Mirror, mirror on the wall: The factors that influence consumers' behavioural intention to use smart mirrors in Canada

by

Chelsea Heney

Honours BComm, Ryerson University, Toronto, 2012

A thesis

presented to Ryerson University

in partial fulfillment of the

requirements for the degree of

Master of Science in Management

in the program of Master of Science in Management

Toronto, Ontario, Canada, 2018

Author's Declaration for Electronic Submission of a Thesis

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I authorize Ryerson University to lend this thesis to other institutions or individuals for the purpose of scholarly research.

I further authorize Ryerson University to reproduce this thesis by photocopying or by other means, in total or in part, at the request of other institutions or individuals for the purpose of scholarly research.

I understand that my thesis may be made electronically available to the public.

Abstract

Title: Mirror, mirror on the wall: The factors that influence consumers' behavioural intention to use smart mirrors in Canada

Chelsea Heney, Master of Science in Management, in the program Master of Science in Management, Ryerson University, 2018

The retail industry is currently in a state of disruption and significant change. Successful retailers will be those that put their customers in the center of the shopping journey and create exceptional total retail experiences. Increasingly, retailers are turning to smart technology as a means of satisfying consumer demand for unique experiences and offerings. Adapting the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) this research seeks to explain the factors that influence Canadian consumers' behavioural intention to use smart mirrors in a retail stores. Results from the PLS-SEM analysis suggest that perceived value (PV), performance expectancy (PE), hedonic motivation (HM) and social influence (SI) are significant. Interestingly, results of the multigroup analysis (MGA) technique suggest that the moderating variables of age, gender, and income are not significant and have no effect on the relationship between the primary constructs and behavioural intention.

Acknowledgements

As this chapter in my life is coming to a close I would like to take a moment and acknowledge those that have supported and guided me through this journey.

First and foremost, I want to thank my husband, David Burden, for his love, support and constant encouragement. Knowing that you were in my corner made it possible to reach this point. You were always there when I needed someone to listen and have been unwavering in your belief of my abilities, even when I doubted myself. I love you and I am excited to celebrate our 10th anniversary this summer, and see what the next 10 years bring.

I want to thank my supervisor, Dr. Frances Gunn, for her guidance and positive support throughout this master's program. You have pushed me when I needed to be pushed and have been my friend when I needed someone to lean on. I have learned so much from you and will carry those lessons with me as I embark on my next chapter.

Another person I would like to thank is Dr. Norman Shaw for agreeing to be on my committee and for giving me the opportunity to be his graduate assistant. You were there to help when I had questions about my analysis, and for that I will always be grateful.

I would also like to thank Dr. Tina West for being on my committee and for her invaluable comments and suggestions.

A special thank you to Dr. Richard Michon for his contributions and for being a member of my thesis committee prior to his passing last year.

I would be remiss if I did not take a moment and thank my family for their unconditional love. I would especially like to acknowledge my mother, Donna Nixon, and my stepfather, Jeremy Byatt. You were the first to encourage me to pursue this program, and for that, I will forever be in your debt. Words cannot express the impact that both of you have had on my life. You have taught me the value of hard work and supported me every step of the way. I love you both very much, and I thank you for being the best role models a daughter could ask for.

Last, but certainly not least, I would like to thank my friends. I am so fortunate to be surrounded by such a strong group of women, and I want to thank every one of you for your love and encouragement. I would also like to take a moment and thank everyone in the Ted Rogers School of Retail Management. You have been incredibly welcoming, and I want to thank you for all of the opportunities you have given me.

TABLE OF CONTENTS

List of Figures

List of Tables

1. Introduction

"2017 was a terrible year for Canadian retailers – and 2018 could be even worse" (Alini, 2017); "It's more than Amazon: Why retail is in distress now" (Regan & Pickler, 2017); and "Dire predictions for retail stoked by another bad week of full store closures and looming bankruptcy" (Thomas, 2017) are a small fraction of the headlines that touted the retail industry's distress in 2017. Despite these dire assertions traditional retailing may not be imploding as quickly as many fear. According to their 2018 Canadian Retail Forecast, Retail Insider (Patterson, 2018) noted that 50 new international retailers entered the Canadian market by opening stores or concessions in 2017. This reality is in direct contrast to their 2017 forecast (Patterson, 2017) which predicted a slow year for expansion. Furthermore, recent reports suggest that 2017 was a year of growth for retailers in the United States and Canada. According to the United States Census, retail sales hit a record high of $5.7 trillion in 2017 (Amadeo, 2018). Canadian retail sales also saw an increase of approximately seven per cent to reach $590 billion in 2017 (Toneguzzi, 2017). While no one can say with absolute certainty what 2018 bring for the retail industry, the one thing that is certain is that this industry is undergoing a massive shift.

Kenneth Cole, a New York City based designer, in a recent discussion on the state of retail, noted that what consumers want more than anything else is a unique experience, and that it is up to retailers to provide it to them (Cole, 2017). A recent report by PWC (2015) supports Mr. Cole's statements by stating that successful retailers will be the ones who put their customers in the center of the shopping journey and create an exceptional total retail experience. To satisfy consumers' demands for unique experiences and offerings, retailers are increasingly turning to implementing smart technology in their retail stores (Pantano, 2010; Pantano, 2014; Pantano & Viassone, 2014). Smart retail technology can include everything from beacons, applications and mobilePOS to smart mirrors and other devices that utilize augmented reality (AR) and virtual reality (VR). Despite the plethora of choice many retailers are overwhelmed and are hesitant to adopt any of these technologies without a clear idea of how the technology will fit with their strategy or how shoppers will react (Inman & Nikolova, 2017).

Consumers' behavioural intention towards and use of smart technologies is an important and critical field of study and research. A review of the technology acceptance literature within the context of retail reveals that research has been concentrated in the areas of online and mobile retailing (Ahn, Ryu & Han, 2015; Gillenson & Shemell, 2002; Ha & Stoel, 2009; Klopping & McKinney, 2004; O'Cass & Fenech, 2003; Yang, 2010; Faqih & Jaradat, 2015; Shaw, 2014;); and online financial services retailing (Mckechnie, Winklehofer & Ennew, 2006). Individual smart technologies including beacons (Dudhane & Pitambare, 2015), kiosks (Chiu, Fang & Tseng, 2010), virtual fitting rooms (Huang & Qin, 2011; Kim & Forsythe, 2008) and AR applications (Rese, Baier, Geyer-Schulz & Schreiber, 2017) have also been the focus of enquiry. Absent from these investigations is smart mirrors, a device that has the potential to optimize consumers' in-store experience and has piqued the interest of retail behemoth Amazon, who recently received a patent for their idea (Lumb, 2016; Yurieff, 2018).

A smart mirror, also called a magic mirror or an interactive mirror, is a mirror with "smart" capabilities much like those of a cell phone (Gold, Sollinger & Indratmo 2016). "That is, it is a display that looks and acts like a mirror, but has the capability of displaying multimedia data through the mirror glass as if the mirror was a screen of its own accord" (Gold et al., 2016, p. 1). Though not in widespread use, retailers and developers are hoping to one day have customers virtually "try-on" clothing thereby eliminating the need to physically try the garments on. While developers are still a few years away from this idea becoming a reality, cosmetic companies Sephora and Charlotte Tilbury are beta-testing versions of smart mirrors in their boutiques that allow shoppers to "try-on" different cosmetics and looks without ever having to pick up a makeup brush (Marian, 2016; Groeber, 2014).

Smart mirrors first emerged on the market in the mid to late 2000's, and retailers were naturally skeptical. Would this technology actually be able to enhance the shopping experience, generate a return on investment, and help sales associates, or was it just another gimmick that detracts from the excitement and human interaction of shopping (Weinswig, 2015)? First adopted by department store retailers Macy's and Neiman Marcus, smart mirrors can now be found in select specialty boutiques including Rebecca Minkoff and Polo Ralph Lauren (Weinswig, 2015).

One area that retailers are most keen to see smart mirrors implemented is inside the fitting room. For example, by utilizing radio frequency identification (RFID) technology sensors the mirror would be able to recognize which items (including size and colour) the customer brought into the fitting room. Based on this information the mirror could then make wardrobe and styling recommendations and show the customer other pieces they may not have initially considered (Weinswig, 2015). Additionally, some smart mirror platforms can be integrated with a store's e-commerce or point-of-sale (POS) system thereby allowing individuals to make purchases inside the fitting room, via the mirror. This could be very useful especially if the item the customer wanted was out of stock in the store. Using smart mirrors in this context is key for many apparel retailers as expediting and enhancing the fitting room experience can result in increased sales and loyalty. According to Laney (2015) most consumers must try-on apparel in order to make a buying decision and they want to do this in the most convenient way possible. By utilizing smart mirrors to merge the fitting room with the selling environment retailers would likely observe a continuity in the apparel buying process which could result in consumers using the fitting rooms more, and which thereby increases the probability that they will buy (Laney, 2015). Furthermore, smart mirrors and other smart connected technologies have ability to provide bricks and mortar retailers with far more in-store data on their customers and products than was previously available (Lumb, 2016). This data can then be used to optimize the offline experience and make it as seamless as the online experience (Lumb, 2016).

As Weinswig (2015) notes, the possibilities and impact that smart mirrors can have in retail stores is intriguing, however, there is little scientific knowledge on consumers' behavioural intention towards the technology. This gap in knowledge along with smart mirrors' potential for enhancing the consumer experience forms the main motivation for this thesis.

The remainder of this thesis is organized as follows: first, the research question, the goals and motivation behind this research are presented. The overall research design is then introduced along with the philosophical paradigm that forms this approach. Further, literature on smart retailing, technology rich retail environments and smart mirrors is reviewed along with that of technology adoption and technology acceptance models. Then, based on the extended unified theory of acceptance and use of technology (UTAUT2) (Venkatesh, Thong & Xu, 2012), a series of hypotheses are proposed that will examine the relationship between the predictive variables and the outcome variable of behavioural intention. Following the hypotheses, the methodology will be outlined. Results of the study are then communicated and the findings discussed. Lastly, this research concludes with the implications and limitations of the study in addition to suggestions for future research.

2. Research Question, Goals, and Motivation

As noted in the introduction, research on consumer adoption of technologies in a retail context has focused mainly on e-tailing and mobile shopping with limited research investigating other smart technologies within the retail context. Therefore, the overarching goal of this research is to uncover the specific factors that influence consumers' behavioural intention to use a smart mirror in a retail store. Specifically, this research seeks to answer the following question:

- *To what extent does performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, perceived risk, perceived value, and domain-specific innovativeness explain the behavioural intention of consumers to use smart mirrors in retail stores?*

Additionally, this research will consider how the moderating variables of age, gender, and income act in conjunction with the primary constructs on the behavioural intention of consumers.

This question is both relevant and persisting. Its relevance is supported by the number of recent studies that highlight smart mirrors' potential in retail environments (Poncin & Mimoun, 2014; Pantano & Naccarato, 2010; Gold et al., 2016; Saakes, Yeo, Noh, Han & Woo 2016; Chu, Dalal, Walendowski & Begole, 2010; Javornik, Rogers, Moutinho & Freeman, 2016). Furthermore, consumer and practitioner interest in the technology has been gaining momentum with a number of new developers entering the market and an increased presence at international trade shows and expositions such as the Consumer Electronics Show (CES) (Clark-Thompson, 2018). The persistence of this question stems from the infrequency of technology adoption literature on smart retail technologies despite the breadth of research into other organizational and consumer contexts. As interest in smart mirrors increases and with the rapid advancement of the technology, the goal of this research is to explore and explain the phenomenal behaviour under investigation. Specifically, exploring the antecedents of behavioural intention of individuals to use a smart mirror within the offline retail environment.

For many consumers, brick and mortar stores are still at the center of their shopping journeys (PwC, 2015). As noted in the introduction, the continued success of these stores will lie in how well they can integrate digital technologies into their environments to create unique and brand-defining experiences (PwC, 2015; Poncin & Mimoun, 2014). Keeping this in mind, the motivation of this research is to investigate how smart mirrors may be used by retailers to enhance the in-store experience and positively impact consumer behavior.

This study investigates smart mirrors using an established technology adoption model and makes a contribution to both the retailing and technology adoption literature. It builds on prior research of smart mirrors within a retail context (Poncin & Mimoun, 2014; Pantano & Naccarato, 2010) and extends the literature on technology adoption by empirically investigating established constructs of UTAUT2 along with the added constructs of perceived risk and domain-specific innovativeness.

3. Research, Design, Approach and Paradigms

Following a deductive research approach this quantitative research seeks to explore and explain which exogenous constructs have the strongest effect on consumers' behavioural intention to use smart mirrors in retail stores. As Blaikie (2010) notes, "the aim of the deductive research strategy is to find an explanation for an association between two concepts by proposing a theory, the relevance of which can be tested" (p. 85). The theory can either be invented or borrowed and used to deduce hypotheses. The hypotheses can then be tested using the data to provide an explanation (Blaikie, 2010) This explanation, he states, is the "major task of the deductive research strategy" (Blaike, 2010, p. 105).

Using UTAUT2 (Venkatesh et al., 2012) as a framework, several hypotheses were developed to explain consumers' behavioural intention towards use of a smart mirror. These hypotheses are discussed in more detail in Chapter Five. UTAUT2 is an extension of UTAUT (Venkatesh, Morris, Davis & Davis, 2003) which was based on a systemic review and synthesis of eight acceptance models/theories for the purposes of progressing towards a unified view of user acceptance. As Venkatesh et al. (2012) note UTAUT "distilled the critical factors and contingencies related to the prediction of behavioural intention to use a technology and technology use primarily in organizational contexts" (p. 157). Given this organizational focus the authors determined it was necessary to revisit UTAUT and develop UTAUT2 paying attention to the consumer use contexts (Venkatesh et al, 2012). Furthermore, the authors note that there is a need for systematic investigation of different contexts and consumer technologies (Venkatesh et al, 2012). Thus, as interest in smart mirror technology is increasing, as is evident by its use and interest from apparel and cosmetics retailers and its heightened presence at CES, it is an appropriate time to undertake an investigation into consumers' behavioural intention to use smart mirrors in a retail context.

This research is positioned under the philosophical paradigm of positivism. According to Blaikie (2010), "positivism regards reality as consisting of discrete events that can be observed by the human senses. The only knowledge of this reality that is acceptable is that which is derived from experience" (p. 97). Not without its critics, positivism has remained an important paradigm in marketing and business management research (Hasan, 2016). One of its main critiques, cites Hasan (2016), is positivism's sole reliance on objective observation. However, Hasan (2016) counters that "complete objectivity is impossible and subjectivity should also be accepted as an inherent part of human nature" (p. 323). Therefore, positivism has the ability to aid in our understanding and analysis of the social world (Hasan, 2016).

Coined by August Comte, positivism "emphasizes the doctrine's rejection of value judgements, its privileging of observable facts and relationships, and the application of knowledge gained by this approach to the improvement of human society" (Calhoun, 2002, p. 373). According to Cruickshank (2012) and Giddens (1995) after Comte, positivism held that human sciences need to be based on the method used by the natural sciences. As Cruickshank (2012) states, "the use of the scientific method would guarantee certainty in knowledge, with outputs of science being accurate reflections of this reality" (p. 72). Corroborating this view is positivists' commitment to an empiricist epistemology which holds that one can "directly observe fixed empirical effects of underlying causes" (Cruickshank, 2012, p. 72). Supporting this claim, Creswell (2013) notes that these effects need to be tested, verified and refined to assist our understanding of the world. This verification or falsification of the hypotheses therefore leads to ideology that knowledge is a cumulative process, constantly adding to its existing cache

(Burrel & Morgan, 1988). Thus, while this research is built using previously established theories, its unique findings and insights will fill a gap in the existing literature and extend the knowledge base.

4. Literature Review

4.1 Smart Retailing

In 1974 a pack of gum was sold using a scanner at a supermarket in Troy, Ohio in the United States (Priporas, Stylos & Fotiadis, 2017). Since then advancements in technology have radically transformed the retail industry and forever changed the consumer-retailer interaction (Priporas et al., 2017). Technology adoption for retailers is no longer "a matter of if – it is a matter of when" (Deloitte, 2015, p. 4), and there is no advantage to being behind the curve. In 2015, research by IHL Group noted that information technology (IT) spend for the retail and hospitality industries was projected to exceed $190 billion, with IT spend in North America projected to be greater than the BRIC (Brazil, Russia, India and China) countries (Wilson, 2014; Inman & Nikolova, 2017). As many retailers seek to create unique and engaging consumer experiences, while simultaneously creating a competitive advantage for their firms, they are leveraging their resources to acquire smart technologies (e.g. RFID, beacons, mobilePOS, apps, AR mirrors and VR stores) as solutions to this challenge (Priporas, Stylos & Fotiadis, 2017; Inman & Nikolova, 2017). While it is critical that one understands and recognizes the importance these technologies bring to the retail environment they must also be understood within the broader context of smart retailing.

In their seminal work on smart retailing, Pantano and Timmermans (2014 p. 102) emphasize that "the emerging idea of smart retailing reflects a particular idea of retailing, where firms and consumers use technology to reinvent and reinforce their role in the new service economy by improving the quality of their shopping experiences." Furthermore, they link this concept of smart retailing with the smart city concept that first emerged in the 1980s which considered new approaches for managing urban environments (Pantano & Timmermans, 2014).

The smart city concept is founded on the idea that the smart use of technology can improve the quality of life in cities through the employment of pervasive systems (Pantano & Timmermans, 2014). Linking this concept with retailing, smart retailing emerges as a broader concept of smart cities, whereby the use of technology becomes smart with retailers and consumers seeking to create partnerships with the ultimate goal of creating satisfying experiences for both parties (Pantano & Timmermans, 2014).

Extending Pantano and Timmermans' (2014) concept of smart retailing, Roy, Balaji, Sadeque, Nguyen and Melwar (2016) define smart retailing as "an interactive and connected retail system which supports the seamless management of different customer touchpoints to personalize the customer experience across different touchpoints and optimize performance over these touchpoints" (p. 259). Furthermore, smart retailing is changing consumer behaviour at all stages of the purchase decision and is becoming an essential strategic initiative that is key for retailers' success (Vrontis, Thrassou & Amirkhanpour, 2017; Priporas et al, 2017). In comparison with traditional retailing, smart retailing provides a sense of flexibility and "goes beyond the application of a modern technology to the retailing process by including a further level of 'smartness' related to the enjoyment of technology" (Priporas et al, 2017, p. 375).

While the concept of smart retailing is omnipresent in the retail industry it is also worth noting that concerns about this shift towards an increasingly connected environment have been raised as to how it will ultimately impact the shopping experience. As Pantano and Timmermans (2014) note, this shift towards smart retailing and smart technologies presents a challenge for retail managers as it may become difficult to obtain employees' buy-in to use technologies that may one day be a substitute for their role. This sentiment is echoed in Priporas et al (2017), in which Generation (Gen) Z UK consumers worry that retail unemployment may rise as smart technologies become more pervasive, and directly impact their generation's employability as retail and other service industries often employee a high number of youth and young adults in front-line, consumer facing roles. Additionally, Gen Z consumers noted that while they do expect smart technologies to enrich the shopping experience, smart technologies could negatively affect their shopping enjoyment as Gen Z consumers tend to view shopping as a social event (Priporas et al., 2017).

While it is generally accepted that smart retailing and the widespread use of smart technologies by retailers enables them to provide superior customer experiences and can lead to increases in profitability and performance metrics, one must also keep in mind the potential concerns that consumers and employees have. This research takes the view that smart retailing and the various smart technologies used in the delivery of retail products and services can be seen as a breakthrough in their ability to enable retailers to develop new capabilities and strategies, manage relationships, and improve consumer experiences.

According to Pantano (2014) and Pantano, Priporas & Dennis (2017), one of the most potentially impactful smart approaches is AR (Pantano, 2014: Pantano et al., 2017), which is the basis for many in-store retail technologies including smart mirrors and virtual fitting rooms. The ensuing section provides a brief overview of AR, followed by a discussion of the literature on smart mirrors within the context of smart retailing.

4.2 Augmented Reality and the Smart Mirror

AR emerged in the 1950s when Morton Heilig, a cinematographer, thought that cinema could have the ability to induce the viewer into the onscreen activity by having them taking in all their available senses (Carmigniani, Furht, Anisetti, Ceravolo, Damiani & Ivkovic, 2011). Heilig, predating digital computing, built a prototype of his vision for cinema in 1962 and named it Sensorama (Carmigniani et al., 2011). According to Rese, Baier, Geyer-Schulz and Schreiber (2017) commercial applications using AR were first developed in the 1990s but the devices were often large and bulky which had a negative impact on the widespread adoption and popularity of the technology.

The most widely accepted definition of AR was coined by Ronald Azuma (1997), who defined AR as a system “in which 3D virtual objects are integrated into a 3D real environment in real time” (p. 355). Carmigniani et al. (2011) extended this definition and defined AR, “as a real-time direct or indirect view of a physical real-world environment that has been enhanced/ augmented by adding virtual computer-generated information to it” (p. 342). To simplify, “AR enhances the user’s perception of and interaction with the real world” (Carmigniani et al., 2011, p. 342). Although AR enriches the senses and is based on the techniques developed for VR (Azuma, 1997) it “does not replace the real environment, rather AR uses the real environment as a ‘background’” (Fonseca, Martí, Redondo, Navarro & Sánchez, 2014, p. 435). Conversely,VR completely immerses a user in a synthetic world without any visibility with the real world (Carmigniani et al., 2011).

As processing power increased and the size of the devices decreased, interest in AR by organizations and developers grew significantly. Furthermore, Daponte, De Vito, Picariello and Ricco (2014) note that AR is moving from the laboratory into consumer markets,” (p. 54), as evidenced by its use in creating virtual fashion shows, AR-based virtual pop-up stores, and applications for gamers, car dealers, cosmetics and apparel retailers. This is especially true of the retail industry where smart or virtual mirrors are considered AR front-runners (Rese et al., 2017; Grewal, Roggeveen & Nordfält, 2017) with the potential to “capture consumers’ attention and influence their purchase decision” (Pantano, 2014, p. 348).

While research pertaining to smart mirrors has primarily focused on the retail application of the technology, uses of smart mirrors in non-retail settings have also been investigated. Bichlmeier, Heining, Feuerstein and Navab (2009) introduced the concept of a tangible and controllable virtual mirror for medical AR applications, specifically in the operating room as a way to assist with the surgical workflow. Furthermore, Blum, Kleeberger, Bichlmerier and Navab (2012) presented an augmented smart mirror to assist in the teaching of anatomy. In this research the smart mirror system is designed to show 3D models of organs and display other relevant text and imagery about the organs. Within the context of retail, research into the use of smart mirrors has predominantly focused on, i) development of the technical components and/or the technology platform (Gold, Solinger & Indratmo, 2016; Nguyen & Lui, 2017; Mahfujur Rahman, Tran, Alamgir Hossain & El Saddik, 2010; Javornik, Rogers, Moutinho & Freeman, 2016; Nakagawa & Siio, 2009; Chu, Dalal, Walendowski & Begole, 2010), or ii) conceptual papers that highlight the potential use of the technology in retail environments (Poncin and Mimoun, 2014; Pantano and Naccarato, 2010).

Poncin and Mimoun (2014) sought to uncover how new retail technologies, including smart mirrors, could be integrated into physical store atmospherics, and considered the effect these technologies have on consumers' holistic perceptions of the store's atmospherics. Furthermore, the authors tested the technologies' perceived shopping value and concluded that a smart mirror using AR offers strong positive benefits with respect to both satisfaction and patronage (Poncin & Mimoun, 2014). Similarly, Pantano and Naccarato (2010) reviewed smart mirrors along with other advanced smart technologies (RFID and shopping assistant systems) and analyzed how the introduction of these technologies modifies the retailing context, by providing new and enjoyable elements that affect consumers' shopping experiences. Their results suggest that consumers have a positive response to the introduction of the technologies, and are willing to engage and purchase more due to the fun they had in the store (Pantano & Naccarato, 2010). As insightful as these findings are, it should be noted that the researchers did not engage in an empirical analysis to support their findings. Pantano and Naccarato (2010) acknowledge this as a limitation and suggest that more research should be undertaken in order to understand the detailed factors that influence consumers' acceptance of these advanced smart technologies, and propose the use of the Technology Acceptance Model (TAM) (Davis, 1989) as a method for doing so. A further review of the TAM literature by Pantano and Di Pietro (2012) suggest new variables (e.g., subjective norm, self-efficacy, satisfaction, social influence, perceived cost, behavioural control, perceived security, perceived risk, enjoyment and trust) that they believe warrant inclusion when using the model to assess acceptance of retail technologies. Similar to Pantano and Naccarato (2010), the research put forward by Pantano and Di Pietro (2012) was conceptual in nature and suggests a path for future acceptance research on smart mirrors.

The ensuing section traces the evolution of technology acceptance theories, beginning with TAM (Davis, 1989) through to the development of UTAUT2, which serves as the framework for this research.

