2021

Adoption of AI-enabled technology: taking the bad with the good

George Dagliyan

Pepperdine University

Graziadio School of Business

ADOPTION OF AI-ENABLED TECHNOLOGY: TAKING THE BAD WITH THE GOOD

A dissertation submitted in partial fulfilment

of the requirements for the degree of

DOCTOR OF BUSINESS ADMINISTRATION

by

George Dagliyan

July, 2021

Cristel Russell, Ph.D. – Dissertation Chair

This dissertation, written by

George Dagliyan

under the guidance of a Dissertation Committee and approved by its members, has been submitted to and accepted by the Pepperdine Graziadio Business School in partial fulfilment of the requirements for the degree of

DOCTOR OF BUSINESS ADMINISTRATION

Doctoral Dissertation Committee:

Cristel Russell, Ph.D., Supervisor and Chairperson

Nelson Granados, Ph.D., Secondary Advisor 1

Kathleen M. Grave, DBA, External Reviewer

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

VITA

George Dagliyan is a cross-disciplinary scholar specializing in the intersection of marketing, diffusion of innovation, decision science, and artificial intelligence. He became interested in cross-disciplinary research through his work at Commonwealth Casualty Company, where he serves as the chairman and the chief operating officer. He received his bachelor's, master's, and doctorate degrees in Business Administration.

ABSTRACT

From autonomous vehicles to smart home assistants and telemedicine, artificial intelligence enabled (AI-enabled) technologies are increasingly available in the market. Consumers are saddled between the benefits and the risks of these new technologies, yet prior research has not accounted for the coexistence of inhibitory and faciliatory factors and how they affect intentions to use AI-enabled technology. The current research introduces a conceptual model to address these relationships and integrates the role of subjective ambivalence and brand trust. The model was tested using structural equation modeling with a cross sectional survey of U.S. consumers across three distinct categories of AI: autonomous vehicles for robotic AI, smart home assistants for virtual AI, and telemedicine for embedded AI. The findings reveal that the coexistence of the facilitators and inhibitors gives rise to ambivalence, which itself affects the adoption of novel technology and that brand trust also plays a critical role in affecting facilitators and inhibitors. Theoretical and practical implications are discussed in terms of the diffusion of innovation and the psychological processes that underlie consumer adoption of new technologies often laden in ambivalence.

Keywords: diffusion of innovation, technology adoption, brand trust, ambivalence, artificial intelligence

CHAPTER 1: INTRODUCTION

Overview

With possibilities that extend to many mental tasks performed by consumers, artificial intelligence (AI) technology could transform the consumer experience with their humanlike characteristics (Russel & Norvig, 2013). Consumers can benefit from the convenient, low-cost, reliable, and personalized services offered by AI-enabled technology (Huang & Rust, 2020). However, existing cross-disciplinary research also suggests that consumers continue to be concerned about issues related to safety (Zmud et al., 2016), reliability (Foehr & Germelmann, 2020), and loss of control (Del Bucchia et al., 2020; Howard & Dai, 2014). As a result, consumers may hold conflicting views of AI's potential, and this ambivalence could itself affect the adoption of AI-enabled technology. Prior research has prioritized facilitators of technology adoption, and only limited research accounts for the existence of inhibitors. To my knowledge, there is no research that accounts for the potential role of ambivalence.

Understanding the factors that influence the decision-making process for the adoption of novel technologies is critical for developing and marketing new products and services (Claudy et al., 2015). Studies in the technology adoption domain have primarily applied traditional behavioral models, including the technology acceptance model (TAM; Davis, 1989) and its extension, unified theory of acceptance and use of technology (UTAUT; Venkatesh, 2003). The traditional approach to AI-enabled technology adoption with existing frameworks leaves out critical concepts specific to novel technologies, such as ambivalence, trust, and inhibiting factors. While a growing number of researchers are critical of traditional approaches that neglect the factors leading to resistance (Claudy et al., 2015; Garcia et al., 2007; Ram & Sheth, 1981) and insist that managers and researchers should consider factors that prevent the adoption of innovations (Antioco & Kleijen, 2010), only a few have developed a model that accounts for resisting factors (Claudy et al. 2015; Janis & Mann, 1977; Westaby et al. 2010). Claudy et al. (2015) tested the relative influence of both reasons for and against the adoption of an innovation. The results indicated that both factors contributed to the adoption of innovations, and they called for future research to examine relationships of other influencing factors.

Building on extant frameworks of technology adoption, this research adds two new dimensions to the understanding of consumer adoption of AI-enabled technology. First, it accounts for ambivalence, the coexistence of positive and negative reactions towards an attitudinal object (Priester & Petty, 1996). Perhaps surprisingly, ambivalence has not been accounted for in research concerning technology acceptance. Second, because AI-enabled applications are usually embedded within a brand (e.g., Amazon Alexa's smart home assistants, Tesla's autonomous vehicles), most research examines the role of brand trust, with its different facets, on consumer adoption of AI-enabled technologies.

Given the variety of product categories that rely on AI, this research investigates consumer adoption across three AI categories at different stages of adoption in the market: virtual, robotic, and embedded AI. AI-enabled smart home virtual assistance (SHVA) technologies, such as Alexa or Siri, have gained popularity in many households in recent years. When summoned with their given name, SHVAs quickly respond to consumers' questions with interactive communication using typical sentences. Virtual AI empowers consumers with immediate personalized services through digital interactions. Yet, consumers continue to harbor mixed feelings between the benefits of empowerment and the vulnerability it conceals (Del Bucchia et al., 2020).

Autonomous Vehicles (AVs), representing robotic AI in this study, have demonstrated the potential to make radical changes in the future of automobile transportation (Anderson, 2014) with far-reaching implications regarding tangible benefits and convenience (Fagnant & Kockelman, 2015; Hedlund, n.d.; Suresh & Manivannan, 2014). A critical promise of AVs is the reduction of accident fatalities (Fagnant & Kockelman, 2014; Silberg & Wallace, 2012); others include reducing traffic congestion (Leicht et al., 2018), lowering the cost of transportation (Goddin, 2015; Milakis et al., 2017; Wadud et al., 2016), reducing greenhouse gas emissions (Jones & Leibowicz, 2019), and increasing mobility (Choi & Ji, 2015; Payre et al., 2014). However, these promising AV attributes will better materialize with mass consumer adoption (Zhang et al., 2019).

Finally, telemedicine (TM), representing embedded AI in this study, promises to decrease the cost of healthcare by yielding quick and accurate results from the convenience of consumers' location (Donelly, 2017; Liu et al., 2019). AI can revolutionize the healthcare industry with accurate, cost-effective, and scalable solutions (Longoni et al., 2019). In addition to cost savings, AI-based diagnoses can be more accurate than ones made by doctors (Donnelly, 2017; Liu et al., 2019). Yet, public adoption of AI still lags all these documented benefits (Longoni et al., 2019).

I argue that although virtual, robotic, and embedded AI categories differ in the level of AI's machine intelligence, capabilities, and complexities, they all exhibit facilitating and inhibiting factors that ultimately affect consumers' adoption. Indeed, while perceived efficiency, convenience, and personalization may facilitate consumer adoption of AI-enabled technology, perceived privacy risk, loss of control risk, and uncertainty across all three categories can impair adoption. In turn, the coexistence of facilitating and inhibiting factors, which can lead to ambivalence, as well as the role of brand trust, influence technology adoption.

In what follows, I first review related literature on technology acceptance, artificial intelligence, ambivalence, and trust. Next, I propose a new theoretical framework and develop a set of key hypotheses. I then present the research design and methodology. Subsequently, I test the hypotheses across three studies of consumers who are non-users of the technologies, followed by the fourth study examining the differences between current users and non-users. I conclude with a discussion of findings, limitations, and recommendations for future research.

Research Question(s)

Across all forms of AI, existing research signals that consumers are saddled between the benefits and risks associated with AI-enabled technology, which gives rise to ambivalence. The issue of trust and its influence on consumer adoption is another critical factor in this domain. For this reason, the current study addresses the role of ambivalence and trust in consumer adoption of AI-enabled technology by seeking answers to the following questions:

- How do facilitating and inhibiting factors independently affect consumers' intention to use AI-enabled technology?
- How does ambivalence relate to consumer's intention to use AI-enabled technology?
- What is the role of 'brand trust in AI-enabled technology' in these relationships?

Significance of the Proposed Research

Currently, marketers lack a comprehensive and balanced model with concrete levers that can influence the adoption of novel technology. Existing research across multiple disciplines strictly focuses on a single AI category (Broadbent et al., 2009; Cook et al., 2009; Smith & Kirby, 2011) or application with specific facilitators, inhibitors, or trust constructs tested separately. To the best of my knowledge, there is no empirical study that examines facilitators, inhibitors, and trust constructs across different categories of consumer-related AI-enabled technology. Moreover, while researchers have focused on exploring the relationships between independent and dependent variables, little attention has been given to the ambivalence generated by the coexistence of facilitating and inhibiting factors of consumers' intention to use AI-enabled technology.

This research explores both consumers' intentions to use AI-enabled technology, with three studies that include non-users, and consumers' intentions to continue using a technology (in the category of virtual AI, SHVA). Continuous usage or retention is the desired outcome for manufacturers and service providers because companies incur high costs on new customer acquisition and retaining existing customers to maximize customer returns (Livne et al., 2011). Research suggests that customer satisfaction (which refers to the overall evaluation of performance based on experience with the firm) is associated with higher intentions to repurchase or continuous usage (Bitner & Hubbert, 1994; Johnson & Fornell, 1991). Additionally, the relationship between customer satisfaction and retention may be contingent on other factors such as switching barriers (Jones et al., 2000). Supplementing non-users with a study of actual AI application users allows us to compare and contrast the dynamics of how consumers' perceptions of facilitators and inhibitors relate to potential adoption, when consumers are at the consideration stage, with the dynamics of facilitators, inhibitors, brand trust, and ambivalence in the phase of actual usage of AI-enabled technology. To capture these distinctions and switching barriers, the variables in the model remain the same except for the dependent variable, which was modified from intention to use to continuing usage.

The focus on three AI-enabled technologies at different stages of adoption allows us to identify the demographics of early adopters for each category. This research makes both theoretical and practical contributions. From a theoretical perspective, the new framework would measure consumer adoption with additional factors designed for emerging technology. From a practical perspective, practitioners can utilize the levers of the framework (e.g., trust, ambivalence) to develop more efficient marketing strategies with a view to increasing the adoption of AI-enabled technology as well as maintaining usage.

CHAPTER 2: LITERATURE REVIEW

What is Artificial Intelligence?

The best way to describe what AI is to start from what it is not. AI is not automation; automation, which is often confused with AI, refers to sequential and pre-programmed rules by humans to perform repetitive and monotonic tasks that were otherwise performed by humans (Glikson & Woolley, 2020; Parasuraman & Riley, 1997). Scholars have defined AI-enabled technology in many ways, in different disciplines, with two main approaches: a human-centered approach and a rationalist approach (Russel & Norvig, 2013). The human-centered approach defines AI-enabled technology as machines that perform functions that require intelligence when performed by people (Kurzweil, 1990). The rationalist camp takes an agent-based approach, where the agent acts to achieve the best outcome or the best-expected outcome when there is uncertainty (Russel & Norvig, 2013). Winston (1992) defines thinking rationally as a study of computations that make it possible to perceive, reason, and act.

My approach borrows from both camps, and I define AI as a new generation of technology that is capable of observing (sensing, hearing, or analyzing data), storing the information it knows, reasoning (concluding), and perceiving and manipulating objects (Russel & Norvic, 2013). I adopt the three categories of AI identified by Glikson and Woolley (2020). These categories include robotic AI, which refers to physically present AI-enabled robots (e.g., room cleaning robots, AVs); virtual AI, which refers to an AI-enabled virtual agent that has a distinguished identity (e.g., Alexa, Siri, or chatbot) but no physical presence; and embedded AI, which refers to invisible AI, that is, it does not have a physical presence or distinguished identities (e.g., an AI-powered search engine or TM) (Glikson & Woolley, 2020).

Technology Adoption / Acceptance

As defined by Dillon and Morris (1996), user acceptance represents a consumer's willingness to use technology for the activities that the technology is designed to support. Although seemingly simple, understanding why consumers accept or reject new technologies is one of the most daunting challenges of information technology research. Thus, to address this challenge, researchers developed theories and frameworks to capture the complex process of consumer acceptance of new technologies and to model the factors that underline this process.

The Technology Acceptance Model (TAM; Davis, 1989) is perhaps the most tested theoretical framework. TAM is based directly on the theory of reasoned action (TRA; Fishbein & Ajzen, 1975), a psychological theory that seeks to explain behavior in a specific situation. The TAM focuses on the driving factors for the acceptance of new technologies (Venkatesh & Davis, 2000) and postulates that the two main drivers of acceptance are perceived usefulness, defined as the user's belief that the technology will advance their goals, and perceived ease of use, defined as the judgment that the new technology will not require significant effort to learn (Venkatesh & Davis, 2000). From the causal perspective, the relation between these two drivers suggests that "ease of use may be an antecedent of usefulness, rather than parallel, direct determinant of usage" (Davis, 1989 p. 334). Perceived usefulness is a stronger driver than ease of use in guiding technology acceptance. For example, Koul and Eydgahi (2018) found perceived usefulness to be the primary predictor of consumers' intention to use driverless car technology.

The constructs within TAM have demonstrated reliability across multiple studies, with items within each construct showing Cronbach's alpha values of 0.9 on average (Davis & Venkatesh, 1996; Yousafzai et al., 2007). TAM is primarily used to determine the acceptance of innovations, which is measured by estimating the relationship between perceived ease of use, perceived usefulness, and the eventual rate of usage (Horton et al., 2001). TAM has been applied in the domains of research pertaining to social networking, smartphones, the internet, and online learning. For example, TAM was found to explain consumer adoption intentions within the field of mobile commerce (Yang, 2005), as well as consumers' acceptance and use of eco-friendly alternative fuel vehicle technology (Jansson et al., 2010).

Although TAM was initially designed to investigate non-intelligent innovations, researchers in the AI domain have also used TAM (Sundar et al., 2016; Wu et al., 2019; Zhang et al., 2019) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to investigate willingness or intent to use smart technology (Deb et al., 2017; Fritz et al., 2016; Madigan et al., 2016; Rahman et al., 2017). UTAUT is an extension of the TAM framework, which combines the essential components of eight established models (i.e., TAM, the motivational model, the theory of planned behavior, TAM + the theory of planned behavior, the model of personal computer utilization, the innovation diffusion theory, and the social cognitive theory) in one structure to explain and predict the intention to use and usage behavior with regards to information technology (Venkatesh et al., 2003). As a result, they identified seven constructs that appeared to have significant direct determinants of intention or usage. Of those, they theorized four constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003) and added four moderators: gender, age, experience, and voluntariness.

TAM has been applied as a theoretical framework to explain consumers' intentions to use novel technologies. However, not every study finding is in complete support of TAM. The outcome of the study on AVs conducted by Buckley et al. (2018) supported a relationship of intention to use with perceived usefulness but not perceived ease of use. Hu et al. (1999)

examined TAM for TM technology, and perceived usefulness was found to be a significant determinant of attitude and intention, but perceived ease of use was not. Other studies also found no relationship between perceived ease of use and perceived usefulness (Jackson et al., 1997; Subramanian, 1994). This highlights the fact that these traditional theoretical frameworks are useful, but other variables are necessary related to the adoption of novel technology to explain better and predict the complex phenomenon. The perceived ease of use construct appears to be less relevant to AI-enabled technologies because the main attraction of AI is that it requires less learning and effort to use (Gursoy et al., 2019). For example, an AV does not require any input from the driver as the vehicle drives itself. In the case of SHVA, the user communicates with the smart speaker by speaking to it.

The perceived usefulness construct, due to its positive essence, is biased toward the facilitating factors and does not capture the inhibiting factors related to AI, such as loss of control risk, privacy risk, and uncertainty. Furthermore, the perceived usefulness construct, which has the strongest relationship with willingness to use new technology, may also be less relevant to AI technologies compared to other non-intelligent innovations (Gursoy et al., 2019); hence new generation technologies enabled by AI require a theoretical framework that incorporates both facilitators and inhibitors of adoption.

Facilitators and Inhibitors of Technology Adoption

The technology adoption literature generally focuses on the facilitators of adoption through perceived usefulness and perceived ease of use using TAM and its extensions, as well as product attributes (e.g., relative advantage, compatibility, trialability) using TRA and its extensions (Claudy et al., 2015). Another, less established, branch of innovation adoption research concentrates on inhibitors of adoption (Garcia et al., 2007; Kleijnen et al., 2009; Ram

1987; Ram & Sheth 1989), arguing that a high percentage of innovation failures and new product failures should not be surprising because it represents change, and resistance to change is a normal consumer response (Claudy et al., 2015). Marketers, product developers, service providers, and other stakeholders need to overcome the resistance before the adoption may begin (Claudy et al., 2015; Laukkanen et al., 2007). Finally, a small group of scholars introduce a more balanced approach (Claudy et al. 2015), arguing that while some constructs could be logical opposites of the same dimension (e.g., the cost-benefit ratio or positive image), others have distinct positive and negative influences on adoption. I follow the latter approach. As an example, within the context of this study, consumers may find it beneficial to use SMVA or other novel technologies for convenience, customization, and efficiency, but they may still be hesitant due to their perceptions of privacy, uncertainty, and loss of control risks. These facilitating and inhibiting factors are not opposite ends of the same dimension; they coexist.

Based on a review of relevant literature and by extracting common themes, I identified six facilitating and inhibiting factors that could influence novel technology adoption. The facilitating factors are perceived customization, convenience, and efficiency (Table 1) and inhibiting factors are perceived privacy, uncertainty, and loss of control risks (Table 2). This section reviews each of these factors, which were then grouped into two second-order categories: facilitators and inhibitors.

INSERT TABLES 1 AND 2 ABOUT HERE

Convenience

Convenience is one of the leading benefits of AI-enabled technologies. De Kerviler et al. (2016) report that perceived convenience was one of the critical constructs explaining intentions to use proximity mobile payments. The construct relates to the amount of time and effort required to accomplish a task (Collier & Kimes, 2013). It has also been viewed as representing the cognitive, emotional, and physical burdens (Chang et al., 2012). Some scholars claim that convenience is a more comprehensive construct than ease of use, arguing that the ease-of-use construct focuses on the interface of the technology while convenience addresses the time and effort applied before, during, and after the transaction (Collier & Kimes, 2013).

Customization

Customization is another facilitator relevant to AI-enabled technology adoption which represents value; hence, mass customization has been the central focus of organizations and marketers for decades, introduced by Davis (1987) and developed by Pine (1993), who defined it as "developing, producing, marketing, and delivering affordable goods and services with enough variety and customization that nearly everyone finds exactly what they want" (as cited in Merle et al. 2010, p. 503). To satisfy the consumer's desire for customization, an entire body of research is focused on the trade-off between customization and operational performance (Huang et al., 2008; Liu et al., 2006; MacCarthy, 2004; Squire et al., 2006; Tu et al., 2001). AI-enabled technologies can ease the trade-off between cost and customization with machine learning algorithms that customize products and services for each user without incurring significant additional costs.

Efficiency

Consumer perceptions of efficiency are essential for AI-enabled technology. Components of the construct appear in most of the technology adoption studies. Researchers often measure efficiency under different latent variables. For example, in his technology readiness model, Parasuraman (2000) measures efficiency under the optimism construct (e.g., technology makes you more efficient in your occupation), and Gursoy et al. (2019) associates perceptions of efficiency with performance expectancy (e.g., AI devices are more accurate with less human errors). Based on this research, efficiency is treated as one of three facilitating factors in my framework.

Uncertainty

Turning now to inhibitors, uncertainty hinders the adoption of novel technology due to a lack of information in the early diffusion stages (Claudy et al., 2015). When there is uncertainty about the technology's outcome, it may negatively influence the technology adoption outcome (Lee & Turban, 2001). Uncertainty avoidance is defined as "the extent to which people feel threatened by and try to avoid uncertainty and ambiguity" (Hofstede, 1991, p. 113). Uncertainty avoidance deals with the concepts of risk and reliance on risk-reducing strategies (Hwang, 2009); thus uncertainty would be perceived as an inhibitor of AI-enabled technology because the virtual or the black-box environment is ambiguous. Perceptions of uncertainty become an important inhibiting construct in the context of AI-enabled technology adoption.

Privacy Risk

Perceived privacy risk would be one of the prices consumers pay for benefiting from the facilitating factors. AI can only provide customization, convenience, and efficiency if the consumer shares personal data such as medical history, location, likes, dislikes, habits, behaviors, associations with people, brands, and other sensitive information. Studies have confirmed that perceived privacy risk has an influence on intention to use technology (Cazier et al., 2007; Kyriakidis et al., 2015; Li et al., 2016; Schoettle & Sivak, 2014), consumers' approach to digital advertisements (Miltgen et al., 2019), and e-service adoption (Featherman et al., 2010), which underlines the importance of addressing privacy risk for technology adoption.

Loss of Control Risk

Fear of losing control of technology is another inhibiting factor of technology adoption. Research suggests that people like to be in control (Burger & Cooper, 1979), especially when it comes to AI-enabled technology such as home care robots (Ziefle & Valdez, 2017) or AVs (Buckley et al., 2018). Yet, relinquishing some control is an essential condition for how AI-enabled technologies work. AVs drive themselves and take full control over the passenger's destination and safety, as well as the safety of others. Consumers' fear of losing control may also be due to AI-enabled applications use of personal information to power their services. For instance, SHVAs take control over sharing the consumer's information with other parties to benefit the consumer; thus perceived loss of control risk is a relevant inhibiting factor across AI technology applications.

Given the potential co-existence of facilitating and inhibiting factors discussed, a framework of adoption must also account for the possibility of attitudinal ambivalence.

Ambivalence Toward AI-enabled Technology

Scholars define ambivalence as when an individual experiences both negative and positive reactions towards an attitudinal object (Hamby & Russell, 2020; Kaplan, 1972; Priester & Petty, 1996; Thompson et al., 1995). Studies suggest that ambivalence is connected to risk avoidance actions (Foster et al., 2016; Menninga et al., 2011; Oser et al., 2010; Plambeck &

Weber, 2009). Furthermore, the experience of ambivalence is common in the context of risky products, such as e-cigarettes or energy drinks, that have immediate positive outcomes but long-term negative ones (Hamby & Russell, 2021). In the context of AVs, some consumers might perceive driving an AV to be risky because of perceived uncertainty and lack of control. Yet, these same consumers may also find it convenient to answer emails and run errands while the car is looking for parking. In other words, they may be conflicted and experiencing ambivalence about AVs. Similar assumptions of ambivalence could be drawn for SVHA technology and TM. Interestingly, studies hint at the possibility of the existence of ambivalence in the acceptance of AI-enabled technology. For example, Kyriakidis et al. (2015) surveyed 5,000 respondents in 109 countries to study user acceptance, concerns, and willingness to buy partially, highly, and fully automated vehicles. Results revealed that portions of participants were in favor of AVs, while others were not. The respondents were most concerned about software hacking/misuse (privacy), legal issues, and safety. Although ambivalence was not measured, it is likely that consumers were mixed in their views of AVs, holding favorable views but also concerns.

