	**0.406**	**56.807**	**0.430**	**59.377**	**0.413**	**59.053**
Expect	**0.618**	**62.473**	**0.490**	**56.281**	**0.619**	**62.419**	**0.650**	**61.823**
Privacy	-0.074	68.483	-0.232	64.670	-0.093	64.896	-0.081	66.572
Sat	0.000	62.034	0.000	56.442	0.000	60.286	0.000	61.065
Trust	0.207	59.284	0.345	56.304	0.254	58.070	0.266	60.787
	Females (n = 123)		Higher Income (> $80k) (n = 157)		Non-Siri Digital Assistants (n = 69)			
Confirm	**0.365**	**57.662**	**0.412**	**65.841**	**0.331**	**58.209**		
Expect	0.607	61.157	**0.662**	**64.898**	**0.689**	**60.342**		
Privacy	-0.138	62.413	-0.064	63.655	-0.179	66.760		
Sat	0.000	60.140	0.000	60.522	0.000	63.085		
Trust	**0.305**	**58.757**	0.201	60.296	0.157	61.423		

Note: Bolded scores reflect the top two priorities for that control variable sub-group.

CHAPTER 5

DISCUSSION, MANAGERIAL IMPLICATIONS, AND CONCLUSION

Chapter 5 provides a more in-depth analysis and explanation of hypothesized relationships from the previous chapter and consists of four sections. First, the results presented in Chapter 4 are further elaborated upon to include additional depth. Second, implications for theory are reviewed and discussed. Third, managerial implications stemming from study results are discussed. Fourth, limitations of the study are presented, and future research opportunities are suggested.

5.1 Discussion of Results

Examining customer satisfaction has been a key topic in marketing and information technology literature for quite some time. However, the emergence of AI supported digital assistants has served as a disruptive change agent for established marketing strategies and processes. Businesses must now quickly understand and respond to the changes in attitudes facilitated by customer exposure to digital assistants (V. Kumar, A. Dixit, R. R. G. Javalgi, & M. Dass, 2016). In response to changing attitudes, businesses have begun committing significant capital and resources towards the integration of digital assistants within their infrastructure. While this investment may yield significant productivity gains, this study explored if customers

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were satisfied with digital assistants. The results predicted 79.7% of the variance in customer satisfaction with digital assistants.

Hypothesis 1 predicted that expectations would be positively related to customer satisfaction. This relationship was confirmed suggesting that for some users, customer satisfaction with digital assistants is evaluated through the assimilation effect associated with the user's expectations. This assimilation effect is generally reinforced through media and expert reviews of digital assistants. However, the results of this study also showed the assimilation effect to be generally small and to have a non-significant overall effect. These results depict a smaller segment of users evaluating digital assistants through the assimilation effect. Instead, most users appear to want confirmation that their expectations are being met.

Hypothesis 4 predicted that expectations would be positively related to confirmation of expectations. This relationship was confirmed suggesting that user expectations of digital assistants were quite positive. The results of this study showed the relationship between these two constructs as being large and possessing a significant effect. Given the level of advertising and promotions for digital assistants and the rapid level of product adoption, this result is not unexpected. However, this relationship is so high that it is quite possible that expectations may be too high. If so, then these expectations may be approaching the halo effect zone. Generally, if a firm's product enters this halo effect zone, further product adoption will begin to slow as user and media negative reviews begin to become more prevalent.

Hypothesis 6 predicted that confirmation of expectations would be positively related to customer satisfaction. This relationship was confirmed suggesting that for many users, customer satisfaction with digital assistants was evaluated through the contrast effect associated with confirming the user's expectations. As previously discussed, most users appear to want

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confirmation that their expectations are being met. The study results generally align with this observation.