4.3 Technology Acceptance

4.3.1 TAM

Understanding why people accept or reject technology is one of the main lines of research in the information systems (IS) literature (Rondan-Catalūna, Arenas-Gaitán and Ramirez-Correa, 2015). Since the 1970s a number of theoretical models have attempted to address this objective, the most influential of which is TAM (Davis, 1989). According to

Benbasat and Barki (2007) TAM's origins can be traced back to the Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1975), which was one of the first models that studied the acceptance of technology. Drawn from social psychology, TRA is an influential theory that can be applied to countless fields as it is a general model and was not designed for a specific behaviour or technology, and therefore made it more efficient to conduct IT adoption research (Venkatesh et al, 2003; Rondan-Catalūna et al., 2015).

TAM has two key influencing variables: perceived usefulness (PU) and perceived ease of use (PEOU). As Benbasat and Barki (2007) note, after so many years of research investigating TAM and its many variations, it is known almost to the point of certainty that "PU is a very influential belief and that PEOU is an antecedent of PU and an important determinant of use in its own right" (p. 212). IS researchers' heavy reliance on TAM can be viewed as the "putting on blinders" and treating PU and PEOU as hallowed concepts that very few have tried to uncover (Benbasat and Barki, 2007). Despite this, TAM models, including TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008) have been widely used in the last few decades and have been applied to a multitude of technologies across a number of disciplines (Rondan-Catalūna et al., 2015; Pantano and Di Pietro, 2012).

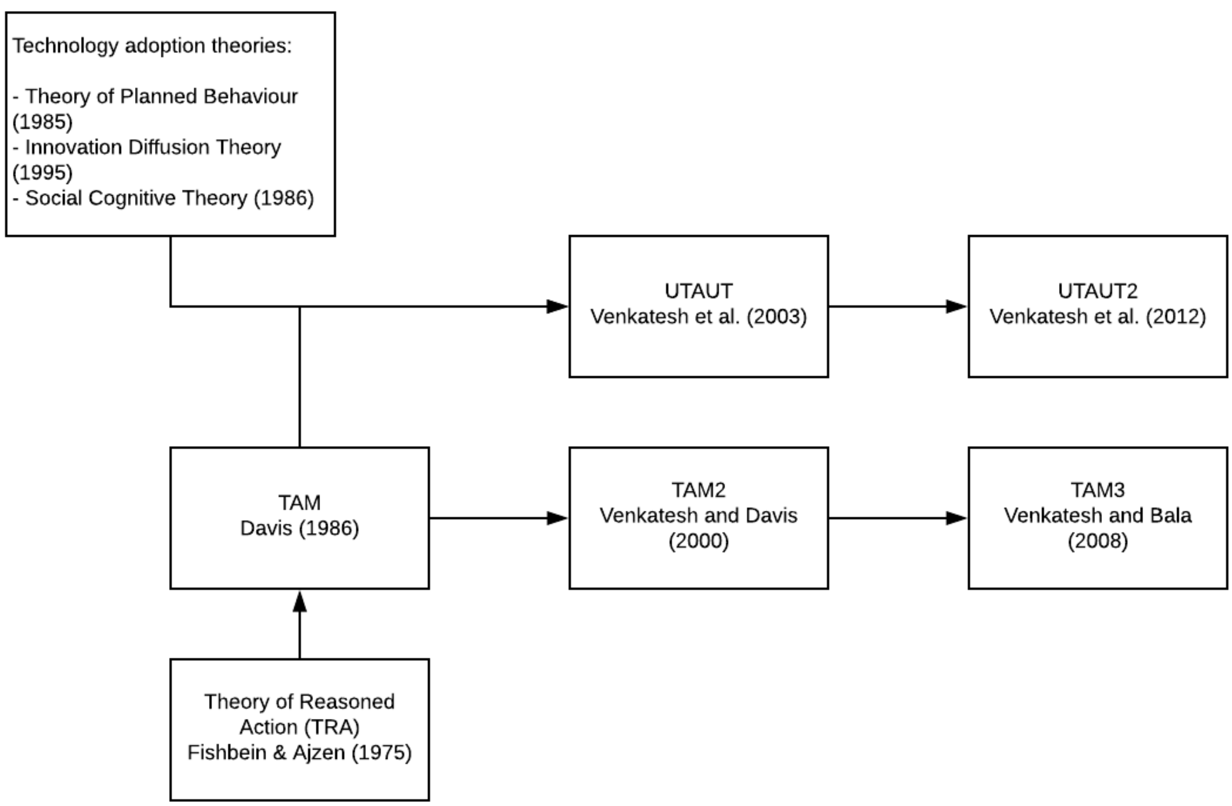
Further extending TAM, Heijden (2000) proposed the electronic-TAM or eTAM framework, adapting the original TAM for a Web site context. In eTAM, PU and the additional construct of perceived enjoyment are strong indicators of intention to revisit a Web site and PEOU indirectly effects revisit intentions (Kim & Forsythe, 2008). According to Kim and Forsythe (2008) the eTAM model "is consistent with previous research on retail shopping behaviour and supports the presence of both utilitarian and hedonic motivations for online shopping" (p. 47). Extending eTAM, Kim and Forsythe (2008), propose an adaptation of the model to explain the adoption process of "virtual try-on" for online apparel shopping.

Used by online apparel shopping sites "virtual try-on" is a technology that allows shoppers to create virtual models of themselves based on their own measurements (body type), facial features, and hair colour (Kim and Forsythe, 2008). It then allows shoppers to view the garment or outfit from different angles and zoom in on specific product features. Additionally, consumers can view the garment in all available colours and patterns. Similar to smart mirrors, "virtual try-on" is viewed as a technology that can enhance the experience and entertainment value of shopping (Kim & Forsythe, 2008). Their results provide support for "PU and perceived entertainment value as strong predictors of consumers' attitudes towards using "virtual try-on" for online apparel shopping" (Kim & Forsythe, 2008 p. 55). Furthermore, Kim and Forsythe (2008) note that while Virtual Try-on technology contributed to the hedonic dimension of online shopping, consumers were not confident in the technology being able to model how a garment would actually look on them. Representing the first study to investigate the adoption of the previously unexplored retail technology, Kim and Forsythe (2008) encourage further exploration of similar technologies and suggest that researchers propose and identify additional constructs that would influence consumers' intentions.

4.3.2 From TAM to UTAUT

UTAUT (Venkatesh, Morris, Davis & Davis, 2003) was proposed as theoretical advancement and synthesis of eight existing models/theories of user acceptance of new technologies. The need for this synthesis, the authors argued, was the result of "researchers being confronted with a choice among a multitude of models and finding that they must 'pick and choose' constructs across the models, or choose a 'favoured model' and largely ignore the contributions from alternative models" (Venkatesh et al., 2003 p. 426). The eight theories and models unified in UTAUT are (a) Theory of Reasoned Action (TRA), (b) TAM, (c) Motivational Model (Davis, Bagozzi, & Warshaw, 1992), (d), Theory of Planned Behavior (TPB) (Ajzen, 1991), (e) Combined TAM and TPB (C-TAM-TPB) (Taylor & Todd, 1995), (f) Model of PC Utilization (MPCU) (Thompson, Higgins & Howell, 1991), (g) Innovation Diffusion Theory (IDT) (Moore & Benbasat 1991), and (h) Social Cognitive Theory (SCT) (Compeau & Higgins, 1995). Figure 4.1 illustrates the evolution of technology acceptance theories that were unified into UTAUT and subsequently UTAUT2.

Figure 4.1 *Evolution of theories about technology adoption*



Source: Adapted from Rondan-Catalūna et al. (2015)

UTAUT points to four key influencing variables that act as direct determinants of user acceptance and usage behaviour: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). These individual constructs will be discussed in greater detail in Chapter Five which focuses on hypotheses development. The UTAUT constructs of PE and EE are similar to the PU and PEOU influencing variables proposed by Davis (1989). UTAUT also suggests that factors including age, gender, experience, and voluntariness of use act as key moderators that affect the four constructs (PE, EE, SI and FC). Considered one of the newest and oft cited acceptance models, UTAUT (Venkatesh et al., 2003) has 19687 citations in Google Scholar as of February 4, 2018. Moreover, evidence of its widespread acceptance is its application to other organizational contexts including educational institutions, academic societies, government agencies, and hospitals (Venkatesh, Thong & Xu, 2016)

Venkatesh et al. (2003) assert that UTAUT accounts for as much as 70 percent of explained variability in users' intention; a result better than any of the eight theories considered individually that were unified in UTAUT.

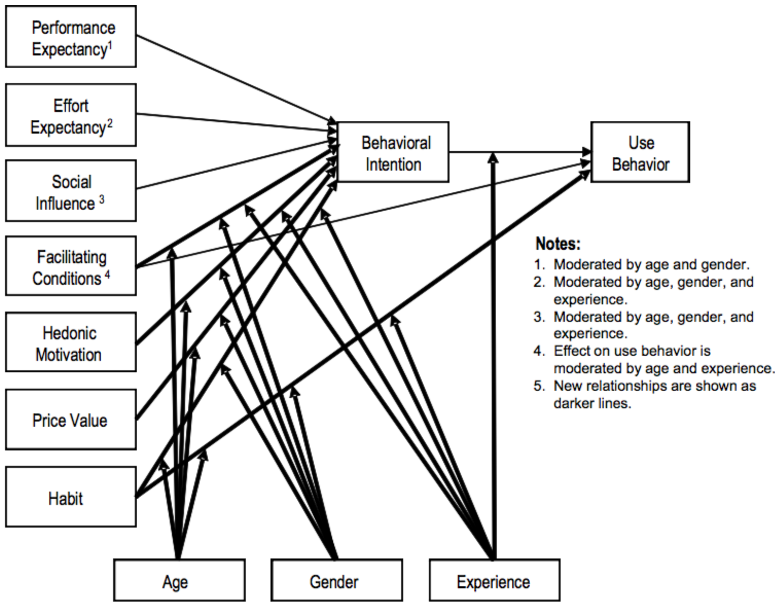
Though not common given its divergence from the original organizational context examined by Venkatesh et al. (2003), UTAUT has been employed by researchers to investigate consumers' behavioural intention and use of smart technologies in the retail context. Huang and Qin (2011) adapted UTAUT to examine the adoption of online virtual fitting rooms. In addition to the exogenous mechanisms of PE, EE, SI and FC the researchers included the construct perceived risk (PR), hypothesizing that privacy and security concerns would have a significant influence on PR. Also, they hypothesized that PR would negatively impact consumers' behavioural intentions to use the technology in question. The results of their study indicate that

PR, EE, SI and PR significantly influence consumers' intention to use online virtual fitting rooms (Huang & Qin, 2011). FC was not shown to have a significant influence on consumers' intention to use. This result is consistent with that of Martins, Oliveira & Popovic (2014) who noted that contrary to their expectations the effect of FC on usage behaviour was not significant. Despite UTAUT's wide acceptance its original research context was that of traditional business organizations. As such, there became a need to investigate the "salient factors that would apply to a consumer technology use context" like retailing (Rondan-Cataluña et al., 2015 p. 795).

4.3.3 UTAUT2

Venkatesh et al. (2012) revisited UTAUT and sought to extend the study of acceptance and use of technology in a consumer context. Within organizations the technology under investigation is typically provided by the company and its use is likely mandated by the organization. In contrast, when investigating in a consumer setting like retailing, technology use is voluntary and in the absence of mandated use there are likely to be additional motivators that will impact consumers' behavioural intention and use (Badura, 2016). The extended model, UTAUT2 (Figure 4.2), incorporates three new constructs: hedonic motivation (HM), price value, and habit into UTAUT. In addition, Venkatesh et al. (2012) hypothesize that age, gender, and experience are expected to moderate the effects of these constructs on behavioural intention and technology use. Compared with UTAUT, the extensions proposed in UTAUT2 produced a substantial improvement in the variance explained. For behavioural intention, the variance explained increased from 56 percent to 74 percent and technology use increased from 40 percent to 52 percent (Venkatesh et al., 2012).

Figure 4.2 *Extended Universal Theory of Acceptance and Use of Technology (UTAUT2)*



Source: "Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology," by V. Venkatesh, et al., 2012, MIS Quarterly, 36(1), p. 160. Copyright 2012 by MIS Quarterly. Reprinted with permission (Appendix A)

Within the retail context and following the work of Escobar-Rodríguez and Carvajal-Trujillo (2014), Juaneda-Ayensa, Mosquera and Murillo (2016) used UTAUT2 model to investigate the antecedents of omnichannel shoppers' intentions to use new technologies during the shopping process. Furthermore, the authors (Juaneda-Ayensa et al., 2016) hypothesized that the added constructs of personal innovativeness and perceived security would positively affect purchase intention, replacing behavioural intention from UTAUT2 (Venkatesh et al., 2012). In this context perceived security is the belief that the Internet is secure and that personal information is safe. This definition is strongly associated with the construct of perceived value (PV), which will be discussed in Chapter Five.

The second construct, personal innovativeness, is defined as the "degree to which a person prefers to try new and different products, channels, and to seek out new experiences…"

(Juaneda-Ayensa et al., 2016, p.4). According to Juaneda-Ayensa et al. (2016) prior research has shown that innovativeness is a highly influential factor in information and communication technology (ICT) adoption and purchase intention (San Martín & Herrero, 2012).

One concern with this study (Juaneda-Ayensa et al., 2016) is that it proposes to equate behavioural intention with purchase intention. While similar, these two constructs are conceptually different. Behavioural intention (BI) is “a person's perceived likelihood or "subjective probability that he or she will engage in a given behaviour" (CCBC, 2002, p. 31), whereas, purchase intention could be defined as a person’s intention to buy particular goods or services sometime in the near future. Although both concepts deal with a persons’ likelihood of doing or not doing something it is a stretch to presume that these concepts are interchangeable. Consider the case of smart mirrors, an individual may intend to use the technology in their shopping journey, however, there is no certainty that this positive behavioural intention would result in positive purchase intentions. As such researchers should be careful conflating the two terms.

UTAUT2 is selected as the theoretical foundation for this research for four reasons: one, it has received wide acceptance (Blake, Neuendorf, LaRosa, Luming, Hudzinski & Hu, 2015; Shaw & Sergueeva, 2016); second, as proposed by Venkatesh et al. (2012), UTAUT2 needs to be applied to different technologies and contexts; third, UTAUT2 can be easily contracted or extended with other factors and researchers are encouraged to do so to verify its applicability, especially in the context of consumer behaviour (Juaneda-Ayensa, et al., 2016); and finally, the scales are readily available within the extant literature and its core constructs have been validated across many disciplines, explaining up to 70% of the variance in behavioural intention (Shaw & Sergueeva, 2016).

The next chapter describes the constructs of the UTAUT2 and proposes a series of hypotheses. In addition, two added constructs, PR and domain-specific innovativeness (DSI), are discussed as the literature has suggested these constructs could help explain consumers' behavioural intention to use smart mirrors in retail stores (Juaneda-Ayensa, et al., 2016; Huang & Qin, 2011).

5. Hypotheses Development

This study focuses on the effects of the exogenous variables (PE, EE, SI, FC, HM, PV, PR and DSI) on the endogenous variable of behavioural intention (BI). Simply put, this study seeks to explain the specific factors that influence consumers' behavioural intention to use a smart mirror in a retail store. Furthermore, this research will consider how the moderating variables of age, gender, and income act in conjunction with the primary constructs on the consumers' behavioral intentions. This chapter will describe each of the constructs used in this thesis and present a corresponding hypothesis along with the research model.

5.1Performance Expectancy

Defined as "the degree to which an individual believes that using the system (technology) will help him or her to attain gains in job performance" (Venkatesh et al., 2003, p.447), PE is a significant measure of how effectively an individual completes a task (Haywood, 2017). Based on the definition put forward by Juaneda-Ayensa et al. (2016), PE could also be defined as the degree to which using a technology during the shopping journey will provide consumers with benefits. Linked with PU in TAM, PE has consistently been shown to be the strongest predictor of behavioural intention and remains significant at all points of measurement in both voluntary and mandatory settings (Venkatesh, 2003; Venkatesh et al., 2003; Juaneda-Ayensa et al., 2016). In their meta-analysis of UTAUT, Dwivedi, Rana, Chen and Williams (2011) note that PE "shows the highest number of significant relations with behavioural intention" (p. 162). Shaw and Suergueeva (2016) did support their hypothesis concluding that PE was not-significant in influencing consumers' intention to use smartphone apps for mobile commerce. However, the authors (Shaw & Sergueeva, 2016) subsequently put forward the notion that other constructs could be masking the effect of PE on intention. Further analysis proved this to be the case.

When the authors re-ran their model without the masking constructs they confirmed that the influence of PE on intention to use was significant (Shaw & Sergueeva, 2016). Thus, the following hypothesis is put forward:

H1: There is a positive relationship between performance expectancy and consumers' behavioural intention to use smart mirrors in retail stores.

H1a: The effect of performance expectancy on consumers' behavioural intention to use smart mirrors in retail stores is moderated by age, gender, and income.

5.2 Effort Expectancy

EE includes the concepts of PEOU in TAM (Davis, 1989) and ease of use in IDT (More and Benbasat, 1991). EE is defined as, "the degree of ease associated with the use of the system" (Venkatesh et al., 2003, p.450). As smart mirror instruction manuals are not readily made available to the consumer it is important that their design be intuitive, and not be perceived as being difficult to use. As with PE, EE is significant in both voluntary and mandatory use contexts and positively effects intention (Venkatesh et al., 2012; Juaneda-Ayensa et al., 2016). Following the work of Chang, Fu and Jain (2016) EE in this study is defined as the degree of ease associated with using a smart mirror in a retail store.

According to Dwivedi et al. (2011), EE has generally been seen as a significant antecedent of behavioural intention. However, Morosan and DeFranco (2016) commented that a number of studies did not find a significant relationship, or that the relationship between EE and BI was of a low magnitude. Smart technologies, especially those used by consumers are increasingly being developed and designed with an emphasis on the user experience (UX). As a result, these technologies tend to be intuitive and are designed to be operated without substantial effort by the majority of consumers. Therefore, the following hypothesis is put forward:

H2: There is a positive relationship between effort expectancy and consumers' behavioural intention to use smart mirrors in retail stores.

H2a: The effect of effort expectancy on consumers' behavioural intention to use smart mirrors in retail stores is moderated by age, gender, and income.

5.3 Social Influence

SI is defined as "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003, p. 451). Adapted from the construct of subjective norm (TRA, TAM2, TPB, and C-TAM-TPB), social factors (MPCU), and image (IDT), SI postulates that users are influenced by 'referent' others who are important to them (Venkatesh 2003; Shaw and Sergueeva, 2016). Alternatively, SI could be defined as the extent to which consumers' perceive that people who are important to them (friends, family, social influencers, etc.) believe they should use the new technology. As Priporas et al. (2017) note, shopping is an inherently social activity and consumers can be greatly influenced by those close to them (friends, family, and peers) along with other influencers (celebrities, social media stars, and society in general). Based on this assertion the following hypothesis was developed:

H3: There is a positive relationship between social influence and consumers' behavioural intention to use smart mirrors in retail stores.

H3a: The effect of social influence on consumers' behavioural intention to use smart mirrors in retail stores is moderated by age, gender, and income.

5.4 Facilitating Conditions

FC is defined as “the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system” (Venkatesh et al., 2003, p. 453). Each of the concepts captured in the construct (perceived behavioural use, and compatibility) is operationalized to include aspects of the consumer environment that is designed to remove barriers to use (Blake et al., 2017). In the case of smart mirrors consumers expect the system to work perfectly, and that it will provide them with the information they expected to receive. In the event that the system is not working perfectly there is the expectation that a support apparatus will be available to resolve any issues quickly.

Of the four constructs in UTAUT (PE, EE, SI and FC), FC is the least likely to show a significant relationship with behavioural intention. As Dwivedi et al. (2011) point out only nine of the 43 studies examined were able to show a significant relationship between FC and behaviouural intention. Furthermore, the authors (Dwivedi et al., 2011) found that 32 of 43 studies using UTAUT either did not discuss the relationship between FC and behavioural intentions or that the study used qualitative as opposed to quantitative data (Dwivedi et al., 2011). Despite the lack of concrete findings supporting the inclusion of FC, this thesis follows UTAUT2 as proposed by Venkatesh et al. (2012) and recent works of Morosan and DeFranco (2016) Martins et al. (2014) Shaw and Sergueeva (2016) in putting forward the following hypothesis:

H4: There is a positive relationship between facilitating conditions and consumers’ behavioural intention to use smart mirrors in retail stores.

H4a: The effect of facilitating conditions on consumers’ behavioural intention to use smart mirrors in retail stores is moderated by age, gender, and income.

5.5 Habit

Included as a new construct in the UTAUT2 model, habit is defined as "the extent to which people tend to perform behaviours automatically because of learning" (Venkatesh et al., 2012, p. 161). Although this construct has been considered a predictor of behavioural intention to use and usage in a number of studies (Juaneda-Ayensa et al., 2016; Morosan & DeFranco, 2014; Escobar-Rodríguez and Carvajal-Trujillo, 2014), it is not being considered in this study. As Morosan and DeFranco (2014) note in their study on consumers' intention to use near field communication (NFC) mobile payments (NFC-MP) in hotels, habit forms as a result from consumers' usage of their mobile devices in contexts outside of hotels provides them with the necessary means to be able to use NFC-MP in a hotel environment. Since smart mirrors are fairly new and are not in widespread use by retailers, few consumers have had the opportunity to interact with or use one. As a result, it is impossible for individuals to get in the habit of using a technology that few have ever read or heard about. Therefore, in this thesis the construct of habit will not be considered moving forward and a hypothesis will not be developed.

5.6 Hedonic Motivation

While utilitarian motivation is included within the construct of PE, HM was added as a separate construct in UTAUT2 (Venkatesh et al., 2003, 2012; Juaneda-Ayensa et al., 2016). HM is defined as the "fun or pleasure derived from using a technology and it has been shown to play an important role in determining technology acceptance and use" (Venkatesh et al., 2012, p. 161). In the context of retail, apparel is typically classified as a high hedonic product due to its symbolic and pleasing properties (Juaneda-Ayensa et al., 2016). When shopping in a physical store for hedonic goods, consumers are more likely to choose strong, physical environments that elevate their mood and provide sensory stimulation (Juaneda-Ayensa et al., 2016). When building the technology platforms and its interface, smart mirror developers need to be aware of consumer's hedonic motivations to ensure that they are developing mirrors with user friendly interfaces but ones that are also pleasurable to use and interact with. As such, the following hypothesis is proposed:

H5: There is a positive relationship between hedonic motivation and consumers' behavioural intention to use smart mirrors in retail stores.

H5a: The effect of hedonic motivation on consumers' behavioural intention to use smart mirrors in retail stores is moderated by age, gender, and income.

5.7 Price Value (Perceived Value)

In addition to habit and HM, price value was added as a construct to the organization-focused UTAUT framework in an effort to make UTAUT2 consumer-focused. Price value has a number of different meanings and is important in many forms of consumer behaviour (Blake et al., 2017). Venkatesh et al. (2012) define price value as "consumers' cognitive tradeoff between the perceived benefits of the applications and the monetary cost for using them" (p. 161). When the benefits of using a technology is perceived to be greater than the monetary cost the price value is positive and it is predicted to have a positive effect on intention (Venkatesh et al., 2012). Equally, a consumer may perceive value in a product or technology not necessarily in relation to its cost, but because of its social value, emotional value or convenience.

In the context of ecommerce, the sharing of personal data including credit card information electronically can raise concerns about security and unauthorized use of the data. In spite of these concerns most consumers are willing to provide their personal data in exchange for increased benefits and a greater personalization of services (Shaw & Sergueeva, 2016).

Ultimately, consumers weigh the perceived value of the technology or application with the perceived risks and benefits.

Shaw and Sergueeva (2016), propose that the construct of price value in UTAUT2 could be replaced with that of PV (perceived value). Pura (2005) defines value as the tradeoff between benefits and sacrifices, and this trade-off is represented by “the willingness to share information. Consumers will be willing to share if they believe that there is value…therefore, willingness to share is replaced by perceived value” (Shaw and Sergueeva, 2016, p. 6). Eventually, it represents consumers’ cognitive tradeoff between benefits of disclosing their personal information with the perceived risk of loss of privacy (Shaw and Sergueeva, 2016). For example, in a retail store if a consumer perceives that using a smart mirror will provide them with greater convenience and social value that consumer will be more likely to use the technology despite the loss of privacy from being asked to provide personal or payment information. Given the above discussion this thesis replaces the construct of price value with PV, and proposes the following hypothesis:

H6: There is a positive relationship between perceived value and consumers’ behavioural intention to use smart mirrors in retail stores.

H6a: The effect of perceived value on consumers’ behavioural intention to use smart mirrors in retail stores is moderated by age, gender, and income.