Researchers generally assess ambivalence with one of two approaches: subjective ambivalence or objective ambivalence (Priester & Petty, 1996). The objective ambivalence approach is calculated with mathematical formulas, such as Griffin's formula, to combine the positive and negative reactions into an ambivalence index. Objective ambivalence is usually used to predict or verify subjective ambivalence (Priester et al., 1996). By contrast, the subjective ambivalence approach directly asks individuals about their feelings toward an attitude object and captures the degree to which these feelings are conflicted or ambivalent (e.g., I have strong feelings both for and against TM) (Hamby & Russell 2021; Priester et al., 2007). I rely on the subjective ambivalence approach to capture the degree to which consumers experience conflicting feelings about AI-enabled applications.

The Role of Brand Trust on Consumers Intention to Use AI-enabled Technology

Like ambivalence, brand trust would also have relationships with facilitating and inhibiting factors. Prior research signals that trust has a role to play in the process of adoption of automation (Carter & Belanger, 2005; Gefen et al., 2003; Lee & Moray, 1992, 1994; Lee & See, 2004; Parasuraman et al., 2008; Pavlou, 2003), adoption of AVs (Chio & Ji, 2015; Zhang et al., 2019), acceptance of medical assistance devices (Hengstler et al., 2016). Trust is also an important construct in the domain of AI technology (Choi & Ji, 2015).

There are many similar, yet distinct, definitions of trust in the literature. As Jonson-George and Swap (1982) stated, the "willingness to take risks may be one of the few characteristics common to all trust situations" (p. 1306). However, the most applicable definition of trust across multiple domains is famously defined by Mayer et al. (1995), who modified the definition of Gambetta (1990) with a critical addition of vulnerability. Mayer et al. (1995) defined trust as "the willingness of a party to be vulnerable to the actions of another party based on the expectations that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (p. 712). This definition is also applicable to trust in AI-enabled technology (Glikson & Woolley, 2020). A review of 150 empirical studies addressing human trust in AI underscored the important role of trust on AI-enabled technology (Glikson & Woolley, 2020). The uncertainty and ambiguity inherent to AI-enabled technology are likely to raise doubts that may constrain the adoption and increasing trust can mitigate such constraints (Brown et al., 2004).

In AI-enabled applications, the technology is typically hosted within a brand (e.g., Alexa). As such, brands can be considered as the 'other party' or the trustee. Indeed, consumer research has long embraced the view that brands can be considered relationship partners (Delgado-Ballester, 2004; Fournier, 1998). If direct contact between consumers and companies is not possible, consumers develop a relationship with their brands (Delgado-Ballester, 2004; Sheth & Parvatiyar, 1995). Thus, the focal trust entity in the AI domain (i.e., the other party) as defined in the trust definition by Mayer et al. (1995) is the brand.

Although researchers agree that trust plays a role in technology acceptance, they disagree on the pathways of how trust influences behavioral intention to use (Zhang et al., 2018). It is also unclear how context influences the relationship of trust and willingness to use technology (Wu et al., 2011). Some researchers in the technology acceptance domain proposed trust as an antecedent or an important factor in influencing perceived usefulness (PU) and perceived ease of use (PEOU) indirectly while having a direct influence on behavioral intention to use (Choi & Ji; 2015; Ghazizadeh et al. 2012; Xu et al. 2018). Others hypothesized that PU and PEOU have a positive influence on trust in technology (Kaur & Rampersad, 2018; Zhang et al., 2018). I take the former approach where brand trust is an antecedent with two distinct components: brand reliability, based on the consumer's belief that the brand will deliver the promised value (Delgado-Ballester, 2004) and brand benevolence, based on consumers' perceptions of the brand's decency, goodwill, and intentions. I take this approach because trust is considered a prerequisite for consumer interaction with novel technology (Foehr & Germelmann, 2020), and I use a brand trust instead of trust in technology. Trust in the brand and trust in the technology have distinct differences. The main difference is that brand trust is formed from previous experience that trustors (consumers) have with the brand (trustee), whereas trust in the technology may come from general trust propensity or technology savviness because the trustee is the technology itself.

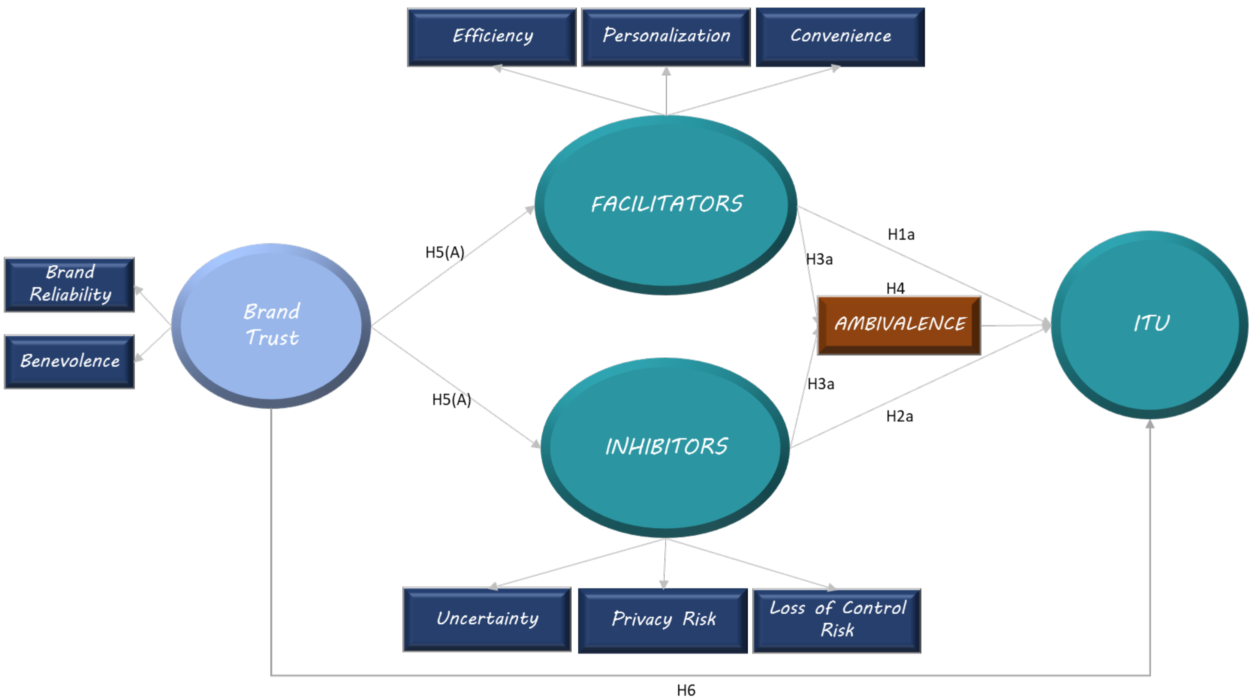
Brand trust has been understudied in technology adoption. In the context of new or novel technology adoption, brand trust would be an important decision-making construct for consumers who never used the technology as well as for consumers who are using the technology. I posit that consumers' trust in the brand associated with AI-enabled technology will affect both the adoption-related decision-making process as well as the ways in which consumers feel toward AI applications once they become users. Specifically, I predict that brand trust will be positively related to facilitating factors positively and negatively related to inhibiting factors.

Proposed Framework

The proposed framework assesses facilitators and inhibitors as separate constructs, brand trust as antecedent, and the role of ambivalence in consumers' adoption of AI-enabled technologies (Figure 1). The research investigates consumers' acceptance of AI-enabled technologies across the three categories and compares the studies between the users and non-users under the same constructs and framework.

Figure 1

Proposed Empirical Model



As discussed previously, facilitators include three factors: perceptions of convenience, customization, and efficiency and are applicable to the three identified categories of AI-enabled technology. The examination of the AI-enabled technologies used in this study, representing the three categories of AI, affirms that the three facilitating factors are relevant to TM, SHVA, and AV; hence, I hypothesize that:

> H1a: Non-user perceptions of facilitators are positively related to intention to use AI-enabled technology, …
>
> H1b: …and this relationship is similar across telemedicine, personal assistance, and AV technologies.

The proposed framework examines both the facilitating and inhibiting factors with a structured and balanced approach. Like its facilitating counterpart, the inhibiting construct also contains three subconstructs: perceptions of uncertainty, privacy, and loss of control risks. I argue that inhibiting factors are also common and applicable across the three AI-enabled technology categories. Hence, I hypothesize that:

> H2a: Non-user perceptions of inhibitors are negatively related to intention to use AI-enabled technology, …
>
> H2b: and this relationship is similar across telemedicine, personal assistance, and AV technologies.

The inhibitory factors of consumer adoption of AI-enabled technology are assumed to operate independently from the facilitating factors because scoring high in facilitating factors is not the same as scoring low in them. A person can be keen to leverage AI-enabled technology owing to the facilitating factors while simultaneously having serious concerns about the inhibiting factors. I propose that facilitating and inhibiting factors are not mutually exclusive and can coexist, which, in turn, gives rise to ambivalence. Ambivalence is thus positioned as a mediating variable in the proposed framework. I hypothesize that:

> H3a: Ambivalence is positively related to Facilitators.
>
> H3b: Ambivalence is positively related to Inhibitors.
>
> H4: Ambivalence mediates the relationship between facilitators and inhibitors and consumers' intention to use AI-enabled technology.

In this study, I suggest that brand trust is an antecedent of facilitators, inhibitors, and the intention to use AI-enabled technology; hence, I hypothesize that:

> H5a: Brand Trust will have a direct positive relationship with facilitators.

H5b: Brand Trust will have a direct negative relationship with Inhibitors.

H6: Trust will have a direct effect on the intention to use AI-enabled technology.

The above hypotheses focus on the pre-adoption phase and perceptions of non-users, which is done in the first three studies. I examine the differences in the model dynamics in later stages of adoption by comparing non-users with users of AI-enabled applications in studies 4A and 4B. Additionally, in all studies, I also measure the TAM constructs of PEOU and PU to compare TAM with my proposed model.

CHAPTER 3: RESEARCH DESIGN AND METHODS

Overview

I conducted four studies to test the hypotheses. I recruited different subjects for each study, sampling a population in the U.S. with distinct categories of AI. Studies 1-3 focus on the perceptions of the non-users of AVs, SHVA technology, and TM, representing Robotic AI, Virtual AI, and Embedded AI, respectively. Finally, studies 4A and 4B examine the difference between users and non-users of Virtual AI and Embedded AI categories.

Study Population and Sampling

Attempting to determine the minimum sample size for any study is a difficult challenge due to a variety of factors (e.g., study design, availability, attainability, complexity, resources). However, researchers have created some general rules to follow for determining the minimum sample size. The common denominator of all recommendations and methods is that the larger the sample size, the more reliable the results. In this case, the challenge is more difficult because our proposed model involves structural equation modeling (SEM), which is a large-sample technique. According to Kline (2015), many published SEM studies are based on samples that are too small.

Since the structural SEM framework in the research is also complex, I conclude that the sample size should be based on the number of parameters being estimated rather than the number of cases (N); hence, the basis of the minimum sample size in this research is determined by the *N:q rule* (Jackson, 2003) where N is the number of cases, and q is the number of model parameters that require statistical estimates. Per Kline (2015), an N:q ratio of 10:1 is the minimum threshold that is necessary to estimate sample size.

The number of parameters is limited by the number of observed variables, which can be calculated with a simple rule: "if *v* is the number of observed variables in the model, the number of observations equals $v\ (v+1)/2$ when means are not analyzed" (Kline, 2015, p. 127). By using the simple rule, the number of the parameters in our model is 14(11)/2, or 77. When applying the N:q ratio of 10:1, the model will require a minimum of 770 cases.

Data Collection Methods and Instruments

I received Institutional Review Board (IRB) approval on December 10, 2020 to proceed with the data collection (Appendix A). Survey data were collected online from a Qualtrics consumer panel representative of the U.S. population. I contracted with Qualtrics to collect national cross-sectional data from adults (19 years and older) living in the U.S. The research company recruits participants from various sources, including member referrals, targeted email lists, gaming sites, customer loyalty web portals, permission-based networks, social media, etc. Qualtrics contacted their qualified panelists via email with my survey links and offered participation in my study. Qualifications included being the age of 19 or older, not having any disabilities, and being fluent in English. Those who were interested in the study used the link to access the consent form (Appendix B). Participants could only continue after agreeing to the consent form. A mandate was placed on every question to be answered. When participants refused to answer any question for any reason, they had the option to terminate the survey. Each participant could only participate in one survey from one of three categories of AI. Qualtrics received $5.00 per completed survey for their services to incentivize participants.

To collect a sample close to the general population of the U.S., I used a proportionate stratified sampling (Ruel et al., 2015) method to ensure that gender distribution would be representative of the population in the United States. I also placed controls to ensure geographical and race distribution within the panel representing the population in the United States (Table 3). Additionally, the quality of the surveys was controlled by adding two quality check items to the instrument (i.e., To show that you are paying attention, please select ‘strongly disagree' on this question). The first quality check item appeared at the 25% completion point, and the second quality check item appeared at the 75% completion point. A time duration constraint was also installed at the 50% completion point by applying the median half-point duration from the soft launches. Finally, the order of items was randomized to reduce the risk of common method bias (Babić-Rosario et al., 2021).

Table 3

Proportionate Stratified Distribution Quota

		Quota
Gender	Female	50%
	Male	50%
Region	Midwest	21%
	Northeast	18%
	South	37%
	West	23%
Race	White	62%
	Non-white	38%

The research involved three phases of data collection. First, I designed and soft-launched three surveys (one for each AI category) to obtain preliminary data for general information about the participant's experience and analyze other factors such as time duration and the performance of the process design. I requested a total of 150 observations for the soft launch, 50 for each AI category: AVs for Robotic AI, SHVAs for Virtual AI, and TM for Embedded AI. Second, I analyzed the process, added the midpoint quality check measure, and launched the second phase of the data collection as a pilot study to assess the internal validity of the scales and make necessary modifications. After receiving the data from phase two, I performed an Exploratory Factor Analysis (EFA) for new scales and Confirmatory Factor Analysis (CFA) for established scales. The analysis resulted in the deletion of 24 of 165 items, excluding the demographics items (Appendix C), before launching the final phase of the data collection.

Study 1 focused on AV technology, representing Robotic AI, with a sample of n=1237 non-users since the technology is not yet available on the market (Tables 4-9). This represents the uniqueness of Study 1 compared to the others. Study 2 was for non-users of the SHVA technology, representing Virtual AI, with a sample of n=894. Study 3 was for the TM technology, representing embedded AI, with a sample of n=903. Studies 4A and 4B were for the users of SHVA and TM, with a sample of n=344 and n=346, respectively.

Table 4

Chi-Square Test and Sample Statistics on Gender

Gender		Study 1 (AV)	Study 2 SHVA Non Users	Study 3 TM Non Users	Study 4a SHVA Users	Study 4b TM Users	**Total**
Male	N	624	395**	437	222**	187	***1865***
	Expected N	619	448	452	172	173	***1865***
	% within Studies	50.4%	44.2%	48.4%	64.5%	54.0%	***50.1%***
	Std. Residual	0.18	-2.49	-0.72	3.79	1.04	
Female	N	613	499**	466	122**	159	***1859***
	Expected N	618	446	451	172	173	***1859***
	% within Studies	49.6%	55.8%	51.6%	35.5%	46.0%	***49.9%***
	Std. Residual	-0.18	2.50	0.72	-3.79	-1.04	
Total	***N***	***1237***	***894***	***903***	***344***	***346***	***3724***

** Significance indicates that standardized residuals are < -1.96 or > 1.96

Table 5

Chi-Square Test and Sample Statistics on Age

Age		Study 1 (AV)	Study 2 SHVA Non Users	Study 3 TM Non Users	Study 4a SHVA Users	Study 4b TM Users	Total
19-25	N	84	69	66	23	14**	***256***
	Expected N	85	61	62	24	24	***256***
	% within Studies	6.8%	7.7%	7.3%	6.7%	4.0%	***6.9%***
	Std. Residual	-0.11	0.96	0.50	-0.13	-2.01	
26-35	N	232	122**	149	77**	51	***631***
	Expected N	210	151	153	58	59	***631***
	% within Studies	18.8%	13.6%	16.5%	22.4%	14.7%	***16.9%***
	Std. Residual	1.55	-2.40	-0.32	2.45	-1.00	
36-45	N	284	132**	163	98**	98**	***775***
	Expected N	257	186	188	72	72	***775***
	% within Studies	23.0%	14.8%	18.1%	28.5%	28.3%	***20.8%***
	Std. Residual	1.66	-3.96	-1.82	3.12	3.06	
46-55	N	169	129	135	30**	58	***521***
	Expected N	173	125	126	48	48	***521***
	% within Studies	13.7%	14.4%	15.0%	8.7%	16.8%	***14.0%***
	Std. Residual	-0.31	0.35	0.77	-2.61	1.38	
56-65	N	186	138	181**	60	66	***631***
	Expected N	210	151	153	58	59	***631***
	% within Studies	15.0%	15.4%	20.0%	17.4%	19.1%	***16.9%***
	Std. Residual	-1.63	-1.10	2.26	0.22	0.96	
66+	N	282	304**	209	56**	59**	***910***
	Expected N	302	218	221	84	85	***910***
	% within Studies	22.8%	34.0%	23.1%	16.3%	17.1%	***24.4%***
	Std. Residual	-1.17	5.79	-0.78	-3.06	-2.78	
	N	***1237***	***894***	***903***	***344***	***346***	***3724***

** Significance indicates that standardized residuals are < -1.96 or > 1.96

Table 6

Chi-Square Test and Sample Statistics on Race

Race		Study 1 AV	Study 2 SHVA Non Users	Study 3 TM Non Users	Study 4a SHVA Users	Study 4b TM Users	**Total**
White	N	774	540	543	229	240	***2326***
	Expected N	773	558	564	215	216	***2326***
	% within Studies	62.6%	60.4%	60.1%	66.6%	69.4%	***62.5%***
	Std. Residual	0.05	-0.78	-0.88	0.96	1.63	
Non-white	N	463	354	360	115	106**	***1398***
	Expected N	464	336	339	129	130	***1398***
	% within Studies	37.4%	39.6%	39.9%	33.4%	30.6%	***37.5%***
	Std. Residual	-0.06	1.00	1.14	-1.24	-2.10	
Total	***N***	***1237***	***894***	***903***	***344***	***346***	***3724***

** Significance indicates that standardized residuals are < -1.96 or > 1.96

Table 7

Chi-Square Test and Sample Statistics on Education

Education		Study 1 AV	Study 2 SHVA Non Users	Study 3 TM Non Users	Study 4a SHVA Users	Study 4b TM Users	**Total**
High School or Equivalent	N	397	368**	358**	77**	94**	***1294***
	Expected N	430	311	314	120	120	***1294***
	% within Studies	32.1%	41.2%	39.6%	22.4%	27.2%	***34.7%***
	Std. Residual	-1.58	3.25	2.50	-3.89	-2.39	
2-year college	N	192	168	151	47	57	***615***
	Expected N	204	148	149	57	57	***615***
	% within Studies	15.5%	18.8%	16.7%	13.7%	16.5%	***16.5%***
	Std. Residual	-0.86	1.68	0.15	-1.30	-0.02	
4-year college	N	321	234	229	107	98	***989***
	Expected N	329	237	240	91	92	***989***
	% within Studies	25.9%	26.2%	25.4%	31.1%	28.3%	***26.6%***
	Std. Residual	-0.41	-0.22	-0.70	1.64	0.64	
Master's degree	N	268**	100**	124**	96**	79**	***667***
	Expected N	222	160	162	62	62	***667***
	% within Studies	21.7%	11.2%	13.7%	27.9%	22.8%	***17.9%***
	Std. Residual	3.12	-4.75	-2.97	4.38	2.16	
Professional degree	N	27	14	16	12	11	***80***
	Expected N	27	19	19	7	7	***80***
	% within Studies	2.2%	1.6%	1.8%	3.5%	3.2%	***2.1%***
	Std. Residual	0.08	-1.19	-0.77	1.70	1.31	
Doctorate or Equivalent	N	32	10**	25	5	7	***79***
	Expected N	26	19	19	7	7	***79***
	% within Studies	2.6%	1.1%	2.8%	1.5%	2.0%	***2.1%***
	Std. Residual	1.12	-2.06	1.34	-0.85	-0.13	
Total	***N***	***1237***	***894***	***903***	***344***	***346***	***3724***

** Significance indicates that standardized residuals are < -1.96 or > 1.96

Table 8

Chi-Square Test and Sample Statistics on Household Income

Household Income		Study 1 AV	Study 2 SHVA Non Users	Study 3 TM Non Users	Study 4a SHVA Users	Study 4b TM Users	**Total**
Less than $60,000	N	589**	541**	527**	128**	156	***1941***
	Expected N	645	466	471	179	180	***1941***
	% within Studies	47.6%	60.5%	58.4%	37.2%	45.1%	***52.1%***
	Std. Residual	-2.20	3.48	2.60	-3.83	-1.81	
$60,000 to $119,999	N	348	246	230	92	92	***1008***
	Expected N	335	242	244	93	94	***1008***
	% within Studies	28.1%	27.5%	25.5%	26.7%	26.6%	***27.1%***
	Std. Residual	0.72	0.26	-0.92	-0.12	-0.17	
$120,000 to $179,999	N	200**	68**	95**	86**	68**	***517***
	Expected N	172	124	125	48	48	***517***
	% within Studies	16.2%	7.6%	10.5%	25.0%	19.7%	***13.9%***
	Std. Residual	2.16	-5.04	-2.71	5.53	2.88	
$180,000 to $249,999	N	70	22**	31	31**	20	***174***
	Expected N	58	42	42	16	16	***174***
	% within Studies	5.7%	2.5%	3.4%	9.0%	5.8%	***4.7%***
	Std. Residual	1.61	-3.06	-1.72	3.72	0.95	
>$250,000	N	30	17	20	7	10	***84***
	Expected N	27.90	20.17	20.37	7.76	7.80	***84.00***
	% within Studies	2.4%	1.9%	2.2%	2.0%	2.9%	***2.3%***
	Std. Residual	0.40	-0.70	-0.08	-0.27	0.79	
Total	***N***	***1237***	***894***	***903***	***344***	***346***	***3724***

** Significance indicates that standardized residuals are < -1.96 or > 1.96

Table 9

Chi-Square Test and Sample Statistics on US Region

US Region		Study 1 AV	Study 2 SHVA Non Users	Study 3 TM Non Users	Study 4a SHVA Users	Study 4b TM Users	**Total**
Midwest	N	264	193	185	76	59	777
	Expected N	258	187	188	72	72	777
	% within Studies	21.30%	21.60%	20.50%	22.10%	17.10%	20.90%
	Std. Residual	0.40	0.50	-0.20	0.50	-1.60	
Northeast	N	225	155	150	72	76	678
	Expected N	225	163	164	63	63	678
	% within Studies	18.20%	17.30%	16.60%	20.90%	22.00%	18.20%
	Std. Residual	0.00	-0.60	-1.10	1.20	1.60	
South	N	463	344	329	115	112	1363
	Expected N	453	327	331	126	127	1363
	% within Studies	37.40%	38.50%	36.40%	33.40%	32.40%	36.60%
	Std. Residual	0.50	0.90	-0.10	-1.00	-1.30	
West	N	285	202	239	81	99	906
	Expected N	301	218	220	84	84	906
	% within Studies	23.00%	22.60%	26.50%	23.50%	28.60%	24.30%
	Std. Residual	-0.90	-1.10	1.30	-0.30	1.60	
Total	***N***	1237	894	903	344	346	3724

** Significance indicates that standardized residuals are < -1.96 or > 1.96

Measures

I designed five self-administered questionnaires to collect consumer data for this research. Each survey instrument was adapted to the focal technology context. For example, the [X] from an item "I am likely to use [X]" was replaced with Autonomous Vehicles, Smart Home Virtual Assistant, or Telemedicine for each one of the three surveys. The survey included all the constructs and items listed in Table 10, which also reports the references for each item. I developed some new measures specific to this research and fine-tuned the overall questionnaire to fit the context of this study (Babić-Rosario et al., 2021). All items were measured with a seven-point Likert scale ranging from (1) Strongly Agree to (7) Strongly Disagree.