Hypothesis 7 predicted that perceived trust would positively moderate the relationship between confirmation of expectations and customer satisfaction. This study confirmed that the higher a respondent's perceived trust, the stronger the relationship between customer satisfaction and confirmation of expectations. Yet, based upon the study results, both the direct and moderating effects of perceived trust have little to no predictive value. On the surface, such a finding might lead managers to believe that there is no need to focus upon this construct. However, most of the digital assistants identified by the survey respondents were associated with strong brands. Given the strength of these brands, it is possible that perceived trust was heavily weighted towards institutional trust and has already been factored into the user's expectations in the form of brand satisfaction. Most successful companies have devoted significant resources and investment over a long period of time to establish high trust. These firms typically identify establishing a strong trust relationship with their customers as part of its core operating principles. Managers must continue to reaffirm the principles of trust with customers in every interaction. Future studies should explore the influences of brand satisfaction and other trust building elements.

Hypothesis 8 predicted that information privacy concerns would negatively moderate the relationship between confirmation of expectations and customer satisfaction. This study confirmed that higher levels of information privacy concerns weaken the relationship between confirmation of expectations and customer satisfaction. Yet, like perceived trust, both the direct and moderating effects of information privacy concerns have little to no predictive value. If managers interpret these findings to be an indication that only limited focus is required for this

construct, then they are likely introducing significant risk to the firm. The lack of predictive value identified in the study may be due to high levels of brand satisfaction. It may have already been factored into the user's expectations. Thus, given the magnitude of potential risk, managers must invest in physical and systematic safeguards of personal information. In addition, firms must provide customers with readily accessible tools which allow for sufficient transparency to that user as to how their personal information is being used. Future studies should explore the influences of brand upon information privacy related service failures.

5.2 Implications for Theory

This study focused upon examining two primary gaps in the literature. The first gap was associated with examining the alignment of digital assistant user expectations and performance perceptions towards customer satisfaction. The second gap was linked to exploring the cognitive considerations of information privacy concerns and perceived trust towards the expectations confirmation theory relationships. As an outcome of examining these gaps, three contributions to the literature were identified.

First, to the best of our knowledge, this study is one of the first attempts to empirically examine the theoretical foundations for customer satisfaction as related to a new AI technology platform. In the past, this focus has been conveyed to the introduction of new technologies. Research, however, has yet to explore this focal point for AI technologies due to the relative infancy of AI-supported digital assistants. This study filled the gap in research as it confirmed the relevance and significance of core satisfaction concepts to this new technology.

Customer satisfaction has long been a focal point of extant marketing and information technology literature. Thus, the second contribution extends the research on ECT relationships

with these fields of research. In particular, this study extends the findings of Bhattacherjee and Lin (2015); Guo et al. (2015); Lankton et al. (2014) and Lin et al. (2017). Each of these studies provides supporting linkage of different marketing and technology applications to customer satisfaction and related outcomes through the ECT model. This study adds another dimension of utilization to these genera of research.

Lastly, with the explosive growth of digital and advance technology capabilities, information privacy and trust implications represent important topics within the disciplines of marketing and IT. Individuals are increasingly challenged with managing the complex trade-offs of trusting technology innovation and accepting the risks of violations of information privacy (Alessandro Acquisti, Laura Brandimarte, & George Loewenstein, 2015). To the best of our knowledge, this study is one of the first attempts to empirically examine the influences of trust and information privacy concerns within the context of digital assistants.

5.3 Implications for Practice

5.3.1 Creating a cycle of high customer satisfaction. The findings from this study provide actionable insights to managers, which allow them to have a better understanding of the drivers of satisfaction and the magnitude of customer satisfaction with digital assistants. As with most new technology launches, it is critical that firms invest significant resources to promote its products. This promotion must ensure that users have a level of awareness which is appropriately matched to realistic performance levels, as well as relevant and meaning knowledge of the product features, functions and benefits. Firms typically utilize advertising, promotions, product tutorials and demonstrations and other marketing tactics to capture and influence the individual's mindset to purchase and use the product. Because expectations represent of a dynamic

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compilation of experience, knowledge, and desires, these efforts cannot cease after the product purchase occurs. Rather, the cycle of awareness building and education must extend across the entire product lifecycle as competitors can quickly replicate and improve technology to displace the product of your firm.