5.8 Additional Constructs

5.8.1 Perceived Risk

Overall, a consumer’s perception of risk can result from their uncertainty and anxiousness about behaviours and the potential negative outcomes that may follow (Mandrik & Bao, 2005; Slade, Dwivedi, Piercy & Williams, 2015). New technological products, including smart mirrors and other smart technologies are typically seen as risky in the early stages of their product life cycle as they have yet to be fully developed. Consider the case of online retailing, in its infancy large swaths of consumers often expressed concerns around the transactions noting that it was risky to enter their personal information online (Slade et al, 2015). Despite technology advancements and heightened security around the storage of sensitive information, new technologies that are not widely disseminated (i.e., smart mirrors) will continue to be seen as risky until such a time when they are widely used.

According to Featherman and Pavlou (2003), perceived risk (PR) "is commonly thought of as the felt uncertainty regarding possible negative consequences of using a product or service" (p. 453). Furthermore, the authors view perceived risk as being comprised of, (i) performance risk, the failure of the product or service to deliver the desired benefits; (ii) financial risk, the potential monetary loss; (iii) time risk, when a user or consumer loses time by making poor purchase decisions; (iv) psychological risk, that a products performance will have a negative effect on a consumer mental state stemming from their frustration of not achieving a buying goal; (v) social risk, a potential loss in status from choosing to adopt a product or service, (vi) privacy risk, the potential loss or compromise of a consumer's personal information; and (vii) the overall risk, a general measurement that comprising all criteria together (Featherman & Pavlou, 2003). Together all of these perceived risks compromise the construct of PR (Martins et al., 2014).

A common extension of UTAUT and UTAUT2 (Slade et al, 2015; Martins et al, 2014; Huang & Qin, 2011), perceived risk typically is hypothesized as a negative relationship in the adoption models. This is in contrast to the other base constructs of UTAUT and UTAUT2, which generally propose a positive relationship between the construct and behavioural intention

(Slade et al, 2015). Given the previous literature and the fact that smart mirrors are not widely disseminated the following hypothesis is put forward:

H7: There is a negative relationship between perceived risk and consumers' behavioural intention to use smart mirrors in retail stores.

H7a: The effect of perceived risk on consumers' behavioural intention to use smart mirrors in retail stores is moderated by age, gender, and income.

5.8.2 Domain-Specific Innovativeness

Lastly, as noted by Araujo, Ladeira, Santini and Sampaio (2016) the concept of DSI was put forward in Robertson's (1971) seminal study, stating "that the consumer has the ability to innovate within a given category, and occasionally, between related class products" (p. 50). This effectively means that while consumers can choose to be innovative in one context they may be conservative in another context at the same-time (Araujo et al., 2016). Elaborating on the DSI construct Goldsmith and Hofacker (1991) define DSI as "the tendency to learn about and adapt product innovations (new products within a specific domain of interest)" (p. 211). Furthermore, Varma Citrin ,Sprott, Silverman and Stem Jr. (2000) suggest that "domain- or product category-specific innovation reflects this tendency to learn about and adopt innovations within a specific domain of interest and, therefore, taps a deeper construct of innovativeness more specific to an area of interest" (p. 296). Given this belief, it is thought that DSI may also be an indicator of technology adoption (Varma Citrin et al., 2000). However, others suggest that the relationship between DSI and behavioural intention to adopt a technology is weak (Jeong, Kim, Park & Choi, 2017). Goldsmith and Hofacker's (1991) scale, validated by Goldsmith, Freiden and Eastman (1995) has proved to be unidimensional and highly reliable (Roehrich, 2004).

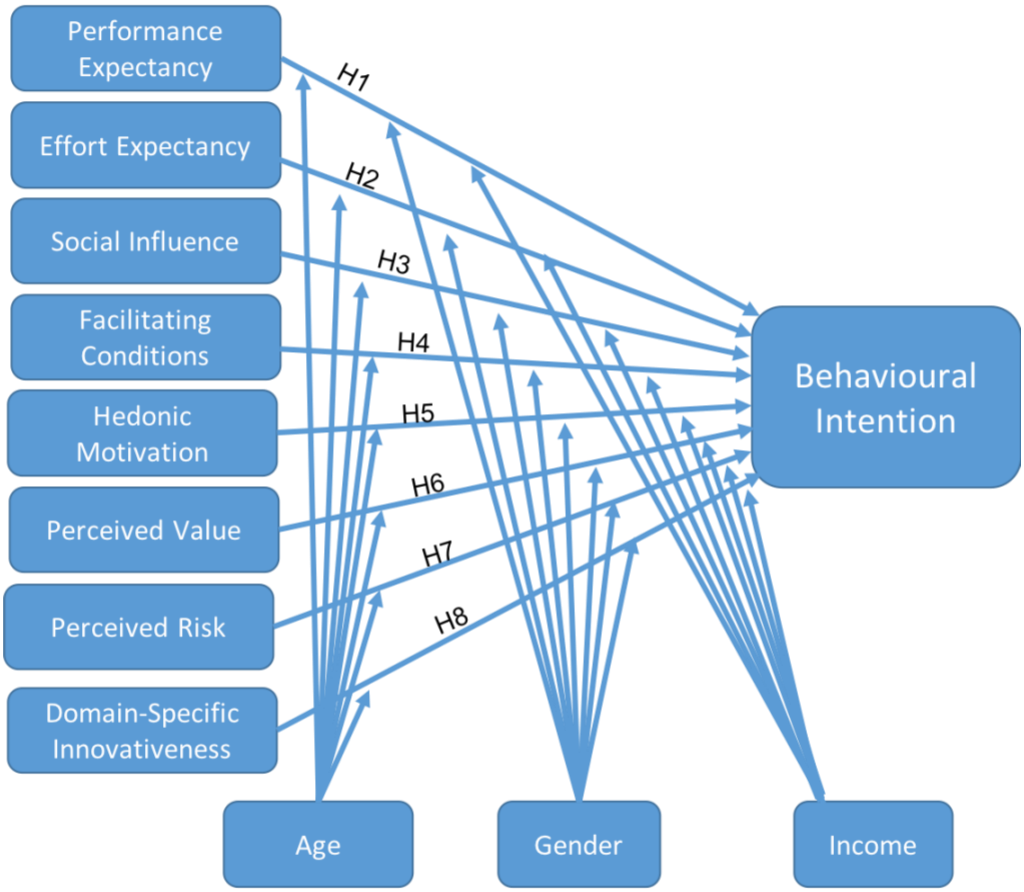
Although not as common as other constructs in adaptations of UTAUT or UTAUT2, Slade et al. (2015) consider the concept of DSI of critical importance to marketers and thus worthy of inclusion in studies that use UTAUT or UTAUT2 as their framework. While, Slade, Williams and Dwivedi (2013) hypothesized that innovativeness will positively affect users behavioural intention to use mobile technology, Nguyen, Nguyen, Pham and Misra (2014) found that innovativeness also has a direct influence on usage. Based on this discussion, this research takes that view that in the context of consumers' behavioural intention to use smart mirrors in a retail store it is appropriate to include DSI as a construct. Therefore, the following hypothesis is proposed:

H8: There is a positive relationship between domain-specific innovativeness and consumers' behavioural intention to use smart mirrors in retail stores.

H8a: The effect of domain-specific innovativeness on consumers' behavioural intention to use smart mirrors in retail stores is moderated by age, gender, and income.

Using the constructs of PE, EE, SI, FC, HM, PV from UTAUT2 as well as the added constructs of PR and DSI, this thesis seeks to provide a meaningful extension of UTAUT2 and apply it to the context of smart technology in the retail domain. Noted by Venkatesh et al. (2012) a downfall of many studies using UTAUT was that they eliminated or removed the moderating variables and discounted the impact of these variables on behavioral intention. As such, this thesis will also examine the effect of age, gender and income (refer to hypotheses H1a to H8a) on the relationship between the constructs listed above and behavioural intention. Based on the hypotheses outlined in this chapter, Figure 5.1 illustrates the proposed research model used in this study. Following this, Chapter Six will detail and outline the methodology using in the construction of this thesis research.

Figure 5.1 *Proposed Research Model*



Hypotheses H1a to H8a

6. Methodology

This quantitative study, approved by the Ryerson Ethics Board (REB; see Appendix B), employs a non-experimental approach to investigate the relationships between the antecedents and consumers' behavioural intention to use smart mirrors in retail stores via a cross-sectional survey design. Cross-sectional data is collected from participants at one point in time and is typically used by researchers to collect data that cannot be directly observed such as opinions attitudes, values and beliefs (Lavrakas, 2008). While cross-sectional data is useful in examining a proposed research model and in testing the associations between variables, its greatest limitation is that the data does not allow for the testing of casual relationships (Lavrakas, 2008). The exception to this limitation is when an experiment is embedded within the survey design (Lavrakas, 2008). That being said, cross-sectional data is used extensively in social science research.

6.1 Instrument

This non-experimental research design adapted the scale items (Table 6.1) from UTAUT2 (Venkatesh et al., 2012). Permission was obtained from Dr. Viswanath Venkatesh to use the survey items from UTAUT2, which was based on prior UTAUT (Venkatesh et al, 2003) research. The four constructs originally described in UTAUT, in addition to behavioural intention, are PE, EE, SI, and FC. UTAUT2 included three additional constructs: price value, HM and habit. As discussed in Chapter Five, the construct of price value was modified to become PV (Yang, Liu, Li & Yu, 2015), and habit has been dropped as smart mirror usage in retail stores has not reached widespread adoption by retailers or consumers. Scales (Table 6.1) for PR (McKnight, Chouhury & Kacmar, 2002; Park, Gunn, Han, 2012) and DSI (Goldsmith &

Hofacker, 1991; Varma Citrin et al, 2000) were also adapted to reflect the specific context under investigation.

All items were measured using a seven-point Likert scale from “strongly disagree” (1) to “strongly agree” (7). With respect to the DSI scale, adapted from Goldsmith and Hofacker (1991) and Varma Citrin et al. (2000), the original items in this scale were reverse-coded. For example, “in general, I am among the last in my circle of friends to use new technology when I see it in a retail store”. There are some that consider the inclusion of reverse-coded items appropriate and preferable in scale development as there is concern that in scales with a significant number of items respondents might lose focus and quickly zip through the items only checking off one level of response (Bruner, n.d.). Conversely, reverse-coding can often lead to a number of problems including poor fit of factor models (Weijters, Baumgartner & Schillewaert, 2013) and unexpected factor structures (Netemeyer, Bearden & Sharma, 2003). Furthermore, respondents can misinterpret the phrasing, which can lead to miscomprehension of the items (Swain, Weathers & Niedrich, 2008). Given this, the decision was made in this research not to reverse-code the DSI scale items. In an effort to reduce respondent fatigue all scales used in this research had six or fewer items, which is within the three to eight item range considered sufficient to measure unidimensional constructs (Bagozzi & Baumgarter, 1994; Green & Rao, 1970). Additionally, the scale items were randomized and presented to the respondents in blocks of six or seven items instead of all 31 items at once.

Table 6.1 *The Scale Items*

Constructs	Items		Source
Performance Expectancy (PE)	I find smart mirrors are useful in retail stores.	PE1	Venkatesh et al, 2012
	Using a smart mirror in retail store would help me accomplish things more quickly.	PE2	
	Using a smart mirror in a retail store would enhance my shopping experience.	PE3	
Effort Expectancy (EE)	Learning how to use a smart mirror in a retail store would be easy for me.	EE1	Venkatesh et al, 2012
	My interaction with a smart mirror in retail stores would be clear and understandable.	EE2	
	It would be easy for me to become skilful at using a smart mirror in a retail store.	EE3	
Social Influence (SI)	People who are important to me would encourage me to use a smart mirror in a retail store.	SI1	Venkatesh et al, 2012
	People who influence my behaviour would think that I should use a smart mirror in a retail store.	SI2	
	People whose opinions that I value would prefer that I use a smart mirror in a retail store.	SI3	
Facilitating Conditions (FC)	I have the knowledge necessary to use a smart mirror in a retail store.	FC1	Venkatesh et al, 2012
	Smart mirrors would be compatible with other technologies I use.	FC2	
	I could get help from others if I have difficulties using a smart mirror in a retail store.	FC3	
Hedonic Motivation (HM)	Using a smart mirror in a retail store would be fun.	HM1	Venkatesh et al, 2012
	Using a smart mirror in a retail store would be enjoyable.	HM2	
	Using a smart mirror in a retail store would be very entertaining.	HM3	
Perceived Value (PV)	In spite of the risks involved in sharing my personal information and payment data, I believe that using a smart mirror in a retail store would be valuable.	PV1	Yang et al. (2015)
	In spite of the risks involved in sharing my personal information and payment data, I believe that using a smart mirror in a retail store would be worthwhile.	PV2	
	In spite of the risks involved in sharing my personal information and payment data, I believe that using a smart mirror in a retail store would deliver good value.	PV3	
	In spite of the risks involved in sharing my personal information and payment data, I believe that using a smart mirror would be beneficial to me.	PV4	
Perceived Risk (PR)	I think that it is risky to provide one's credit card information to a smart mirror in a retail store	PR1	McKnight et al. (2002) Park et al. (2012)
	I would hesitate to enter my credit card information when making purchase using a smart mirror.	PR2	
	I would hesitate to enter personal information like my name, address, and phone number when making a purchase using a smart mirror.	PR3	
Domain-Specific Innovativeness (DSI)	In general, I am among the first in my circle of friends to use new technology when I see it in a retail store.	DSI1	Goldsmith & Hoefacker (1991) Citrin et al. (2000)
	If I heard that a smart mirror was available in a retail store, I would be interested enough to use it.	DSI2	
	Compared to my friends, I seek out a lot of information about new technology in retail stores.	DSI3	
	In general, I am the first in my circle of friends to know of any retail stores using new technologies.	DSI4	
	I would use a smart mirror in a retail store even if I have not heard of it before.	DSI5	
	I know about new technology in retail stores before most other people in my circle do.	DSI6	
Behavioural Intention (BI)	Once I tried a smart mirror in a retail store my intention would be to use it again.	BI1	Venkatesh et al, 2012
	I would always try to use a smart mirror, if available, in a retail store.	BI2	
	I would plan to continue to use smart mirrors in retail stores frequently.	BI3	

The questionnaire included demographic questions related to age, gender, level of household income and education. Age was measured in years and gender was measured categorically using the variables (1) male, (2) female, and (3) non-binary. Household income was also measured categorically using a scale from one to five where, (1) less than $25,000, (2) $25,000 to $49,999, (3) $50,000 t- $74,999, (4) $75,000 to $99,999, and (5) $100,000 or greater. Level of education was also measured in a similar way using a categorical scale where, (1) high school diploma, (2) college diploma, (3) bachelor's degree, (4) master's degree, and (5) doctoral degree. For the demographic questions relating to income and level of education, given the sensitive nature of these questions respondents were also presented with a sixth selection of "prefer not to answer". In total 16 percent of respondents selected this option when answering the demographic question relating to income and two percent selected this answer with respect to the question on education.

Lastly, the questionnaire included four additional questions that asked respondents to (1) rate their level of awareness of smart mirrors; (2) state their level of interest in using a smart mirror at home; (3) describe the functions and features they would find most beneficial; and (4) where in their shopping journey (e.g., fitting room for apparel, at the makeup counter for cosmetics) they would find a smart mirror most useful. These questions were provided by OAK Labs, a San Francisco-based smart mirror developer, and the results of the questions will be directly reported back to the company and will not be considered further.

6.1.1 "The OAK Mirror" Video

Respondents to the questionnaire were not screened or assumed to have any prior knowledge of smart mirrors and their potential use in retail stores or settings. Instead they were shown a video, titled "The OAK Mirror" that illustrated customers' experience using a smart mirror in a retail store (fitting room) and outlined some of its functionality. Screenshots of the video are included in Appendix C. OAK Labs, the mirror developer, was co-founded by Healey Cypher a former Head of Retail Innovation at eBay. The company currently has partnerships with a number of retailers including Rebecca Minkoff and Polo Ralph Lauren who have implemented the versions of the mirror in a select number of boutiques. Permission to use the video in this research was granted in exchange for including four questions, outlined in the previous paragraph, and will be reported directly to OAK Labs.

6.2 Data Collection

Data collection took place in January 2018. A Canadian market research firm and panel provider was contracted to administer the survey online and to recruit participants. The selected panel provider uses incentives to reward its panelists for participating its various surveys. These incentives can include reward points for various retailers and service providers including Hudson's Bay, Walmart, Via Rail and Petro Canada. Alternatively, they may also provide respondents with an entry into a random drawing to win a larger prize. Panelists were selected at random to participate in this study and were provided with incentive points in exchange for their participation. The only criteria required for inclusion in this study was that the respondents needed to be 18 years of age or older. Consent was sought from each respondent prior to completing the questionnaire. Respondents were asked to read through the consent form approved by REB (Appendix D) and were also provided with an opportunity to download the form. They then had to click on a button labeled "yes, I agree to participate" to move forward with the questionnaire. Those that did not agree to participate were immediately removed from the survey.

First, a field test was conducted at the beginning of January 2018 in order to refine the individual questions and the structure of the questionnaire. Feedback from the 110 respondents resulted in minor changes to the phrasing of the four questions provided by OAK Labs. No changes, save for one grammatical modification, were made to any of the scale items. The data from the field test was not included in the main analysis.

A total of 1656 Canadians completed the survey in January 2018. The survey was only conducted in English. Due to cost and time constraints the survey was not translated into French, which resulted in the exclusion of all respondents (French and English) from the province of Quebec. Although regional quotas were not required, soft quotas of 40 percent, 40 percent and 20 percent were assigned as a parameter to ensure reasonable coverage across the West, Ontario, and Eastern Canada respectfully.

6.2.1 Sample

Following the work of Venkatesh et al. (2012), Morosan and Defranco (2016), Martins et al. (2014) and Shaw and Sergueeva (2016) partial least squares (PLS) will be used to test the proposed research model as there is a number of interaction terms and PLS is capable of testing these effects (Chin, Marcolin & Newsted, 2003). With respect to sample size, the often-cited rule of thumb is the 10-times rule from Barclay, Higgins and Thompson (1995). This rule indicates that the sample should be equal to the larger of:

1. 10 times the largest number of formative indicators used to measure a single construct, or
2. 10 times the largest number of structural paths directed at a particular construct in the structural model (Hair, Hult, Ringle & Sarstedt, 2017 p. 25).

Were this research to follow the above stated rule of thumb the minimum sample required for this study would be n = 80. Hair et al. (2017) discourage the use of above stated rule. Instead they propose the minimum sample size required to detect minimum R^2 values of 0.10 in the endogenous construct in the structural model for a significance level of five percent assuming a statistical power of 80 percent and the level of complexity in this model is n = 144 (Hair et al., 2017).

While a sample of 144 is considered the baseline for a study of this nature, this research looks to the previous work of Venkatesh et al (2012) and Morosan and DeFranco (2016) to determine the minimum sample. Both studies used UTAUT2 to examine the relationships between the antecedents and behavioural intention of a broad population of consumers in Hong Kong and the United States, respectfully. Structurally these two studies are similar with this research which seeks to investigate the same relationships between the antecedents and behavioural intention of Canadian consumers to use smart mirrors in retail stores. As such, their sample sizes of 794 (Morosan & DeFranco, 2016) and 1,512 (Venkatesh et al., 2012) is considered an appropriate range for this research. Therefore, a minimum sample of n = 800 was sought for this analysis.

The subsequent chapter presents the results from the evaluation of the measurement and structural model along with the descriptive statistics. Following this, Chapter Eight presents a summary of the results and a more detailed discussion. Chapter Nine concludes this research and outlines the study's implications, limitations, and recommendations for future research.

7. Results

"Structural equation modeling (SEM) is a statistical technique for testing and estimating causal relations using a combination of statistical data and qualitative causal assumptions" (Martins et al., 2014 p. 6). PLS is a variance-based technique that will be used in this investigation as it is capable of testing complex models and the effects of interaction terms (Martins et al., 2014; Venkatesh et al., 2012). SmartPLS version 3.2.7, was selected as the software used to analyze data and test the research model as it has gained prominence in the marketing and business literature (Hair et al., 2017; Hair, Ringle, & Sarstedt, 2011) and has previously been used in research employing UTAUT and UTAUT2 frameworks (Venkatesh et al., 2012; Baptista & Oliveira, 2015; Alaiad, Zhou, & Koru, 2014; Nair, Ali, & Leong, 2015).

The analysis of the empirical data was performed in two phases. First, the evaluation of the measurement model is performed followed by the evaluation of the structural model in phase two. The activities within each phase are outlined below:

1. Evaluation of Measurement Model (Hair et al, 2017, p.106-107, 122)

- Determine internal consistency through the evaluation of Cronbach's alpha (greater than 0.70) and composite reliability (greater than 0.70). It should be noted when one is conducting exploratory research a composite reliability between 0.60 and 0.70 is considered appropriate.
- Determine convergent validity through the evaluation of indicator reliability (outer loadings should be greater than 0.70) and average variance extraction (AVE) (greater than 0.50).
- Determine discriminant validity, evaluating the cross-loadings, the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT) statistic.

2. Evaluation of the Structural Model (Hair et al, 2017, p.106-107, 191)

- Assess structural model for collinearity issues
- Calculate coefficients of determination (R^2)
- Examine the size and significance of the path coefficients
- Evaluate the effect sizes (f^2)
- Evaluate the predictive relevance (Q^2) and effect sizes (q^2)

A total of 1656 valid responses were collected in January 2018. Following the recommendations outlined in Hair et al. (2017), including the elimination of observations with missing data and suspicious and inconsistent response patterns a final sample of 985 Canadians will be used to evaluate the proposed research model. The following four subsections detail the characteristics of the sample, evaluate the measurement model (without the moderators), test the structural model, and finally evaluate the proposed research model with the moderators of age, gender, and income.

7.1 Descriptive Analysis

An analysis of the demographic characteristics (Table 7.1) of respondents was performed using Microsoft Excel. It was found that the sample was almost equally split between male and female with two respondents identifying themselves as non-binary. Most respondents (33.9 percent) had an annual household income of $100,000 or greater, and the majority had obtained either a college diploma (22.2 percent) or a bachelor’s degree (38.0 percent). Furthermore, respondents were equally split amongst three defined age categories.

Table 7.1 *Sample Characteristics*

	%		%		%
Gender		**Age**		**Geographic Region**	
Male	45.5	18-34	32.5	British Columbia	14.7
Female	54.3	35-49	36.3	Alberta	14.0
Non-binary	0.2	50+	31.2	Saskatchewan	7.1
				Manitoba	5.6
Income (annual per household)		**Education (highest level attained)**		Ontario	39.1
Less than $25,000	5.2	High School Diploma	15.3	New Brunswick	4.8
$25,000 to $49,999	12.7	College Degree	22.2	Newfoundland	5.6
$50,000 to $74,999	16.0	Bachelor's Degree	38.0	Nova Scotia	8.6
$75,000 to $99,999	15.3	Master's Degree	17.9	Prince Edward Island	0.5
$100,000 or greater	33.9	Doctoral Degree	4.3		
Prefer not to answer	16.9	Prefer not to answer	2.3		

With respect to gender and geography, the sample was similarly distributed to the general Canadian population (Statistics Canada, 2017b). The provinces from the west (British Columbia, Alberta, Saskatchewan and Manitoba) and the east (Newfoundland and Labrador, New Brunswick, Nova Scotia and Prince Edward Island) are over represented given that the survey excluded individuals from Quebec.

Looking at household income, Statistics Canada estimates that more than 29 percent of households have an annual income of less than $25,000 (Asking Canadians, 2017). This percentage is significantly different from the sample where just over five percent of respondents noted an annual household income of less than $25,000. While not representative of the general Canadian population this result closely aligns with the distribution of the panel providers one million members.

With respect to age, the sample is over represented with respondents aged 18 to 34 and 34 to 49, and underrepresented by those aged 50 years and older when compared to the Canadian population. Lastly, the most recent Canadian census determined that more than 54 percent of the population had at a minimum a college diploma, while approximately 25 percent of the population listed a high school diploma as their highest level of educational attainment (Statistics

Canada, 2017a). Compared with the Canadian population, the sample respondents indicated higher levels of educational attainment, with more than 82 percent of respondents indicating they had achieved a minimum of a college diploma.

7.2 The Measurement Model

7.2.1 Path Model 1

Using the initialization options suggested by Hair et al. (2017) shown in Table 7.2, the PLS-SEM analysis was conducted using the software, SmartPLS version 3.2.7, provided by Ryerson University. The algorithm converged in four iterations; the structural model (excluding moderators) is shown in Figure 7.1 and includes the results from the PLS-SEM algorithm's output.

Table 7.2 *Rules of Thumb for Initializing the PLS-SEM Algorithm (Hair et al, 2017, p. 91)*

Weighting Method	Path weighting scheme
Initial Value of Outer Weights	+1
Stop Criterion	0.0000001
Maximum Number of Iterations	300

Assessment of the path model indicates that all the outer loadings (indicator reliability) are above the minimum threshold of 0.70, as required by Hair et al. (2017). The indicator FC1 had the lowest loading at 0.718. Table 7.3 is a summary evaluating the measurement model for reliability and validity. These results consist of the Cronbach's Alpha (CA), Composite Reliability (CR) and the Average Variance Extracted (AVE). Both CA and CR are a measure of internal consistency and have a minimum threshold of 0.70. AVE, along with Indicator Reliability (IR) is a measure of convergent validity and is the mean of the squared loadings of the constructs' indicators. While not of particular interest at this stage of the analysis the R^2

(Coefficient of Determination) measures the explained variance of the endogenous construct (BI).