INSERT TABLE 10 ABOUT HERE

The questionnaires included four sections. Following the informed consent process, the first section began with a video introduction of the technology. The first video described AVs (Appendix D). The second video described SHVA (Appendix E), and the third video described TM (Appendix F). Following the description, the respondents were asked if they had heard of the technology (AV, SHVA, or TM) before taking the survey. If they answered yes, the follow-up question asked to provide the source, such as Internet, TV, newspaper, friends, or other ways (Zhang et al., 2018). Finally, the last question of section one asked participants who answered yes to the familiarity question if they had used the technology in any form, which allowed us to differentiate users from non-users in studies 4A and 4B.

In the second section, the respondents completed the measurement instruments for each construct in the model. The third section was designed to measure the brand trust construct, with a series of questions adapted to each technology context. For AVs, informants were provided a list of 10 auto manufacturer brands; for SVHA, they were provided four brands and to choose the one that comes to mind when they think about that technology with which they had prior experience. Participants could also propose another brand if none on the lists fit their situation. The selection of the list of brands was based on the brand's innovativeness towards AI-enabled technology and their exposure or footprint in the market. In the case of TM, the survey asked the participants, "We want to measure your trust in a technology company brand that comes to your mind when you think of Telemedicine," with which they had prior experience. Finally, in the last section, I collected demographics, including age, gender, education, marital status, and income.I adapted scales and items from previous research to measure the constructs in this study; however, new items were also developed. The convenience construct is taken from Collier and Kimes (2013) with minimum alteration to fit the setting of the study. The reliability of the items in Collier and Kimes (2013) exhibited an acceptable level of reliability ($\alpha \geq .70$), and the average variance extracted (AVE) exceeded .50 with no shared variance exceeding the average variance for each construct. Table 11 details the items by source.

Table 11

Perceived Convenience Construct

Subconstruct	Item ID	Item	Sources
Perceived Convenience	CON1	[X] would allow me to receive services whenever I choose.	Collier & Kimes (2013)
	CON2	[X] would allow me to receive services at a convenient time.	
	CON3	I would value the ability to receive services from [X] wherever I am.	
	CON4	I would enjoy having [X] adapted to my needs.	New
	CON5	I would enjoy the flexibility that [X] provide.	New
	CON6	[X] would be convenient to use	New
	CON7	[X] would make my life easier.	New

The customization construct is adapted from Merle et al. (2010) who developed a 14-item customization experience scale. I selected and modified three items to fit this study's context (Table 12). The scale achieved an acceptable discriminant validity with the chi-square difference test (Δx^2=57.59, p<0.001). However, discriminant validity was not fully supported by using the more conservative Fornell and Larker procedure. I modified the wording of the items to ensure clarity.

Table 12

Perceived Customization Construct

Subconstruct	Item ID	Item	Sources
Perceived Customization	CUST1	With [X], I would have customized services that others will not have.	Merle et al. (2010)
	CUST2	I would enjoy having [X] tailored to my needs.	
	CUST3	The customization enabled by [X] would be very valuable.	
	CUST4	I would enjoy having [X] adapted to my needs.	New
	CUST5	I would feel more connected to [X] because it would be tailored for me.	New
	CUST6	It would be very useful to receive information and services from [X] that are customized for me.	New

The items to measure the Efficiency construct were adapted from the existing technology acceptance research (Davis et al., 1989; Kailani & Kumar, 2011; Zhang et al., 2019). The discriminant validity achieved Fornell and Larcker's criterion, and the internal consistency achieved higher than 0.7 Cronbach's alpha. Kailani and Kumar (2011) did not report discriminant validity statistics. I developed three new items for this construct (EFF3, EFF5, and EFF6), which can be seen in Table 13.

Table 13

Perceived Efficiency Construct

Subconstruct	Item ID	Item	Sources
Perceived Efficiency	EFF1	Using [X] would save me time to do other things.	Zhang et al. (2019) ; Davis et al. (1989)
	EFF2	I would save time by using [X].	New
	EFF3	[X] would lower the cost of __________ (transportation, health care, goods and services)	New
	EFF4	I would save money by using [X].	Kailani & Kumar (2011)
	EFF5	I would be more efficient thanks to [X].	New
	EFF6	[X] would help me to do my tasks quicker and easier.	New

Three of six items for the Uncertainty construct were adapted from consumer technology acceptance research (Bhatnagar et al., 2000; Lee & Turban, 2001; Shui et al., 2011), and three new items were developed for this study. The statistics of the adapted items were not reported in prior research. Table 14 details the items by source.

Table 14

Perceived Uncertainty Construct

Subconstruct	Item ID	Item	Sources
Perceived Uncertainty	UR1	I am worried about not knowing how [X] would make decisions for me.	New
	UR2	The information available about [X] is unclear to me.	Shiu et al. (2011)
	UR3	I don't understand exactly how [X] works.	New
	UR4	I'm not sure about how [X] would perform.	New
	UR5	[X] cannot be trusted; there are just too many uncertainties.	Lee & Turban, (2001)
	UR6	Using [X] entails uncertainty.	

The perceived Privacy Risk construct items were adapted from technology and advertising acceptance research (Kyriakidis et al., 2015a; Miltgen et al., 2019; Zhang et al., 2019). The statistics of all items of this construct achieved recommended Cronbach's alpha criterion for internal consistency and Fornell Larcker's criterion for discriminant validity. Table 15 details the items by source.

Table 15

Perceived Privacy Risk Construct

Subconstruct	Item ID	Item	Sources
Perceived Privacy Risk	PR1	I am concerned that [X] would collect too much personal information from me.	Kyriakidis et al. (2015a); Zhang et al. (2019)
	PR2	I am concerned that [X] would use my personal information for other purposes without my authorization.	
	PR3	I am concerned that [X] would share my personal information with other entities without my authorization.	
	PR4	I worry that [X] would invade my privacy.	Miltgen et al. (2019)
	PR5	I worry that [X] would intrude on my privacy.	
	PR6	I worry that [X] would compromise my privacy.	

The Loss of Control Risk items were adapted from different disciplines. The measures were selected because they represent the personality, motivation, and cognitive aspects of perceived control. Items LOC1 and LOC2 were taken from socio-political control research (Dean, 1961; Zimmerman & Zahnister, 1991). I adopted scales from other control literature. Items LOC1 and LOC2 were part of the retained items that had greater than one eigenvalue. Convergent validity was measured by split-half reliability for each scale (Dean, 1961). Item LOC3 was adapted from a psychological construct of the desirability of control (Burger & Cooper, 1979). The scale had substantial internal consistency (.80) and test-retest reliability (.75) (Burger & Cooper, 1979). Item LOC4 was adapted from the locus of control research (Paulhus, 1983). Item LOC5 was new, and LOC6 was adapted from research on advertising acceptance (Miltgen et al., 2019). Table 16 details the items by source.

Table 16

Perceived Loss of Control Risk Construct

Subconstruct	Item ID	Item	Sources
Perceived Loss of Control Risk	LOC1	[X] does(do) not provide enough control.	Zimmerman & Zahnister, (1991); Dean, (1961)
	LOC2	I worry about [X] taking full control.	
	LOC3	I prefer to avoid situations where [X] would tell me what I should do.	Burger & Cooper (1979)
	LOC4	Even when I'm feeling self-confident about most things, I may still lack the ability to control [X].	Paulhus (1983
	LOC5	I worry that [X] would take too much control.	New
	LOC6	It is important to me that I can control what [X] could do with my information.	Miltgen et al. (2019)

The Subjective Ambivalence items (AMB1, AMB2, and AMB3) were adopted from the ambivalence research (Hamby & Russell, 2021; Priester et al., 2007). These items are well established within the ambivalence research, and the results from Hamby and Russell's (2021) recent study indicate a high-reliability test ($\alpha = .91$). Table 17 details the items by source.

Table 17

Subjective Ambivalence Construct

Subconstruct	Item ID	Item	Sources
Subjective Ambivalence	AMB1	I have strong mixed feelings both for and against using [X].	Priester et al. (2007); Hamby & Russell (2021)
	AMB2	I feel divided between the positive and negative sides of [X].	
	AMB3	I feel an inner conflict while thinking about using [X].	

The brand trust scale in this study included two sub-constructs: Brand Reliability and Brand Benevolence. The brand reliability construct was adapted from brand trust research (Delago, 2004). The benevolence construct was adopted from interpersonal trust research (Crosby et al., 1990; Gefen & Straub, 2004). Gefen and Straub (2004) reported that the AVE of each construct was larger than its correlations with the other constructs, and all the items loaded very significantly with p-values within 0.01 level. Table 18 details the items by source.

Table 18

Brand Reliability and Brand Benevolence Constructs

Subconstruct	Item ID	Item	Sources
Brand Reliability	BR1	[Brand] meets my expectations	Delgado (2004)
	BR2	I feel confident in [X brand].	
	BR3	[X brand] is a reliable company.	
	BR4	I can always trust the performance of [X brand] to be good.	
	BR5	I could rely on [Brand] to solve any problem.	Garbarino & Johnson (1999)
	BR6	I can always trust the performance of [Brand] to be good.	
Brand Benevolence	BB1	I would count on [Brand] to consider how its actions affect me.	Gefen & Straub (2004); Crosby et al. (1990)
	BB2	I believe that [X brand] places the customers' interests first.	
	BB3	[Brand] is well-meaning.	
	BB4	[X brand] cares about my needs.	Li et al. (2008); Huaman-Ramirez & Merunka (2019)
	BB5	[X brand] gives me a sense of security.	

Intention to Use, Perceived Ease of Use, and Perceived Usefulness were adopted from established technology acceptance research (Davis et al., 1989; Venkatesh & Davis, 2000). Table 19 details the items by source.

Table 19

Items for Intention to Use, PU, and PEOU Constructs

Subconstruct	Item ID	Item	Sources
Intention to Use	ITU1	I am likely to use [X].	Venkatesh & Davis (2000)
	ITU2	I would like to use [X].	
	ITU3	I intend to use [X].	
Perceived Ease of Use	PEOU1	Learning to use [X] would be easy for me.	Davis et al. (1989)
	PEOU2	I would find it easy to get [X] to do what I want to do.	
	PEOU3	I would find [X] easy to use.	
Perceived Usefulness	PU1	Using [X] would be useful in meeting my needs.	Davis et al. (1989)
	PU2	Using [X] would increase my effectiveness.	
	PU3	I would find [X] to be useful.	

CHAPTER 4: DATA ANALYSIS AND FINDINGS

Data Analysis Methods

I carefully screened the datasets for unusual patterns and missing values, and I validated the data quality with the quality check controls discussed in Chapter 3. Next, I screened for duplications to ensure that each observation was unique, and each participant was surveyed once by using the demographics and longitudinal and latitudinal data. The data did not have duplicates or missing values. All participants who completed the survey matched the required age range (19 and older) and the distribution quota that was targeted. Finally, I organized the data into five groups (Study 1, Study 2, Study 3, Study 4A, Study 4B) as planned during the scale development and distribution process. I applied the described screening process to the pretest and the final datasets. The following section discusses the measurement validity procedures and methods applied for the measurement assessment using SPSS-27 and STATA-17 software packages.

Measurement Validation

In phase one, I conducted an initial preparatory analysis to assess the psychometric properties of the new and existing items, including internal consistency reliability and discriminant validity of the scales based on the pretest data. As described previously, I provided short videos describing and introducing the technologies. Then, I asked participants to rate the efficacy of the videos. 89.9% of respondents thought that the videos were helpful, and 89.3% believed the videos provided factual information about the technologies.

An EFA was conducted with pretest data to discover the nature of the constructs influencing the responses and to remove the extra items. The results supported the adequacy of most measures, and discriminant validity was established through factor analysis for all five groups. However, after careful evaluation of the data across all studies, I removed 24 of 51 items that did not make positive contributions to Cronbach's alpha, reducing to three items for each sub-construct to improve survey duration and thus reduce participant fatigue. For the remaining 28 items, I conducted another principal axis factor analysis with oblique rotation (direct oblimin). The Exploratory Kaiser-Meyer-Olkin measure verified the sampling adequacy for the analysis, KMO = 0.93, 0.93, 0.93, 0.74, 0.82 (Study 1 through 4B, respectively). All KMO values for individual items of all five groups were greater than 0.711, which is well above the acceptable limit of 0.5 (Kaiser & Rice, 1974). From the initial analysis, four factors had eigenvalues over Kaiser's criterion of 1 and in combination explained 77.30, 76.44, 77.91, 71.04, 77.40 percent of the variance (Study 1 through 4B, respectively) (Field, 2013).

Appendices G-K show the factor loadings after rotation. The bolded item loadings that cluster on the same factor suggest that factor one represents Facilitators, factor two represents Inhibitors, factor three represents Brand Trust, and factor four represents Ambivalence. This was true for Study 1, 2, 3, and 4A. However, the factor analysis of study 4B, TM users, suggests five factors. It splits the inhibitors construct into two factors by separating the uncertainty subconstruct. Although factor analysis of the fifth group presents five constructs, I opted for keeping the constructs consistent with the other four groups. Additionally, it is expected to have weaker factor loadings for inhibitors in studies 4A and 4B because they focused on users of the novel technologies to analyze how the factors change when the non-users become users. Facilitators, inhibitors, brand trust, and ambivalence had high reliabilities with Cronbach's alphas ranging from 0.78 – 0.99. To identify potential common method bias, I conducted Harman's one-factor test. The test results for common-method bias revealed that single factor extractions were 42.34%, 42.70%, 46.27%, 33.76%, and 32.21% (Study 1 through 4B, respectively) of the total variance f, which was less than 50%; thus we can conclude that there is no common method bias.

In phase two, I analyzed the complete dataset, including the retained items from the pretest data. Cronbach's alpha values greater than 0.7 for all subconstructs support the adequacy of all measures. Then, I conducted a measurement invariance test to assess whether merging the data across categories was justified. I used a four-step procedure for testing four types of measurement invariance (Vandenberg & Lance, 2000):

- Configural invariance: groups have the same factor loading configuration (+/-/0)
- Weak factor invariance: groups have the same factor loadings (metric invariance)
- Strong factor invariance: groups have the same factor loadings and measurement intercepts (scalar invariance)
- Strict factor invariance: groups have the same factor loadings, measurement intercepts, and measurement error variances

The results indicate that the factor structure was the same across the studies through configural invariance. However, the results did not support the other measurement invariances. This finding is not surprising because the measurement invariance tests the invariance between groups assessing the same target, such as measuring intention to use AVs across cultural groups or countries. Yet, this research included five different targets: 1) non-users' intention to use AVs, 2) non-users' intention to use SHVAs, 3) non-users' intention to use TM, 4a) users' intention to continue using SHVA, and 4b) users' intention to continue using TM. Cronbach's alpha and intercorrelations between subconstructs for Study 1 (Table 20), Study 2 (Table 21), and Study 3 (Table 22) are provided.

Table 20

Cronbach's Alpha and Intercorrelations Between the Subconstructs* for Study-1 (N=1237)

Subconstruct	Mean	S.D.	1	2	3	4	5	6	7	8	9	10
1. Customization	4.989	1.515	**0.922**									
2. Convenience	4.886	1.575	.914**	**0.931**								
3. Efficiency	4.776	1.594	.855**	.902**	**0.932**							
4. Uncertainty	4.549	1.370	-.536**	-.549**	-.521**	**0.808**						
5. Privacy Risk	4.266	1.555	-.287**	-.312**	-.262**	.596**	**0.880**					
6. Loss of Control Risk	4.581	1.379	-.419**	-.432**	-.393**	.762**	.651**	**0.765**				
7. Brand Reliability	5.305	1.409	.573**	.576**	.581**	-.378**	-.181**	-.249**	**0.945**			
8. Brand Benevolence	5.012	1.426	.558**	.568**	.597**	-.370**	-.161**	-.223**	.888**	**0.936**		
9. Ambivalence	4.604	1.423	.064*	0.055	0.045	.382**	.345**	.425**	0.041	0.051	**0.844**	
10. Intention to Use	4.543	1.833	.837**	.853**	.811**	-.545**	-.278**	-.418**	.564**	.562**	-0.028	**0.965**

*Cronbach's alpha coefficients are presented on the diagonal.

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Table 21

Cronbach's Alpha and Intercorrelations Between the Subconstructs* for Study-2 (N=894)

Subconstruct	Mean	S.D.	1	2	3	4	5	6	7	8	9	10
1. Customization	4.544	1.664	**0.936**									
2. Convenience	4.465	1.674	.943**	**0.940**								
3. Efficiency	4.408	1.575	.888**	.904**	**0.938**							
4. Uncertainty	4.252	1.328	-.439**	-.444**	-.416**	**0.761**						
5. Privacy Risk	4.925	1.636	-.470**	-.485**	-.451**	.725**	**0.935**					
6. Loss of Control Risk	4.037	1.518	-.367**	-.370**	-.323**	.652**	.722**	**0.851**				
7. Brand Reliability	4.749	1.388	.688**	.702**	.683**	-.468**	-.532**	-.394**	**0.907**			
8. Brand Benevolence	4.297	1.486	.661**	.686**	.685**	-.423**	-.518**	-.301**	.843**	**0.915**		
9. Ambivalence	4.478	1.408	0.056	0.034	0.049	.368**	.416**	.383**	-0.059	-0.038	**0.856**	
10. Intention to Use	3.958	1.819	.860**	.862**	.782**	-.429**	-.477**	-.344**	.656**	.651**	-0.008	**0.969**

*Cronbach's alpha coefficients are presented on the diagonal.

** Correlation is significant at the 0.01 level (2-tailed). * Correlation is significant at the 0.05 level (2-tailed).

Table 22

Cronbach's Alpha and Intercorrelations Between the Subconstructs* for Study-3 (N=903)

Subconstruct	Mean	S.D.	1	2	3	4	5	6	7	8	9	10
1. Customization	5.009	1.357	**0.916**									
2. Convenience	5.130	1.395	.919**	**0.935**								
3. Efficiency	4.882	1.338	.871**	.882**	**0.908**							
4. Uncertainty	3.908	1.319	-.508**	-.519**	-.483**	**0.812**						
5. Privacy Risk	4.085	1.607	-.355**	-.365**	-.340**	.625**	**0.930**					
6. Loss of Control Risk	3.818	1.422	-.384**	-.410**	-.348**	.659**	.787**	**0.869**				
7. Brand Reliability	4.891	1.423	.437**	.447**	.464**	-.258**	-.190**	-.193**	**0.927**			
8. Brand Benevolence	4.689	1.443	.460**	.466**	.491**	-.273**	-.221**	-.202**	.867**	**0.952**		
9. Ambivalence	4.218	1.309	-0.038	-0.046	-0.054	.447**	.477**	.477**	-0.020	-0.048	**0.852**	
10. Intention to Use	4.626	1.547	.834**	.841**	.785**	-.492**	-.350**	-.358**	.410**	.443**	-.090**	**0.954**

*Cronbach's alpha coefficients are presented on the diagonal.

** Correlation is significant at the 0.01 level (2-tailed). * Correlation is significant at the 0.05 level (2-tailed).

Results

The default setting of SEM is a maximum likelihood estimation for STATA and most other software packages. Maximum likelihood is derived under the assumption that the observed variables follow a multivariate normal distribution. I performed a normality test with the datasets using the Shapiro-Wilk test of normality. The results revealed that the data was not normally distributed. Consequently, the analysis proceeded with the Satorra-Bentler robust maximum likelihood option to relax the assumption of multivariate normality. When the Satora-Bentler option is specified, another variation of standard errors that are robust to nonnormality is reported (Satorra & Bentler, 1994).

The EFA with the pretest data indicated that the first order subconstructs customization, convenience, and efficiency are highly correlated and loaded under the second-order facilitators construct. Similarly, uncertainty, privacy risk, and loss of control risk loaded under the second-order inhibitors construct. Finally, the brand reliability and brand benevolence subconstructs loaded under the second-order brand trust construct. I conducted a CFA testing the model with the first-order subconstructs to verify the earlier indications. Results confirmed the earlier findings, and the first-order subconstructs within the second-order constructs were highly correlated. The square root of the AVE was lower than the correlations of the first-order subconstructs. Thus, the items of each subconstruct are summed, and the subconstructs are treated as items in the model.

The overall fit indices of all five measurement models demonstrated good fit (Table 23). As recommended by Kline (2015), I used the ratio of chi-square value to the degree of freedom, comparative fit index (CFI), standard root mean square residual (SRMR), and root mean square error of approximation (RMSEA) as a goodness of fit indices. A model is considered a good fit when $\frac{X^2}{df} < 2$, CFI > 0.95, SRMR < 0.08, and RMSEA < 0.06 (Hu & Bentler, 1999; Kline, 2015). Although the chi-square test of the models was statistically significant, normally an indication of misfit, this indicator is sensitive to a large sample size. Indeed, scholars agree that the chi-square test is sensitive to sample size because the exact-fit test detects statistically significant but slight model-data discrepancies (Kline, 2015). All CFI values are greater than .95, SRMR values are lower than .08, and RMSEA values are equal to or lower than 0.6.