The current generation of digital assistant is based upon new and advanced AI capabilities. The leading digital assistant providers are rapidly deploying new capability skills. However, because of the rapid deployment pace and the diversity of skill capabilities, it is highly likely that most individuals are not fully aware of these skills or how to use them. Management should focus priorities on assisting users become aware of these new skills and provide relevant examples of how the application skills can be used to meet user needs. By doing so, users will gain a greater understanding of how digital assistants can provide newer relevant information and efficiently perform important tasks for them.

Management should also focus priorities on assisting users with understanding how the average person can use digital assistants to perform more than just mundane tasks with relative ease. By doing so, it expands opportunities for users to more fully integrate digital assistant into their everyday life. If this occurs, then digital assistants move from a 'cool new technology' evaluation to a necessary everyday tool with a high level of customer satisfaction which tends to be more frequently recommended to friends and family.

While improvement can and should occur with managing user expectations, firms must exercise caution and not create unrealistic expectations. If a halo effect becomes prevalent, then users might experience positive disconfirmation if the digital assistant performance fails to meet or exceed these high expectations. Thus, impacted firms might experience an increase in user

defections to competitor products which promote expectations more aligned with that of the defecting user's expectations.

5.3.2 Perceptions of trust. Digital assistants represent one of the most visible applications involving an AI-based tech stack and are a key disrupter for digital transformation. Their adoption rate continues to grow, and they will likely be paired with other future AI applications. Each generation of digital assistants is expected to make it even easier for people to have personalized brand experiences without having any actual direct human interaction. By 2020, the digital disruption associated with AI is expected to enable the average person to have more conversations with digital assistants and other AI applications than with their immediate family (Levy, 2016, October 18). Cohn and Wolfe (2017) found that 75% of consumers would readily share their personal information with brands they trust. Perhaps this explains why the study also identified that the top five authentic and trustworthy firms to be Amazon, Apple, Microsoft, Google and Paypal. Interestingly, Facebook only ranked 92nd (even before knowledge of the Russian ad controversy became public knowledge) likely due to residual negative fallout from some past trust-compromising product features and policies. Facebook's ranking tends to illustrate the fact that size and dominance do not guarantee consumer trust.

Individual beliefs provide the foundation for a customer's perception of trust. Because this foundation is not based on hard facts, trust can be fragile and subjective (Yannopoulou et al., 2011). Managers must recognize that trust is an important performance item for most control variable subgroups. However, the trust effects are 32% higher for females than males and 42% higher for low/middle income users than higher income users. Similarly, the length of experience with digital assistants does matter. Trust effects are 17% higher for users with greater than 2 years of experience than those with less experience. Such findings suggest that managers should

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establish gender-specific programs, communications, and user experiences that focus upon important trust topics associated with their products and services. In addition, managers must fight the temptation of catering programs to the higher income. While they may have higher discretionary spending, the adverse effects of trust erosion are more impactful for the low/middle income group. Finally, managers may view that longer tenure digital assistant users might require less attention than more less tenured users. Such a viewpoint could lead to disastrous outcomes. Longer tenured users have significant foundational experiences not shared by others. These finding highlights that educational programs, communications, and user experiences are a life-long need and not limited to newer users. Further research is needed to more fully understand the trust building process (Luhmann & Schorr, 1979) in AI environments. In the meantime, managers must continue to reaffirm the principles of trust with customers in every interaction.