Figure 7.1 *PLS Path Model 1 (without moderators)*

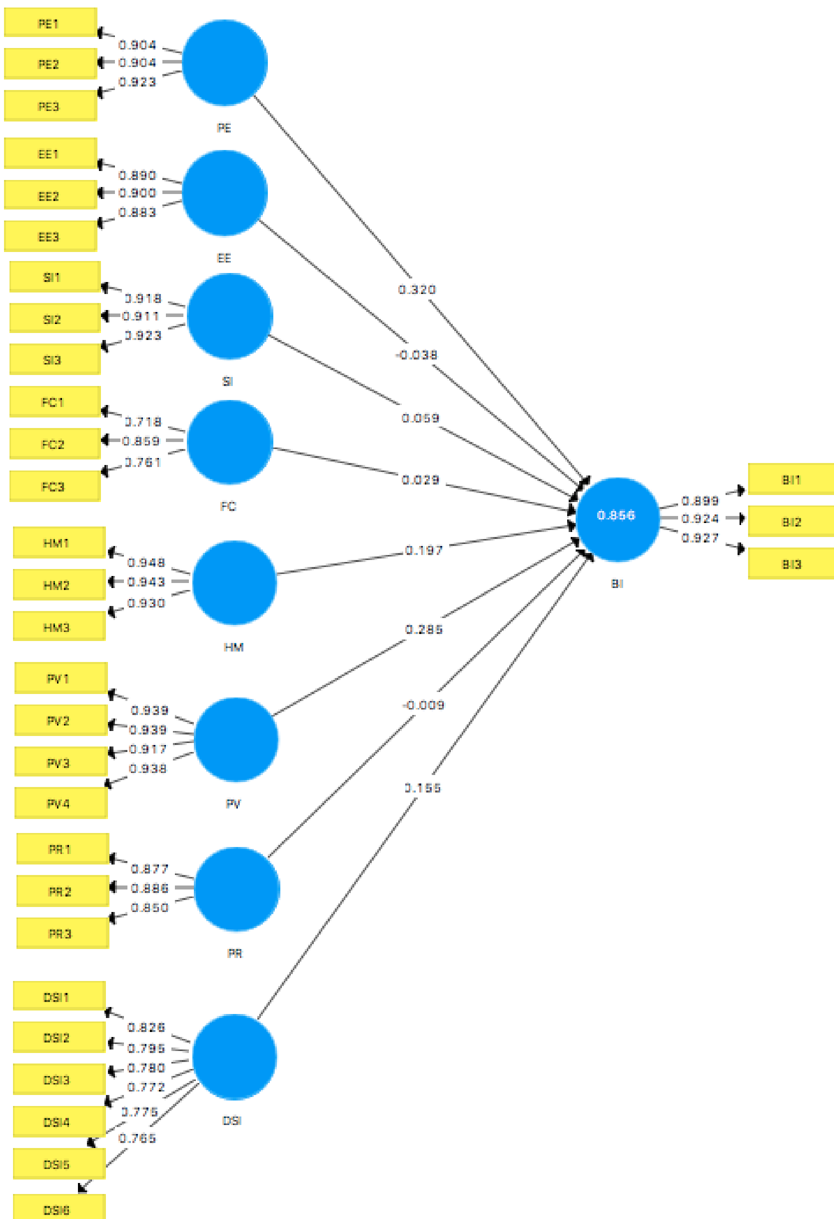


Table 7.3 *Model 1 Results*

	Cronbach's Alpha	Composite Reliability	AVE
BI	0.905	0.940	0.840
DSI	0.883	0.906	0.617
EE	0.872	0.920	0.794
FC	0.688	0.824	0.611
HM	0.935	0.958	0.885
PE	0.897	0.936	0.829
PR	0.841	0.904	0.759
PV	0.951	0.964	0.872
SI	0.906	0.941	0.841

As indicated in Table 7.3, CA for the construct FC is below the threshold of 0.70. Though its AVE is above the minimum threshold of 0.50, at 0.611 it is much lower than the other constructs, save for DSI. Examination of the cross-loadings, Table 7.4, as part of the criteria to assess discriminant validity, show two indicators for DSI (DSI2 and DSI5) and one for FC (FC1) that have equal or higher loadings on other constructs. This suggests that discriminant validity has not been established and the decision was made at this time to remove these indicators and to re-evaluate the measurement model.

Table 7.4 *Path Model 1 Cross-Loadings*

	BI	DSI	EE	FC	HM	PE	PR	PV	SI
BI1	0.899	0.682	0.529	0.606	0.719	0.774	-0.263	0.773	0.604
BI2	0.924	0.722	0.550	0.579	0.772	0.827	-0.256	0.799	0.623
BI3	0.927	0.753	0.554	0.641	0.803	0.828	-0.260	0.817	0.616
DSI1	0.517	0.826	0.498	0.513	0.428	0.487	-0.208	0.502	0.485
DSI2	0.821	**0.795**	0.596	0.651	0.820	0.789	-0.210	0.758	0.553
DSI3	0.491	0.780	0.453	0.459	0.411	0.495	-0.169	0.470	0.498
DSI4	0.435	0.772	0.423	0.440	0.340	0.413	-0.145	0.420	0.469
DSI5	0.755	**0.775**	0.602	0.631	0.758	0.713	-0.228	0.702	0.505
DSI6	0.443	0.765	0.447	0.432	0.354	0.428	-0.158	0.421	0.482
EE1	0.446	0.559	0.890	0.674	0.500	0.468	-0.113	0.418	0.288
EE2	0.630	0.642	0.900	0.676	0.626	0.637	-0.189	0.589	0.471
EE3	0.477	0.556	0.883	0.669	0.536	0.509	-0.121	0.456	0.313
FC1	0.368	0.488	0.716	**0.718**	0.369	0.385	-0.081	0.347	0.262
FC2	0.641	0.660	0.613	0.859	0.625	0.651	-0.215	0.612	0.491
FC3	0.495	0.448	0.491	0.761	0.499	0.486	-0.103	0.473	0.370
HM1	0.791	0.690	0.599	0.611	0.948	0.805	-0.180	0.755	0.535
HM2	0.812	0.684	0.616	0.630	0.943	0.830	-0.200	0.774	0.561
HM3	0.751	0.669	0.561	0.613	0.930	0.737	-0.148	0.694	0.508
PE1	0.802	0.682	0.566	0.606	0.757	0.904	-0.223	0.784	0.587
PE2	0.778	0.660	0.536	0.583	0.729	0.904	-0.218	0.745	0.580
PE3	0.833	0.714	0.578	0.642	0.811	0.923	-0.230	0.803	0.619
PR1	-0.237	-0.221	-0.159	-0.164	-0.151	-0.205	0.877	-0.331	-0.202
PR2	-0.250	-0.214	-0.139	-0.153	-0.164	-0.208	0.886	-0.327	-0.194
PR3	-0.252	-0.207	-0.132	-0.162	-0.175	-0.229	0.850	-0.329	-0.190
PV1	0.806	0.691	0.526	0.589	0.738	0.794	-0.356	0.939	0.628
PV2	0.813	0.708	0.529	0.599	0.732	0.801	-0.380	0.939	0.626
PV3	0.790	0.652	0.508	0.565	0.733	0.767	-0.322	0.917	0.589
PV4	0.834	0.707	0.526	0.609	0.744	0.828	-0.352	0.938	0.628
SI1	0.612	0.566	0.351	0.458	0.505	0.584	-0.212	0.601	0.918
SI2	0.622	0.606	0.408	0.468	0.548	0.613	-0.196	0.613	0.911
SI3	0.609	0.594	0.382	0.447	0.511	0.603	-0.209	0.608	0.923

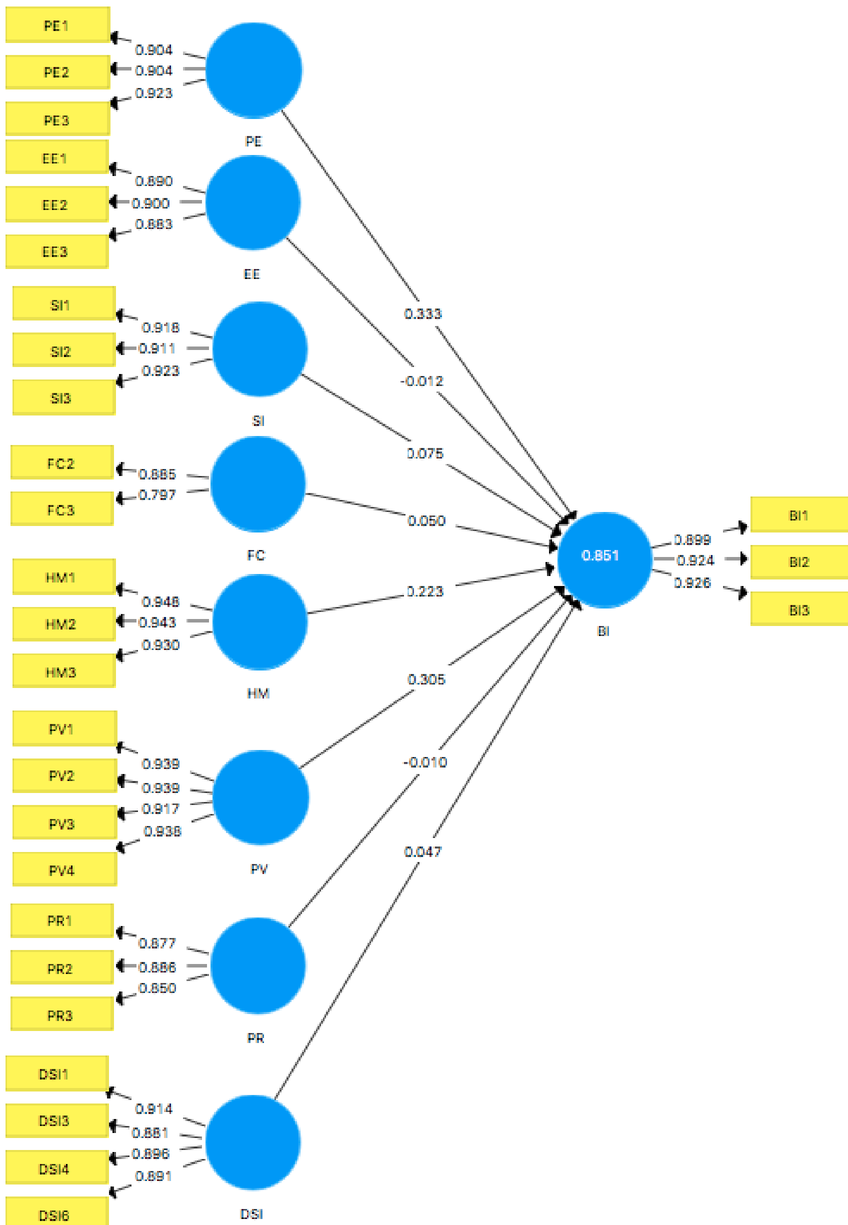
7.2.2 Path Model 2

Using the same initialization options outlined in Table 7.2, the PLS algorithm was re-calculated without the constructs DSI2, DSI5 and FC1. Again the model converged in four iterations and the results of the output can be seen in Table 7.5, and in Figure 7.2.

Table 7.5 *Model 2 Results*

	Cronbach's Alpha	Composite Reliability	AVE
BI	0.905	0.940	0.840
DSI	0.918	0.942	0.802
EE	0.872	0.920	0.794
FC	0.596	0.830	0.709
HM	0.935	0.958	0.885
PE	0.897	0.936	0.829
PR	0.841	0.904	0.759
PV	0.951	0.964	0.872
SI	0.906	0.941	0.841

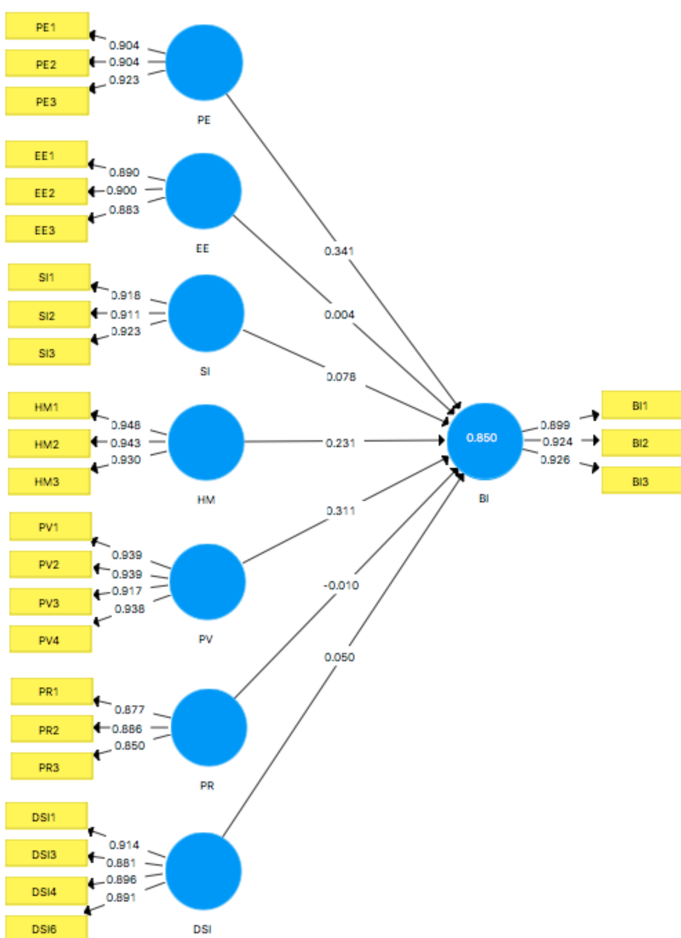
Figure 7.2 *PLS Path Model 2 (no FC1, DSI2, DSI5)*



The outer loadings for Path Model 2 remain above the minimum threshold of 0.70, with all indicators at 0.797 or above. With the elimination of FC1, CR and AVE for FC improved, however, its CA dropped further below the minimum threshold of 0.70 to 0.596. Additionally, while R^2 is not considered at this this stage of the evaluation it is worth noting that with the removal of DSI2, DSI5 and FC1, the R^2 remained virtually unchanged between the two models, 0.856 in Model 1 and 0.851 in Model 2.

At this point in the analysis, and to obtain internal consistency reliability, the decision was made to remove FC as a construct from the measurement model. In their meta-analysis of UTAUT, Dwivedi et al. (2011) note that FC is the weakest of the four original constructs of UTAUT with only nine of 43 studies showing a significant relationship between FC and BI. Two studies showed FC to be non-significant and the relationship between FC and BI was classified as not applicable in the remaining 32 studies. After removing the construct FC, the PLS algorithm was recalculated. The resulting path model, Model 3, is shown in Figure 7.3.

Figure 7.3 *Path Model 3 (no FC)*



7.2.3 Path Model 3

A summary of the results assessing the model for internal consistency, shown in Table 7.6, indicate that the model has achieved internal consistency and convergent validity. CA and CR values for all constructs are above the minimum threshold of 0.70, and the AVE for all constructs is well above the threshold of 0.50. Along with the outer loadings which were 0.877 or higher the measurement model can now be evaluated for discriminant validity.

Table 7.6 *Path Model 3 Results*

	Cronbach's Alpha	Composite Reliability	AVE
BI	0.905	0.940	0.840
DSI	0.918	0.942	0.802
EE	0.872	0.920	0.794
HM	0.935	0.958	0.885
PE	0.897	0.936	0.829
PR	0.841	0.904	0.759
PV	0.951	0.964	0.872
SI	0.906	0.941	0.841

In assessing discriminant validity one historically has evaluated the Fornell-Larcker criterion and the cross-loadings. Results of both are shown in Tables 7.7 and 7.8. According to Hair et al. (2017) the cross-loadings are the first approach to assessing discriminant validity. “Specifically, an indicator’s outer-loading on the associated construct should be greater than any of its cross-loadings (i.e. its correlation) on other constructs” (Hair et al., 2017, p. 115). The Fornell-Larcker criterion is the second method in establishing discriminant validity. This criterion “compares the square root of the AVE values with the latent variable and its correlations. Specifically, the square root of each construct’s AVE should be greater than its highest correlation with any other construct” (Hair et al., 2017, p. 115-116). Evaluation of the cross-loadings and Fornell-Larcker criterion would indicate that discriminant validity has been achieved as the cross-loadings and the AVE for each construct are higher than on any other construct.

Table 7.7 *Path Model 3 Cross-Loadings*

	BI	DSI	EE	HM	PE	PR	PV	SI
BI1	**0.899**	0.463	0.529	0.719	0.774	-0.263	0.773	0.604
BI2	**0.924**	0.494	0.550	0.772	0.827	-0.256	0.799	0.623
BI3	**0.926**	0.496	0.554	0.803	0.828	-0.260	0.817	0.616
DSI1	0.517	**0.914**	0.498	0.428	0.487	-0.208	0.502	0.485
DSI3	0.491	**0.881**	0.453	0.411	0.495	-0.169	0.470	0.498
DSI4	0.435	**0.896**	0.423	0.340	0.413	-0.145	0.420	0.469
DSI6	0.443	**0.891**	0.447	0.354	0.428	-0.158	0.421	0.482
EE1	0.446	0.445	**0.890**	0.500	0.468	-0.113	0.418	0.288
EE2	0.630	0.480	**0.900**	0.626	0.637	-0.189	0.589	0.471
EE3	0.477	0.432	**0.883**	0.536	0.509	-0.121	0.456	0.313
HM1	0.791	0.422	0.599	**0.948**	0.805	-0.180	0.755	0.535
HM2	0.812	0.408	0.616	**0.943**	0.830	-0.200	0.774	0.561
HM3	0.751	0.384	0.561	**0.930**	0.737	-0.148	0.694	0.508
PE1	0.802	0.466	0.566	0.757	**0.904**	-0.223	0.784	0.587
PE2	0.778	0.465	0.536	0.729	**0.904**	-0.218	0.745	0.580
PE3	0.833	0.466	0.578	0.811	**0.923**	-0.230	0.803	0.619
PR1	-0.237	-0.186	-0.159	-0.151	-0.205	**0.877**	-0.331	-0.202
PR2	-0.250	-0.169	-0.139	-0.164	-0.208	**0.886**	-0.327	-0.194
PR3	-0.252	-0.147	-0.132	-0.175	-0.229	**0.850**	-0.329	-0.190
PV1	0.806	0.479	0.526	0.738	0.794	-0.356	**0.939**	0.628
PV2	0.813	0.490	0.529	0.732	0.801	-0.380	**0.939**	0.626
PV3	0.790	0.436	0.508	0.733	0.767	-0.322	**0.917**	0.589
PV4	0.834	0.492	0.526	0.744	0.828	-0.352	**0.938**	0.628
SI1	0.612	0.470	0.351	0.505	0.584	-0.212	0.601	**0.918**
SI2	0.622	0.498	0.408	0.548	0.613	-0.196	0.613	**0.911**
SI3	0.609	0.518	0.382	0.511	0.603	-0.209	0.608	**0.923**

Table 7.8 *Path Model 3 Fornell-Larcker Criterion*

	BI	DSI	EE	HM	PE	PR	PV	SI
BI	0.917							
DSI	0.529	0.896						
EE	0.594	0.510	0.891					
HM	0.835	0.430	0.630	0.941				
PE	0.884	0.511	0.616	0.842	0.910			
PR	-0.283	-0.192	-0.164	-0.188	-0.246	0.871		
PV	0.869	0.509	0.560	0.789	0.854	-0.378	0.934	
SI	0.670	0.540	0.415	0.569	0.655	-0.224	0.662	0.917

Despite numerous studies relying on the cross-loadings and the Fornell-Larcker criterion (Morosan & DeFranco, 2016; Martins et al., 2014; Shaw & Sergueeva, 2016), Hair et al. (2017)

suggest using the HTMT ratio of the correlations to further establish discriminant validity. "HTMT is the mean of all correlations of indicators across constructs measuring different constructs relative to the (geometric) mean of the average correlations of indicators measuring the same construct" (Hair et al., 127, p. 118). Furthermore, Hair et al. (2017) note that "the HTMT approach is an estimate of what the true correlation between two constructs would be, if they were perfectly measured (i.e., if they were perfectly reliable)" (p. 118). Prior research (Henseler, Ringle & Sarstedt, 2015) indicates constructs in the path model are conceptually very similar if the HTMT ratio is above 0.90, or the more conservative 0.85. Therefore, according to Hair et al. (2017) an HTMT value above 0.90 suggests a lack of discriminant validity even if the cross-loadings and Fornell-Larcker criterion are not indicative of such.

Table 7.9 *Path Model 3 Heterotrait-Monotrait Ratio*

	BI	DSI	EE	HM	PE	PR	PV	SI
BI								
DSI	0.577							
EE	0.652	0.564						
HM	**0.906**	0.461	0.686					
PE	**0.980**	0.561	0.681	**0.917**				
PR	0.325	0.217	0.185	0.211	0.283			
PV	**0.936**	0.541	0.600	0.836	**0.924**	0.422		
SI	0.740	0.592	0.450	0.617	0.726	0.257	0.713	

Assessment of the HTMT ratio, as shown in Table 7.9, indicates that discriminant validity has not been achieved as there are five values above the threshold of 0.90. Hair et al. (2017) suggest a number of ways for addressing discriminant validity problems. One way is to "eliminate items (indicators) that are strongly correlated in opposing constructs, or to reassign these indicators to the construct if theoretically possible" (Hair et al., 2017, p. 120). Another approach involves merging the problem constructs into a more general construct (Hair et al., 2017). Again, this approach is warranted only if it is theoretically possible. As neither of the approaches to reassign indicators or to merge constructs are well supported in the literature this thesis follows the approach of eliminating the indicators that are strongly correlated in an opposing construct.

To undertake this method an exploratory factor analysis with a verimax rotation was conducted using IBM SPSS, the output of which can be seen in Appendix E. The cross-loadings (correlation matrix in SPSS) were reexamined to determine which indicators were strongly correlating on opposing constructs. As Field (2013) notes, items loading on opposing constructs above 0.80 should be considered for possible removal. Referring back to Table 7.7, indicators BI2, BI3, PE1, HM2, and PV4 were strongly correlated above 0.80 on opposing constructs. Not wanting to remove the constructs in their entirety these indicators were selected for removal and the PLS algorithm was rerun with the modified path model.

Table 7.10 *Path Model 3 (Modified) Heterotrait-Monotrait Ratio (no BI2, BI3, PE1, HM2, and PV4)*

	BI	DSI	EE	HM	PE	PR	PV	SI
BI								
DSI	0.480							
EE	0.553	0.564						
HM	0.731	0.459	0.675					
PE	0.812	0.554	0.671	0.896				
PR	0.287	0.217	0.185	0.196	0.280			
PV	0.789	0.536	0.600	0.817	0.896	0.424		
SI	0.635	0.592	0.450	0.603	0.723	0.257	0.711	

The HTMT of the modified path model, see Table 7.10, indicates that discriminant validity has been achieved as none of the HTMT values are above 0.90. To confirm discriminant validity, the Fornell-Larcker criterion was reevaluated, see Table 7.11, which indicates that discriminant validity has been achieved as each construct's AVE is greater than its highest correlation with any other construct.

Table 7.11 *Path Model 3 (Modified) Fornell-Larcker Criterion*

	BI	DSI	EE	HM	PE	PR	PV	SI
BI	1.000							
DSI	0.464	0.896						
EE	0.528	0.510	0.891					
HM	0.696	0.423	0.607	0.955				
PE	0.755	0.497	0.594	0.795	0.938			
PR	-0.263	-0.193	-0.164	-0.171	-0.239	0.871		
PV	0.763	0.500	0.554	0.751	0.806	-0.375	0.940	
SI	0.604	0.540	0.413	0.545	0.640	-0.224	0.654	0.917

The modified path model was also reevaluated to confirm internal consistency and convergent validity as the elimination of indicators to improve HTMT can adversely impact the model's CA, CR and AVE. The model converged in two iterations and a summary of the results, Table 7.12, indicate that internal consistency and convergent validity is achieved as CA and CR are well above the minimum 0.70 threshold, and AVE is significantly above the threshold of 0.50. Furthermore, the outer loadings, see Figure 7.4, are well above the threshold of 0.70 with the lowest being 0.840.