Table 23

Goodness of Fit Indices of Measurement Models

	N	Setorra-Bentler chi2	RMSEA-SB	CFI-SB	SRMR
Study 1	1237	chi2sb (67)=325.634; p≈.000	0.056	0.982	0.044
Study 2	894	chi2sb (67)=300.201; p≈.000	0.062	0.979	0.034
Study 3	903	chi2sb (67)=276.429; p≈.000	0.059	0.978	0.051

All factor loadings were statistically significant, ranging from 0.69 to 0.98, above the cut-off value of 0.5. The measures achieved high reliability and convergent validity with assessments of composite reliabilities (CR) and AVE exceeding the recommended level of 0.5 for AVE (Hair et al., 2006) and 0.7 for CR (Bagozzi & Yi, 2012). I followed the Fornell and Larcker criterion to assess discriminant validity. The square root of AVE for each construct was greater than any bivariate correlations involving the constructs in the model (Fornell & Larcker, 1981). The maximum shared variances (MSV) and average shared variances (ASV) were also smaller than the AVE for each construct. The results provided evidence that the constructs maintained a good overall convergent and discriminant validity, and the measurement model showed satisfactory reliability and validity. Tables 24, 25, and 26 show discriminant validity results.

Table 24

Correlations and Discriminant Validity for Study 1

Subconstruct	CR	AVE	MSV	ASV	1	2	3	4	5
1. FAC	0.962	0.893	0.804	0.384	**0.945**				
2. INH	0.860	0.674	0.318	0.243	(0.564)**	**0.821**			
3. BT	0.941	0.888	0.405	0.227	0.637**	(0.363)**	**0.942**		
4. AMB	0.850	0.656	0.223	0.058	0.082*	0.472**	0.060	**0.810**	
5. ITU	0.965	0.903	0.804	0.368	0.897**	(0.547)**	0.607**	(0.011)	**0.950**

N = 1,237
Square root of the AVE is presented on the diagonal.
*p < 0.05; ** p < 0.01; ***p < .0001 (2-tailed).

Table 25

Correlations and Discriminant Validity for Study 2

Subconstruct	CR	AVE	MSV	ASV	1	2	3	4	5
1. FAC	0.969	0.912	0.802	0.422	**0.955**				
2. INH	0.874	0.700	0.355	0.282	(0.532)***	**0.836**			
3. BT	0.915	0.844	0.598	0.369	0.773***	(0.596)***	**0.919**		
4. AMB	0.861	0.675	0.222	0.057	0.064	0.471***	(0.054)	**0.822**	
5. ITU	0.969	0.912	0.895	0.397	0.895***	(0.518)***	0.721***	0.002	**0.955**

N = 894
Square root of the AVE is presented on the diagonal.
*p < 0.05; ** p < 0.01; ***p < .0001 (2-tailed).

Table 26

Correlations and Discriminant Validity for Study 3

Subconstruct	CR	AVE	MSV	ASV	1	2	3	4	5
1. FAC	0.961	0.891	0.799	0.327	**0.944**				
2. INH	0.876	0.703	0.315	0.211	(0.494)**	**0.838**			
3. BT	0.929	0.868	0.266	0.141	0.516**	(0.270)**	**0.932**		
4. AMB	0.860	0.672	0.315	0.081	0.030	0.562**	(0.036)	**0.820**	
5. ITU	0.954	0.874	0.799	0.310	0.894**	(0.460)**	0.472**	(0.086)*	**0.935**

N = 903
Square root of the AVE is presented on the diagonal.
*p < 0.05; ** p < 0.01; ***p < .0001 (2-tailed).

In general, non-users were interested in adopting AI-enabled technology, as reflected in high intentions to use (ITU) across all three categories. Mean ITU scores ranged from 3.96 to 4.63 (on a scale of 1-7 with 7 reflecting strongly agree). Amongst the categories, non-user respondents had the lowest ITU for virtual AI, $M = 3.96$, $SD = 1.82$ (Study 2) and the highest ITU for embedded AI, $M = 4.63$, $SD = 1.55$ (Study 3). Not surprisingly, amongst those already using the technology, intentions to continue using (ITCU) were high, $M = 6.34$, $SD = 0.84$ for SHVA (Study 4A) and $M = 6.03$, $SD = 1.11$ for TM (Study 4B).

The results reveal the importance of age, income, and education. Potential adopters between the ages of 26 and 45 had the highest ITU across all three categories (bolded in the tables that follow). Among existing users, the age group 26-35 had the highest ITCU. In contrast, people older than 56 had relatively lower ITU and ITCU across all three categories (colored red in the tables that follow). Overall, across users and non-users, age groups 26-35 and 36-45 had the highest ITU and ITCU. I tested users and non-users ITU and ITCU across age groups with independent-samples Kruskal-Wallis test to assess the differences between age groups. Table 27 shows the descriptive statistics of age groups on ITU and Table 28 shows the age groups that were significantly different from each other by a pairwise comparison. Finally, Figure 2 shows the ITU and ITCU across age groups.

Table 27

Descriptive Statistics of Age Groups on ITU

	Study 1		**Study 2**		**Study 3**		**Study 4a**		**Study 4b**	
Age Groups	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
19-25 (1)	4.83	1.59	4.49	1.44	4.42	1.35	6.23	0.69	6.10	1.01
26-35 (2)	5.35	1.57	**4.68**	1.85	5.14	1.21	**6.45**	0.84	**6.28**	0.75
36-45 (3)	**5.44**	1.54	4.64	1.70	**5.17**	1.41	6.40	0.90	6.11	1.14
46-55 (4)	4.32	1.67	3.92	1.74	4.75	1.61	6.26	0.77	6.08	1.24
56-65 (5)	3.74	1.87	3.47	1.70	4.42	1.64	6.44	0.65	5.94	1.01
66 + (6)	3.55	1.68	3.49	1.81	3.99	1.53	6.06	0.97	5.69	1.29
Total	4.54	1.83	3.96	1.82	4.63	1.55	6.34	0.84	6.03	1.11

Table 28

Pairwise Comparisons of Age Groups

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
6.00-5.00	270.675	55.462	4.880	0.000
6.00-4.00	418.097	58.818	7.108	0.000
6.00-1.00	487.796	75.742	6.440	0.000
6.00-2.00	880.080	55.462	15.868	0.000
6.00-3.00	924.670	52.330	17.670	0.000
5.00-4.00	147.422	63.375	2.326	0.020
5.00-1.00	217.121	79.333	2.737	0.006
5.00-2.00	609.406	60.274	10.111	0.000
5.00-3.00	653.995	57.406	11.393	0.000
4.00-1.00	69.699	81.714	0.853	0.394
4.00-2.00	461.984	63.375	7.290	0.000
4.00-3.00	506.573	60.654	8.352	0.000
1.00-2.00	-392.285	79.333	-4.945	0.000
1.00-3.00	-436.874	77.176	-5.661	0.000
2.00-3.00	-44.590	57.406	-0.777	0.437

Independent-Samples Kruskal Wallis Test

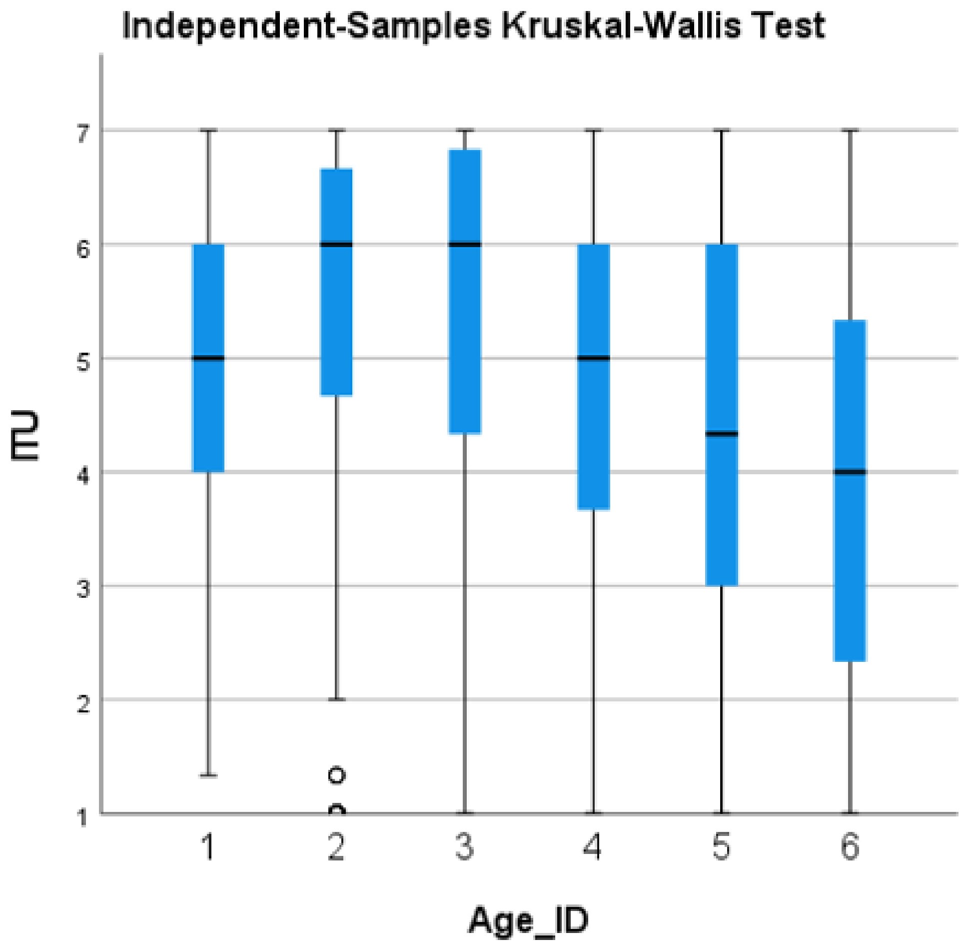
Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.

Asymptotic significances (2-sided tests) are displayed. The significance level is .050.
Group 1 = 19-25; 2 = 26-35; 3 = 36-45; 4 = 46-55; 5 = 56-65; 6 = 66 and over

Sample 1 and sample 2 reflect to the side-by-side age groups

Figure 2

Intention to Use of Users and Non-Users Across Age Groups



1 = 19-25; 2 = 26-35; 3 = 36-45; 4 = 46-55; 5 = 56-65; 6 = 66 and over

Income was relevant to AI-enabled technology adoptions, as the highest ITU and ITCU (Figure 3). Conversely, people with relatively lower income had lower ITU and ITCU as can be seen in Table 29, which follows the same bold/red color scheme from the previous section. The independent-samples Kruskal-Wallis test shows that most income level groups are significantly different from each other except for those shown with a non-significant result in Table 30.

Table 29

Descriptive Statistics of Income Level on ITU

	Study 1		Study 2		Study 3		Study 4a		Study 4b	
Income	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
<60K	3.96	1.82	3.77	1.77	4.39	1.56	6.23	0.92	6.03	1.11
60K - 119K	4.72	1.73	4.01	1.84	4.76	1.43	6.34	0.94	5.98	1.08
120K - 179K	5.47	1.54	4.83	1.82	5.22	1.49	6.45	0.63	5.98	1.21
180K - 249K	**5.58**	1.40	4.42	1.68	**5.51**	1.34	**6.46**	0.69	6.13	1.21
>250K	5.37	1.61	**5.00**	1.80	4.95	1.81	6.33	0.92	**6.47**	0.50
Total	4.54	1.83	3.96	1.82	4.63	1.55	6.34	0.84	6.03	1.11

Table 30

Pairwise Comparisons of Income Levels

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
1-2	-285.235	41.564	-6.862	0.000
1-5	-661.980	119.313	-5.548	0.000
1-3	-765.274	52.986	-14.443	0.000
1-4	-804.206	84.722	-9.492	0.000
2-5	-376.745	121.582	-3.099	0.002
2-3	-480.038	57.914	-8.289	0.000
2-4	-518.971	87.888	-5.905	0.000
5-3	103.293	125.944	0.820	0.412
5-4	142.226	142.240	1.000	0.317
3-4	-38.933	93.831	-0.415	0.678

Independent-Samples Kruskal Wallis Test

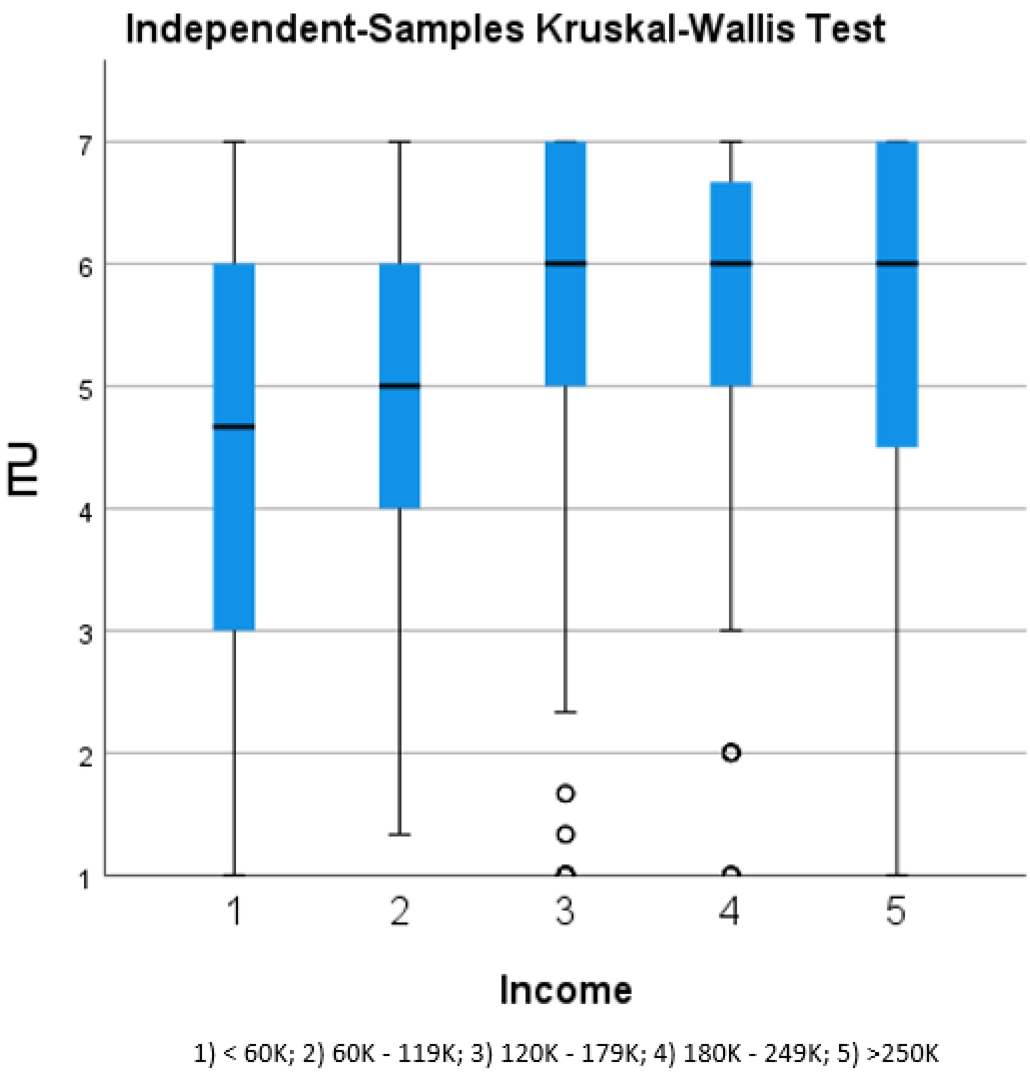
Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.

Asymptotic significances (2-sided tests) are displayed. The significance level is .050.
Group 1: < 60K; 2) 60K - 119K; 3) 120K - 179K; 4) 180K - 249K; 5) >250K

Sample 1 and Sample 2 reflect to the side-by-side income groups

Figure ***3***

Intention to Use of Users and Non-Users Across Income Levels



Education also played a role as consumers with the highest ITU and ITCU were amongst those with high education (Figure 4) and lowest for those with lower education, which can be seen in Table 31 and follows the same bold/red color scheme from the previous section. The independent-samples Kruskal-Wallis test shows that most income level groups are significantly different from each other except for those shown with a non-significant result in Table 32.

Table 31

Descriptive Statistics of Education Levels on ITU

	Study 1		Study 2		Study 3		Study 4a		Study 4b	
Education	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
High School	3.99	1.87	3.81	1.76	4.41	1.49	6.16	1.04	5.81	1.29
2-year college	4.20	1.84	4.03	1.88	4.32	1.66	6.54	0.54	6.12	1.06
4-year college	4.56	1.62	3.83	1.74	4.72	1.48	6.23	0.95	6.09	1.04
Masters	5.44	1.66	4.63	1.89	**5.31**	1.46	6.48	0.66	6.11	1.04
Doctoral	**5.74**	1.20	3.83	2.03	5.25	1.99	6.47	0.46	**6.15**	0.92
Professional	4.74	1.90	**4.40**	2.29	4.88	1.30	**6.67**	0.41	6.14	1.14
Total	4.54	1.83	3.96	1.82	4.63	1.55	6.34	0.84	6.03	1.11

Table 32

Pairwise Comparisons of Education Levels

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.
1-2	-154.215	52.435	-2.941	0.003
1-3	-256.190	45.218	-5.666	0.000
1-6	-406.235	124.074	-3.274	0.001
1-5	-747.558	123.341	-6.061	0.000
1-4	-767.348	51.031	-15.037	0.000
2-3	-101.974	54.979	-1.855	0.064
2-6	-252.020	127.954	-1.970	0.049
2-5	-593.343	127.244	-4.663	0.000
2-4	-613.133	59.851	-10.244	0.000
3-6	-150.045	125.170	-1.199	0.231
3-5	-491.369	124.443	-3.949	0.000
3-4	-511.158	53.641	-9.529	0.000
6-5	341.324	169.811	2.010	0.044
6-4	361.113	127.385	2.835	0.005
5-4	19.790	126.671	0.156	0.876

Independent-Samples Kruskal Wallis Test

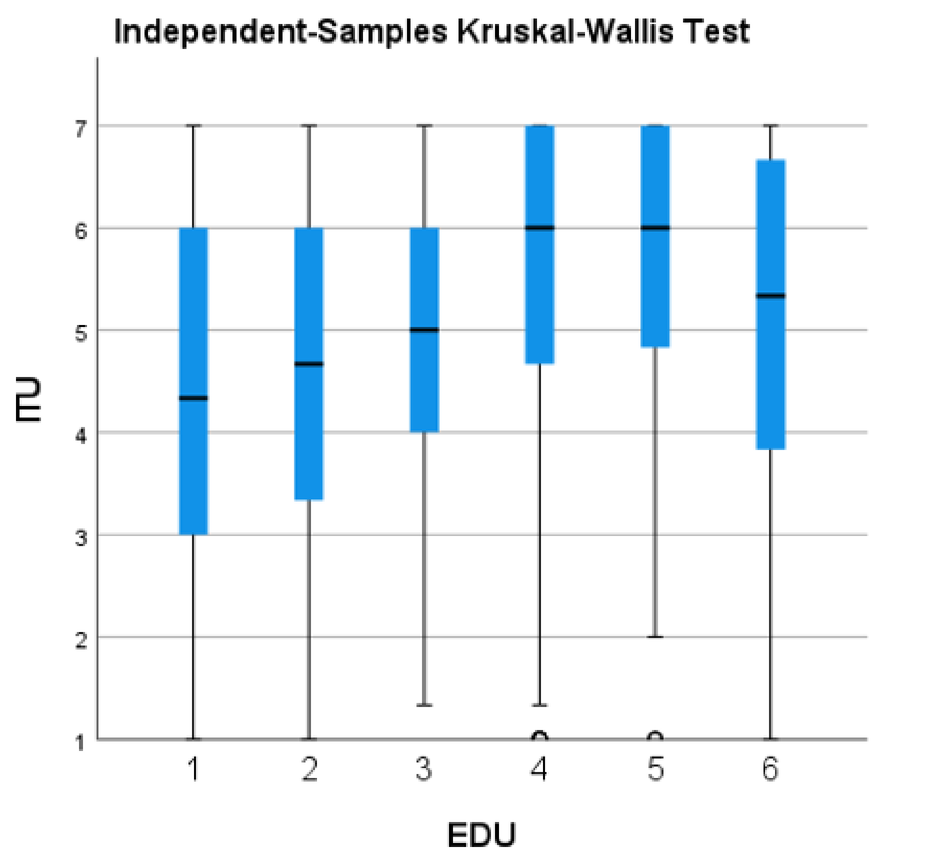
Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.

Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

Group 1= High School; 2 = 2-year college; 3 = 4-year college; 4 = Masters; 5 = Doctoral; 6 = Proff.

Figure 4

Intention to Use of Users and Non-Users Across Education Levels



1= High School; 2 = 2-year college; 3 = 4-year college; 4 = Masters; 5 = Doctoral; 6 = Proff.

Gender affected ITU and ITCU. Men (n = 1,865) reported higher ITU and ITCU values (M = 5.04, SD = 1.75) than women (n = 1,859, M = 4.42, SD = 1.79). To test the hypothesis that men and women reported statistically significantly different ITU and ITCU values, an independent samples t-test was performed. As can be seen in Table 33, the male and female distributions were sufficiently normal for the purposes of conducting a t-test (i.e., skew < |2.0| and kurtosis < |9.0|; Schmider et al. 2010). Additionally, the assumption of homogeneity of variances was tested and satisfied via Levene's F test, $F(3722) = 1.53$, $p = .21$. The independent sample t-test revealed a statistically significant effect, $t(3722) = 10.74$, $p = .00$. Thus, males reported statistically significantly higher mean ITU and ITCU values than females.

Table 33

Descriptives for Gender

Gender	*N*	*Mean*	*SD*	*SE*	*Skewness*	*Kurtosis*
Male	1865	5.037	1.750	0.041	-0.805	-0.290
Female	1859	4.415	1.786	0.041	-0.366	-0.794

Finally, marital status affected ITU and ITCU. Married people ($n = 1{,}954$) had higher ITU and ITCU ($M = 4.99$, $SD = 1.74$) than unmarried people ($n = 1{,}770$, $M = 4.43$, $SD = 1.80$). To test the hypothesis that married and unmarried people are associated with statistically significantly different ITU and ITCU values, an independent samples t-test was performed. As can be seen in Table 34, the unmarried and married distributions were sufficiently normal for the purposes of conducting a t-test (Schmider et al. 2010). Additionally, the assumption of homogeneity of variances was tested and satisfied via Levene's F test, $F(3722) = 3.04$, $p = .08$. The t-test was associated with a statistically significant effect, $t(3722) = -9.60$, $p = .00$. Thus, married individuals reported higher mean ITU and ITCU values than unmarried people.

Table 34

Descriptives for Marital Status

Marital Status	*N*	*Mean*	*SD*	*SE*	*Skewness*	*Kurtosis*
Unmarried	1770	4.433	1.804	0.043	-0.404	-0.809
Married	1954	4.991	1.744	0.040	-0.733	-0.389

I used non-parametric tests for the demographic variables instead of including them in the model as control variables because demographic variables tend to be highly correlated and that multicollinearity would destabilize the parameter estimates and would affect the model's overall goodness of fit indices.