 5.3.3 Perceptions of information privacy. Across all technology-dependent business sectors, customers are increasingly concerned about the vulnerability of their personal data and the possibility of it being compromised or misused. A recent study identified substantive negative outcomes associated with data breaches including (but not limited to) brand reputation, stock valuation, and customer churn and revenue loss. "Specifically, the study found that the stock value index of 113 companies declined an average of five percent the day the breach was disclosed and experienced up to a seven percent customer churn. What's more, thirty-one percent of consumers impacted by a breach stated they discontinued their relationship with an organization that experienced a data breach" (Centrify, 2017, May 15). Users want and expect that the personal information collected by a digital assistant is confidential, protected and used within the parameters that they approved. Protecting user information privacy is necessary for

expanding the integration of digital assistants into everyday lifestyles. Managers must recognize that privacy is the top ranked IPMA performance item for both males and females. However, the effects of information privacy concerns are 46% higher for females than males and 72% higher for low/middle income users than higher income users. Similarly, the length of experience with digital assistants does matter. The negative effects are 64% higher for users with greater than 2 years of experience than those with less experience. Like trust, such findings suggest that managers establish gender-specific programs, communications, and user experiences, which focus upon important privacy topics associated with their products and services. Focus should not be limited to higher income groups nor to less-tenured users. At a minimum, these findings highlight that educational programs, communications, and user experiences are needed for all to reaffirm user confidence that their information privacy concerns are being addressed. Certainly, this topic is complex and far-reaching. Thus, further research is needed to more fully understand the impacts of information privacy concerns in AI environments.

5.4 Limitations and Future Research

As with any empirical research, this study has certain limitations. These limitations need to be acknowledged when considering the findings of this study. These limitations may also create interesting opportunities for future research.

5.4.1 Continuation intention. The study sample largely consisted of current (and continuing) users of digital assistants plus a small group of never users. Users who have discontinued use of digital assistants were not included due to the limitations of identifying and contacting such participants. It is reasonable to assume that inclusion of such sample participants would likely lower that overall satisfaction relationship scores. It could also unmask other

predictor variables, which might influence the satisfaction evaluation process. Future studies could explore the dimensions of commitment and continuation intention of existing users as well as why prior users have discontinued use of digital assistants.

Deep knowledge of commitment type differences and characteristics allow managers to avoid negative performance traps associated with homogeneous program designs. Instead, programs and resources can be developed and supported that complement these differences. It is equally important to gain insights from former users, as it is important to understand why these users no longer use the digital assistant. Pairing learning from both current users and former users might yield important future managerial actions that will reinforce user loyalty, highlight competitive vulnerabilities, or direct new product features or capabilities for digital assistants. To the extent that the antecedents and resources used to optimize each type of commitment are likely to vary among digital assistant users, managers will need to have a differentiated and relevant implementation and communications strategy.

5.4.2 Brand satisfaction. While the instrument invited respondents to identify any digital assistant used, only those associated with established and strong brands were identified (i.e., Apple's Siri, Amazon's Alexa and Echo, Google's Google Now and Google Home, Microsoft's Cortana, Samsung's Bixby and Facebook's M). These brands have strong images with established perceptions of trust and respect for individual privacy. In addition, these firms do not have major, unrepaired damages associated with large data breaches. Thus, future research should explore if brand satisfaction impacts expectations, trust and privacy concerns for digital assistants.

5.4.3 Influence of self-efficacy. Extant literature has established the importance of customer participation in the achievement of higher customer satisfaction and productivity gains (Chi Kin Yim, Kimmy Wa Chan, & Simon SK Lam, 2012). Self-efficacy considerations

associated with personal confidence, conviction, skill/knowledge attainment, and pride can influence how users perceive their mastery of a digital assistant. Thus, it is reasonable to believe that such beliefs can substantively impact satisfaction assessments for digital assistants. Future research should assess the relative importance of self-efficacy in the adoption and integration of digital assistants into the user's lifestyle. These insights would assist managers in functional product design as well as in program structures and content to support knowledge attainment associated with digital assistants.