Table 7.12 *Path Model 3 (Modified) Results*

	Cronbach's Alpha	Composite Reliability	AVE
BI	1.000	1.000	1.000
DSI	0.918	0.942	0.802
EE	0.872	0.921	0.794
HM	0.905	0.955	0.913
PE	0.864	0.936	0.880
PR	0.841	0.904	0.759
PV	0.934	0.958	0.883
SI	0.906	0.941	0.841

Figure 7.4 *Path Model 3 (Modified)*

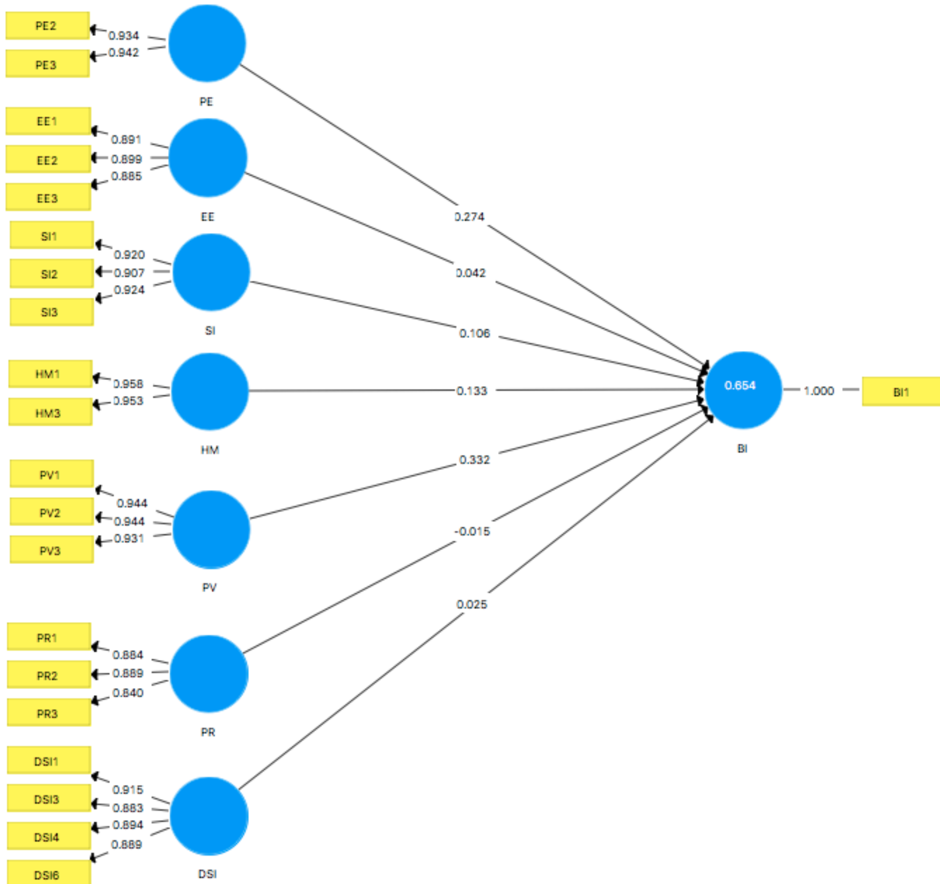


Table 7.13, presents a summary of the results of the modified path model, see Figure 7.4, and indicates that the measurement model has achieved internal consistency, convergent validity and discriminant validity. As such, the analysis can move forward to phase two and evaluate the structural model.

Table 7.13 *Results Summary for the Measurement Model*

Latent Variable	Indicators	Convergent Validity			Internal Consistency Reliability		Discriminant Validity
		Loadings	Indicator Reliability	AVE	Composite Reliability	Cronbach's Alpha	
		>0.70	>0.50	>0.50	>0.70	>0.70	HTMT and Fornell-Larcker Achieved
DSI	DSI1	0.915	0.837	0.802	0.942	0.918	Yes
	DSI3	0.883	0.780				
	DSI4	0.894	0.799				
	DSI6	0.889	0.790				
EE	EE1	0.891	0.794	0.794	0.921	0.872	Yes
	EE2	0.899	0.808				
	EE3	0.885	0.783				
HM	HM1	0.958	0.918	0.913	0.955	0.905	Yes
	HM3	0.953	0.908				
PE	PE2	0.934	0.872	0.88	0.936	0.864	Yes
	PE3	0.942	0.887				
PR	PR1	0.884	0.781	0.759	0.904	0.841	Yes
	PR2	0.889	0.790				
	PR3	0.840	0.706				
PV	PV1	0.944	0.891	0.883	0.958	0.934	Yes
	PV2	0.944	0.891				
	PV3	0.931	0.867				
SI	SI1	0.920	0.846	0.841	0.941	0.906	Yes
	SI2	0.907	0.823				
	SI3	0.924	0.854				

7.3 The Structural Model

Having confirmed that the measurement model meets the requirements established by Hair et al. (2017), the analysis will continue with the assessment of the structural model. The following are the list of activities that will be undertaken in this stage:

- Assess structural model for collinearity issues
- Examine the size and significance of the path coefficients
- Calculate coefficients of determination (R^2)
- Evaluate the effect sizes (f^2)
- Evaluate the predictive relevance (Q^2) and effect sizes (q^2)

7.3.1 Collinearity Assessment

To assess the collinearity of a reflective measurement model, Hair et al. (2017) apply the same criteria as in the evaluation of formative measurement models. Using the variance inflation factor (VIF), Hair et al. (2017) suggest that VIF values above five in the predictor constructs would indicate critical levels of collinearity. "The term VIF is derived from its square root being the degree to which the standard error has been increased due to the presence of collinearity" (Hair et al., 2017, p. 143). Examining the inner VIF values, Table 7.14, only one of the values is above four and none are above the threshold of five indicating that collinearity has been established.

Table 7.14 *Collinearity Statistic – VIF Values*

	VIF Values
BI	
DSI	1.669
EE	1.861
HM	3.271
PE	4.049
PR	1.206
PV	3.919
SI	2.055

7.3.2 Significance of Structural Model Coefficients

To assess the significance of the structural model path coefficients, the bootstrapping procedure was used to calculate the significance of the PLS-SEM results including the *t* statistic, the *p* value and the related path coefficients. Following the recommendations from Hair et al. (2017) Table 7.15 lists the conditions that were set in SmartPLS prior to initiating the bootstrapping process.

Table 7.15 *Bootstrapping Conditions*

Subsamples	5,000
Sign Change	No sign changes
Confidence Interval Method	Bias-Corrected & Accelerated (BCa) Bootstrap
Amount of Results	Complete Bootstrapping

Table 7.16 shows the values of the path coefficients along with their *t* values, *p* values, confidence intervals and the significance level.

Table 7.16 *Significance of Testing Results of the Structural Model Path Coefficients*

	Path Coefficients	*t* Values	*p* Values	95% Confidence Intervals	Significance Level
DSI -> BI	0.025	0.957	0.338	(-0.025-0.074)	NS
EE -> BI	0.042	1.500	0.134	(-0.011-0.097)	NS
HM -> BI	0.133	3.177	0.001	(0.056-0.218)	<0.05
PE -> BI	0.274	5.938	0.000	(0.178-0.358)	<0.001
PR -> BI	-0.015	0.711	0.477	(-0.054-0.026)	NS
PV -> BI	0.332	7.519	0.000	(0.247-0.419)	<0.001
SI -> BI	0.106	3.754	0.000	(0.051-0.160)	<0.001

NS - Not significant (p>0.05)

7.3.3 Coefficient of Determination (R^2) and Effect Size (f^2)

Most commonly used to evaluate the structural model, the coefficient of determination (R^2) measures the models predictive accuracy (Hair et al., 2017). It is calculated “as the squared correlation between a specific endogenous construct’s actual and predicted values” (Hair et al., 2017, p. 198). R^2 values above 0.75 are seen as substantial, 0.50 as moderate and 0.25 as weak. In this model for BI, R^2 = 0.654, and is considered moderate.

As Hair et al. (2017) note, in addition to evaluating R^2 values, “the change in the R^2 value when a specified exogenous construct is omitted from the model can be used to evaluate whether the omitted construct has a substantive impact on the endogenous construct" (Hair et al., 2017, p. 201). This measure is referred to as the effect size f^2. Guidelines, according to Hair et al. (2017), for assessing f^2 values are as follows: 0.02 (small); 0.15 (medium); and 0.35 (large); effect sizes below 0.02 indicate there is no effect. Table 7.17 shows the effect size which range from no effect to a small effect.

Table 7.17 *Results of the Effect Size (f^2)*

	f^2	Effect Size
DSI -> BI	0.001	no effect
EE -> BI	0.003	no effect
HM -> BI	0.016	no effect
PE -> BI	0.053	small
PR -> BI	0.001	no effect
PV -> BI	0.081	small
SI -> BI	0.016	no effect

7.3.4 Evaluation of Predictive Relevance (Q^2) And Path Sizes (q^2)

"The Q^2 value is obtained by using the blindfolding procedure for a specified omission distance" (Hair et al., 2017, p. 202). The Q^2 value is indicative of the model's predictive relevance, or how well the path model can predict the empirical observations. Similarly, to the f^2 which measures the effect size for R^2, "the relative impact of predictive relevance can be compared by means of the measure of the q^2 effect size" (Hair et al., 2017, p. 207).

Following the guidelines by Hair et al. (2017) the following conditions were set in SmartPLS for running the blindfolding procedure: path weighting method, and omission distance (D) is set to seven. Table 7.18 shows the blindfolding algorithm with the Q^2 and q^2 values.

Table 7.18 *Results of the Q^2 and effect size (q^2)*

	Q^2	q^2	Effect Size
BI	0.631		
DSI		0.000	no effect
EE		0.000	no effect
HM		0.002	no effect
PE		0.043	small
PR		0.000	no effect
PV		0.068	small
SI		0.014	no effect

7.4 Multigroup Analysis: Using Age, Gender and Income as Moderators

To determine what effect, if any, age, gender, and income have on the structural equation model a multigroup analysis of these moderating variables was undertaken. As Henseler and Fassott (2010) note, group comparisons are an alternative technique for identifying moderating effects in structural equation modeling provided that the indicators or moderating variables are not continuous. Essentially, the group comparisons, known in SmartPLS as multigroup analysis (MGA), is another way of saying categorical moderation where the "differences in the model parameters between different data groups are interpreted as moderating effects" (Henseler and Fassott, 2010, p. 720). This is supported by Rigdon, Schumacker, and Wothke (1998) who suggest that the interaction effects, when using a 'multisample' or multigroup approach can "become apparent as differences in parameter estimates when the same model is applied to different but related sets of data" (p. 1).

While MGA was not a technique that was available in earlier versions of SmartPLS (e.g. version two), SmartPLS 3 has made it very easy for researchers to conduct this analysis. One caveat of an MGA approach is that the software can only compare two groups at once (i.e., male and female), and does not have the ability to evaluate more than two groups at once. There are ways to overcome this limitation when more than two groups are involved and will be discussed in the subsections on age and income.

7.4.1 Gender

Using the same rules of thumb for initializing the PLS-SEM algorithm (Table 7.2) and bootstrapping conditions (Table 7.15) the MGA technique was run in SmartPLS selecting males (n = 448) and females (n = 535) as the two groups. While a third gender, non-binary, was provided as an option and selected by a small percentage of respondents this group was not analyzed as the number of observations was smaller than the minimum 10 cases required to make up a group. Furthermore, following the sampling guidelines set forth by Hair et al. (2017) and discussed in Chapter 6.2.1 the minimum sample required for this analysis is n = 144.

Table 7.19 details the differences in the path coefficients (males- females) and their corresponding *t* and *p* values. It indicates there are no significant differences in any of the path coefficients between males and females.

Table 7.19 *Evaluation of Gender on the Structural Model*

	Path Coefficients-diff (| Males - Females |)	*t*-Value(Males vs Females)	*p*-Value(Males vs Females)	Significance Level
DSI -> BI	0.076	1.472	0.141	NS
EE -> BI	0.056	0.995	0.320	NS
HM -> BI	0.146	1.763	0.078	NS
PE -> BI	0.080	0.874	0.382	NS
PR -> BI	0.028	0.678	0.498	NS
PV -> BI	0.132	1.515	0.130	NS
SI -> BI	0.097	1.712	0.087	NS

NS - Not significant (p>0.05)

7.4.2 Age

To analyze the effect of age as a moderating variable the same process was undertaken as the analysis for gender with one exception. Following widely accepted generational definitions (Statistics Canada, 2011; Bump, 2014; Howe & Strauss, 2002) age was broken into three generational groups, (1) Millennials, ages 18-34 (n = 320), (2) Generation X, ages 35-49 (n = 358), and (3) Baby Boomers and above, ages 50 plus (n = 307). Given the limitation of MGA, in that only two groups can be compared at once, the analysis was run three times to ensure that each group was compared with each other group.

First, the age groupings of 18-34 and 50 plus were compared. The results of the analysis, Table 7.20, indicate no significant differences in the path coefficients between the youngest and oldest age groups. Second, the 18-34 and 35-49 (Table 7.21) groups were examined. The results from this evaluation and the third analysis of the 35-49 and 50 plus age groups (Table 7.22) indicate no significate moderating effect for age at the five percent level or below.

Table 7.20 *Evaluation of Age (18-34 vs. 50+) on the Structural Model*

	Path Coefficients-diff (Age18-34 - Age50+)	*t*-Value (Age18-34 vs Age50+)	*p*-Value(Age18-34 vs Age50+)	Significance Level
DSI -> BI	0.112	1.858	0.064	NS
EE -> BI	0.036	0.501	0.616	NS
HM -> BI	0.053	0.519	0.604	NS
PE -> BI	0.038	0.354	0.723	NS
PR -> BI	0.009	0.190	0.849	NS
PV -> BI	0.002	0.020	0.984	NS
SI -> BI	0.090	1.451	0.147	NS

NS - Not significant (p>0.05)

Table 7.21 *Evaluation of Age (18-34 vs. 35-49) on the Structural Model*

	Path Coefficients-diff (| Age18-34 - Age35-49 |)	*t*-Value (Age18-34 vs Age35-49)	*p*-Value (Age18-34 vs Age35-49)	Significance Level
DSI -> BI	0.102	1.686	0.092	NS
EE -> BI	0.022	0.358	0.720	NS
HM -> BI	0.052	0.608	0.543	NS
PE -> BI	0.056	0.541	0.589	NS
PR -> BI	0.024	0.456	0.648	NS
PV -> BI	0.097	0.969	0.333	NS
SI -> BI	0.051	0.719	0.472	NS

NS - Not significant (p>0.05)

Table 7.22 *Evaluation of Age (34-49 vs. 50+) on the Structural Model*

	Path Coefficients-diff (| Age35-49 - Age50+ |)	*t*-Value (Age35-49 vs Age50+)	*p*-Value (Age35-49 vs Age50+)	Significance Level
DSI -> BI	0.010	0.150	0.881	NS
EE -> BI	0.058	0.800	0.424	NS
HM -> BI	0.001	0.009	0.993	NS
PE -> BI	0.017	0.148	0.883	NS
PR -> BI	0.033	0.650	0.516	NS
PV -> BI	0.100	0.883	0.377	NS
SI -> BI	0.039	0.532	0.595	NS

NS - Not significant (p>0.05)

7.4.3 Income

Similar, to the evaluation of age, income was also segmented into three groups from the original six categories. The first group consists of those with an annual household income of less than \$25,000 to \$49,999 and was labeled as low to moderate income. Those with moderate to high income, \$49,999 to \$99,999, were placed in the second group and those with a high annual household income, \$100,000 or greater make up the third group. The sample sizes for each group are: (1) n = 176, (2) n = 309, and (3) n = 334. The rational for choosing these segments was to ensure strength in the sample size for each group and to ensure that those who selected “prefer not to answer” to this question were excluded from the analysis.

Using the same PLS-SEM and bootstrapping procedures as outlined above the MGA technique was run. First groups with low to moderate, and high annual household incomes were compared. Table 7.23 details these results. Similar to the results from gender and age, while some results are significant at the 10 percent level, none are considered significant at the five percent level.

Table 7.23 *Evaluation of Income (Low/Moderate vs. High) on the Structural Model*

	Path Coefficients-diff (| IncomeLow/ Moderate - IncomeHigh |)	*t*-Value (IncomeLow/ Moderate vs IncomeHigh)	*p*-Value (IncomeLow/ Moderate vs IncomeHigh)	Significance Level
DSI -> BI	0.062	0.822	0.411	NS
EE -> BI	0.146	1.749	0.081	NS
HM -> BI	0.032	0.298	0.766	NS
PE -> BI	0.073	0.563	0.573	NS
PR -> BI	0.080	1.226	0.221	NS
PV -> BI	0.157	1.164	0.245	NS
SI -> BI	0.107	1.238	0.216	NS

NS - Not significant ($p>0.05$)

Tables 7.24 and 7.25 detail the analysis of the MGA for the remaining two comparisons. The results from this analysis are similar to those from the first group, while there are differences in some of the path coefficients, and these differences appear to be large, they are not significant at the five percent level based on their *p*-values.

Table 7.24 *Evaluation of Income (Low/Moderate vs. Moderate/High) on the Structural Model*

	Path Coefficients-diff (| IncomeLow/ Moderate - IncomeModerate/ High |)	*t*-Value (IncomeLow/ Moderate vs IncomeModerate/ High)	*p*-Value (IncomeLow/ Moderate vs IncomeModerate/ High)	Significance Level
DSI -> BI	0.012	0.153	0.878	NS
EE -> BI	0.072	0.799	0.425	NS
HM -> BI	0.058	0.480	0.631	NS
PE -> BI	0.012	0.090	0.928	NS
PR -> BI	0.005	0.091	0.928	NS
PV -> BI	0.244	1.661	0.097	NS
SI -> BI	0.088	0.933	0.351	NS

NS - Not significant (p>0.05)

Table 7.25 *Evaluation of Income (Moderate/High vs. High) on the Structural Model*

	Path Coefficients-diff (| IncomeModerate/ High - IncomeHigh |)	*t*-Value (IncomeModerate /High vs IncomeHigh)	*p*-Value (IncomeModerate /High vs IncomeHigh)	Significance Level
DSI -> BI	0.074	1.276	0.203	NS
EE -> BI	0.075	1.214	0.225	NS
HM -> BI	0.025	0.310	0.756	NS
PE -> BI	0.085	0.865	0.387	NS
PR -> BI	0.085	1.697	0.090	NS
PV -> BI	0.087	0.825	0.409	NS
SI -> BI	0.019	0.285	0.776	NS

NS - Not significant (p>0.05)

7.5 Overview of Results

The PLS-SEM analysis of the empirical data was conducted in two phases: an analysis of the measurement model followed by an analysis of the structural model. During the first phase of the analysis indicators for FC and DSI were found to be highly correlated with other constructs and were subsequently removed. Additionally, the construct of FC was removed in its entirety due to its sub-optimal CA value, which resulted in a lack of internal consistency reliability. Further, in the measurement model analysis a concern arose with respect to the

HTMT ratio. An exploratory factor analysis was conducted in SPSS using a verimax rotation and the cross-loadings table (correlation matrix) were reexamined. This analysis revealed that indicators for constructs BI, PE, HM and PV were correlating above 0.80 on other constructs. Following the recommendations by Henseler et al. (2015) and Hair et al. (2017) those indicators (BI2, BI3, PE1, HM2, and PV4) were removed. The exclusion of these indicators qualified the measurement model to proceed to the succeeding phase and evaluation of the structural model.

In total the model explains the intention to use smart mirrors in retail stores moderately well, with an R^2 value of 0.654. Additionally, as the Q^2 value was > 0, specifically, 0.631 this would indicate moderate predictive power of the proposed model. A summary of the results from the analysis of the structural model is detailed in Table 7.26. In addition to analyzing the structural model an MGA technique was used to determine if the relationships between the constructs and behavioural intention is moderated by age, gender and income.

Table 7.26 *Summary of Structural Model and MGA Results*

	Path Coefficients	p Values	Significance Level	Moderated By		
				Gender	Age	Income
DSI -> BI	0.025	0.338	NS	No	No	No
EE -> BI	0.042	0.134	NS	No	No	No
HM -> BI	0.133	0.001	<0.05	No	No	No
PE -> BI	0.274	0.000	<0.001	No	No	No
PR -> BI	-0.015	0.477	NS	No	No	No
PV -> BI	0.332	0.000	<0.001	No	No	No
SI -> BI	0.106	0.000	<0.001	No	No	No

NS - Not significant (p>0.05)

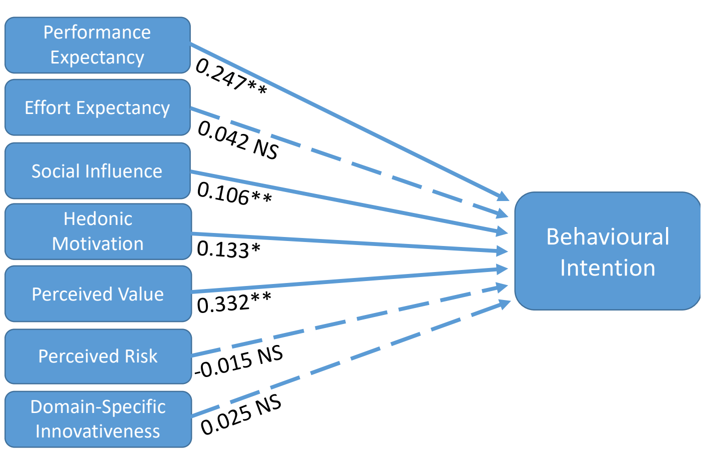
To conclude, this chapter detailed the statistical analysis of the empirical data and presented the results. A descriptive analysis of the data was performed using Excel, and the PLS-SEM analysis was conducted using SmartPLS version 3.2.7. Additionally, an exploratory factor analysis was conducted using IBM SPSS. Following the analysis of the structural model a MGA approach was used to determine the moderating effect of age, gender and income on the path coefficients. The results obtained in this chapter will be summarized and discussed in Chapter Eight. Implications, limitations and future research will also be addressed in Chapter Nine.

8. Summary of Results and Discussion

Recognizing that the retail industry is in the midst of a significant shift, and that smart technologies are increasingly being used as a means of enhancing consumers' in-store experience, this thesis set out to uncover the specific factors that influence consumers' behavioural intention to use smart mirrors in a retail store. Utilizing an adapted UTAUT2 (Venkatesh et al., 2012) framework (Figure 8.1) this PLS-SEM analysis (Hair et al., 2017) sought to determine the significance of the relationship between the exogenous constructs of PE, EE, SI, FC, HM, PV, PR, and DSI and the endogenous construct of BI. Additionally, the moderating variables of age, gender and income were examined using MGA in SmartPLS version 3.2.7 to determine their effect on the relationships.

This chapter is intended to provide a summary and interpretation of the results presented in Chapter Seven and to discuss the findings as they pertain to the proposed hypotheses. Following this discussion, the implications of the study for scholars and practitioners will be addressed along with the limitations and recommendations for future research in Chapter Nine.

Figure 8.1 *Final Research Model*



NS – not significant; *<0.05; **<0.001

8.1 Summary of Results

The survey instrument used in the data collection was adapted from UTAUT2 (Venkatesh et al., 2012). A reputable Canadian panel provider was recruited to assist in administering and recruiting participants to complete the questionnaire in January, 2018. A final sample of 985 participants was used in the PLS-SEM analysis. In addition to assessing the significance of the structural model (i.e., path coefficients, R^2, and effect sizes) a MGA technique was used to determine the moderating influence of age, gender, and income on the path relationships.

As noted in the paragraphs below not all of the hypothesized relationships are supported. Specifically, the estimations of the path coefficients between DSI and BI, EE and BI, and PR and BI were all determined to be not significant. Furthermore, hypotheses H1a to H8a which hypothesized that the relationship between the exogenous constructs and the endogenous construct of BI would be moderated by age, gender, and income; results do not support these hypotheses. Therefore, hypotheses H1a to H8a are rejected while failing to reject the corresponding null hypothesis.

H1: There is a positive relationship between performance expectancy and consumers' behavioural intention to use smart mirrors in retail stores.

As hypothesized by Venkatesh et al. (2003), Morosan and DeFranco (2016), Martins et al. (2014) and Juaneda-Ayensa et al. (2016) there is a positive relationship between PE and BI. Results of the PLS-SEM (Hair et al., 2017) analysis support this hypothesis. The path coefficient (0.274) for this hypothesized relationship was found to be significant at the 0.001 level. Therefore, the following statement can be made: PE positively influences consumers' BI to use smart mirrors in a retail store. However, these results suggest that even though the influence of PE and BI was positive and significant its effect on BI's R^2 was small with an effect size (f^2) of 0.053.

H2: There is a positive relationship between effort expectancy and consumers' behavioural intention to use smart mirrors in retail stores.

Following the work of Venkatesh et al. (2003), Martins et a., (2014), Morosan and DeFranco (2016) and Juaneda-Ayensa et al. (2016) EE is hypothesized to have a positive effect on consumers' behavioural intention to use smart mirrors in a retail store. Linked with the concepts of PEOU in TAM/TAM 2 models or ease of use in IDT (Juaneda-Ayensa et al., 2016) it was found to be significant in both mandatory (Venkatesh et al., 2003) and voluntary (Venkatesh et al., 2012) contexts. However, although the analysis calculated a path coefficient greater than zero (0.042), indicating that EE has some effect on BI, its corresponding *p value* (0.134) indicates the hypothesized relationship is not significant. Therefore, this hypothesis is rejected while failing to reject the null hypothesis. Furthermore, EE was found to have no effect on BI ($f^2 = 0.000$) and no predictive relevance with a q^2 value of 0.003, despite the overall predictive power of the proposed model.