Findings

SEM was used to test the hypotheses in the proposed model. The same goodness of fit criteria was applied, $\frac{X^2}{df} < 2$, CFI > 0.95, SRMR < 0.08, and RMSEA < 0.06, to evaluate the fit of the proposed model. The proposed model failed to provide acceptable goodness of fit indices. Aside from a significant chi-square test, which is acceptable for large sample SEM models because the chi-square variate is a direct function of *N* (Bentler et al., 1980), the model failed to stay below the SRMR and RMSEA thresholds. After further evaluations of the relationships between constructs and revisiting the literature, I identified that the primary reason for the poor performance is that ambivalence did not mediate the relationships between facilitators and inhibitors and intention to use, as hypothesized. Instead, facilitators mediated the relationships between brand trust, inhibitors, and ambivalence with intentions to use.

This first finding prompted further exploration of the role of ambivalence in the conceptual model. As noted in the literature review, this is the first research that includes ambivalence in the technology adoption literature. As such, prior literature was not as informative about the exact role of ambivalence. The initial empirical test of the model revealed that ambivalence was strongly related to facilitators and to inhibitors, as hypothesized, but that the originally proposed array of relationships was statistically inept and thus deserved reconsideration. Revisiting the literature on ambivalence led me to consider that the nature of subjective ambivalence as a general feeling of conflict suggested that it may be treated as an antecedent instead of the proposed outcome of inhibitors and facilitators. In other words, consumers' general feeling of ambivalence toward these new technologies may instead precede their specific beliefs about facilitators and inhibitors. This interesting new finding led me to conduct additional analyses related to the role of ambivalence in the model.

Qualification for participation in the survey included three yes or no pretest questions. The first pretest question was: "Have you heard of [the technology] before taking the survey?" The second pretest question was: "Have you used any form of [the technology]?" Finally, the third pretest question was: "Are you currently using [the technology]?" These data allowed me to classify participants as users who are aware of the technology (aware group), non-users who are somewhat aware of the technology (somewhat aware group), and non-users who are not aware of the technology (unaware group). The latter group stated that they had not heard of the technology prior to the survey; as such, it is fair to assume that they would not hold prior beliefs (facilitating or inhibiting) about the technology in question. To empirically analyze if ambivalence is an antecedent to inhibitors and facilitators or if people can be ambivalent towards an emerging technology without even knowing about it, I conducted non-parametric tests on ambivalence.

A one-way between subjects ANOVA was conducted to compare the effect of technology awareness on ambivalence under aware, somewhat aware, and unaware conditions. There was a significant effect of awareness on ambivalence for the three conditions, $F(2, 3721) = 28.318$, $p = .00$. Post hoc comparisons using the Turkey HSD test indicated that the mean ambivalence score for the aware group ($M = 4.05$, $SD = 1.60$) was significantly lower than the somewhat aware group ($M = 4.39$, $SD = 1.41$) and the unaware group ($M = 4.59$, $SD = 1.35$). Additionally, the somewhat aware group was significantly different than the unaware group (Table 35). Taken together, these results suggest that, in the context of emerging technologies, individuals who are unaware of the technology experience the highest ambivalence, whereas current users of the technology experienced the lowest ambivalence (Figure 5).

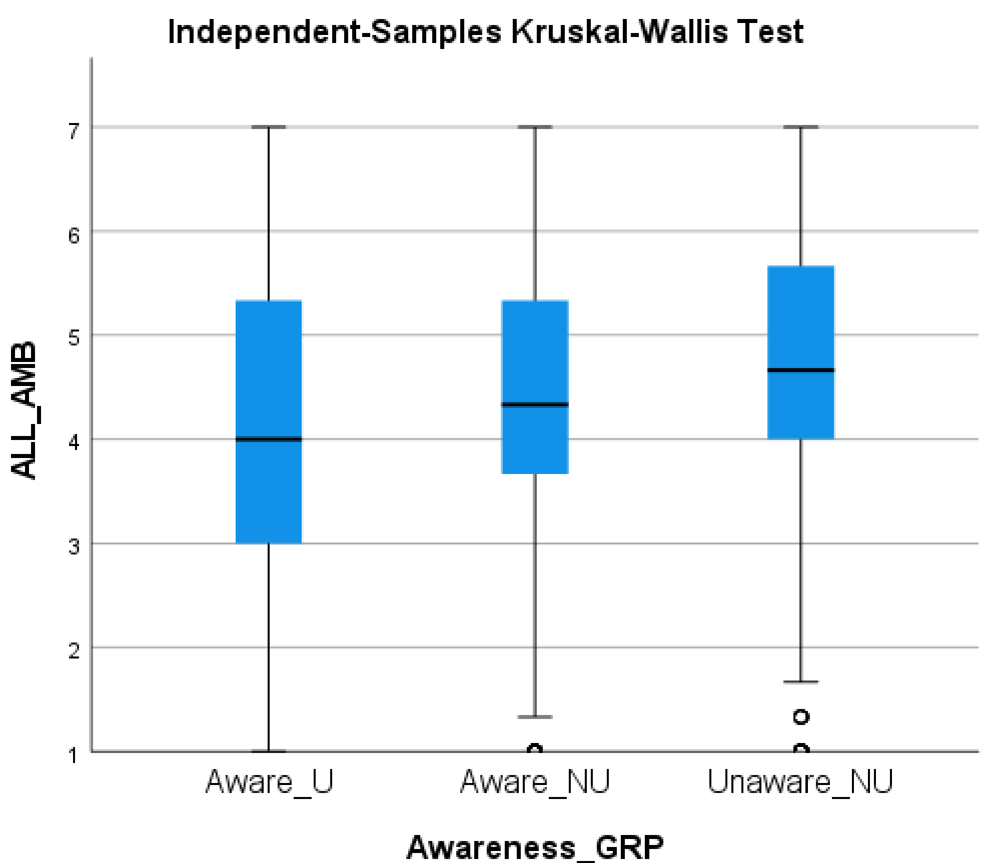
Table 35

Descriptives for Awareness Groups

Ambivalence	*N*	*Mean*	*SD*	*SE*	*Skewness*	*Kurtosis*
Aware	690	4.046	1.60	0.061	-0.073	-0.795
Somewhat Aware	2137	4.394	1.41	0.030	-0.297	-0.317
Unaware	897	4.59	1.35	0.045	-0.388	0.028

Figure 5

Ambivalence Across Awareness Levels



Since the analysis showed that the three groups (aware, somewhat aware, and unaware) are significantly different and the unaware group had the highest ambivalence, I tested the proposed model with only the unaware group to verify that ambivalence does not mediate the relationships between facilitators and inhibitors with ITU. The results show that facilitators and Inhibitors are strongly correlated with ambivalence. However, ambivalence does not have a direct effect on ITU in any of the groups as can be seen in Tables 36, 37, and 38. These findings provide empirical evidence that subjective ambivalence towards emerging technology may be better conceptualized as preceding beliefs about facilitating and inhibiting factors instead as an outcome. Consequently, a new model emerged (Figure 6) to test the proposed hypotheses.

Table 36

Results of The Proposed Model Testing with Unaware Group (AV)

Relationships	Standardized Path Coefficients	Effect
FAC --> ITU	.864***	Yes
INH --> ITU	(0.053)	No effect
AMB-->ITU	(0.079)	No effect
BT --> ITU	0.077*	Weak effect
INH --> FAC	(0.384)***	Yes
BT --> FAC	0.519***	Yes
FAC --> AMB	0.360***	Yes
INH --> AMB	0.731***	Yes
BT --> INH	(0.161)**	Yes

*p < 0.05; ** p < 0.01; ***p < .0001 (2-tailed).

Table 37

Results of The Proposed Model Testing with Unaware Group (SHVA)

Relationships	Standardized Path Coefficients	Effect
FAC --> ITU	.815***	Yes
INH --> ITU	(0.060)	No effect
AMB-->ITU	0.044	No effect
BT --> ITU	0.059	No effect
INH --> FAC	(0.103)*	Yes
BT --> FAC	0.722***	Yes
FAC --> AMB	0.318***	Yes
INH --> AMB	0.700***	Yes
BT --> INH	(0.480)***	Yes

*p < 0.05; ** p < 0.01; ***p < .0001 (2-tailed).

Table 38

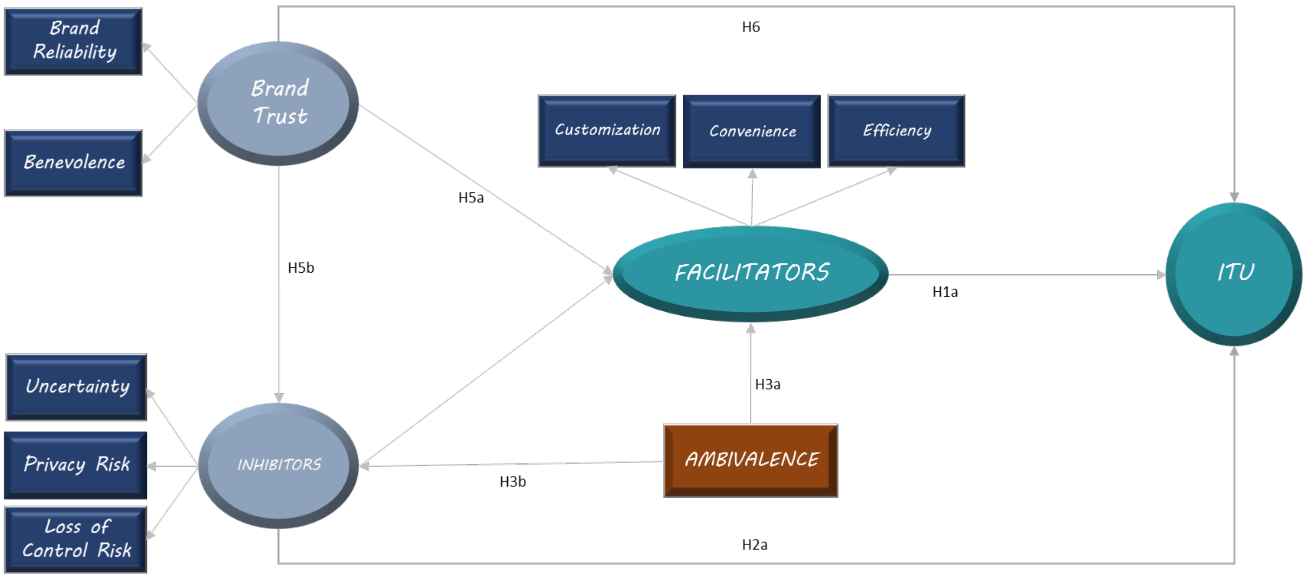
Results of The Proposed Model Testing with Unaware Group (TM)

Relationships	Standardized Path Coefficients	Effect
FAC --> ITU	.867***	Yes
INH --> ITU	(0.042)	No effect
AMB-->ITU	(0.107)	No effect
BT --> ITU	0.020	No effect
INH --> FAC	(0.166)**	Yes
BT --> FAC	0.554***	Yes
FAC --> AMB	0.275***	Yes
INH --> AMB	0.788***	Yes
BT --> INH	(0.215)**	Yes

*p < 0.05; ** p < 0.01; ***p < .0001 (2-tailed).

Figure 6

Emerging Framework from the Findings



The CFA results remained the same because the emerging model has the same bivariate correlations between the constructs. The overall goodness of fit of the emerged structural models was acceptable (Table 39). The chi-square test was significant due to its sensitivity to large sample sizes. The CFI was greater than .95, ranging from .979 to .983. The RMSEA values were at and below the recommended value of 0.6. Finally, the SRMR values ranged from .040 to .053, well below the recommended value of .08.

Table 39

Goodness of Fit Indices of The Structural Models

	N	Setorra-Bentler chi2	RMSEA-SB	CFI-SB	SRMR
Study 1	1237	chi2sb (66)=318.150; p≈.000	0.056	0.983	0.047
Study 2	894	chi2sb (66)=292.294; p≈.000	0.062	0.98	0.040
Study 3	903	chi2sb (66)=269.186; p≈.000	0.058	0.979	0.053

Hypothesized Relationships

The summary of the hypothesis testing with path coefficients for H1a, H2a, H3a, H3b, H5a, H5b, and H6 appears in Tables 40, 41, and 42. The results of H1b, H2b, and H4 are not in a table because H1b and H2b did not involve coefficient testing and H4 was rejected from the previously proposed model. The results support H1a and H2a in all hypothesized studies. However, due to the weak effect of INH → ITU (β=-0.032), the path coefficient in Study 3 was not significant. For H1b and H2b, the facilitators showed positive effects on ITU across the three categories of AI (Studies 1-3). Moreover, inhibitors showed negative effects on ITU across the three categories of AI. The evidence of configural invariance tested and discussed previously and the configuration of the effects of FAC→ ITU and INH → ITU shown in Tables 40, 41, and 42 support H1b and H2b. The results also support H3a, H3b, H5a, and H5b across all hypothesized studies. Finally, H6 is rejected across studies 1, 2, and 3.

Table 40

Results of Hypothesis Testing for Study 1

Hypotheses	Standardized Path Coefficients	Supported?
H1a: FAC --> ITU	.793***	Yes
H2a: INH --> ITU	(0.168)**	Yes
INH --> FAC	(0.523)***	Not Hypothesized
H3a: AMB --> FAC	0.304***	Yes
H3b: AMB --> INH	0.489***	Yes
H5a: BT --> FAC	0.433***	Yes
H5b: BT --> INH	(0.385)***	Yes
H6: BT --> ITU	0.040	No

*p < 0.05; ** p < 0.01; ***p < .0001 (2-tailed).

Table 41

Results of Hypothesis Testing for Study 2

Hypotheses	Standardized Path Coefficients	Supported?
H1a: FAC --> ITU	.794***	Yes
H2a: INH --> ITU	(0.097)**	Yes
INH --> FAC	(0.257)***	Not Hypothesized
H3a: AMB --> FAC	0.217***	Yes
H3b: AMB --> INH	0.447***	Yes
H5a: BT --> FAC	0.626***	Yes
H5b: BT --> INH	(0.582)***	Yes
H6: BT --> ITU	0.050	No

*p < 0.05; ** p <0.01; ***p < .0001 (2-tailed).

Table 42

Results of Hypothesis Testing for Study 3

Hypotheses	Standardized Path Coefficients	Supported?
H1a: FAC --> ITU	.882***	Yes
H2a: INH --> ITU	(0.105)**	Yes
INH --> FAC	(0.696)***	Not Hypothesized
H3a: AMB --> FAC	0.373***	Yes
H3b: AMB --> INH	0.555***	Yes
H5a: BT --> FAC	0.339***	Yes
H5b: BT --> INH	(0.254)***	Yes
H6: BT --> ITU	0.012	No

*p < 0.05; ** p < 0.01; ***p < .0001 (2-tailed).

Model Findings Amongst Existing Users

Study 4A and 4B examined the model with data from existing users of the technologies (TM and SHVA). These studies provide empirical evidence of the dynamics in perceptions of facilitators, inhibitors, ambivalence, and brand trust once adoption has taken hold. The results in Tables 43 and 44 provide a side-by-side summary of the path coefficients of users (Studies 4A and 4B) and non-users (Studies 2 and 3) of the same technologies (i.e., users and non-users of SHVA with studies 2 and 4a, and TM with studies 3 and 4b).

Table 43

Side-By-Side Results of Users and Non-Users of SHVA

Effects	Non-Users of SHVA Study 2 (N=894)	Users of SHVA Study 4a (N=344)
FAC --> ITU	.794***	1.06***
INH --> ITU	(0.097)**	(0.073)
INH --> FAC	(0.257)***	(0.347)***
AMB --> FAC	0.217***	0.299***
AMB --> INH	0.447***	0.798***
BT --> FAC	0.626***	0.704***
BT --> INH	(0.582)***	(0.141)**
BT --> ITU	0.050	(0.320)***

*p < 0.05; ** p < 0.01; ***p < .0001 (2-tailed).

Table 44

Side-By-Side Results of Users and Non-Users of TM

Effects	Non-Users of TM Study 3 (N=903)	Users of TM Study 4b (N=346)
FAC --> ITU	.882***	0.712***
INH --> ITU	(0.105)**	(0.054)
INH --> FAC	(0.696)***	0.108
AMB --> FAC	0.373***	(0.296)***
AMB --> INH	0.555***	0.820***
BT --> FAC	0.339***	0.555***
BT --> INH	(0.254)***	0.004
BT --> ITU	0.012	(0.072)

*p < 0.05; ** p < 0.01; ***p < .0001 (2-tailed).

Decomposition of Direct and Indirect Effects

The study's model is depicted in Figure 7. The diagram corresponds to three equations:

$$y = B_{y0} + B_{y1x_1} + B_{y2x_2} + B_{y3x_3} + \varepsilon_1$$

$$x_3 = B_{20} + B_{21x_1} + B_{22x_2} + \varepsilon_3$$

$$x_4 = B_{30} + B_{31x_1} + B_{32x_2} + B_{33x_3} + \varepsilon_4$$

Where x_1 = brand trust, x_2 = ambivalence, x_3 = inhibitors, x_4 = facilitators, and y = intention to use. The decomposition of the total effect of x_1 on y:

β_{y1} Direct Effect

$\beta_{31}\beta_{y2}$ Indirect effect through x_4

$\beta_{21}\beta_{y3}$ Indirect effect through x_3

$\beta_{21}\beta_{33}\beta_{y2}$ Indirect effect through x_3 and x_4

The decomposition of the total effect of x_3 on y:

β_{y3} Direct Effect

$\beta_{33}\beta_{y2}$ Indirect effect through x_4

The decomposition of the total effect of x_2 on y:

$\beta_{32}\beta_{y2}$ Indirect effect through x_4

$\beta_{22}\beta_{33}\beta_{y2}$ Indirect effect through x_3 and x_4

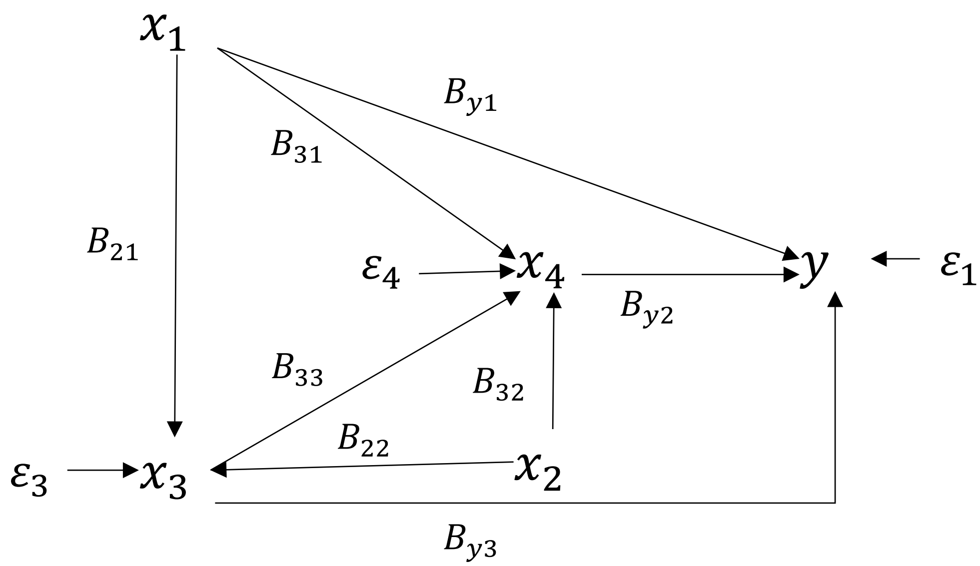
$\beta_{21}\beta_{33}\beta_{y2}$ Indirect effect through x_3 and x_4

The decomposition of the total effect of x_4 on y:

β_{y2} Direct Effect

Figure 7

Model Diagram



The decomposition results of the direct and indirect effects are shown in Tables 45, 46, 47, and 48. Facilitators almost fully mediate the relationships of brand trust, inhibitors, and ambivalence with ITU. The direct effect of facilitators on ITU ranges from 0.71 to 1.06 (Table 48). The indirect effect of inhibitors on ITU showed a strong negative effect in all studies except study 4B (users of TM). The indirect effects of ambivalence showed modest positive and negative total effects in studies 1, 2, and 4 and stronger effects on studies 3 and 4B (users and non-users of SMVA) as can be seen in Table 47. Finally, brand trust shows very strong indirect effects on ITU across all the studies, ranging from 0.40 - 0.67 (Table 45).

Table 45

Decomposition of Brand Trust Effect on ITU/ITCU

Brand Trust	Study 1	Study 2	Study 3	Study 4a	Study 4b
Direct	0	0	0	-0.32	0
Indirect through FAC	0.34	0.50	0.30	0.75	0.40
Indirect through INH	0.06	0.06	0.03	0.00	0.00
Indirect through INH -> FAC	0.16	0.12	0.16	0.05	0.00
Total Effect	**0.57**	**0.67**	**0.48**	**0.48**	**0.40**

Table 46

Decomposition of Inhibitors Effect on ITU/ITCU

Inhibitors	Study 1	Study 2	Study 3	Study 4a	Study 4b
Direct	-0.17	-0.10	-0.11	0.00	0.00
Indirect through FAC	-0.41	-0.20	-0.61	-0.37	0.00
Total Effect	**-0.58**	**-0.30**	**-0.72**	**-0.37**	**0.00**

Table 47

Decomposition of Ambivalence Effect on ITU/ITCU

Ambivalence	Study 1	Study 2	Study 3	Study 4a	Study 4b
Indirect Through FAC	0.24	0.17	0.17	0.33	-0.21
Indirect Through INH	-0.08	-0.04	-0.06	0	0
Indirect Through INH -> FAC	-0.20	-0.09	-0.34	-0.29	0
Total Effect	**-0.04**	**0.04**	**-0.23**	**0.04**	**-0.21**

Table 48

Decomposition of Facilitators Effect on ITU/ITCU

Facilitators	Study 1	Study 2	Study 3	Study 4a	Study 4b
Direct	0.79	0.79	0.88	1.06	0.71
Total Effect	**0.79**	**0.79**	**0.88**	**1.06**	**0.71**

Competing Model Findings

I also collected data to test and compare TAM with the framework of this study. The overall goodness of fit indices was acceptable for studies 1 and 3 (Table 49); however, Study 2 showed a poor fit. The chi-square test was significant for all three studies due to its sensitivity to large sample sizes. The CFI was greater than .95, ranging from .972 to .991. The RMSEA values were at and below the recommended value of 0.6 for studies 1 and 3; however, Study 2 was well above the recommended value of 0.6. Finally, the SRMR values ranged from .020 to .050, well below the recommended value of .08.