      5.4.4 Longitudinal study. The cross-sectional data collected for this study reflected only one point in time. Rarely can such a snapshot fully capture the dynamic and interactive nature of many relationship variables. Any assumption that these study results are reflective of future generations of digital assistants would be speculative at best. There is no empirical study to support such an assumption. Given the rapid and continuing advancements in digital assistants and the underlying AI technologies, this current study cannot be viewed as a predictor of where this technology may be headed. Nor can this current study explicitly predict customer behavior and evolving expectations. New developments in technology can change consumer behavior and habits. Not long ago, telephone calls were used to quickly gather updates about changes in the lives of family and friends. Next, email quickly replaced the dominance of telephone calls in such matters. Lately, social media has become the dominant communication tool. Each step in that technology migration journey provoked changes in consumer behavior, habits and expectations. While it is sometimes difficult to directly identify the immediate impact of technology changes, overtime these changes become more visible as the technology adoption rate increases. It is reasonable to expect new such changes associated with digital assistants. Future studies should endeavor to collect longitudinal data to provide a fuller view of the

stability of customer expectations and customer satisfaction perceptions involving digital assistants overtime as well as their contributions to firm profitability.

5.5 Conclusion

Customer satisfaction has long been a focal point of extant marketing and information technology literature. This study advances our understanding of the theoretical foundations for customer satisfaction as related to a new AI technology platform involving digital assistants. Given the relative infancy of current digital assistant adoption and utilization, there is limited empirical work directly related to the consumer experience and customer satisfaction. This study affirmed the role of the expectations confirmation process in the customer satisfaction evaluation. Further, it provides insights that allow managers to understand the drivers and the degree of customer satisfaction with digital assistants. It also underscores the importance of establishing strong user perceptions of trust while also addressing user concerns about information privacy. These elements can influence customer satisfaction evaluations.

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APPENDIX A

CONSTRUCT SCALES

Description	Measurement	

Customer Satisfaction

S1	Overall, how satisfied are you with your digital assistant?	Extremely displeased	Extremely pleased
S2	Overall, how satisfied are you with your digital assistant?	Extremely frustrated	Extremely contented
S3	Overall, how satisfied are you with your digital assistant?	Extremely miserable	Extremely delighted
S4	Overall, how satisfied are you with your digital assistant?	Extremely dissatisfied	Extremely satisfied

Expectations

Usefulness

EU1	Based on my experience so far, I expect that my digital assistant will increase my productivity.	Strongly disagree	Strongly agree
EU2	Based on my experience so far, I expect that my digital assistant will improve my performance.	Strongly disagree	Strongly agree
EU3	Based on my experience so far, I expect that my digital assistant will enhance my effectiveness.	Strongly disagree	Strongly agree
EU4	Based on my experience so far, I expect that my digital assistant will be useful.	Strongly disagree	Strongly agree
EU5	Based on my experience so far, I expect that my digital assistant will allow me to complete tasks more quickly.	Strongly disagree	Strongly agree
EU6	Based on my experience so far, I expect that my digital assistant will make it easier to complete my tasks.	Strongly disagree	Strongly agree

Perceived Performance

Usefulness

PU1	Based on my experience with my digital assistant, it increased my productivity.	Strongly disagree	Strongly agree
PU2	Based on my experience with my digital assistant, it improved my performance.	Strongly disagree	Strongly agree
PU3	Based on my experience with my digital assistant, it enhanced my effectiveness.	Strongly disagree	Strongly agree
PU4	Based on my experience with my digital assistant, it was useful.	Strongly disagree	Strongly agree
PU5	Based on my experience with my digital assistant, it allowed me to complete tasks more quickly.	Strongly disagree	Strongly agree
PU6	Based on my experience with my digital assistant, my tasks were easier to complete.	Strongly disagree	Strongly agree

Confirmation of expectations

Usefulness

CU1	My increased productivity due to my digital assistant was _____ than expected.	Much worse than expected	Much better than expected
CU2	My improved performance due to my digital assistant was _____ than expected.	Much worse than expected	Much better than expected
CU3	My enhanced effectiveness due to my digital assistant was _____ than expected.	Much worse than expected	Much better than expected
CU4	The usefulness of my digital assistant was _____ than expected.	Much worse than expected	Much better than expected
CU5	My ability to complete tasks more quickly with my digital assistant was _____ than expected.	Much worse than expected	Much better than expected
CU6	The ease with which I complete my tasks with my digital assistant was _____ than expected.	Much worse than expected	Much better than expected