H3: There is a positive relationship between social influence and consumers' behavioural intention to use smart mirrors in retail stores.

SI is hypothesized to positively influence behavioural intentions (Venkatesh et al., 2003; Martins et al., 2014; Yuan, Ma, Kanthawala, & Peng, 2015; Juaneda-Ayensa et al., 2016). Results from the PLS-SEM analysis support this hypothesis. Adopted from TPB (Ajzen, 1991), SI refers to the degree to which consumers perceive that influencers important to them believe they should use a technology (Venkatesh et al., 2003). The path coefficient for this hypothesized relationship is 0.106 and was found to be significant at the 0.001 level. Therefore, the following statement can be made, SI positively influences consumers' BI to use smart mirrors in a retail store. In contrast with PE, the effect sizes (f^2 = 0.016; q^2 = 0.014) for SI are minimal and indicate no effect or predictive relevance as they are below the threshold value of 0.02.

H4: There is a positive relationship between facilitating conditions and consumers' behavioural intention to use smart mirrors in retail stores.

FC is defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh et al., 2003, p. 453). While this relationship was hypothesized to positively influence consumers' behavioural intention to use smart mirrors in retail stores, this construct was removed during phase one of the analysis (evaluation of the measurement model) due to its lack of convergent validity and low CA value. FC was shown to be significant in UTAUT2 (Venkatesh et al., 2012) as well as in subsequent studies (Morosan & DeFranco, 2016). In contrast, other studies and a meta-analysis of UTAUT (San Martín & Herrero, 2012; Shaw & Sergueeva, 2016; Dwivedi et al., 2011) indicate that FC is the weakest of the original UTAUT constructs in predicting behavioural intentions. With the removal of this construct the corresponding hypothesis was discarded and not considered further.

H5: There is a positive relationship between hedonic motivation and consumers' behavioural intention to use smart mirrors in retail stores.

Added to the UTAUT2 (Venkatesh et al., 2012), HM is hypothesized to positively influence consumers' behavioural intention to use a smart mirror. Defined as "the pleasure or enjoyment derived from using a technology" (Venkatesh et al., 2012, p. 161), HM is usually associated with adjectives such as fun, enjoyable and pleasurable (Juaneda-Ayensa et al., 2016), and is seen as an important predictor of behavioural intention and actual usage of technology (Gupta & Dogra, 2017). Furthermore, Zhang, Zhu and Lui (2012) suggest that a consumers' intention to use a technology increases if the user perceives higher levels of enjoyment and entertainment value. The PLS-SEM analysis of the structural model corroborates these earlier findings. The path coefficient of 0.133 is considered significant at the 0.05 level. Therefore, the following statement can be made, HM positively influences consumers' BI to use smart mirrors in a retail store. Similarly, to SI, HM was also shown to have a minimal effect and little predictive relevance as indicated by the f^2 (0.016) and q^2 (0.002) values.

H6: There is a positive relationship between perceived value and consumers' behavioural intention to use smart mirrors in retail stores.

In an effort to make UTAUT2 more consumer focused, price value was added to the original UTAUT model. This construct has a number of different meanings and is important in many forms of consumer behaviour (Blake et al., 2017). When the benefits of using a technology is perceived to be greater than the monetary cost the price value is positive and it is predicted to have a positive impact on intention (Venkatesh et al., 2012). Following the research of Shaw and Sergueeva (2016), the construct of price value was reconceptualized as perceived value (PV). Ultimately, it represents consumers' cognitive tradeoff between benefits of disclosing personal information with the perceived risks involved in using the technology.

In this analysis PV has the largest path coefficient of all the constructs (0.332) and is considered a significant predictor of BI at the 0.001 level. As such the proposed hypothesis is accepted and the following statement can be made, PV positively influences consumers' BI to use smart mirrors in retail stores. Additionally, PV was shown to have a small effect (f^2 = 0.81) and predictive relevance (q^2 = 0.068) on the model.

H7: There is a negative relationship between perceived risk and consumers' behavioural intention to use smart mirrors in retail stores.

According to Featherman and Pavlou (2003), PR "is commonly thought of as the felt uncertainty regarding possible negative consequences of using a product or service" (p. 453). While not included in UTAUT2 (Venkatesh et al., 2012) PR is a common extension of both UTAUT (Venkatesh et al., 2003) and UTAUT2 (Slade et al, 2015; Martins et al, 2014; Huang & Qin, 2011). PR is hypothesized to have a negative effect on BI, and previous empirical findings support this assertion (Huang & Qin, 2011; Roy et al., 2017; Martins et al., 2014). While this analysis showed a slight negative relationship with a path coefficient of -0.015, this was not considered significant, as $p = 0.477$. Therefore, this hypothesis is rejected while failing to reject the null hypothesis.

H8: There is a positive relationship between domain-specific innovativeness and consumers' behavioural intention to use smart mirrors in retail stores.

The final construct added to the proposed research model, DSI, is hypothesized to positively influence behavioural intention to use a smart mirror in a retail store. While not a common extension of UTAUT2 (Venkatesh et al., 2012), Slade et al. (2015) consider the concept of critical importance to marketers and thus worthy of inclusion in research extending UTAUT2. In this PLS-SEM analysis DSI is shown to have the second smallest path coefficient (0.025) and is not significant with a p value of 0.388. Therefore, the hypothesis H8 is rejected while failing to reject the null hypothesis. Furthermore, DSI was shown to have no effect or predictive relevance with an f^2 value (0.001) and q^2 value (0.000) at or close to zero. These results are contrary to previous studies (Slade et al., 2015; Juaneda-Ayensa et al., 2916; San Martín & Herrero, 2012) and will be discussed further in section 8.2.

In addition, to evaluating the structural model an MGA technique was used to determine the moderating effect of age, gender, and income on the hypothesized path relationships.

Hypotheses H1a to H8a were put forward stating that, the effect of (PE, EE, SI, FC, HM, PV, PR, or DSI) on consumers' behavioural intention to use smart mirrors in retail stores is moderated by age, gender and income. Using the same initialization process for the PLS-SEM algorithm and bootstrapping procedures the MGA approach commenced first looking at gender, followed by age and then income. While there were some path coefficients between the groups that at first glance appeared to be significant, the key with an MGA approach is to look at the difference in the path coefficients and their corresponding *t* and *p* values to determine significance. Results from the analysis of all three moderating variables indicate there is no significance at the 0.05 or 0.001 level. As such hypotheses H1a to H8a are rejected while failing to reject the corresponding null hypothesis.

Table 8.1 summarizes the findings of the hypotheses between the exogenous constructs (PE, EE, SI, FC, HM, PV, PR, and DSI) and the endogenous construct of BI. Similarly, Table 8.2 summarizes the hypotheses relating to the moderating variables of age, gender, and income. Results of the PLS-SEM analysis confirm that H1, H3, H5, and H6 are supported. The remaining hypotheses are rejected while failing to reject their corresponding null hypothesis. A discussion of these results is presented in the following section.

Table 8.1 *Summary of Findings by Hypothesis*

Hypothesis	Independent Variable	Dependent Variable	Result
H1	PE	BI	Accepted
H2	EE	BI	Rejected
H3	SI	BI	Accepted
H4	FC	BI	Construct removed and not considered
H5	HM	BI	Accepted
H6	PV	BI	Accepted
H7	PR	BI	Rejected
H8	DSI	BI	Rejected

Table 8.2 *Summary of Findings of Moderated Variables by Hypothesis*

Hypothesis	Independent Variable	Dependent Variable	Moderated By	Result
H1a	PE	BI	Age	Rejected
			Gender	Rejected
			Income	Rejected
H2a	EE	BI	Age	Rejected
			Gender	Rejected
			Income	Rejected
H3a	SI	BI	Age	Rejected
			Gender	Rejected
			Income	Rejected
H4a	FC	BI	Age	Construct removed and not considered
			Gender	
			Income	
H5a	HM	BI	Age	Rejected
			Gender	Rejected
			Income	Rejected
H6a	PV	BI	Age	Rejected
			Gender	Rejected
			Income	Rejected
H7a	PR	BI	Age	Rejected
			Gender	Rejected
			Income	Rejected
H8a	DSI	BI	Age	Rejected
			Gender	Rejected
			Income	Rejected

8.2 Discussion

This thesis employed and expanded UTAUT2 (Venkatesh et al., 2012) to investigate consumers' behavioural intention to use smart mirrors in a retail store. Canadians from across the country were recruited to participate in this survey and were not required to have any prior knowledge of smart mirrors or their use within the retail industry. To illustrate a consumers' experience with a smart mirror and detail its functionality respondents were required to view a video, courtesy of OAK Labs, before proceeding with the questionnaire. In total 985 responses were validated from all Canadian provinces, excluding Quebec.

According to the findings presented above these results suggest that the proposed research model has been able to achieve an acceptable level, in terms of predictive power (65.4%), in the endogenous variable of behavioural intention. As indicated by the significance of the path coefficients, perceived value and performance expectancy were the strongest predictors of behavioural intention to use smart mirrors in retail stores.

In UTAUT2 price value is defined as "consumers' cognitive tradeoff between the perceived benefits of the applications and the monetary cost for using them" (Venkatesh et al., 2012, p. 161), however, in other contexts the concept of value may be more nuanced. For example, a consumer may perceive value in a product that is not necessarily related to the monetary cost of using the technology. Instead they may feel that it provides social value, emotional value or it is convenient. Widely accepted as a construct in predicting behavioural intention in UTAUT2 (Alalwan, Dwivedi, & Rana, 2017; Macedo, 2017; Yuan et al., 2015; Nair et al., 2015), Shaw and Sergueeva (2016) reconceptualized the construct of price value into perceived value. Shaw and Sergueeva's (2016) findings indicate that perceived value is the largest predictor of behavioural intention to use smartphones for mobile commerce. Similarly, the results of this analysis indicate that perceived value is the largest predictor of consumers' behavioural intention to use a smart mirror in a retail store. Therefore, this thesis's findings suggest that consumers' are highly influenced by the positive outcomes and benefits they expect to receive from using a smart mirror in a retail store in spite of the risks involved in sharing their personal information.

As expected, performance expectancy is a significant predictor of behavioural intention with a path coefficient of 0.274 and a p value <0.001. According to Dwivedi et al. (2011), in their meta-analysis of UTAUT, performance expectancy is consistently shown to be the largest predictor of behavioural intention. When Venkatesh et al. (2012) extended UTAUT for the consumer context into UTAUT2, performance expectancy again was shown to be a significant predictor of behavioural intention to adopt and then use technology. Recent literature (e.g., Alalwan et al., 2017; Macedo, 2017; Herrero, San Martín, & Garcia-De los Salmones, 2017; Weinhard, Hauser, & Thiesse, 2017; Morosan & DeFranco, 2016) that have employed all or part of UTAUT2 support the findings of Venkatesh et al. (2012), and is consistent with the results of this research. One could, therefore, postulate that consumers believe using smart mirrors as part of their in-store shopping journey will not only provide them with added benefits but will also enhance their shopping experience.

In spite of their smaller path weights hedonic motivation (0.133) and social influence (0.106) are shown to be significant in determining the behavioural intention of Canadian consumers to use smart mirrors. While not included in the organizational focused UTAUT model (Venkatesh et al., 2003) hedonic motivation was added to UTAUT2 when Venkatesh et al. (2012) revised their framework for the consumer context. Defined as the "fun or pleasure derived from using a technology" (Venkatesh et al., 2012, p. 161), literature has consistently shown hedonic motivation to be a significant predictor of behavioural intention (Gupta & Dogra, 2017; Morosan & DeFranco, 2016; Yuan et al., 2015; Herrero et al., 2017). Escobar-Rodríguez and Carvajal-Trujillo (2013) found that hedonic motivation was not a significant predictor of consumers' behavioural intention to use websites for the purchase of airline tickets. The authors suggest this result was due to consumers' routine use of other websites and social media platforms that are far more entertaining and fun than airline company sites. In the context of intention to use smart mirrors in retail stores, the significance of hedonic motivation suggests that consumers are interested in using mirrors that provide some measure of pleasure and enjoyment in addition to also being useful providing utilitarian benefits.

Social influence has been a significant predictor of behavioural intention in both the organizational (Venkatesh et al., 2003) and consumer (Venkatesh et al., 2012) contexts. Recent literature across different contexts including, social networking platforms (Herrero et al., 2017), travel and tourism (Escobar-Rodríguez & Carvajal-Trujillo, 2013), health management (Yuan et al., 2015), and mobile banking (Alalwan et al., 2017), however, has found no significance in social influence to predict users' intention to use and adopt the specific technology under investigation. Despite inconsistency in the predictive ability of social influence on behavioural intention, results from this PLS-SEM analysis are consistent with those of Venkatesh et al. (2012), Weinhard et al. (2017), and Morosan and DeFranco (2016) who have validated the relationship between social influence and behavioural intention. In this context consumers' intention to use smart mirrors in retail environments are influenced by people who are important and whose opinions matter to them. Therefore, it would be prudent for mirror developers and retailers to recognize this factor and incorporate ways in which consumers can share their experiences using the mirror via social networking platforms.

Interestingly, effort expectancy, an original construct in UTAUT and subsequently in UTAUT2, was not shown to be significant in predicting behavioural intention. While some recent studies employing UTAUT or UTAUT2 have identified effort expectancy as influential in predicting behavioural intention (Alalwan et al., 2017; Macedo et al., 2017; Nair et al., 2015; Leong, Ping & Muthuveloo, 2017) an equal number found no significant relationship (Herrero et al., 2017; Yuan et al., 2015; Escobar-Rodríguez & Carvajal-Trujillo, 2013; Gupta & Dogra, 2017; Weinhard et al., 2017). In their adoption research on mobile health apps, Yuan et al. (2015) postulate that lack of relationship between effort expectancy and behavioural intention may be due to the "advancement of smart phone interfaces in terms of usability, which reduces the amount of effort people might need for usage" (p. 740). Similarly, Morosan and DeFranco (2016) suggest that today's technological systems are "by design, geared toward easy utilization, the perceptions regarding the effort needed to complete tasks using such systems do not represent a variable anymore" (p. 26). Furthermore, Weinhard et al. (2017) propose that people perceive smart retail technologies as enjoyable and "thus do not perceive the process of learning to use the application as an effort" (p. 24).

Given the assertions presented in the preceding paragraph it is, therefore, not surprising that effort expectancy was not shown to be a predictor of behavioural intention in this thesis. With more than 91% of Canadians using the Internet at least a few times a month and 76% owning a smart phone (Statistics Canada, 2017c) the effort required to use similar technologies (e.g., smart mirrors) is minimal. Moreover, results from this research suggest that age does not act as a moderator in the relationship between effort expectancy and behavioural intention. Macedo (2017) claims that there is a digital divide in Europe and the United States with older adults less likely to use the Internet than other age groups. As a result, Macedo (2017) hypothesized that effort expectancy would be a significant predictor of behavioural intention amongst older adults. In Canada, while Internet usage rates are over 90% for individuals aged 15 to 44. Some of the highest increases in Internet use in Canada were among individuals aged 65 to 74 and 75 and older (Statistics Canada, 2017c). This would suggest that older Canadians are embracing technology and are becoming more adept at using these connected devices.

This thesis adapted UTAUT2 to include perceived risk and domain-specific innovativeness. These constructs were hypothesized to have a negative (perceived risk) and positive (domain-specific innovativeness) relationship in consumers' behavioural intention to use smart mirrors. Interestingly, the results from this PLS-SEM analysis indicate that neither relationship is significant and are contrary to recent findings (Slade, et al., 2015; Tandon, Kiran, & Sah, 2018; Martins et al., 2014; Juaneda-Ayensa et al., 2016).

With respect to perceived risk, Tandon, Kiran and Sah (2018) confirmed the negative effect of risk on customer satisfaction (a substitute for behavioral intention and use behaviours in UTAUT2) and suggest that attention be paid to lowering perceived risk in an effort to enhance online shopping in India. Additionally, Martins et al. (2014) concluded that perceived risk is an important factor in users' intention to use Internet banking in Portugal. Moreover, they suggest that Internet banking platforms should be technically sound and have good security protocols (Martins et al., 2014). Lastly, Huang and Qin (2011) found that perceived risk is of great significance in consumers' intention to use technology. They go on to suggest that online retailers in China must create safe environments for consumers to share their personal information, and is crucial in the adoption of virtual fitting rooms (Huang & Qin, 2011).

Despite these prevailing assertions other researcher have found no significance in risk, or at least components of risk (privacy and security), influencing intentions. Herrero et al. (2017) suggest that consumers who using social networking sites to publish content related to their tourism experiences do not view this as impacting their privacy. They further postulate that users view the risk as a "necessary condition to share their experiences with other people" (Herrero et al., 2017, p. 215). Lastly, in their evaluation of the behavioural intention of users in Malaysia to adopt Internet of Things (IoT) in the context of smart cities, Leong et al. (2017) concluded that perceived security risk did not have a significant negative influence on behavioural intention. Their reasoning is that users believe IoT technology is inherently better at encrypting and transmitting data than non-IoT technology (Leong et al., 2017). In the context of behavioural intention to use smart mirrors in retail stores, one could argue that consumers increasing familiarity and ease with online and mobile commerce has not only reduced the effort required to use the technology but has also reduced the associated perceived risk.

Lastly, results from this analysis indicate that domain-specific innovativeness is not significant in predicting consumers' behavioural intention. As opposed to general innovativeness, which relates to an individuals' willingness to follow new paths, domain-specific innovativeness is related to an individual wanting to be the first to adopt new innovations or technologies in a specific sphere (Nguyen et al., 2014). Following the research of San Martín and Herrero (2012), Nguyen et al. (2014) and Juaneda-Ayensa et al. (2016) domain-specific innovativeness was included in the proposed research model and hypothesized to positively influence intention. While both Juaneda-Ayensa et al. (2016), and San Martín and Herrero (2012) found innovativeness to be one of the top two predictors of intention, Nguyen et al. (2014) found no significant relationship to intention but did find a significant positive relationship between innovativeness and usage. Providing that retailers continue to experiment with and install smart mirrors in more locations it would be appropriate to revisit innovativeness with respect to measuring actual usage in addition to behavioural intention.

9. CONCLUSIONS

9.1 Implications

Recent literature has recommended researchers adopt and expand established technology acceptance models to examine the antecedents of behavioural intention in the retail context. Motivated by the belief that smart mirrors have the potential to enhance and create unique experiences, this thesis set out to uncover the specific factors that influence consumers' behavioural intention to use smart mirrors in a retail store. Specifically, this research sought to answer the following question:

- *To what extent does performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, perceived risk, perceived value, and domain-specific innovativeness explain the behavioural intention of consumers to use smart mirrors in retail stores?*

In addition to examining the relationships between the exogenous and endogenous constructs outlined in the research question, this thesis considered how the moderating variables of age, gender, and income act in conjunction with the primary constructs on consumers' behavioural intention.

Employing UTAUT2, this thesis expands and contributes to the existing literature on technology acceptance and retail. Moreover, while the results of this thesis indicate a moderate level in the ability to predict consumers' intention to use smart mirrors in retail stores, the development of this conceptual model also suggests that further examination and the potential incorporation of additional constructs (e.g., satisfaction, enjoyment, trust) is warranted as 34 percent of behavioural intention was left unexplained. Additionally, as smart mirrors move beyond the beta-testing phase and are installed in more settings, future research employing technology acceptance models should take a longitudinal approach which would enable the investigation of both intentions and use behaviour (Slade et al., 2015). This would also allow researchers to revisit the construct of domain-specific innovativeness which the literature has shown to influence behavioural intention as well as usage.

Given the size and representativeness of the sample, the results presented and discussed above can be generalized to the English speaking Canadian population and indicate that perceived value, performance expectancy, hedonic motivation and social influence are positively related to Canadian consumers' intention to use smart mirrors in their bricks and mortar shopping journey. As such, smart mirror developers should focus on creating technology that is perceived as not only fun and enjoyable to use but one that can provide consumers with added value and benefits thereby enhancing and creating a unique customer experience. Examples of these benefits could include personalized portals for each customer. Customers could then log into these pages which might display or list previous purchases along with other items that the customer has liked or commented on.

Developers and retailers should also be aware of the role that social influence plays in consumers' willingness and intention to use smart mirror technology. As an example, a mirror interface could incorporate links to various social media platforms that allow users to share their favourite looks and post about their recent experiences. Additionally, retailers could look to recruit and partner with influencers in the communities around their store locations and have these influencers share and extol the benefits of using this new technology.

Regarding perceived risk, although it was not shown to be significant in predicting behavioural intention, this construct should be revisited in future studies as advancements and improvements to the technology are made. As scanners and cameras are incorporated into the mirror platforms perceived risk may play a more significant role than was indicated by this study.

9.2 Limitations

First and foremost, this study is limited in that smart mirrors are not widely used by retailers across Canada. Any prior knowledge Canadians have regarding the technology is likely derived from print and video resources as opposed to their firsthand experience with the technology in a retail environment. Despite survey respondents being shown a video illustrating a consumers' interaction with a smart mirror and its functionality, there is the possibility that a study using a real mirror would produce different results.

Secondly, the use of online sampling and administration of the questionnaire electronically may have limited the results and produced an effect on the nature of the sample. Regardless of age, those who were already familiar and comfortable with technology were more inclined to participate than those who had a lower comfort level. In addition, the compensation (retailer rewards points) may have been an influence and had a spill-over effect on the income distribution of the sample.

Another limitation of this study is tied to the generalizability of the results to the Canadian population. While the results can rationally be generalized to the English speaking Canadian population, residents of Quebec, both English and French, were excluded from participating in this research. The specific circumstances of this study and associated costs did not permit translation of the questionnaire from English to French. With nearly one quarter of the Canadian population residing in Quebec, not including these individuals contributes to the lack of generalizability of the results nationally.

Further, the modification of the UATUT2 instrument and the addition of the constructs perceived risk and domain-specific innovativeness for this context may be seen as a limitation. Despite conducting a field test to refine and test the survey questions, the language and structure of the questions could be considered arbitrary. Consequently, this may limit the efficacy of the instrument and henceforth the results.

Additionally, the use of PLS-SEM as the statistical technique used to analyze the results may be seen as a limitation given that it is exploratory rather than confirmatory.

The most significant limitation of this thesis is that the structural model does not contain all of the original UTAUT2 constructs and indicators. During the hypothesis development habit was removed as a construct as this would require consumers to have experience using smart mirrors. The evaluation of the measurement model also led to the removal of facilitating conditions due to its low internal consistency reliability. This was unsurprising as a number of studies have elected to not consider facilitating conditions or it has been shown to be not-significant in predicting behavioural intention.

Evaluation of the measurement model also led to the removal of indicators from domain-specific innovativeness, performance expectancy, hedonic motivation, perceived value and behavioural intention. While it is not uncommon to remove indicators in reflective measurement models when the indicators are correlating highly on other constructs one must consider the impact that removing the indicator has on construct validity. This is certainly the case with the endogenous construct, behavioural intention. When analyzing discriminant validity and the HTMT ratio the decision was made to remove the indicators BI2 and BI3 from the model. As a result, behavioural intention became a single item measure which, according to Diamantopoulos, Sarstedt, Fuchs, Wilczynski, & Kaiser (2012) do not perform as well as multi-item scales.

However, it can be argued that the remaining scale item, BI1 “once I tried a smart mirror in a retail store my intention would be to use it again,” is an accurate measure of consumers’ behavioural intention and that it can stand alone as a single item construct.

9.3 Future Research

More research is necessary to better understand smart mirrors along with other new and emerging retail technologies. Specifically, future studies should take a longitudinal approach to explore actual usage in addition to consumers’ behavioural intentions. In the context of smart mirrors researchers should look to partner with retailers who are currently using or beta-testing the mirrors in an effort to obtain these observations.

In addition, as growth in ecommerce sales continues to outpace growth in physical store sales, researchers should consider investigating use of smart technologies that are present in both online and offline channels. For example, a cosmetics retailer may have a countertop smart mirror installed in their stores that allow users to virtually try-on different makeup looks. A nearly identical application may also be made available virtually to users via the retailers’ ecommerce site. Offering a nearly identical experience, researchers could use the technology acceptance models to assess any significant differences between the online and offline users’ intentions and use.

Furthermore, future researchers should explore the effect of behavioural intention to use smart mirrors, or similar retail technology, on purchase intention. While some have suggested that behavioural intention and purchase intention are interchangeable terms when evaluating technology acceptance models (Juaneda-Ayensa et al., 2016) they are conceptually different constructs and should be regarded as such.

Lastly, researchers should consider revisiting the construct of perceived risk. As smart mirrors evolve to the point where they have the potential to fit clothing onto consumers without the need to try the item on, this type of smart mirror would likely require the integration of both a camera and a body scanning device. Although, perceived risk was not identified in this research as positively or negatively influencing consumers' behavioural intention to use a smart mirror the incorporation of scanners and cameras into future devices could change this outcome.