Table 49

Goodness of Fit Indices of The Structural Models for TAM

	N	Setorra-Bentler chi2	RMSEA-SB	CFI-SB	SRMR
Study 1	1237	chi2sb (23)=116.660; p≈.000	0.056	0.991	0.020
Study 2	894	chi2sb (23)=229.224; p≈.000	0.100	0.972	0.050
Study 3	903	chi2sb (23)=100.074; p≈.000	0.061	0.987	0.032

Tables 50, 51, and 52 display the coefficients of PU and PEOU on ITU for studies 1-3, 4A, and 4B. The results indicate that TAM did not achieve configural invariance in the current studies, which means that groups did not have the same factor loading configuration (+/-/0). The relationship between PEOU and ITU had a different sign in Study 3 (non-users of TM) compared to studies 1 and 2. This configural variance indicates a major limitation of TAM to estimate novel technologies because it implies that the PEOU construct is not measuring the same thing across different types of novel technologies. All coefficients were statistically significant.

Table 50

Results of TAM (Non-Users of AV)

Effects	Non-Users N=1237
PU --> ITU	0.739***
PEOU --> ITU	0.176***
PEOU --> PU	0.859***

*p < 0.05; ** p < 0.01; ***p < .0001 (2-tailed).

Table 51

Results of TAM (Non-Users and Users of SHVA)

Effects	Non-Users N=894	Users N=344
PU --> ITU	0.678***	.304***
PEOU --> ITU	0.195***	.374***
PEOU --> PU	0.784***	.863***

*p < 0.05; ** p < 0.01; ***p < .0001 (2-tailed).

Table 52

Results of TAM (Non-Users and Users of TM)

Effects	Non-Users N=903	Users N=346
PU --> ITU	1.18***	.797***
PEOU --> ITU	-0.291***	.039***
PEOU --> PU	0.860***	.846***

*p < 0.05; ** p < 0.01; ***p < .0001 (2-tailed).

Summary

The findings offered answers to the questions posed in this research. With question one, I wanted to know how facilitating and inhibiting factors independently related to consumers' intention to use AI-enabled technology. The findings revealed that: a) facilitators is a salient construct relating to intention to use AI-enabled technology across all the studies; b) facilitators almost fully mediate the relationships between inhibitors, ambivalence, brand trust, and intention to use in all studies; c) inhibitors have a strong and independent indirect influence on intention to use through facilitators; and d) facilitators and inhibitors coexist, especially for people who have not yet used novel technologies.

With the second question, I wanted to know how ambivalence related to consumers' intention to use AI-enabled technology. The findings showed that there is evidence of ambivalence towards new/emerging technologies, but that subjective ambivalence is an antecedent to facilitators and inhibitors. Although the indirect effects of ambivalence showed a modest impact on intention to use for studies 1, 2, and 4A, the construct remained strong with its direct relationships with inhibitors and facilitators (stronger with inhibitors) across all studies. In the case of users and non-users of telemedicine, ambivalence showed a strong indirect negative effect on ITU. As predicted in H3a and H3b, findings indicated that ambivalence influences both facilitators and inhibitors positively; thus, the overall effect of ambivalence on ITU partially depends on the category of AI (i.e., higher effect on embedded AI) and partially on the effect sizes of the inhibitors and facilitators on ITU. As I observed the decomposition of the indirect effects, ambivalence had a much greater influence on users and non-users of TM, not only because the effect of ambivalence was greater on the embedded category (TM), but also because the effects of facilitators and inhibitors on ITU were greater for embedded category (TM).

With question three, I wanted to find out the role of brand trust in AI-enabled technology. The findings suggest that brand trust plays a critical role in the adoption of novel technologies. Like inhibitors and ambivalence, the relationship between brand trust ITU was also mediated by facilitators. The strong indirect effects of brand trust showed in all studies. Like ambivalence, brand trust influences ITU through the same three indirect paths. However, unlike ambivalence, it affects inhibitors negatively and facilitators positively.

Finally, the descriptive statistics and non-parametric tests revealed that demographics play a key role in smart technology diffusion. Married men between the ages of 26 – 45, who are highly educated, and who are earning greater than $120,000 are the early adopters.

CHAPTER 5: DISCUSSION

Overview

This research began with a review of the artificial intelligence, technology acceptance, ambivalence, and trust literature and determined that prior models of technology acceptance and adoption were missing important determining factors such as inhibitors, ambivalence, and brand trust. A thorough review of literature signaled that these missing factors would likely be particularly important to the adoption of AI-enabled technology and would help us understand the nuances of the consumer's decision-making process related to adoption. The extant literature further identified that there are different representations of AI (robotic, virtual, and embedded) with different levels of machine intelligence (Glikson & Wooley, 2020) in different diffusion stages. For example, the highly intelligent, fully autonomous vehicles representing robotic AI are not yet available in the market. Fully autonomous vehicles are still in the development and testing stages, while semi-autonomous vehicles are already in the market. Other technologies, such as smart home virtual assistants, have been in the market for a long time. This allowed me to conduct four studies to capture consumers' perceptions and assess the factors underlying the adoption process across different categories of novel technology in different stages.

I first developed a conceptual model that incorporates previously unexplored constructs in this domain and, more importantly, that can apply to different categories of AI-enabled technology in different stages. In the first study, I examined robotic AI with autonomous vehicles by assessing the perceptions of consumers who had never used the technology. The sample included 1,237 participants from across the U.S. I examined the virtual AI category with the second study, using smart home virtual assistance technologies. For this study, I sampled 894 participants from the U.S. who had never used smart home virtual assistants. Next, I examined consumers' perceptions of the embedded AI category using telemedicine with the third study. The study captured the perceptions of 903 people residing in the U.S. who had never used telemedicine. Finally, in the fourth study I tested the model and examined differences between users and non-users of the technology by sampling 344 U.S. consumers who were using smart home virtual assistants and 346 U.S. consumers who were using telemedicine.

This research points to several important theoretical contributions for technology acceptance, ambivalence, and trust theories. After discussing these theoretical contributions, I present a discussion of methodological contributions, implications of the practice, limitations, and future research directions.

Implications for Advancing Theory

The findings of this cross-disciplinary research make contributions across three bodies of research: technology acceptance, ambivalence, and trust. First, several new measures were developed in addition to adapting existing scales to fit the context of the research. The new measures capture consumers' perception of customization (one new item), convenience (two new items), efficiency (three new items), uncertainty risk (one new item), and loss of control (one new item) constructs. The measures archived high reliability and validity in all four studies; they are valid across users and non-users and across all three categories of AI.

Second, the model addresses the interplay of four key constructs (brand trust, ambivalence, facilitators, and inhibitors) and provides new theoretical insight into the adoption process for novel technologies. In particular, the two newly introduced elements, brand trust and ambivalence, enhance our understanding of the adoption process. To the best of my knowledge, this research is the first to include brand trust and ambivalence in the technology acceptance literature. Although the framework cannot account for every possible construct that might affect technology adoption, it provides a theoretically grounded and empirically demonstrated foundation for understanding the adoption process for AI-enabled technology. Additionally, the fact that this framework was developed and tested across different categories of AI-enabled technology in different diffusion stages enhances ecological validity. Notably, the framework performed well to explain the array of relationships amongst constructs for users of the technology.

Third, previous technology acceptance research has positivity bias towards facilitating factors such as perceived usefulness and perceived ease of use as a single dimension (Davis, 1989; Kleijnen et al., 2009; Venkatesh et al., 2003). The addition of inhibiting factors, ambivalence, and brand trust in this research identifies nuances and novel insights beyond existing technology acceptance literature. An important contribution comes from theoretical and empirical evidence that facilitating and inhibiting factors are not opposite ends of the same dimension - they coexist.

Although it makes intuitive sense for ambivalence to influence technology adoption, it was never applied in this domain. The finding that ambivalence plays an instrumental role in understanding and indirectly influencing consumers' intentions to use emerging technologies thus paves the way for a new, more elaborate models of consumer adoption beyond the focus on positive drivers. The initial proposed model of this research posited that ambivalence would mediate the relationship between facilitators and inhibitors with intentions to use. Yet, the studies revealed a different role for ambivalence: instead of mediating the relationships between facilitators and inhibitors and intention to use, facilitators mediated all other constructs in the model (brand trust, ambivalence, and inhibitors). The emergent model identified that consumers' conflicted state of subjective ambivalence toward new technologies precedes, and perhaps shapes, their perceptions of facilitators and inhibitors.

Indeed, the evidence suggests that consumers develop ambivalence towards new technologies as soon as they hear about the technology, without having prior knowledge of its existence. This explanation is consistent with definitional aspects of ambivalence as a phenomenon of having conflicting feelings toward an attitude object (here, a technology) which creates a state of negative mood, discomfort, and psychological arousal (Hamby & Russell, 2021; Nohlen et al., 2013; van Harreveld et al., 2009). States of discomfort and psychological arousal do not necessarily require knowledge of the technology to form a subjective ambivalence. The presence of ambivalence toward emerging technologies is also justified given that technology is inherently paradoxical and consumers are often ambivalent towards technology (Babic-Rosario et al., 2021; Mick & Fournier, 1998; Ratchford & Barnhart, 2012), which brings fears and concerns (Mick & Fournier, 1998). Such feelings of fear and perceptions of benefits do not require prior knowledge of the technology. Love and hate are another set of emotional conflicts that initiate subjective ambivalence (Freud, 1918; Kris, 1984), which could also apply to new technology. Although prior research has not applied subjective ambivalence to the technology adoption model, there are hints in extant literature that subjective ambivalence can indeed precede consumers' perceptions (and reporting) of the factors that facilitate and inhibit adoption of technology.

The construct of brand trust is also new to the technology acceptance literature, which has prioritized the broader construct of trust in technology (Hengstler et al., 2016; Obaid et al., 2016; Zhang et al., 2019). In line with prior studies related to trust in technology (Chio & Ji, 2015) and automation (Parasuraman et al., 2008; Pavlou, 2003), I also captured consumers' trust in technology using existing instruments of ability and predictability constructs to avoid omitting relevant explanatory variables and endogeneity. Whereas trust in technology did not achieve discriminant validity due to a high correlation with facilitators, brand trust did. In fact, brand trust was a critical component in all four studies, revealing an important role of brands in influencing technology adoption by shaping consumers' perceptions of their inhibitors and facilitators. As such, findings related to brand trust contribute to the growing body of consumer research on brands as relationship partners (Delgado-Ballester, 2004; Fournier, 1998). The four empirical studies offer evidence of the role of brand trust in technology adoption: when direct contact between consumers and companies is not possible, consumers develop a relationship with the brand (Delgado-Ballester, 2004; Fournier, 1998). Indeed, the role of brand trust was so focal that even when users and non-users of telemedicine were asked to imagine a technology brand when they are thinking of telemedicine and answer the brand trust questions, the results showed remarkable effects and significance. The current research further shows that not only is brand trust an antecedent to facilitators and inhibitors, but its effect on intentions to use is also fully mediated through facilitators.

Next, this research contributes to the literature on ambivalence and technology adoption. In the context of technology adoption, ambivalence is understudied. Recent research examined ambivalence and consumption of risky products (Hamby & Russell, 2021). In the context of energy drinks, tobacco, e-cigarettes, and cognitive enhancers, Hamby and Russell (2021) showed that ambivalence enhances interest in using risky products if the consumer perceives immediate positive benefits. The findings of this research extend their findings in the context of technology adoption. All three categories of AI in the current research posed risks in the form of inhibitors (privacy risk, uncertainty, and loss of control risk); thus, ambivalence enhanced intentions to use through facilitators, suggesting that the consumers perceived immediate benefits from customization, convenience, and efficiency. Building on that, the decomposition of the effects in the current research also shows that ambivalence reduces intentions to use through inhibitors at the same time. The overall outcome depends on the strength of their perceptions of inhibitors (risks) versus facilitators (benefits), and thus it could also be positive. Ambivalence simultaneously enhances interests through facilitators and reduces interest through inhibitors. The overall effect of ambivalence on intention to use depends on the strength of inhibitors and facilitators. The positive and negative effects of ambivalence cancel each other and the remaining enhance whichever is stronger. In general, ambivalence is not good for technology adoption because any change in consumer perceptions could cause ambivalence to enhance the stronger side, causing inconsistencies and unsustainability.

Finally, I objectively compared the framework of this research with TAM. I included the factors of perceived usefulness and perceived ease of use in all four studies. The findings revealed that TAM had poor goodness of fit indices for virtual AI (smart home virtual assistants), and the model did not achieve configural invariance between the studies. Otherwise, the TAM analysis showed strong relationships between perceived usefulness, perceived ease of use, and intentions to use, as expected. Despite the goodness of fit challenge, TAM does not explain the complex process behind consumer adoption of AI-enabled technologies. The poor fit suggests that TAM may not be well suited for novel technologies. In addition, because the whole premise behind AI-enabled technology is their ease of use, the TAM does not provide implications for business practice for novel technologies. With its parsimonious design, TAM works well with conventional technology or application such as accounting software, not for novel technology.

I also considered combining the models together with extensions. In the process, I looked at the structure of each model and examined each TAM construct for the possibility of combining the models. I concluded that combining the models was not feasible because the current model already uses intention to use as the outcome variable. Next, I examined the remaining TAM constructs: perceived usefulness and perceived ease of use. The constructs were highly correlated with the facilitators construct, which would violate the discriminant validity rule even if we found it beneficial to combine the models. The remaining option was to decide which constructs we should not include. The choice was between taking out facilitators to attempt including perceived usefulness and perceived ease of use or to not include the TAM constructs. At that point, the choice was easy. The main contribution of this study was the inclusion of otherwise omitted constructs such as brand trust, inhibitors, and ambivalence, which were balanced with facilitators. Additionally, the new model has a hierarchical structure with first and second-order variables. Removal of any component from the model would have defeated the purpose of this research. In the end, the poor goodness of fit indices signaled that TAM does not represent the data well and, for these objective reasons, the analyses focused on the new model designed specifically for novel technology.

Implications for Business Practice

The current speed of AI-enabled technology development and its adoption challenges marketers and companies with the adoption of novel technologies in three ways. The first challenge is to increase the number of adopters to use their technologies. This research revealed that only 28% of nationally surveyed respondents were using telemedicine and smart home virtual assistance. As a reminder, I surveyed 1,238 people for smart home virtual assistance, of which only 344 were users (Study 4A). Similarly, I surveyed 1,249 people for telemedicine, of which only 346 people used the technology (Study 4B). Surprisingly, the ratio between the users and non-users is the same for both technologies.

I am not claiming that precisely 28% of the population uses novel technologies because not every technology is the same. This sample may not accurately represent the U.S. population. However, this finding provides a good scope and indication of the adoption challenges facing marketers and technology companies. In addition to asking the respondents if they were currently using the technology, I also asked if they had heard about the technology before taking the survey. Surprisingly, about one-third of non-users had not even heard of these emerging technologies: 26.4%, 31.3%, and 32.1% of the respondents for autonomous vehicles, smart home virtual assistance, and telemedicine, respectively.

The second challenge is the growing competition amongst companies for market share. According to Statista (2020), the global autonomous vehicle market forecast by 2023 is $37 billion in U.S. dollars. The global market for telemedicine is projected to be valued at nearly $460 billion in U.S. dollars by 2030 (Statista, 2020). In the U.S., the telemedicine market is expected to reach $35 billion by 2025. According to Grand View Research (2021), the global intelligent virtual assistant market size was valued at $5.82 billion U.S. dollars in 2020 and it is expected to expand at a compound annual growth rate of 28.5% from 2021 to 2028. The list of AI-enabled technologies is growing daily, and these are just forecasted market-size examples of few technologies and the opportunities they present. Although these forecasts show steady growth rates, the market could manage much more. Additionally, the development speed of AI-enabled technologies places additional pressure on marketers to compete for a market size that is only a fraction of its potential.

Finally, the third challenge is to retain consumers in this competitive environment. Maintaining the relationship and keeping the consumers is just as important and challenging as consumer acquisition. Intention to repurchase or continue usage is related to customer satisfaction and they are contingent on other factors that provide barriers for switching (Jones et al., 2000). The recommendations provide direction to creating barriers for switching and maintaining the consumers.

The current research provides solutions and strategic guidance for tech companies and marketers facing the above challenges. The pressing adoption issues uncovered in this research suggest great potential for the technology industry to improve product and service features. In most cases, novel technologies emphasize facilitating features such as customization, convenience, and efficiency. Few directly tackle the inhibiting issues such as the risks related to privacy, uncertainty risk, and loss of control, which create resistance. The high percentage of innovation or new product failures is a clear signal of consumers' resistance to change (Garcia et al., 2007; Kleijnen et al. 2009; Ram, 1987; Ram & Sheth, 1989). For that reason, companies, marketers, and other stakeholders must overcome resistance before adoption begins (Claudy et al., 2015; Laukkanen et al., 2007). This research provides awareness of important pressure points (privacy risk, uncertainty, and loss of control risk) that cause resistance. The findings suggest that to improve adoption, tech companies should develop features to reduce privacy risk, uncertainty risk, and sense of losing control.

The findings also signal an excellent opportunity for marketers to increase the adoption rate and competitive advantage by effectively communicating and reaching their target audience, the early adopters. Studies show that the success of innovation strongly depends on understanding the early adopters (Bartels & Reinders, 2011; Goldsmith & Hofacker, 1991;

Reinhardt & Gutner 2015; Rogers, 2003). Furthermore, segmenting early adopters of new technology is highly dependent on the type of innovation (Reinhardt & Gutner, 2015). This research provides robust insights into the demographics of the early adopters of AI-enabled technology and their profiles in terms of perceptions of novel technologies. Early adopters of AI-enabled technologies are educated married men, between the ages of 25-45, with household incomes greater than $120,000. The findings suggest that focusing a marketing strategy on communicating with this demographic will increase early adoption, which, in turn, could steepen the adoption curve.

The findings point to a two-fold approach: marketers should not only communicate the facilitating benefits and emphasize customization, convenience, and efficiency, but they should also mitigate the inhibiting factors by comforting consumers about their privacy, reducing uncertainties about the technology and providing a sense of control. The findings show that inhibiting factors are just as important as facilitating factors in shaping consumers' information search and processing and ultimately affecting their adoption of innovation (Claudy et al. 2015; Gregan-Paxton & John 1997). Marketers can assist consumers with their search and processing by addressing both the facilitating and inhibiting factors they care about.

This research also points to consumer ambivalence as an important factor in adoption of new technology. Indeed, consumers may feel ambivalent even without knowing about the technology - people with higher familiarity had lower levels of ambivalence that people who were not familiar. Although prior research suggests that ambivalence enhances interest in risky products if the consumer believes that they will provide immediate benefits (Hamby & Russell, 2021), conditions of ambivalence may not be sustainable in the context of novel technology adoption and ongoing usage. If negative perceptions begin to exceed positive, ambivalent consumers may discontinue usage. Given this, marketers should consider communication strategies to reduce ambivalence. The findings of this research reveal that the more consumers know about the technology, the less ambivalent they are. For that reason, strategies that directly aim to reduce ambivalence are warranted. Recent studies show that ambivalence could be mitigated through social norms (Hamby & Russell, 2021), such as communicating facts and statistics of adopters.

The current findings also highlight the importance of brand trust, especially brand reliability and benevolence. Companies in the novel technology market would benefit from anchoring their technology offering on a trustworthy brand, whether through a parent brand or a brand extension. This study suggests brand trust, even as an imaginary host brand for the new technology, is instrumental to both users and non-users. Brand trust influences perceptions of facilitators and reduces the perceptions of inhibitors. As such, brand trust could mitigate the potentially detrimental effect of ambivalence for both users and non-users; hence, marketers should build or improve their company's brand.

Limitations

The current research is not free of limitations. First, additional testing of the measurement instruments and the framework would further increase generalizability. Although instruments and the framework were tested in five different settings in four studies and across three categories of AI-enabled technology, other novel technologies in different development stages may yield different results. As such, further testing is necessary to strengthen generalizability.

Second, the data collection on an online platform could be seen as a limitation because of the focus on examining and measuring consumers' adoption of novel technology. The data collection context may not have allowed me to capture people who are not using online platforms or technology in general. A related limitation is that the participants responded to hypothetical scenarios. As autonomous vehicles are not yet available and a significant number of respondents were non-users of smart home virtual assistance and telemedicine, it was difficult to collect behavioral markers of intention to use. My focus on users and non-users of the technology presents another sampling limitation that prevented me from collecting a sample of people who were users and stopped using the technology. I mitigated these limitations by increasing the sample size to collect data well above the minimum required amount for the methodology used. I also included a short, unbiased introductory video for each technology in the survey instrument for the participants to watch before answering the questions.

Third, the cross-sectional design used in this study is limited to observations at one point in time. This limitation prevents observing and capturing change patterns and evolutionary effects of factors across time, which may cause a change in the relationships between variables. This limitation is especially true for consumer adoption and technology. Caution must be used when interpreting the results across time, including predictions on the adoption of AI technologies in the future as consumers' perceptions may evolve.

Fourth, the data collected for this study was across U.S. residents so the generalizability of the framework to populations from other countries is unknown. The influence of cultures in different countries could also affect the adoption rate of novel technologies. For instance, the U.S. is among several developed countries with lower uncertainty avoidance factors (Hofstede, 2001). Uncertainty avoidance is a cross-cultural index measuring the ambiguity and unpredictability tolerance levels of innovation adoption. Developing countries have higher levels of uncertainty avoidance, 77%, compared to 50% in developed countries (Hofstede, 2001). This research was unable to capture and test the differences between countries and cultures because the sample was limited to the U.S. population.

Fifth, the current research examined a limited number of factors that can influence consumers' intentions to use AI-enabled technology. Other variables not included in this research may also influence intention to use, such as social influence (Venkatesh et al., 2003), technology disposition, risk averseness, and other factors. I mitigated this limitation by reviewing the literature and using the most relevant components from different models, theories, and concepts.

Finally, every study is limited to potential endogeneity issues stemming from omitted variables, simultaneity, measurement error, common-methods variance, and model misspecifications, among other biases. This research is not an exception to that rule. The efforts to mitigate endogeneity included in the design, sampling, data collection, data analysis, methods, and model specification. Although it is impossible to eliminate endogeneity, I feel confident that the parameter estimates of my studies are stable and reliable.

Recommendations for Future Research

Given the scope of the research, direct comparisons and generalizations of other AI-enabled technologies were not possible, which provides opportunities for future research. Future studies could extend the model to other types of AI-enabled technology across users and non-users, as well as incorporate other constructs related to the technology.

The current research addressed perceptions of non-users and users across three distinct categories of AI (robotic AI, virtual AI, and embedded AI). Examining the differences between the users and non-users explained the adoption process and the interplay between the constructs and their relationships. The research also created an opportunity for future research to expand by studying the population of novel technology users who stopped using it. Such a study would provide a more comprehensive picture of the adoption process of novel technologies.

Future research is warranted to extend the cross-sectional design adopted here to longitudinal designs, which allow investigating related adoption decisions at several different points in time. For instance, growth curve modeling or latent curve modeling, where the effect of time is the focus, could identify trends over time and identify the evolution of the relationships identified herein.