Perceived Trust

Competence

TC1	My digital assistant is like a real expert in providing answers.	Strongly disagree	Strongly agree
TC2	My digital assistant has the expertise to understand my needs and preferences.	Strongly disagree	Strongly agree
TC3	My digital assistant can understand my needs and preferences.	Strongly disagree	Strongly agree
TC4	My digital assistant had good knowledge about the questions and subjects that I am interested in.	Strongly disagree	Strongly agree
TC5	My digital assistant matches my needs to the information available.	Strongly disagree	Strongly agree

Benevolence

TB1	My digital assistant puts my interests first.	Strongly disagree	Strongly agree
TB2	My digital assistant keeps my interests in mind.	Strongly disagree	Strongly agree
TB3	My digital assistant wants to understand my needs and preferences.	Strongly disagree	Strongly agree
TB4	My digital assistant helps me know more about the topic of my inquiry.	Strongly disagree	Strongly agree

Integrity

TI1	My digital assistant provides unbiased information and recommendations.	Strongly disagree	Strongly agree
TI2	My digital assistant provides honest answers.	Strongly disagree	Strongly agree
TI3	I consider my digital assistant to possess integrity.	Strongly disagree	Strongly agree
TI4	My digital assistant is not linked to a specific company, so it is unbiased.	Strongly disagree	Strongly agree

Information Privacy Concerns

General Privacy Concerns

PC1	Compared to others, I am more sensitive about the way online companies handle my personal information.	Strongly disagree	Strongly agree
PC2	To me, it is most important to keep my privacy intact from online companies.	Strongly disagree	Strongly agree
PC3	I am concerned about threats to my personal privacy today.	Strongly disagree	Strongly agree
PC4	I believe other people are too much concerned with online privacy issues.	Strongly disagree	Strongly agree
PC5	I am concerned about threats to my personal privacy today.	Strongly disagree	Strongly agree

Perceived Privacy Protection

PT1	I am concerned that my digital assistant is collecting too much personal information from me.	Strongly disagree	Strongly agree
PT2	I am concerned that my digital assistant provider will use my personal information for other purposes without my authorization.	Strongly disagree	Strongly agree
PT3	I am concerned that my digital assistant provider will share my personal information with other entities without my authorization.	Strongly disagree	Strongly agree
PT4	I am concerned that unauthorized persons (i.e. hackers) have access to my personal information.	Strongly disagree	Strongly agree
PT5	I am concerned about the privacy of my personal information while using a digital assistant.	Strongly disagree	Strongly agree
PT6	I am concerned that my digital assistant provider will sell my personal information to others without my permission.	Strongly disagree	Strongly agree

APPENDIX B

INTERNAL REVIEW BOARD APPROVAL

UNIVERSITY OF **DALLAS** **Institutional Review Board**

June 30. 2017

Thomas Michael Brill
Satish & Yasmin Gupta College of Business
University of Dallas
Irving, TX 75062

RE: IRB expedited review of proposal #2017040

Dear Thomas Brill:

Thank you for submitting your research proposal for prior approval by the Institutional Review Board (IRB). Your proposal was reviewed under the procedure for expedited review, as it poses minimal risk for participants. You indicate that steps will be taken to obtain informed consent from participants as well as the steps to be taken to protect participants' identities. The reviewer(s) recommended approval of your request to complete Phase 1 of the research described in your proposal under the conditions stated above and under the guidance of your instructor.

As you complete your research, please keep in mind that substantive changes to the research method or participant population will require IRB review, and that any participant injuries or complaints must be reported to the IRB at the time they occur. The IRB policies require that you provide an annual report of the progress of this research project, or a report upon completion, whichever occurs first.

On behalf of the members of the IRB, I wish you success in this project.

Sincerely,

Gilbert Garza, Ph.D.
IRB Chair

1845 East Northgate Drive, Irving, TX 75062-4736