Appendices

Appendix A: Permission to Reprint UTAUT2 Model

Copyright Clearance Center

Confirmation Number: 11695468
Order Date: 01/26/2018

Customer Information

Customer: Chelsea Heney
Account Number: 3001242374
Organization: Chelsea Heney
Email: chelsea.heney@ryerson.ca
Phone: +1 (416) 417-0958
Payment Method: Invoice

This is not an invoice

Order Details

MIS quarterly

Billing Status: **N/A**

Order detail ID:	70975023
ISSN:	0276-7783
Publication Type:	e-Journal
Volume:	
Issue:	
Start page:	
Publisher:	Society for Management Information Systems and Management Information Systems Research Center of the University of Minnesota
Author/Editor:	Society for Information Management (U.S.) ; University of Minnesota. Management Information Systems Research Center

Permission Status: **Granted**

Permission type: Republish or display content
Type of use: Thesis/Dissertation
Order License Id: 4276621274681

Requestor type	Academic institution
Format	Print, Electronic
Portion	chart/graph/table/figure
Number of charts/graphs/tables/figures	2
The requesting person/organization	Chelsea Heney
Title or numeric reference of the portion(s)	Figure 1
Title of the article or chapter the portion is from	CONSUMER ACCEPTANCE AND USE OF INFORMATION TECHNOLOGY: EXTENDING THE UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY
Editor of portion(s)	N/A
Author of portion(s)	Venkatesh, Thong & Xu
Volume of serial or monograph	36
Issue, if republishing an article from a serial	1
Page range of portion	160
Publication date of portion	March 2012
Rights for	Main product
Duration of use	Life of current edition
Creation of copies for the disabled	no

Appendix B: REB Approval

REB 2017-313
Project Title: The Factors that Influence Consumer Use of Smart Mirrors.

Dear Chelsea Heney,

Thank you very much for the submission of amendments for the above project. The Research Ethics Board has completed the review of your resubmission and the proposed amendments have been approved. This does not change the approval status nor the original approval date of the project.

Congratulations and best of luck with the project.

Please quote your REB file number (REB 2017-313) on future correspondence.

If you have any questions regarding your submission or the review process, please do not hesitate to get in touch with the Research Ethics Board (contact information below).

No research involving humans shall begin without the prior approval of the Research Ethics Board.

This is part of the permanent record respecting or associated with a research ethics application submitted to Ryerson University.

NOTE: This email account (rebchair@ryerson.ca) is monitored by multiple individuals. If you wish to contact a specific member of the Research Ethics Board, please do so directly.

Yours sincerely,

Zakiya Atcha, MSW
Research Ethics Co-Ordinator

on behalf of:

Dr. Patrizia Albanese, PhD
Chair, Ryerson University Research Ethics Board
(416)979-5000 ext. 6526
palbanes@soc.ryerson.ca
rebchair@ryerson.ca
http://www.ryerson.ca/research

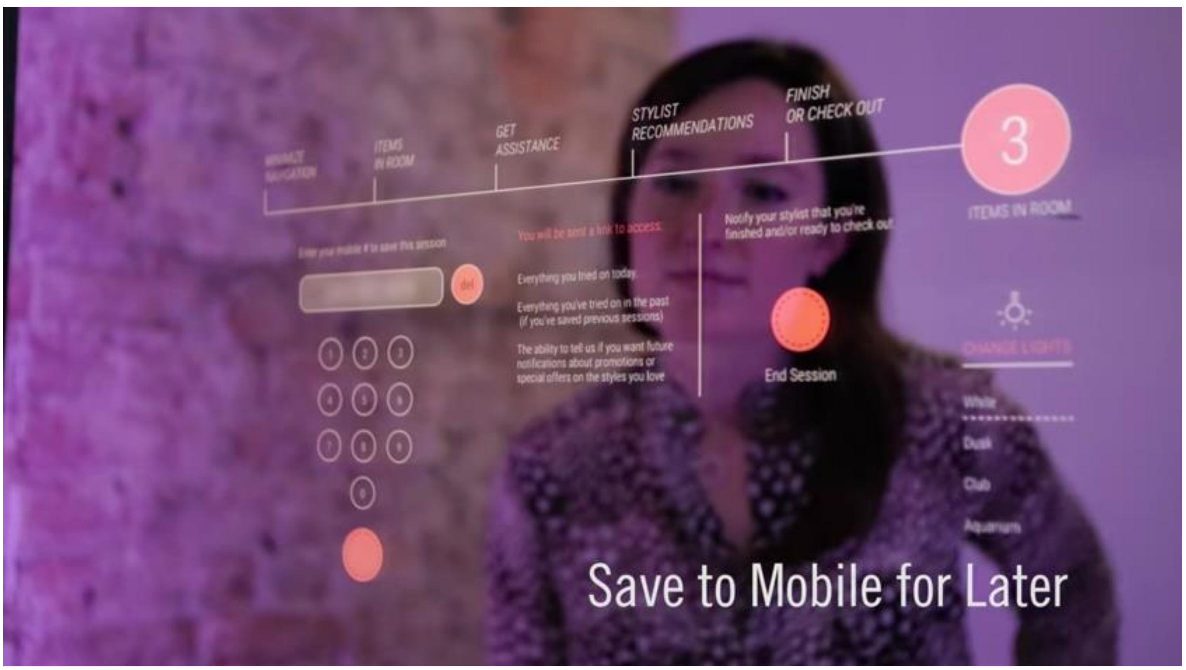
Dr. Asher Alkoby, LL.B., PhD
Vice-Chair, Ryerson Research Ethics Board
(416)979-5000 ext. 2491
aalkoby@ryerson.ca
http://www.ryerson.ca/research

Toni Fletcher, MA
Research Ethics Co-Ordinator
(416)979-5000 ext. 7112
toni.fletcher@ryerson.ca

Zakiya Atcha, MSW
Research Ethics Co-Ordinator
(416)979-5000 ext. 4841
zakiya.atcha@ryerson.ca

Jeffrey D'Souza, PhD
Research Ethics Co-Ordinator
(416)979-5000 ext. 3494
jeffrey.dsouza@ryerson.ca


GET
ASSISTANCE
STYLIST
RECOMMENDATIONS
FINISH
OR CHECK OUT
3
ITEMS IN ROOM
COMPLETE THE LOOK
select size
(8 available)
select color
(8 available)
8
White
Dusk
Club
Request Sizes/Colors


GET
ASSISTANCE
STYLIST
RECOMMENDATIONS
FINISH
OR CHECK OUT
3
ITEMS IN ROOM
End Session
White
Dusk
Club
Save to Mobile for Later

Appendix D: Consent Form

Ryerson University
Consent Agreement

You are invited to participate in a research study being done in partial fulfillment of a master's thesis. Please read this consent form so that you understand what your participation will involve. Before you consent to participate, please ask any questions to be sure you understand what your participation will involve.

<u>Consumer adoption of smart mirrors.</u>

<u>INVESTIGATORS</u>: This research study is being conducted by Chelsea Heney, a Master of Science in Management candidate under the supervision of Dr. Frances Gunn from the Ted Rogers School of Retail Management (TRSM) at Ryerson University.

If you have any questions or concerns about the research, please feel free to contact:

Chelsea Heney
MScM Candidate 2018 at TRSRM
chelsea.heney@ryerson.ca

Dr. Frances Gunn
Associate Professor of Retail Management, TRSM
416-979-5000 ext. 6758
fgunn@ryerson.ca

<u>PURPOSE OF THE STUDY</u>: This study investigates people's beliefs in using smart mirrors in a retail store. You will be asked to review a document with pictograms that describe and illustrates the potential use of a smart mirror in a retail store. You will be asked to compete a questionnaire with several questions related to the study.

<u>WHAT PARTICIPATION MEANS:</u> If you volunteer to participate in this study, you may be asked to do the following things:

- You may be asked to view a document that describes what a smart mirror is and illustrates its potential use in a retail store environment.
- You will spend approximately 14 minutes completing a questionnaire following the review of the video**.**

<u>POTENTIAL BENEFITS</u>: While there may be no direct benefits to you, the project will result in creation of knowledge that could contribute to the field of business education and commerce. In particular, the findings will provide implications to retail organizations that are considering investing in smart mirror technology for their retail stores.

WHAT ARE THE POTENTIAL RISKS TO YOU AS A PARTICIPANT: There is no obligation to answer any questions or to participate in any aspect of this study. Risks associated with participating in this study are minimal, for example, it may cause discomfort when answering some questions of personal nature. You may choose not to answer any questions you don't wish to answer, or end the survey at any time. If you feel uncomfortable during the survey process, you may discontinue your participation either temporarily or permanently without any negative consequences. There are no expected, anticipated or direct benefits to you.

CONFIDENTIALITY: All information will be collected anonymous for analysis, no personal information will be collected, and used only for the purposes of this research project. The information collected in this survey is confidential. As a respondent, your identity will be anonymous and responses will be protected and kept confidential by the Ted Rogers School of Retail Management and by Ryerson University.

VOLUNTARY PARTICIPATION AND WITHDRAWAL: Participation in this study is completely voluntary. You can choose whether to be in this study or not. You may stop participating at any time prior to your submission of the survey. If you wish to withdraw, please close your browser and any recorded responses will be deleted and your survey will be discarded. Please note that once the survey has been submitted the data cannot be withdrawn. Your choice of whether to participate will not influence your future relations with Ryerson or anyone who is involved in this research. All participants must be age of majority (18 in Alberta, Manitoba, Ontario, Prince Edward Island and Saskatchewan, and 19 in British Columbia, New Brunswick, Newfoundland and Nova Scotia) or older.

DATA STORAGE & DISSEMINATION: The data will be stored for a maximum of 5 years in the principal investigator's office. After a five-year period, the data will be discarded. During the five-year period, the data will be stored and backed up on an encrypted hard drive. The researcher will be the only individual who will have access to these responses. The researcher could use the results of this study at educational conferences or to publish papers in academic journals or digital outlets such as websites. The data may also be used by other graduate students. You will be given an opportunity to have access to the general results of this study when available.

This study has been reviewed by the Ryerson University Research Ethics Board. If you have questions regarding your rights as a participant of this study, please contact:

Research Ethics Board	
Ryerson University	c/o Office of the Vice President, Research and Innovation
416-979-5042	350 Victoria Street
rebchair@ryerson.ca	Toronto, Ontario M5B 2K3

Click here to open a new window so you can print a copy of this page for your future reference.

Start survey (Button to be inserted into electronic copy of survey)
Decline to participate [Terminate]

APPENDIX E: IBM SPSS Output

Descriptive Statistics

	Mean	Std. Deviation	Analysis N
PE1	4.33	1.654	985
PE2	4.43	1.759	985
PE3	4.57	1.755	985
EE1	5.55	1.422	985
EE2	4.81	1.539	985
EE3	5.50	1.443	985
SI1	3.45	1.672	985
SI2	3.50	1.710	985
HM1	5.10	1.680	985
HM2	4.88	1.677	985
HM3	5.04	1.716	985
BI1	4.36	1.679	985
BI2	4.14	1.877	985
BI3	4.22	1.733	985
PR1	4.69	1.809	985
PR2	4.80	1.887	985
PR3	4.61	1.901	985
PV1	4.13	1.761	985
PV2	4.17	1.728	985
PV3	4.18	1.715	985
PV4	4.06	1.759	985
DSI1	3.68	1.805	985
DSI3	3.71	1.777	985
DSI4	3.52	1.817	985
DS!6	3.35	1.760	985

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.961
Bartlett's Test of Sphericity	Approx. Chi-Square	23458.185
	df	300
	Sig.	.000

Correlation Matrix[a]

		PE1	PE2	PE3	EE1	EE2	EE3	SI1	SI2	HM1	HM2	HM3	BI1	BI2	BI3	PR1	PR2	PR3	PV1	PV2	PV3	PV4	DSI1	DSI3	DSI4	DSI6
Correlation	PE1	1.000	0.717	0.752	0.421	0.606	0.450	0.513	0.564	0.701	0.766	0.667	0.696	0.750	0.757	-0.181	-0.193	-0.209	0.755	0.729	0.702	0.743	0.434	0.453	0.368	0.407
	PE2	0.717	1.000	0.760	0.396	0.552	0.457	0.529	0.541	0.718	0.717	0.617	0.685	0.731	0.721	-0.186	-0.173	-0.211	0.686	0.686	0.664	0.743	0.444	0.460	0.369	0.382
	PE3	0.752	0.760	1.000	0.461	0.582	0.481	0.553	0.569	0.779	0.781	0.726	0.731	0.777	0.781	-0.192	-0.203	-0.206	0.726	0.770	0.726	0.774	0.454	0.439	0.389	0.381
	EE1	0.421	0.396	0.461	1.000	0.683	0.747	0.241	0.289	0.478	0.476	0.457	0.400	0.408	0.418	-0.119	-0.100	-0.078	0.384	0.401	0.387	0.388	0.449	0.383	0.373	0.381
	EE2	0.606	0.552	0.582	0.683	1.000	0.656	0.397	0.464	0.577	0.633	0.554	0.554	0.597	0.579	-0.175	-0.159	-0.161	0.565	0.554	0.536	0.547	0.456	0.423	0.399	0.438
	EE3	0.450	0.457	0.481	0.747	0.656	1.000	0.271	0.301	0.532	0.507	0.471	0.430	0.428	0.454	-0.120	-0.099	-0.099	0.423	0.431	0.407	0.442	0.424	0.398	0.353	0.364
	SI1	0.513	0.529	0.553	0.241	0.397	0.271	1.000	0.745	0.476	0.492	0.456	0.569	0.557	0.559	-0.189	-0.190	-0.175	0.549	0.562	0.554	0.577	0.439	0.427	0.407	0.408
	SI2	0.564	0.541	0.569	0.289	0.464	0.301	0.745	1.000	0.507	0.550	0.488	0.538	0.589	0.584	-0.179	-0.174	-0.160	0.608	0.564	0.527	0.588	0.445	0.459	0.417	0.463
	HM1	0.701	0.718	0.779	0.478	0.577	0.532	0.476	0.507	1.000	0.847	0.826	0.681	0.734	0.759	-0.152	-0.156	-0.163	0.690	0.702	0.704	0.723	0.416	0.407	0.346	0.333
	HM2	0.766	0.717	0.781	0.476	0.633	0.507	0.492	0.550	0.847	1.000	0.808	0.698	0.763	0.769	-0.167	-0.173	-0.183	0.742	0.711	0.710	0.729	0.398	0.388	0.314	0.354
	HM3	0.667	0.617	0.726	0.457	0.554	0.471	0.456	0.488	0.826	0.808	1.000	0.648	0.677	0.737	-0.105	-0.132	-0.148	0.647	0.651	0.652	0.643	0.392	0.364	0.298	0.310
	BI1	0.696	0.685	0.731	0.400	0.554	0.430	0.569	0.538	0.681	0.698	0.648	1.000	0.740	0.744	-0.231	-0.235	-0.221	0.714	0.731	0.705	0.735	0.463	0.439	0.371	0.376
	BI2	0.750	0.731	0.777	0.408	0.597	0.428	0.557	0.589	0.734	0.763	0.677	0.740	1.000	0.796	-0.209	-0.220	-0.239	0.749	0.741	0.716	0.776	0.477	0.451	0.410	0.426
	BI3	0.757	0.721	0.781	0.418	0.579	0.454	0.559	0.584	0.759	0.769	0.737	0.744	0.796	1.000	-0.212	-0.233	-0.233	0.753	0.763	0.751	0.782	0.481	0.459	0.414	0.414
	PR1	-0.181	-0.186	-0.192	-0.119	-0.175	-0.120	-0.189	-0.179	-0.152	-0.167	-0.105	-0.231	-0.209	-0.212	1.000	0.704	0.601	-0.307	-0.339	-0.279	-0.310	-0.195	-0.164	-0.146	-0.157
	PR2	-0.193	-0.173	-0.203	-0.100	-0.159	-0.099	-0.190	-0.174	-0.156	-0.173	-0.132	-0.235	-0.220	-0.233	0.704	1.000	0.609	-0.305	-0.329	-0.287	-0.301	-0.200	-0.141	-0.125	-0.134
	PR3	-0.209	-0.211	-0.206	-0.078	-0.161	-0.099	-0.175	-0.160	-0.163	-0.183	-0.148	-0.221	-0.239	-0.233	0.601	0.609	1.000	-0.318	-0.325	-0.275	-0.308	-0.150	-0.139	-0.110	-0.123
	PV1	0.755	0.686	0.726	0.384	0.565	0.423	0.549	0.608	0.690	0.742	0.647	0.714	0.749	0.753	-0.307	-0.305	-0.318	1.000	0.845	0.817	0.847	0.465	0.446	0.386	0.413
	PV2	0.729	0.686	0.770	0.401	0.554	0.431	0.562	0.564	0.702	0.711	0.651	0.731	0.741	0.763	-0.339	-0.329	-0.325	0.845	1.000	0.812	0.849	0.477	0.450	0.419	0.402
	PV3	0.702	0.664	0.726	0.387	0.536	0.407	0.554	0.527	0.704	0.710	0.652	0.705	0.716	0.751	-0.279	-0.287	-0.275	0.817	0.812	1.000	0.802	0.447	0.399	0.357	0.350
	PV4	0.743	0.743	0.774	0.388	0.547	0.442	0.577	0.588	0.723	0.729	0.643	0.735	0.776	0.782	-0.310	-0.301	-0.308	0.847	0.849	0.802	1.000	0.484	0.459	0.405	0.405
	DSI1	0.434	0.444	0.454	0.449	0.456	0.424	0.439	0.445	0.416	0.398	0.392	0.463	0.477	0.481	-0.195	-0.200	-0.150	0.465	0.477	0.447	0.484	1.000	0.731	0.787	0.736
	DSI3	0.453	0.460	0.439	0.383	0.423	0.398	0.427	0.459	0.407	0.388	0.364	0.439	0.451	0.459	-0.164	-0.141	-0.139	0.446	0.450	0.399	0.459	0.731	1.000	0.691	0.722
	DSI4	0.368	0.369	0.389	0.373	0.399	0.353	0.407	0.417	0.346	0.314	0.298	0.371	0.410	0.414	-0.146	-0.125	-0.110	0.386	0.419	0.357	0.405	0.787	0.691	1.000	0.753
	DSI6	0.407	0.382	0.381	0.381	0.438	0.364	0.408	0.463	0.333	0.354	0.310	0.376	0.426	0.414	-0.157	-0.134	-0.123	0.413	0.402	0.350	0.405	0.736	0.722	0.753	1.000

Inverse of Correlation Matrix

	PE1	PE2	PE3	EE1	EE2	EE3	SI1	SI2	HM1	HM2	HM3	BI1	BI2	BI3	PR1	PR2	PR3	PV1	PV2	PV3	PV4	DSI1	DSI3	DSI4	DSI6
PE1	3.626	-0.412	-0.409	0.056	-0.360	0.042	0.095	-0.100	0.275	-0.771	-0.039	-0.157	-0.309	-0.455	-0.136	-0.005	-0.007	-0.617	-0.158	-0.049	-0.123	0.176	-0.242	0.086	-0.116
PE2	-0.412	3.246	-0.755	0.162	-0.109	-0.159	-0.142	-0.012	-0.600	-0.250	0.443	-0.226	-0.323	-0.183	0.002	-0.164	0.113	0.061	0.197	0.039	-0.657	-0.069	-0.274	0.127	0.065
PE3	-0.409	-0.755	4.502	-0.299	0.126	0.017	-0.119	-0.120	-0.493	-0.389	-0.358	-0.283	-0.524	-0.312	-0.093	0.037	-0.047	0.477	-0.861	-0.081	-0.398	0.075	0.036	-0.129	0.107
EE1	0.056	0.162	-0.299	2.815	-0.960	-1.377	0.167	0.030	-0.002	-0.037	-0.198	0.019	0.078	0.123	0.064	0.003	-0.081	0.158	-0.033	-0.106	0.139	-0.368	0.035	-0.021	-0.028
EE2	-0.360	-0.109	0.126	-0.960	2.846	-0.582	0.051	-0.228	0.279	-0.505	-0.018	-0.139	-0.363	-0.020	0.058	-0.015	0.028	-0.082	-0.045	-0.090	0.240	0.095	0.102	-0.075	-0.227
EE3	0.042	-0.159	0.017	-1.377	-0.582	2.675	-0.012	0.157	-0.535	-0.006	0.087	-0.023	0.269	-0.034	-0.007	-0.039	0.018	-0.052	0.035	0.177	-0.218	-0.060	-0.174	0.037	0.006
SI1	0.095	-0.142	-0.119	0.167	0.051	-0.012	2.635	-1.545	0.138	0.129	-0.065	-0.423	-0.021	0.004	-0.007	0.021	0.012	0.396	-0.137	-0.445	-0.147	-0.092	-0.023	-0.155	0.027
SI2	-0.100	-0.012	-0.120	0.030	-0.228	0.157	-1.545	2.820	0.036	-0.182	-0.034	0.197	-0.142	-0.165	0.041	0.000	-0.095	-0.705	0.154	0.377	-0.038	0.094	-0.135	0.008	-0.305
HM1	0.275	-0.600	-0.493	-0.002	0.279	-0.535	0.138	0.036	5.389	-1.846	-1.765	0.021	-0.269	-0.186	0.048	-0.047	-0.122	0.358	-0.076	-0.413	-0.413	0.144	-0.156	-0.303	0.312
HM2	-0.771	-0.250	-0.389	-0.037	-0.505	-0.006	0.129	-0.182	-1.846	5.607	-1.177	-0.044	-0.487	-0.136	0.051	-0.022	-0.076	-0.795	0.270	-0.006	0.137	0.168	0.196	0.324	-0.246
HM3	-0.039	0.443	-0.358	-0.198	-0.018	0.087	-0.065	-0.034	-1.765	-1.177	3.985	-0.173	0.134	-0.746	-0.237	-0.031	0.100	-0.042	-0.142	-0.056	0.407	-0.284	0.021	0.252	0.067
BI1	-0.157	-0.226	-0.283	0.019	-0.139	-0.023	-0.423	0.197	0.021	-0.044	-0.173	3.127	-0.506	-0.421	0.064	0.044	-0.091	-0.139	-0.345	-0.170	-0.141	-0.211	-0.109	0.157	0.111
BI2	-0.309	-0.323	-0.524	0.078	-0.363	0.269	-0.021	-0.142	-0.269	-0.487	0.134	-0.506	4.136	-0.820	-0.108	-0.006	0.123	-0.198	0.037	0.039	-0.517	-0.096	0.119	-0.073	-0.159
BI3	-0.455	-0.183	-0.312	0.123	-0.020	-0.034	0.004	-0.165	-0.186	-0.136	-0.746	-0.421	-0.820	4.458	-0.089	0.117	0.012	0.089	-0.221	-0.453	-0.459	0.000	-0.022	-0.195	-0.008
PR1	-0.136	0.002	-0.093	0.064	0.058	-0.007	-0.007	0.041	0.048	0.051	-0.237	0.064	-0.108	-0.089	2.273	-1.153	-0.579	0.007	0.295	0.014	0.169	-0.017	0.038	-0.004	0.049
PR2	-0.005	-0.164	0.037	0.003	-0.015	-0.039	0.021	0.000	-0.047	-0.022	-0.031	0.044	-0.006	0.117	-1.153	2.279	-0.635	0.024	0.087	0.086	0.004	0.272	-0.078	-0.131	-0.043
PR3	-0.007	0.113	-0.047	-0.081	0.028	0.018	0.012	-0.095	-0.122	-0.076	0.100	-0.091	0.123	0.012	-0.579	-0.635	1.818	0.209	0.083	-0.048	0.064	-0.102	0.042	0.001	0.005
PV1	-0.617	0.061	0.477	0.158	-0.082	-0.052	0.396	-0.705	0.358	-0.795	-0.042	-0.139	-0.198	0.089	0.007	0.024	0.209	5.634	-1.548	-1.297	-1.532	-0.031	-0.017	0.150	-0.199
PV2	-0.158	0.197	-0.861	-0.033	-0.045	0.035	-0.137	0.154	-0.076	0.270	-0.142	-0.345	0.037	-0.221	0.295	0.087	0.083	-1.548	5.445	-0.905	-1.391	0.150	-0.025	-0.399	0.109
PV3	-0.049	0.039	-0.081	-0.106	-0.090	0.177	-0.445	0.377	-0.413	-0.006	-0.056	-0.170	0.039	-0.453	0.014	0.086	-0.048	-1.297	-0.905	4.132	-0.568	-0.266	0.132	0.105	0.160
PV4	-0.123	-0.657	-0.398	0.139	0.240	-0.218	-0.147	-0.038	-0.413	0.137	0.407	-0.141	-0.517	-0.459	0.169	0.004	0.064	-1.532	-1.391	-0.568	5.756	-0.190	-0.007	0.060	0.072
DSI1	0.176	-0.069	0.075	-0.368	0.095	-0.060	-0.092	0.094	0.144	0.168	-0.284	-0.211	-0.096	0.000	-0.017	0.272	-0.102	-0.031	0.150	-0.266	-0.190	3.702	-0.849	-1.524	-0.677
DSI3	-0.242	-0.274	0.036	0.035	0.102	-0.174	-0.023	-0.135	-0.156	0.196	0.021	-0.109	0.119	-0.022	0.038	-0.078	0.042	-0.017	-0.025	0.132	-0.007	-0.849	2.775	-0.376	-0.880
DSI4	0.086	0.127	-0.129	-0.021	-0.075	0.037	-0.155	0.008	-0.303	0.324	0.252	0.157	-0.073	-0.195	-0.004	-0.131	0.001	0.150	-0.399	0.105	0.060	-1.524	-0.376	3.357	-1.104
DSI6	-0.116	0.065	0.107	-0.028	-0.227	0.006	0.027	-0.305	0.312	-0.246	0.067	0.111	-0.159	-0.008	0.049	-0.043	0.005	-0.199	0.109	0.160	0.072	-0.677	-0.880	-1.104	3.133

Communalities

	Initial	Extraction
PE1	0.724	0.719
PE2	0.692	0.671
PE3	0.778	0.782
EE1	0.645	0.790
EE2	0.649	0.672
EE3	0.626	0.695
SI1	0.620	0.688
SI2	0.645	0.802
HM1	0.814	0.780
HM2	0.822	0.808
HM3	0.749	0.685
BI1	0.680	0.681
BI2	0.758	0.760
BI3	0.776	0.788
PR1	0.560	0.701
PR2	0.561	0.693
PR3	0.450	0.521
PV1	0.823	0.784
PV2	0.816	0.795
PV3	0.758	0.735
PV4	0.826	0.814
DSI1	0.730	0.788
DSI3	0.640	0.676
DSI4	0.702	0.767
DS!6	0.681	0.736

Extraction Method: Principal Axis Factoring.