Conclusion

Advanced and novel technologies pave the way for our future: how consumers will shop, commute, interact with each other, take care of their health, run errands, work, and live their lives. Emerging technologies continue offering more and more capabilities to make life easier with convenience, customization, and efficiencies. Unfortunately, emerging technologies also present concerns in the form of privacy risk, uncertainty, and losing control risk, which significantly hinders the rate of adoption. I draw attention to the factors that facilitate and inhibit consumer adoption of AI-enabled technologies to make an impact on consumer experience, privacy, safety, and adoption of novel technologies. AI and its potential could be much more impactful and acceptable to consumers when developed and communicated appropriately. While this research has made clear that, in the context of AI-enabled applications, consumers often take the good with the bad, it also identifies important levers, namely brand trust and ambivalence, that can shape the adoption process.

REFERENCES

Al Kailani, M., & Kumar, R. (2011). Investigating uncertainty avoidance and perceived risk for impacting Internet buying: A study in three national cultures. *international Journal of Business and Management*, *6*(5), 76-92.

Anderson, J. M., Nidhi, K., Stanley, K. D., Sorensen, P., Samaras, C., & Oluwatola, O. A. (2014). *Autonomous vehicle technology: A guide for policymakers*. Rand Corporation.

Antioco, M., & Kleijnen, M. (2010). Consumer adoption of technological innovations: Effects of psychological and functional barriers in a lack of content versus a presence of content situation. *European Journal of Marketing*, *44*(11/12), 1700-1724.

Babić Rosario, A., Russell, C.A., & Shanahan, D. (2021). *The Paradox of Social Support in Virtual Support Communities: A Mixed-Method Inquiry of the Social Dynamics in Health and Wellness Facebook Groups*. (Working Paper).

Bagozzi, R. P., & Yi, Y. (2012). Specification, evaluation, and interpretation of structural equation models. *Journal of the Academy of Marketing Science*, *40*(1), 8-34.

Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin*, *88*(3), 588-606.

Bartels, J., & Reinders, M. J. (2011). Consumer innovativeness and its correlates: A propositional inventory for future research. *Journal of Business Research*, *64*(6), 601-609.

Bhatnagar, A., Misra, S., & Rao, H. R. (2000). On risk, convenience, and Internet shopping behavior. *Communications of the ACM*, *43*(11), 98-105.

Broadbent, E., Stafford, R., & MacDonald, B. (2009). Acceptance of Healthcare Robots for the Older Population: Review and Future Directions. *International Journal of Social Robotics*, *1*(4), 319–330.

Brown, H. G., Poole, M. S., & Rodgers, T. L. (2004). Interpersonal traits, complementarity, and trust in virtual collaboration. *Journal of Management Information Systems*, *20*(4), 115-138.

Bitner, M. J., & Hubbert, A. R. (1994). Encounter satisfaction versus overall satisfaction versus quality. *Service Quality: New Directions in Theory and Practice*, *34*(2), 72-94.

Buckley, L., Kaye, S.A., & Pradhan, A.K. (2018). Psychosocial factors associated with intended Use of automated vehicles: A simulated driving study. *Accident Analysis and Prevention.* 202-208.

Burger, J. M., & Cooper, H. M. (1979). The desirability of control. *Motivation and Emotion*, *3*(4), 381-393.

Carter, L., & Bélanger, F. (2005). The utilization of e-government services: citizen trust, innovation and acceptance factors. *Information Systems Journal*, *15*(1), 5-25.

Cazier, J. A., Wilson, E. V., & Medlin, B. D. (2007). The role of privacy risk in IT acceptance: An empirical study. *International Journal of Information Security and Privacy (IJISP)*, *1*(2), 61-73.

Chang, C. C., Yan, C. F., & Tseng, J. S. (2012). Perceived convenience in an extended technology acceptance model: Mobile technology and English learning for college students. *Australasian Journal of Educational Technology*, *28*(5), 809-826.

Choi, J. K., & Ji, Y. G. (2015). Investigating the importance of trust on adopting an autonomous vehicle. *International Journal of Human-Computer Interaction*, *31*(10), 692-702.

Claudy, M. C., Garcia, R., & O'Driscoll, A. (2015). Consumer resistance to innovation—a behavioral reasoning perspective. *Journal of the Academy of Marketing Science*, *43*(4), 528-544.

Cook, D. J., Augusto, J. C., & Jakkula, V. R. (2009). Ambient intelligence: Technologies, applications, and opportunities. *Pervasive and Mobile Computing*, *5*(4), 277-298.

Collier, J. E., & Kimes, S. E. (2013). Only if it is convenient: Understanding how convenience influences self-service technology evaluation. *Journal of Service Research*, *16*(1), 39-51.

Crosby, L. A., Evans, K. R., & Cowles, D. (1990). Relationship quality in services selling: an interpersonal influence perspective. *Journal of Marketing*, *54*(3), 68-81.

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319-340.

Davis, F. D., & Venkatesh, V. (1996). A critical assessment of potential measurement biases in the technology acceptance model: Three experiments. *International Journal of Human-Computer Studies*, *45*(1), 19-45.

Davis, S. M. (1987). Future Perfect. Addison Wesley Publishing Company. *Reading, MA*.

De Kerviler, G., Demoulin, N. T., & Zidda, P. (2016). Adoption of in-store mobile payment: Are perceived risk and convenience the only drivers? *Journal of Retailing and Consumer Services*, *31*, 334-344.

Dean, D. G. (1961). Alienation: Its meaning and measurement. *American Sociological Review*, 753-758.

Deb, S., Strawderman, L., Carruth, D. W., DuBien, J., Smith, B., & Garrison, T. M. (2017). Development and validation of a questionnaire to assess pedestrian receptivity toward fully autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, *84*, 178-195.

Del Bucchia, C., Miltgen, C. L., Russell, C. A., & Burlat, C. (2021). Empowerment as latent vulnerability in techno-mediated consumption journeys. *Journal of Business Research*, *124*, 629-651.

Delgado-Ballester, E. (2004). Applicability of a brand trust scale across product categories: A multigroup invariance analysis. *European Journal of Marketing*, *38*(5/6), 573-592.

Dillon, A., & Morris, M. G. (1996). User Acceptance of Information Technology: Theories and Models. *Annual Review of Information Science and Technology, 31*, 3-32.

Donnelly, L. (2017). Forget Your GP, Robots Will 'Soon Be Able to Diagnose More Accurately than Almost Any Doctor.' *The Telegraph*.

Dorfman, P. W., & Howell, J. P. (1988). Dimensions of national culture and effective leadership patterns: Hofstede revisited. *Advances in International Comparative Management*, *3*, 127–150.

Fagnant, D. J., & Kockelman, K. M. (2014). The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. *Transportation Research Part C: Emerging Technologies*, *40*, 1-13.

Fagnant, D. J., & Kockelman, K. (2015). Pr Urmson ring a nation for autonomous vehicles: opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice*, *77*, 167-181.

Featherman, M. S., Miyazaki, A. D., & Sprott, D. E. (2010). Reducing online privacy risk to facilitate e-service adoption: the influence of perceived ease of use and corporate credibility. *Journal of Services Marketing*, *24*(3), 219-229.

Fishbein, M., & Ajzen, I. (1977). Belief, attitude, intention, and behavior: An introduction to theory and research. *Philosophy and Rhetoric*, *10*(2).

Foehr, J., & Germelmann, C. C. (2020). Alexa, can I trust you? Exploring consumer paths to trust in smart voice-interaction technologies. *Journal of the Association for Consumer Research*, *5*(2), 181-205.

Fornell, C. G., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50.

Foster, D. W., Young, C. M., Bryan, J. L., & Quist, M. C. (2016). Compounding risk: An examination of associations between spirituality/religiosity, drinking motives, and alcohol-related ambivalence among heavy drinking young adults. *Addictive Behaviors*, *63*(1), 1-11.

Fournier, S. (1998). Consumers and their brands: Developing relationship theory in consumer research. *Journal of Consumer Research*, *24*(4), 343-373.

Freud, S. (1918). Totem and Taboo. *The Journal of Nervous and Mental Disease*, *50*(1), 94-95.

Fritz, R. L., Corbett, C. L., Vandermause, R., & Cook, D. (2016). The influence of culture on older adults' adoption of smart home monitoring. *Gerontechnology*, *14*(3), 146-156.

Gambetta, D. (2000). Can we trust trust. *Trust: Making and breaking cooperative relations*, *13*, 213-237.

Garcia, R., Bardhi, F., & Friedrich, C. (2007). Overcoming consumer resistance to innovation. *MIT Sloan Management Review*, *48*(4), 82-88.

Gefen, D. (2004). What makes an ERP implementation relationship worthwhile: Linking trust mechanisms and ERP usefulness. *Journal of Management Information Systems*, *21*(1), 263-288.

Gefen, D., & Straub, D. (2003). Managing user trust in B2C e-services. *e-Service*, *2*(2), 7-24.

Ghazizadeh, M., Lee, J. D., & Boyle, L. N. (2012). Extending the Technology Acceptance Model to assess automation. *Cognition, Technology & Work*, *14*(1), 39-49.

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, *14*(2), 627-660.

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

Goddin, P. (2015). Uber's Plan for Self-Driving Cars Bigger Than Its Taxi Disruption. https://www.govtech.com/fs/perspectives/Ubers-Plan-for-Self-Driving-Cars-Bigger-Than-Its-Taxi-Disruption.html.

Grand View Research (2021, May). Intelligent Virtual Assistant Market Size Worth $51.90 Billion By 2028.

Gregan-Paxton, J., & John, D. R. (1997). Consumer learning by analogy: A model of internal knowledge transfer. *Journal of Consumer Research*, *24*(3), 266-284.

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management*, *49*, 157-169.

Hamby, A., & Russell, C. (2020). Hasty or Hesitant? How "Hot" and "Cold" Ambivalence Influences Risk-Related Behaviors. *Journal of the Academy of Marketing Science*.

Hamby, A., & Russell, C. (2021). *How does ambivalence affect young consumers' response to risky products?* (Working Paper).

Hedlund, J. (n.d.). Autonomous Vehicles Meet Human Drivers: Traffic Safety Issues for States. https://www.ghsa.org/resources/spotlight-av17

Hengstler, M., Enkel, E., & Duelli, S. (2016). Applied artificial intelligence and trust—The case of autonomous vehicles and medical assistance devices. *Technological Forecasting and Social Change*, *105*, 105-120.

Hofstede, G. (2011). Dimensionalizing cultures: The Hofstede model in context. *Online Readings in Psychology and Culture*, *2*(1), 3-26.

Hofstede, G. (1991). Empirical models of cultural differences.

Horton, R. P., Buck, T., Waterson, P. E., & Clegg, C. W. (2001). Explaining Intranet use with the Technology Acceptance Model. *Journal of Information Technology*, *16*(4), 237-249.

Howard, D., & Dai, D. (2014). Public perceptions of self-driving cars: The case of Berkeley, California. In *Transportation Research Board 93rd Annual Meeting*, *14*(4502), pp. 1-16.

Huaman-Ramirez, R., & Merunka, D. (2019). Brand experience effects on brand attachment: the role of brand trust, age, and income. *European Business Review*, *31*(5), 610-645.

Huang, M. H., & Rust, R. T. (2020). Engaged to a Robot? The Role of AI in Service. *Journal of Service Research*, *24*(1), 30-41.

Huang, X., Kristal, M. M., & Schroeder, R. G. (2008). Linking learning and effective process implementation to mass customization capability. *Journal of Operations Management*, *26*(6), 714-729.

Hu, P. J., Chau, P. Y., Sheng, O. R. L., & Tam, K. Y. (1999). Examining the technology acceptance model using physician acceptance of telemedicine technology. *Journal of Management Information Systems*, *16*(2), 91-112.

Hwang, Y. (2009). The impact of uncertainty avoidance, social norms and innovativeness on trust and ease of use in electronic customer relationship management. *Electronic Markets*, *19*(2), 89-98.

Jackson, C. M., Chow, S., & Leitch, R. A. (1997). Toward an understanding of the behavioral intention to use an information system. *Decision sciences*, *28*(2), 357-389.

Jackson, D. L. (2003). Revisiting sample size and number of parameter estimates: Some support for the N: q hypothesis. *Structural equation modeling*, *10*(1), 128-141.

Janis, I. L., & Mann, L. (1977). *Decision making: A psychological analysis of conflict, choice, and commitment*. Free press.

Jansson, J., Marell, A., & Nordlund, A. (2010). Green consumer behavior: determinants of curtailment and eco-innovation adoption. *Journal of Consumer Marketing*, *27*(4), 358-370.

Johnson, M. D., & Fornell, C. (1991). A framework for comparing customer satisfaction across individuals and product categories. *Journal of Economic Psychology*, *12*(2), 267-286.

Johnson-George, C., & Swap, W. C. (1982). Measurement of specific interpersonal trust: Construction and validation of a scale to assess trust in a specific other. *Journal of personality and Social Psychology*, *43*(6), 1306.

Jones, M. A., Mothersbaugh, D. L., & Beatty, S. E. (2000). Switching barriers and repurchase intentions in services. *Journal of Retailing*, *76*(2), 259-274.

Jones, E. C., & Leibowicz, B. D. (2019). Contributions of shared autonomous vehicles to climate change mitigation. *Transportation Research Part D: Transport and Environment*, *72*, 279-298.

Kaiser, H. F., & Rice, J. (1974). Little jiffy, mark IV. *Educational and psychological measurement*, *34*(1), 111-117.

Kaplan, K. J. (1972). On the ambivalence-indifference problem in attitude theory and measurement: A suggested modification of the semantic differential technique. *Psychological bulletin*, *77*(5), 361.

Kaur, K., & Rampersad, G. (2018). Trust in driverless cars: Investigating key factors influencing the adoption of driverless cars. *Journal of Engineering and Technology Management*, *48*, 87-96.

Kleijnen, M., Lee, N., & Wetzels, M. (2009). An exploration of consumer resistance to innovation and its antecedents. *Journal of Economic Psychology*, *30*(3), 344-357.

Kline, R. B. (2015). *Principles and practice of structural equation modeling*. Guilford publications.

Koul, S., & Eydgahi, A. (2018). Utilizing Technology Acceptance Model (TAM) for driverless car technology Adoption. *Journal of Technology Management & Innovation*, *13*(4), 37-46.

Kris, A. O. (1984). The conflicts of ambivalence. *The Psychoanalytic Study of the Child*, *39*(1), 213-234.

Kurzweil, R., Richter, R., Kurzweil, R., & Schneider, M. L. (1990). *The age of intelligent machines* (Vol. 580). MIT press.

Kyriakidis, M., Happee, R., & de Winter, J. C. (2015). Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. *Transportation Research Part F: Traffic Psychology and Behaviour*, *32*, 127-140.

Lancelot Miltgen, C., Cases, A. S., & Russell, C. A. (2019). *Consumers' Responses to Facebook Advertising across PCs and Mobile Phones*. HAL.

Laukkanen, T., Sinkkonen, S., Kivijärvi, M., & Laukkanen, P. (2007). Innovation resistance among mature consumers. *Journal of Consumer Marketing*, *24*(7), 419-427.

Leicht, T., Chtourou, A., & Youssef, K. B. (2018). Consumer innovativeness and intentioned autonomous car adoption. *The Journal of High Technology Management Research*, *29*(1), 1-11.

Lee, J., & Moray, N. (1992). Trust, control strategies and allocation of function in human machine systems. *Ergonomics*, *35*(10), 1243-1270.

Lee, M. K., & Turban, E. (2001). A trust model for consumer internet shopping. *International Journal of Electronic Commerce*, *6*(1), 75-91.

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors*, *46*(1), 50-80.

Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. *Journal of Consumer Research*, *46*(4), 629-650.

Li, H., Wu, J., Gao, Y., & Shi, Y. (2016). Examining individuals' adoption of healthcare wearable devices: An empirical study from privacy calculus perspective. *International journal of medical informatics*, *88*, 8-17.

Li, F., Kashyap, R., Zhou, N., & Yang, Z. (2008). Brand trust as a second-order factor: An alternative measurement model. *International Journal of Market Research*, *50*(6), 817-839.

Lippert, S. K. (2001). *An exploratory study into the relevance of trust in the context of information systems technology*. The George Washington University.

Liu, X., Faes, L., Kale, A. U., Wagner, S. K., Fu, D. J., Bruynseels, A., ... & Ledsam, J. R. (2019). A comparison of deep learning performance against healthcare professionals in detecting diseases from medical imaging: a systematic review and meta analysis. *The Lancet Digital Health*, *1*(6), 271-297.

Livne, G., Simpson, A., & Talmor, E. (2011). Do customer acquisition cost, retention andusage matter to firm performance and valuation? *Journal of Business Finance & Accounting*, *38*(3/4), 334-363.

Madigan, R., Louw, T., Dziennus, M., Graindorge, T., Ortega, E., Graindorge, M., & Merat, N. (2016). Acceptance of Automated Road Transport Systems (ARTS): an adaptation of the UTAUT model. *Transportation Research Procedia*, *14*, 2217-2226.

Nohlen, H, U., van Harreveld, F., Rotteveel, M., Lelieveld, G., & Crone, E. A. (2013). Evaluating ambivalence: Social-cognitive and affective brain regions associated with ambivalent decision-making. *Social Cognitive and Affective Neuroscience*, *9*(7), 924-931.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review*, *20*(3), 709-734.

McCarthy, I. P. (2004). Special issue editorial: the what, why and how of mass customization. *Production Planning & Control*, *15*(4), 347-351.

Menninga, K. M., Dijkstra, A., & Gebhardt, W. A. (2011). Mixed feelings: Ambivalence as a predictor of relapse in ex-smokers. *British Journal of Health Psychology*, *16*(3), 580-591.

Merle, A., Chandon, J. L., Roux, E., & Alizon, F. (2010). Perceived value of the mass customized product and mass customization experience for individual consumers. *Production and Operations Management*, *19*(5), 503-514.

Mick, D. G., & Fournier, S. (1997). *Garden of Paradise Or Paradox?: Coping with Technological Consumer Products in Everyday Life*. Division of Research, Harvard Business School.

Milakis, D., Van Arem, B., & Van Wee, B. (2017). Policy and society related implications of automated driving: A review of literature and directions for future research. *Journal of Intelligent Transportation Systems*, *21*(4), 324-348.

Miltgen, C. L., Cases, A. S., & Russell, C. A. (2019). Consumers' Responses to Facebook Advertising across PCs and Mobile Phones: A Model for Assessing the Drivers Of Approach and Avoidance of Facebook Ads. *Journal of Advertising Research*, *59*(4), 414-432.

Oser, M. L., McKellar, J., Moos, B. S., & Moos, R. H. (2010). Changes in ambivalence mediate the relation between entering treatment and change in alcohol use and problems. *Addictive Behaviors*, *35*(4), 367-369.

Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. *Human Factors*, *39*(2), 230-253.

Parasuraman, A. (2000). Technology Readiness Index (TRI) a multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research*, *2*(4), 307-320.

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2008). Situation awareness, mental workload, and trust in automation: Viable, empirically supported cognitiveengineering constructs. *Journal of Cognitive Engineering and Decision Making*, *2*(2), 140-160.

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce*, *7*(3), 101-134.

Payre, W., Cestac, J., & Delhomme, P. (2014). Intention to use a fully automated car: Attitudes and a priori acceptability. *Transportation Research*, *27*, 252-263.

Plambeck, N., & Weber, K. (2009). CEO ambivalence and responses to strategic issues. *Organization Science, 20*(6), 993-1010.

Paulhus, D. (1983). Sphere-specific measures of perceived control. *Journal of Personality and Social Psychology*, *44*(6), 1253-1265.

Priester, J. R., & Petty, R. E. (1996). The gradual threshold model of ambivalence: relating the positive and negative bases of attitudes to subjective ambivalence. *Journal of Personality and Social Psychology*, *71*(3), 431-449.

Priester, J. R., Petty, R. E., & Park, K. (2007). Whence univalent ambivalence? From the anticipation of conflicting reactions. *Journal of Consumer Research*, *34*(1), 11-21.

Pine, B. J. (1993). *Mass customization* (Vol. 17). Boston: Harvard business school press.

Rahman, M. M., Lesch, M. F., Horrey, W. J., & Strawderman, L. (2017). Assessing the utility of TAM, TPB, and UTAUT for advanced driver assistance systems. *Accident Analysis & Prevention*, *108*, 361-373.

Ram, S. (1987). A model of innovation resistance. *ACR North American Advances*.

Ram, S., & Sheth, J. N. (1989). Consumer resistance to innovations: the marketing problem and its solutions. *Journal of Consumer Marketing*, *6*(2), 5-14.

Ratchford, M., & Barnhart, M. (2012). Development and validation of the technology adoption propensity (TAP) index. *Journal of Business Research*, *65*(8), 1209-1215.

Reinhardt, R., & Gurtner, S. (2015). Differences between early adopters of disruptive and sustaining innovations. *Journal of Business Research*, *68*(1), 137-145.

Rogers, E. M. (2003). Diffusion of innovations. Free Press. *551*.

Ruel, E., Wagner III, W. E., & Gillespie, B. J. (2015). *The practice of survey research: Theory and applications*. Sage Publications.

Russel, S., & Norvig, P. (2013). *Artificial intelligence: a modern approach*. Pearson Education Limited.

Satorra, A., & Bentler, P. M. (1994). Corrections to test statistics and standard errors in covariance structure analysis. In A. von Eye & C. C. Clogg (Eds.), *Latent variables analysis: Applications for developmental research* (pp. 399–419). Sage Publications, Inc.

Sheth, J. N., & Parvatlyar, A. (1995). Relationship marketing in consumer markets: antecedents and consequences. *Journal of the Academy of Marketing Science*, *23*(4), 255-271.

Schmider, E., Ziegler, M., Danay, E., Beyer, L., & Bühner, M. (2010). Is it really robust? *Methodology*, *6*, 147-151.

Schoettle, B., & Sivak, M. (2014). *A survey of public opinion about autonomous and self driving vehicles in the US, the UK, and Australia*. University of Michigan, Ann Arbor, Transportation Research Institute.

Silberg, G., Wallace, R., Matuszak, G., Plessers, J. (2012). Self-driving cars: The next revolution. *White paper, KPMG LLP.*

Smith, C. A., & Kirby, L. D. (2011). The role of appraisal and emotion in coping and adaptation. *The handbook of stress science: Biology, psychology, and health*, 195-208.

Shiu, E. M., Walsh, G., Hassan, L. M., & Shaw, D. (2011). Consumer uncertainty, revisited. *Psychology & Marketing, 28*(6), 584-607.

Squire, B., Brown, S., Readman, J., & Bessant, J. (2006). The impact of mass customisation on manufacturing trade-offs. *Production and Operations Management*, *15*(1), 10-21.

Statista (2021, June 22). Projected size of the global autonomous car market from 2019 to 2023.

Subramanian, G. H. (1994). A replication of perceived usefulness and perceived ease of use measurement. *Decision Sciences*, *25*(5-6), 863-874.