References

Ahn, T., Ryu, S., & Han, I. (2007). The impact of Web quality and playfulness on user acceptance of online retailing. *Information & Management*, *44*(3), 263-275.

Alaiad, A., Zhou, L., & Koru, G. (2014). An exploratory study of home healthcare robots adoption applying the UTAUT model. *International Journal of Healthcare Information Systems and Informatics*, *9*(4), 44-59.

Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust. *International Journal of Information Management*, *37*(3), 99-110.

Alini, E. (2017). *2017 was a terrible year for Canadian retailers – and 2018 could be even worse*. Retrieved 1 March 2018, from https://globalnews.ca/news/3923176/retailers-canada-2018/

Amadeo, K. (2018). *U.S. retail sales report: Current statistics and recent trends*. Retrieved 1 March 2018, from https://www.thebalance.com/u-s-retail-sales-statistics-and-trends-3305717

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, *50*(2), 179-211.

Araujo, C. F., Ladeira, W. J., de Oliveira Santini, F., & Sampaio, C. H. (2016). Domain-specific innovativeness: a meta-analysis in business and consumer. *RAI Revista de Administração e Inovação*, *13*(2), 99-106.

Asking Canadians. (2017). *2017 panel book.* Toronto, ON: Asking Canadians.

Bagozzi, R. P. & Hans Baumgartner (1994). The evaluation of structural equation models and hypothesis testing. R.P. Bagozzi (Ed.). *Principles of Marketing Research*, Blackwell Publishers, Cambridge, pp. 386-422.

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

Benbasat, I., & Barki, H. (2007). Quo Vadis, TAM? *Journal of The Association for Information Systems*, *8*(4), 211-218.

Bennett, D., & El Azhari, J. (2015). Omni-channel customer experience: An investigation into the use of digital technology in physical stores and its impact on the consumer's decision-making process. *AEDEM International Conference*, 1-13.

Bichlmeier, C., Heining, S., Feuerstein, M., & Navab, N. (2009). The Virtual Mirror: A New Interaction Paradigm for Augmented Reality Environments. *IEEE Transactions On Medical Imaging*, *28*(9), 1498-1510.

Blake, B., Neuendorf, K., LaRosa, R., Luming, Y., Hudzinski, K., & Hu, Y. (2017). E-Shopping Patterns of Chinese and US Millennials. *Journal of Internet Commerce*, *16*(1), 53-79.

Blaikie, N. (2010). *Designing social research* (2nd ed.). Malden, MA: Polity.

Blum, T., Bichlmeier, V., & Navab, N. (2012). Miracle: An augmented reality magic mirror system for anatomy education. *Virtual Reality Short Papers and Posters (VRW)*, 115-116.

Bump, P. (2014). *Here is when each generation begins and ends, according to facts*. Retrieved 10 March 2018, from https://www.theatlantic.com/national/archive/2014/03/here-is-when-each-generation-begins-and-ends-according-to-facts/359589/

Burrel, G., & Morgan, G. (1988). Sociological paradigms and organizational analysis. *Aldershot, Gower*.

Calhoun, C. (2002). *Dictionary of the social sciences*. Oxford University Press.

Carmigniani, J., Furht, B., Anisetti, M., Ceravolo, P., Damiani, E., & Ivkovic, M. (2010). Augmented reality technologies, systems and applications. *Multimedia Tools and Applications*, *51*(1), 341-377.

Chu, M., Dalal, B., Walendowski, A., & Begole, B. (2010). Countertop responsive mirror: supporting physical retail shopping for sellers, buyers and companions. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 2533-2542). ACM.

Clark-Thompson, A. (2018). *The mirrors at CES had a lot to say about your life and look*. Retrieved 1 March 2018, from https://www.cnet.com/news/tech-mirrors-at-ces-2018-lot-to-say-about-your-life-looks/

Committee on communication for behaviour change in 21st Century (CCBC). (2002). *Chirr.nlm.nih.gov*. Retrieved 3 April 2017, from https://chirr.nlm.nih.gov/behavioral-intention.php

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS quarterly*, 189-211.

Cole, K. (2017, November). Kenneth Cole in conversation with Jeanne Beker at the Michael Belcourt lecture series. Presentation, Ryerson University.

Creswell, J. W. (2013). *Research design: Qualitative, quantitative and mixed methods approaches* (4th ed.). Los Angeles: SAGE Publications Ltd.

Cruickshank, J. (2012). Positioning positivism, critical realism and social constructionism in the health sciences: a philosophical orientation. *Nursing inquiry*, *19*(1), 71-82.

Daponte, P., De Vito, L., Picariello, F., & Riccio, M. (2014). State of the art and future developments of the augmented reality for measurement applications. *Measurement*, *57*, 53-70.

Davis, F. (1986). *A technology acceptance model for empirically testing new end-user information systems: Theory and results*. Massachusetts Institute of Technology, Cambridge, MA.

Davis, F. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. *Journal of applied social psychology*, *22*(14), 1111-1132.

Deloitte. (2015). *Disruption in retail: From products to pixels*. *Retail Council on Canada*. Retrieved from http://www.retailcouncil.org/sites/default/files/documents/Deloitte-RCC-2015-BC-Retail-Study.pdf

Dudhane, N., & Pitambare, S. (2015). Location Based and Contextual Services Using Bluetooth Beacons: New Way to Enhance Customer Experience. *Lecture Notes On Information Theory*, *3*(1).

Dwivedi, Y., Rana, N., Chen, H., & Williams, M. (2011). A meta-analysis of the unified theory of acceptance and use of technology (UTAUT). *Governance and Sustainability in IS*, *366*, 155-170.

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

Faqih, K. M., & Jaradat, M. I. R. M. (2015). Assessing the moderating effect of gender differences and individualism-collectivism at individual-level on the adoption of mobile commerce technology: TAM3 perspective. *Journal of Retailing and Consumer Services*, *22*, 37-52.

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: a perceived risk facets perspective. *International journal of human-computer studies*, *59*(4), 451-474.

Field, A. (2013). *Discovering statistics using IBM SPSS statistics* (4th ed.). Thousand Oaks, CA: SAGE Publications Ltd.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention and behaviour: An introduction to theory and research* (1st ed.). Reading, MA: Addison-Wesley.

Fonseca, D., Martí, N., Redondo, E., Navarro, I., & Sánchez, A. (2014). Relationship between student profile, tool use, participation, and academic performance with the use of Augmented Reality technology for visualized architecture models. *Computers in Human Behavior*, *31*, 434-445.

Giddens A. (1995). *Politics, sociology and social theory: Encounters with classical and contemporary social thought.* Cambridge: Polity.

Gillenson, M., & Sherrell, D. (2002). Enticing online consumers: an extended technology acceptance perspective. *Information & Management*, *39*(8), 705-719.

Gold, D., Sollinger, D., & Indratmo. (2016). SmartReflect: A modular smart mirror application platform. *Information Technology, Electronics and Mobile Communication Conference (IEMCON), IEEE 7Th Annual*, (1-7).

Goldsmith, R. E., Freiden, J. B., & Eastman, J. K. (1995). The generality/specificity issue in consumer innovativeness research. *Technovation*, *15*(10), 601-612.

Goldsmith, R. E., & Hofacker, C. F. (1991). Measuring consumer innovativeness. *Journal of the Academy of Marketing Science*, *19*(3), 209-221.

Bruner, G. C. (n.d.). *Scale-related pet peeves. Don't use reverse-coded items in scales.' www.scaleresearch.siu.edu.* Retrieved 15 February 2018, from http://scaleresearch.siu.edu/petpeeve5.html

Green, P. E. & Vithala R. R. (1970). Rating scales and information recovery: How many scales and response categories to use? *Journal of Marketing*, *34* (July), 33-39.

Grewal, D., Roggeveen, A., & Nordfält, J. (2017). The Future of Retailing. *Journal of Retailing*, *93*(1), 1-6.

Groeber, J. (2014). Eye of the beholder. *Design: Retail*, (26.8), 26.

Gupta, A., & Dogra, N. (2017). Tourist adoption of mapping apps: a UTAUT2 perspective of smart travelers. *Tourism and hospitality management*, *23*(2), 145-161.

Ha, S., & Stoel, L. (2009). Consumer e-shopping acceptance: Antecedents in a technology acceptance model. *Journal of Business Research*, *62*(5), 565-571.

Hair Jr, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage Publications.

Hair Jr, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139-152.

Hasan, M. N. (2016). Positivism: to what extent does it aid our understanding of the contemporary social world? *Quality & Quantity*, *50*(1), 317-325.

Haywood, D. (2017). *The Relationship between Nonprofit Organizations and Cloud Adoption Concerns* (Doctoral dissertation, Walden University).

Heijden, H. V. D. (2000). *E-Tam: a revision of the Technology Acceptance Model to explain website revisits* (No. 0029).

Helena Chiu, Y. T., Fang, S. C., & Tseng, C, C. (2010). Early versus potential adopters: Exploring the antecedents of use intention in the context of retail service innovations. *International Journal of Retail & Distribution Management*, *38*(6), 443-459.

Henseler, J., & Fassott, G. (2010). Testing moderating effects in PLS path models: An illustration of available procedures. In *Handbook of partial least squares*, 713-735. Heidelberg, Berlin: Springer.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science*, *43*(1), 115-135.

Herrero, Á., San Martín, H., Garcia-De los Salmones, M. (2017). Explaining the adoption of social networks sites for sharing user-generated content: A revision of the UTAUT2. *Computers in Human Behavior*, *71*, 209-217.

Howe, N., & Strauss, W. (2002). Coming soon to a graduate school near you: The millennial generation. *Selections*, *2*(1), 40

Huang, N., & Qin, G. (2011, May). A study of online virtual fitting room adoption based on UTAUT. In *E-Business and E-Government (ICEE), 2011 International Conference on* (pp. 1-4). IEEE.

Inman, J., & Nikolova, H. (2017). Shopper-Facing Retail Technology: A Retailer Adoption Decision Framework Incorporating Shopper Attitudes and Privacy Concerns. *Journal of Retailing*, *93*(1), 7-28.

Iwabuchi, E., Nakagawa, M., & Siio, I. (2009, July). Smart makeup mirror: Computer-augmented mirror to aid makeup application. In *International Conference on Human-Computer Interaction* (pp. 495-503). Springer, Berlin, Heidelberg.

Javornik, A., Rogers, Y., Moutinho, A. M., & Freeman, R. (2016). Revealing the Shopper Experience of Using a" Magic Mirror" Augmented Reality Make-Up Application. In *Conference on Designing Interactive Systems* (Vol. 2016, pp. 871-882). Association for Computing Machinery (ACM).

Jeong, S. C., Kim, S. H., Park, J. Y., & Choi, B. (2017). Domain-specific innovativeness and new product adoption: A case of wearable devices. *Telematics and Informatics*, *34*(5), 399-412.

Juaneda-Ayensa, E., Mosquera, A., & Sierra Murillo, Y. (2016). Omnichannel Customer Behavior: Key Drivers of Technology Acceptance and Use and Their Effects on Purchase Intention. *Frontiers in Psychology*, *7*.

Kim, J., & Forsythe, S. (2008). Adoption of virtual try-on technology for online apparel shopping. *Journal of Interactive Marketing*, *22*(2), 45-59.

Klopping, I., & McKinney, E. (2004). Extending the technology acceptance model and the task-technology fit model to consumer e-commerce. *Information Technology, Learning, And Performance*, *22*(1), 35.

Laney, M. (2015). *Learn why 'Fitting Rooms Matter'*. *www.retailcustomerexperience.com*. Retrieved 2 April 2017, from https://www.retailcustomerexperience.com/articles/learn-why-fitting-rooms-matter/

Lavrakas, P. J. (2008). *Encyclopedia of survey research methods* Thousand Oaks, CA: SAGE Publications Ltd

Leong, G. W., Ping, T. A., & Muthuveloo, R. (2017). Antecedents of Behavioural Intention to Adopt Internet of Things in the Context of Smart City in Malaysia. *Global Business & Management Research*, *9*.

Lumb, D. (2016). *Smart Mirrors Might Be the Future of In-Store Customer Analytics*. *Fast Company*. Retrieved 6 April 2017, from https://www.fastcompany.com/3060448/smart-mirrors-might-be-the-future-of-in-store-customer-analytics

Macedo, I. M. (2017). Predicting the acceptance and use of information and communication technology by older adults: An empirical examination of the revised UTAUT2. *Computers in Human Behavior*, *75*, 935-948.

Mandrik, C. A., & Bao, Y. (2005). Exploring the concept and measurement of general risk aversion. *ACR North American Advances*.

Marian, P. (2016). *The future of beauty: Magic Mirrors on the wall*. *WGSN Insider*. Retrieved 2 March 2017, from https://www.wgsn.com/blogs/the-future-of-beauty-magic-mirrors-on-the-wall/#

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

McKechnie, S., Winklhofer, H., & Ennew, C. (2006). Applying the technology acceptance model to the online retailing of financial services. *International Journal of Retail & Distribution Management*, *34*(4/5), 388-410.

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). The impact of initial consumer trust on intentions to transact with a web site: a trust building model. *The journal of strategic information systems*, *11*(3-4), 297-323.

ModiFace. (2017). *ModiFace Mirror - Live magic mirror for makeup, skin-care, anti-aging, and hair simulations*. *Modiface.com*. Retrieved 6 April 2017, from http://modiface.com/mirror.php

Moore, G., & Benbasat, I. (1991). Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation. *Information Systems Research*, *2*(3), 192-222.

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

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

Netemeyer, R. G., Beardon, W. O., & Sharma, S. (2003). *Scaling Procedures: Issues and Applications*, Newbury Park, CA: Sage Publications, Inc.

Nguyen, T. V., & Liu, L. (2017, October). Smart Mirror: Intelligent Makeup Recommendation and Synthesis. In *Proceedings of the 2017 ACM on Multimedia Conference* (pp. 1253-1254). ACM.

Nguyen, T. D., Nguyen, T. M., Pham, Q. T., & Misra, S. (2014, June). Acceptance and use of e-learning based on cloud computing: the role of consumer innovativeness. In *International Conference on Computational Science and Its Applications* (pp. 159-174). Springer, Cham.

O'Cass, A., & Fenech, T. (2003). Web retailing adoption: exploring the nature of internet users Web retailing behaviour. *Journal of Retailing and Consumer services*, *10*(2), 81-94.

Pantano, E. (2010). New technologies and retailing: Trends and directions. *Journal of Retailing and Consumer Services 17*, 171-172.

Pantano, E. (2014). Innovation drivers in retail industry. *International Journal of Information Management*, *34*(3), 344-350.

Pantano, E., & Di Pietro, L. (2012). Understanding Consumer's Acceptance of Technology-Based Innovations in Retailing. *Journal of Technology Management & Innovation*, *7*(4), 1-19.

Pantano, E., & Naccarato, G. (2010). Entertainment in retailing: The influences of advanced technologies. *Journal of Retailing and Consumer Services*, *17*(3), 200-204.

Poncin, I., & Mimoun, M. (2014). The impact of "e-atmospherics" on physical stores. *Journal of Retailing and Consumer Services*, *21*(5), 851-859.

Pantano, E., Priporas, C. V., & Dennis, C. (2017). Managing consumers' dynamics within the emerging smart retail settings: Introduction to the special issue. *Technological Forecasting & Social Change 124*, 225-227.

Pantano, E., & Timmermans, H. (2014). What is smart for retailing? *Procedia Environmental Sciences*, *22*, 101-107.

Pantano, E., & Viassone, M. (2014). Demand pull and technology push perspective in technology-based innovations for the points of sale: The retailers evaluation. *Journal of Retailing and Consumer Services*, *21*(1), 43-47.

Peterson, C. (2017). *2017 Canadian retail forecast [Analysis]*. Retrieved 1 March 2018, from https://www.retail-insider.com/retail-insider/2017/1/2017-forecast

Peterson, C. (2018). *2018 Canadian retail forecast [Analysis]*. Retrieved 1 March 2018, from https://www.retail-insider.com/retail-insider/2018/1/2018-canadian-retail-forecast-analysis
2018 Canadian Retail Forecast [Analysis]
January 07, 2018

Priporas, C., Stylos, N., & Fotiadis, A. (2017). Generation Z consumers' expectations of interactions in smart retailing: A future agenda. *Computers in Human Behavior*, 374-381.

Pura, M (2005). Linking perceived value and loyalty in location-based mobile services. *Managing Service Quality*, *15*(6), 509-538.

PWC, (2015). *Total Retail Report*. *PwC*. Retrieved from http://www.pwc.com/ca/totalretail

Rahman, A. M., Tran, T. T., Hossain, S. A., & El Saddik, A. (2010, October). Augmented rendering of makeup features in a smart interactive mirror system for decision support in cosmetic products selection. In *Distributed Simulation and Real Time Applications (DS-RT), 2010 IEEE/ACM 14th International Symposium on* (pp. 203-206). IEEE.

Regan, C., & Pickler, L. (2017). *It's more than Amazon: Why retail is in distress now*. Retrieved 1 March 2018, from https://www.cnbc.com/2017/05/05/its-more-than-amazon-why-retail-is-in-distress-now.html

Rese, A., Baier, D., Geyer-Schulz, A., & Schreiber, S. (2017). How augmented reality apps are accepted by consumers: A comparative analysis using scales and opinions. *Technological Forecasting and Social Change*, *124*, 306-319.

Rigdon, E. E., Schumacker, R. E., & Wothke, W. (1998). A comparative review of interaction and nonlinear modeling. In R. E. Schumacker, & G. A. Marcoulides (Eds.), Interaction and nonlinear effects in structural equation modeling, (pp. 1–16). Mahwah, NJ: Lawrence Erlbaum.

Robertson, T. S. (1971). *Innovative behavior and communication*. Holt McDougal.

Roehrich, G. (2004). Consumer innovativeness: Concepts and measurements. *Journal of business research*, *57*(6), 671-677.

Rondan-Cataluña, F., Arenas-Gaitán, J., & Ramírez-Correa, P. (2015). A comparison of the different versions of popular technology acceptance models. *Kybernetes, 44*(5), 788-805.

Roy, S. K., Balaji, M. S., Sadeque, S., Nguyen, B., & Melewar, T. C. (2017). Constituents and consequences of smart customer experience in retailing. *Technological Forecasting and Social Change*, *124*, 257-270.

Saakes, D., Yeo, H., Noh, S., Han, G., & Woo, W. (2016). Mirror, mirror: An on-body t-shirt design system. *Proceedings of The Conference On Human Factors in Computing Systems*, 6058-6063.

San Martín, H., & Herrero, Á. (2012). Influence of the user's psychological factors on the online purchase intention in rural tourism: Integrating innovativeness to the UTAUT framework. *Tourism Management*, *33*(2), 341-350.

Shaw, N. (2014). The mediating influence of trust in the adoption of the mobile wallet. *Journal of Retailing and Consumer Services*, *21*(4), 449-459.

Shaw, N., & Sergueeva, K. (2016). Convenient or useful? Consumer adoption of smartphones for mobile commerce. *DIGIT 2016 Proceedings 3*, 1-19.

Slade, E. L., Dwivedi, Y. K., Piercy, N. C., & Williams, M. D. (2015). Modeling consumers' adoption intentions of remote mobile payments in the United Kingdom: extending UTAUT with innovativeness, risk, and trust. *Psychology & Marketing*, *32*(8), 860-873.

Statistics Canada (2011). *Table 1 generations in Canada.* Retrieved 10 March 2018, from http://www12.statcan.gc.ca/census-recensement/2011/as-sa/98-311-x/2011003/tbl/tbl3_2-1-eng.cfm

Statistics Canada (2017a). *Education in Canada: Key results from the 2016 Census.* Retrieved 2 March 2018, from http://www.statcan.gc.ca/daily-quotidien/171129/dq171129a-eng.pdf

Statistics Canada (2017b). *Canada population by sex and age.* Retrieved 2 March 2018, from http://www.statcan.gc.ca/tables-tableaux/sum-som/l01/cst01/demo10a-eng.htm

Statistics Canada (2017c). *Life in the fast lane: How are Canadians managing?* Retrieved 10 March 2018, from https://www.statcan.gc.ca/daily-quotidien/171114/dq171114a-eng.htm?HPA=1

Swain, S. D., Weathers, D., & Niedrich, R. W. (2008). "Assessing Three Sources of Misresponse to Reversed Likert Items," *Journal of Marketing Research*, 45 (1), 116-131.

Tandon, U., Kiran, R., & Sah, A. N. (2018). The influence of website functionality, drivers and perceived risk on customer satisfaction in online shopping: an emerging economy case. *Information Systems and e-Business Management*, *16*(1), 57-91.

Taylor, S., & Todd, P. (1995). Assessing IT usage: The role of prior experience. *MIS quarterly*, 561-570.

Thomas, L. (2017). *Dire predictions for retail stoked by another bad week full of store closures and looming bankruptcy*. Retrieved 1 March 2018, from https://www.cnbc.com/2017/06/02/another-bad-week-for-retail-store-closures-and-a-possible-bankruptcy.html

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal computing: toward a conceptual model of utilization. *MIS quarterly*, 125-143.

Toneguzzi, M. (2017). *Canadian retail industry sees strong gains in 2017: Report*. Retrieved 1 March 2018, from https://www.retail-insider.com/retail-insider/2017/11/colliers-report

Varma Citrin, A., Sprott, D. E., Silverman, S. N., & Stem Jr, D. E. (2000). Adoption of Internet shopping: the role of consumer innovativeness. *Industrial management & data systems*, *100*(7), 294-300.

Venkatesh, V., & Davis, F. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2), 186-204.

Venkatesh, V., Morris, M., Davis, G., & Davis, F. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425-478.

Venkatesh, V., Thong, J., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157-178.

Venkatesh, V., Thong, J. Y., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems 15*(5), 328-376.

Vrontis, D., Thrassou, A., & Amirkhanpour, M. (2017). B2C smart retailing: A consumer-focused value-based analysis of interactions and synergies. *Technological Forecasting and Social Change*, *124*, 271-282.

Weinhard, A., Hauser, M., & Thiesse, F. (2017). Explaining Adoption of Pervasive Retail Systems with a Model based on UTAUT2 and the Extended Privacy Calculus.

Weinswig, D. (2015). *Are Magic Mirrors the next big thing? Chain Store Age*. Retrieved from http://www.chainstoreage.com/article/are-magic-mirrors-next-big-thing

Wilson, M. (2014). *IHL Forecast: 2015 retail IT spend to surpass $190 billion*. *Chain Store Age*. Retrieved 1 April 2017, from http://www.chainstoreage.com/article/ihl-forecast-2015-retail-it-spend-surpass-190-billion

Wong, N., Rindfleisch, A., & Burroughs, J. E. (2003). Do reverse-worded items confound measures in cross-cultural consumer research? The case of the material values scale, *Journal of Consumer Research*, 30 (June), 72-91.

Yang, K. (2010). Determinants of US consumer mobile shopping services adoption: implications for designing mobile shopping services. *Journal of Consumer Marketing*, *27*(3), 262-270.

Yang, Y., Liu, Y., Li, H., & Yu, B. (2015). Understanding perceived risks in mobile payment acceptance. *Industrial Management & Data Systems*, *115*(2), 253-269.

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

Yurieff, K. (2018). *Amazon's smart mirror patent teases the future of fashion*. Retrieved 1 March 2018, from http://money.cnn.com/2018/01/03/technology/amazon-smart-mirror-patent/index.html