Suresh, P., & Manivannan, P. V. (2014). Reduction of vehicular pollution through fuel economy improvement with the use of autonomous self-driving passenger cars. *Journal of Environmental Research and Development*, *8*(3A), 705.

Sundar, S. S., Waddell, T. F., & Jung, E. H. (2016). The Hollywood Robot Syndrome media effects on older adults' attitudes toward robots and adoption intentions. In *2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI)* (pp. 343-350). IEEE.

Thompson, M. M., Zanna, M. P., & Griffin, D. W. (1995). Let's not be indifferent about (attitudinal) ambivalence. *Attitude strength: Antecedents and consequences*, *4*, 361-386.

Tu, Q., Vonderembse, M. A., & Ragu-Nathan, T. S. (2001). The impact of time-based manufacturing practices on mass customization and value to customer. *Journal of Operations Management*, *19*(2), 201-217.

van Harreveld, F., Van der Pligt, J., & de Liver, Y. N. (2009). The agony of ambivalence and ways to resolve it: Introducing the MAID model. *Personality and Social Psychology Review*, *13*(1), 45-61.

Vandenberg, R. J., & Lance, C. E. (2000). A review and synthesis of the measurement invariance literature: Suggestions, practices, and recommendations for organizational research. *Organizational Research Methods*, *3*(1), 4-70.

Venkatesh, V. & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, *46*(2):186-204.

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

Wadud, Z., MacKenzie, D., & Leiby, P. (2016). Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. *Transportation Research Part A: Policy and Practice*, *86*, 1-18.

Wang, S. W., Ngamsiriudom, W., & Hsieh, C. H. (2015). Trust disposition, trust antecedents, trust, and behavioral intention. *The Service Industries Journal*, *35*(10), 555-572.

Westaby, J. D., Probst, T. M., & Lee, B. C. (2010). Leadership decision-making: A behavioral reasoning theory analysis. *The Leadership Quarterly*, *21*(3), 481-495.

Winston, P. H. (1992). Artificial Intelligence (Third edition). Addison-Wesley.

Wu, J., Liao, H., Wang, J. W., & Chen, T. (2019). The role of environmental concern in the public acceptance of autonomous electric vehicles: A survey from China. *Transportation Research Part F: Traffic Psychology and Behaviour*, *60*, 37-46.

Wu, K., Zhao, Y., Zhu, Q., Tan, X., & Zheng, H. (2011). A meta-analysis of the impact of trust on technology acceptance model: Investigation of moderating influence of subject and context type. *International Journal of Information Management*, *31*(6), 572-581.

Xu, Z., Zhang, K., Min, H., Wang, Z., Zhao, X., & Liu, P. (2018). What drives people to accept automated vehicles? Findings from a field experiment. *Transportation Research Part C: Emerging Technologies*, *95*, 320-334.

Yousafzai, S.Y., Foxall G.R., & Pallister J.G., (2007). Technology acceptance: a meta-analysis of the TAM: Part 1. *Journal of Modelling in Management*, *2*, 251-280.

Yang, K. C. (2005). Exploring factors affecting the adoption of mobile commerce in Singapore. *Telematics and Informatics*, *22*(3), 257-277.

Zhang, T., Tao, D., Qu, X., Zhang, X., Lin, R., & Zhang, W. (2019). The roles of initial trust and perceived risk in public's acceptance of automated vehicles. *Transportation Research Part C: Emerging Technologies*, *98*, 207-220.

Ziefle, M., & Valdez, A. C. (2017). Domestic robots for homecare: a technology acceptance perspective. In *International Conference on Human Aspects of IT for the Aged Population* (pp. 57-74). Springer, Cham.

Zimmerman, M. A., & Zahniser, J. H. (1991). Refinements of sphere-specific measures of perceived control: Development of a sociopolitical control scale. *Journal of Community Psychology*, *19*(2), 189-204.

Zmud, J., Sener, I. N., & Wagner, J. (2016). Consumer acceptance and travel behavior: impacts of automated vehicles (No. PRC 15-49 F). Texas A&M Transportation Institute.

TABLES

Table 1. Literature Review of Facilitating Factors

Study	Research Context	Main Findings	First-Order Factor Categorization	Second-Order Factor Categorization
Collier & Kimes (2013	Evaluation of self-service technologies (SST)	Convenience had a strong positive effect on consumer's perceptions of accuracy, speed, and exploration intentions.	Convenience	Facilitator
De Kerviler et al. (2016)	Adoption of mobile payment technology	Perceived benefits (convenience) and risks have a strong impact on mobile payment technology	Convenience	Facilitator
Chang et al. (2012)	Acceptance of mobile technology	Perceived convenience, perceived ease of use, and perceived usefulness were antecedent factors that affected the acceptance of English mobile learning.	Convenience	Facilitator
Merle et al. (2010)	Mass customization	Mass customization value from a consumer viewpoint is polymorphous, with two higher-order dimensions: product value and experience value.	Customization	Facilitator
Xu et al. (2014)	Mass customization	Service leadership and customization-personalization control have significant direct impacts on information and communication technology (ICT) service providers' brand equity.	Customization	Facilitator
Gursoy et al. (2019)	AI device use and acceptance	Both performance and effort expectancy are significant antecedents of customer emotions, which determines customers' acceptance of AI device use in service encounters.	Efficiency	Facilitator
Claudy et al. (2015)	Adoption of Innovation / behavioral reasoning theory	Reasons *for* and *against* adoption are context-specific and are qualitatively different from each other, and consumers use different psychological paths when evaluating different types of innovations.	Efficiency	Facilitator
Parasuraman (2000)	Technology readiness (TR) to embrace new technology	The results for the four TR components suggest that although people are generally optimistic about technology, they also experience a considerable amount of insecurity concerning its role.	Efficiency, Convenience	Facilitator

Table 2. Literature Review of Inhibiting Factors

Study	Research Context	Main Findings	First-Order Factor Categorization	Second-Order Factor Categorization
Lee & Turban, (2001)	Internet shopping / Trust model	The findings indicate that merchant integrity is a major positive determinant of consumer trust in Internet shopping and that its effect is moderated by the individual consumer's trust propensity.	Uncertainty	Inhibitor
Kailani & Kumar, (2010)	Uncertainty Avoidance / Internet shopping	Results indicate that in cultures where uncertainty avoidance is high, the perceived risk with the internet buying is also high, which negatively impacts internet buying.	Uncertainty	Inhibitor
Miltgen et al. (2019)	Assessing the drivers advertising	Results show that the trade-off between the intrinsic and social value Facebook advertisements bring and their perceived intrusiveness and privacy invasiveness drives consumers' approach and avoidance of Facebook advertising.	Privacy Risk	Inhibitor
Kyriakidis et al. (2015)	Intentions to purchase AVs	Respondents were found to be most concerned about software hacking/misuse and were also concerned about legal issues and safety.	Privacy Risk	Inhibitor

Li et al. (2016)	Adoption of healthcare technology	The individuals' decisions to adopt healthcare wearable devices are determined by their risk-benefit analyses (refer to privacy calculus). If an individual's perceived benefit is higher than the perceived privacy risk, s/he is more likely to adopt the device. Otherwise, the device would not be adopted.	Privacy Risk	Inhibitor
Cazier et al. (2007)	Technology acceptance	Privacy risk factors are found to negatively influence intention to use technology and highlight the importance of privacy risk in the use of IT.	Privacy Risk	Inhibitor
Ziefle & Valdez, (2017)	Technology Acceptance	While overall a positive attitude towards home care robots was found, serious concerns in terms of fear of loss of control and connection to family members are prevailing.	Loss of Control	Inhibitor
Burger & Cooper (1979)	Desirability of Control Scale	The findings suggest that individual differences in the motivation for control interact with situational variables to create the perception of control over outcomes that are chance determined.	Loss of Control	Inhibitor

Table 10

Constructs, Subconstructs, Items, and Sources

Constructs	Subconstruct	Item ID	Item	Sources
DV	Intention to Use	ITU1	I am likely to use [X].	Venkatesh and Davis (2000)
		ITU1	I am likely to continue using [X]	
		ITU2	I would like to use [X].	
		ITU2	I will continue using [X]	
		ITU3	I intend to use [X].	
		ITU3	I intend to continue using [X]	
Facilitators	Perceived Customization	CUST2	I would enjoy having [X] tailored to my needs.	Merle et al.(2010)
		CUST3	The customization enabled by [X] would be very valuable.	
		CUST4	I would enjoy having [X] adapted to my needs.	New
	Perceived Convenience	CON3	I would value the ability to receive services from [X] wherever I am.	Collier & Kimes (2013)
		CON5	I would enjoy the flexibility that [X] provide.	New
		CON7	[X] would make my life easier.	New
	Perceived Efficiency	EFF2	I would save time by using [X].	New
		EFF5	I would be more efficient thanks to [X].	New
		EFF6	[X] would help me to do my tasks quicker and easier.	New

Constructs	Subconstruct	Item ID	Item	Sources
Inhibitors	Perceived Uncertainty	UR1	I am worried about not knowing how [X] would make decisions for me.	New
		UR5	[X] cannot be trusted; there are just too many uncertainties.	Lee & Turban, (2001)
		UR6	Using [X] entails uncertainty.	
	Perceived Privacy Risk	PR1	I am concerned that [X] would collect too much personal information from me.	Kyriakidis et al. (2015a); Zhang et al. (2019)
		PR2	I am concerned that [X] would use my personal information for other purposes without my authorization.	
		PR4	I worry that [X] would invade my privacy.	Miltgen et al. (2019)
	Perceived Locus of Control Risk	LOC2	I worry about [X] taking full control.	Zimmerman and Zahnister, (1991); Dean, (1961)
		LOC4	Even when I'm feeling self-confident about most things, I may still lack the ability to control [X].	Paulhus (1983
		LOC5	I worry that [X] would take too much control.	New

Constructs	Subconstruct	Item ID	Item	Sources
Brand Trust	Brand Reliability	BR2	I feel confident in [X brand].	Delgado (2004)
		BR3	[X brand] is a reliable company.	
		BR4	I can always trust the performance of [X brand] to be good.	
	Brand Benevolence	BB2	I believe that [X brand] places the customers' interests first.	Gefen & Straub (2004); Crosby, Evans, & Cowles (1990)
		BB4	[X brand] cares about my needs.	Li et al. (2008); Huaman-Ramirez & Merunka (2019)
		BB5	[X brand] gives me a sense of security.	
	Trust Disposition	DIS1	I generally trust other people.	Gefen & Straub (2004); Wang et al. (2015)
		DIS2	I tend to count upon other people.	
		DIS3	I feel that people are generally reliable.	
	Subjective Ambivalence	AMB1	I have strong mixed feelings both for and against using [X].	Priester et al. (2007); Hamby & Russell (2021)
		AMB2	I feel divided between the positive and negative sides of [X].	
		AMB3	I feel an inner conflict while thinking about using [X].	

Constructs	Subconstruct	Item ID	Item	Sources
	Perceived Ease of Use	PEOU1	Learning to use [X] would be easy for me.	Davis et al. (1989)
		PEOU2	I would find it easy to get [X] to do what I want to do.	
		PEOU3	I would find [X] easy to use.	
	Perceived Usefulness	PU1	Using [X] would be useful in meeting my needs.	Davis et al. (1989)
		PU2	Using [X] would increase my effectiveness.	
		PU3	I would find [X] to be useful.	

Items were measured with a seven-point Likert scale. Strongly Disagree=1, Strongly Agree=7

APPENDIX A: IRB APPROVAL LETTER

PEPPERDINE

Pepperdine University
24255 Pacific Coast Highway
Malibu, CA 90263
TEL: 310-506-4000

NOTICE OF APPROVAL FOR HUMAN RESEARCH

Date: December 10, 2020

Protocol Investigator Name: George Dagliyan

Protocol #: 20-08-1433

Project Title: ADOPTION OF AI-ENABLED TECHNOLOGY: TAKING THE BAD WITH THE GOOD

School: Graziadio School of Business and Management

Dear Dagliyan:

Thank you for submitting your amended exempt application to Pepperdine University's Institutional Review Board (IRB). We appreciate the work you have done on your proposal. The IRB has reviewed your submitted IRB application and all ancillary materials. Upon review, the IRB has determined that the above entitled project meets the requirements for exemption under the federal regulations 45 CFR 46.101 that govern the protections of human subjects.

Your research must be conducted according to the proposal that was submitted to the IRB. If changes to the approved protocol occur, a revised protocol must be reviewed and approved by the IRB before implementation. For any proposed changes in your research protocol, please submit an amendment to the IRB. Since your study falls under exemption, there is no requirement for continuing IRB review of your project. Please be aware that changes to your protocol may prevent the research from qualifying for exemption from 45 CFR 46.101 and require submission of a new IRB application or other materials to the IRB.

A goal of the IRB is to prevent negative occurrences during any research study. However, despite the best intent, unforeseen circumstances or events may arise during the research. If an unexpected situation or adverse event happens during your investigation, please notify the IRB as soon as possible. We will ask for a complete written explanation of the event and your written response. Other actions also may be required depending on the nature of the event. Details regarding the timeframe in which adverse events must be reported to the IRB and documenting the adverse event can be found in the ***Pepperdine University Protection of Human Participants in Research: Policies and Procedures Manual*** at community.pepperdine.edu/irb.

Please refer to the protocol number denoted above in all communication or correspondence related to your application and this approval. Should you have additional questions or require clarification of the contents of this letter, please contact the IRB Office. On behalf of the IRB, I wish you success in this scholarly pursuit.

Sincerely,

Judy Ho, IRB Chairperson

cc: Dr. Lee Kats, Vice Provost for Research and Strategic Initiatives

Mr. Brett Leach, Regulatory Affairs Specialist

Page: 1

APPENDIX B: CONSENT FORM

PEPPERDINE | GRAZIADIO BUSINESS SCHOOL

IRB Number: 20-08-1433

Study Title: **Adoption of AI-Enabled Technology: Taking the Bad with the Good**

Dear Participant,
My name is George Dagliyan. I am conducting a study on the adoption of Artificial Technology (AI). Artificial Intelligence (AI) enabled technologies are increasingly common in people's lives: from smart home assistants to self-driving cars. The primary purpose of this study is to assess consumers' perceptions of these AI-enabled technologies in order to understand the interplay between the benefit and risk factors of consumer adoption of AI-enabled technology. If you are 19 years of age or older, you may participate in this research.

There are no direct benefits to you, the Participant. However, your involvement will greatly advance the technology acceptance knowledge and our understanding of the nuances of consumers' perceptions in technology acceptance.

Participation in this research project requires one survey, which will take approximately 15 minutes to complete by Qualtrics. The risks associated with this anonymous and confidential online research are minimal. Participants may experience minor discomfort when answering questions related to the privacy risks of the technology under study. The answers you provide will remain confidential because you will only be identified by a random code, and the results will be reported such that no individual can be identified.

You may ask any questions concerning this research and have those questions answered before agreeing to participate in or during the study. For study-related questions, please contact Amanda Oswald of Qualtrics at (385) 241-3738. For questions concerning your rights or complaints about the research, contact the Pepperdine University Institutional Review Board (IRB) at (310)568-2305 or gpsirb@pepperdine.edu.

You can decide not to be in this research study, or you can stop being in this research study ("withdraw') at any time before, during, or after the research begins for any reason. Deciding not to be in this research study or choosing to withdraw will not affect your relationship with Qualtrics. You will not lose any benefits to which you are entitled from Qualtrics.
I truly appreciate your time and help with this study and, thus, my dissertation work.
You are voluntarily making a decision whether or not to participate in this research study. By clicking on the, I Agree button below, your consent to participate is implied. You should print a copy of this page for your records.

I agree

I do not agree

APPENDIX C: RETAINED AND DELETED ITEMS

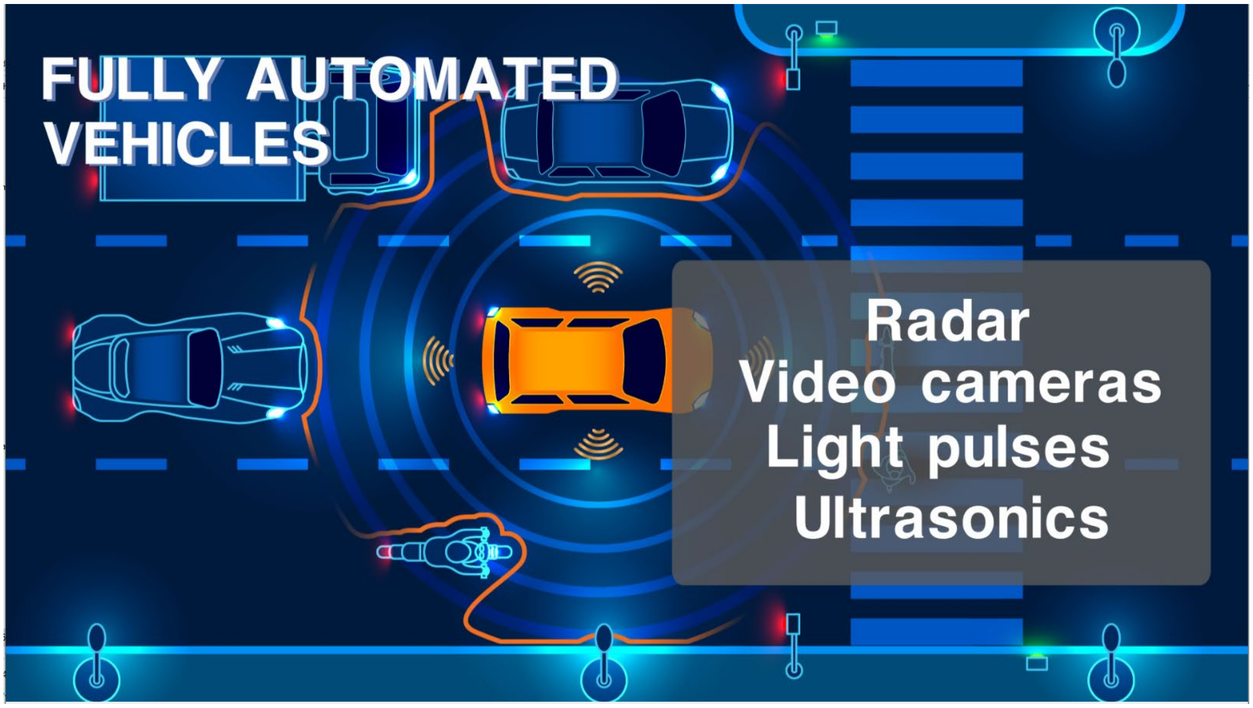
Constructs, Subconstructs, Items, and Sources

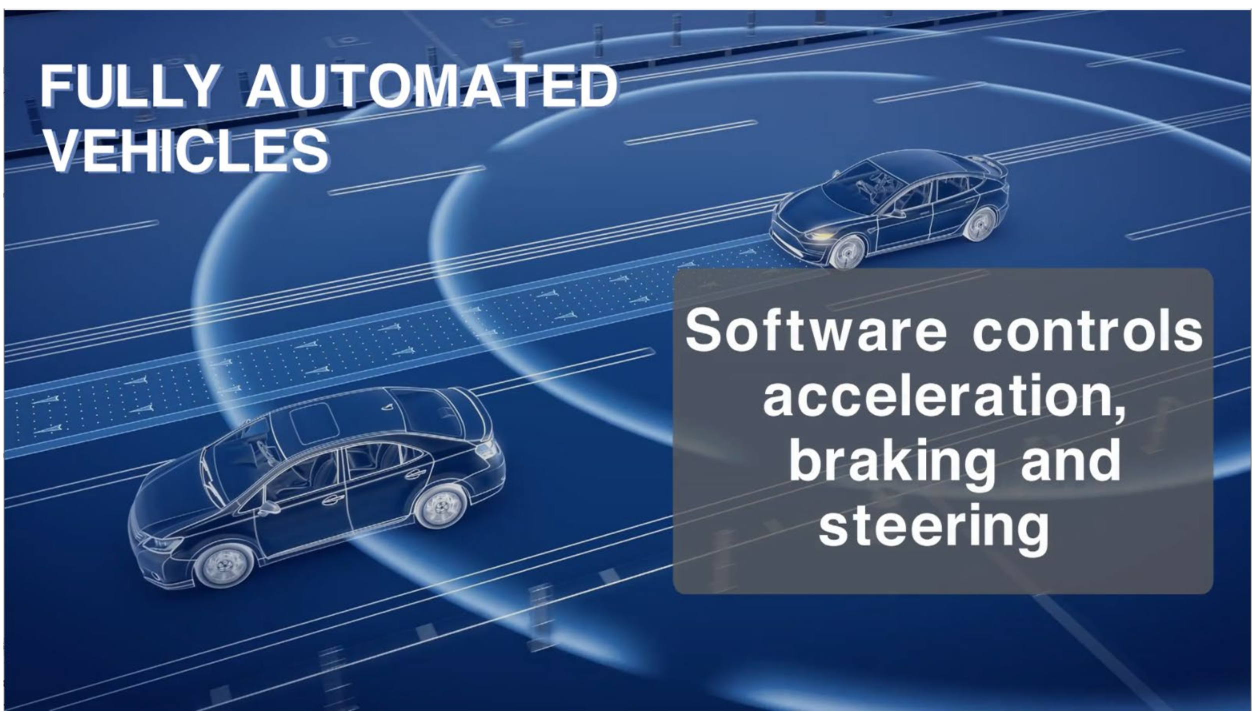
Subconstruct	Item ID	Item	Status
Intention to Use	ITU1	I am likely to use [X].	Retained
	ITU2	I would like to use [X].	Retained
	ITU3	I intend to use [X].	Retained
Perceived Customization	CUST1	With [X], I would have customized services that others will not have.	
	CUST2	I would enjoy having [X] tailored to my needs.	Retained
	CUST3	The customization enabled by [X] would be very valuable.	Retained
	CUST4	I would enjoy having [X] adapted to my needs.	Retained
	CUST5	I would feel more connected to [X] because it would be tailored for me.	Deleted
	CUST6	It would be very useful to receive information and services from [X] that are customized for me.	
Perceived Convenience	CON1	[X] would allow me to receive services whenever I choose.	Deleted
	CON2	[X] would allow me to receive services at a convenient time.	Deleted
	CON3	I would value the ability to receive services from [X] wherever I am.	Retained
	CON4	[X] would help me coordinate my activities	Deleted
	CON5	I would enjoy the flexibility that [X] provide.	Retained
	CON6	[X] would be convenient to use	Deleted
	CON7	[X] would make my life easier.	Retained
Perceived Efficiency	EFF1	Using [X] would save me time to do other things.	Deleted
	EFF2	I would save time by using [X].	Retained
	EFF3	[X] would lower the cost of __________(transportation, health care, goods and services)	Deleted
	EFF4	I would save money by using [X].	
	EFF5	I would be more efficient thanks to [X].	Retained
	EFF6	[X] would help me to do my tasks quicker and easier.	Retained
Perceived Uncertainty	UR1	I am worried about not knowing how [X] would make decisions for me.	Retained
	UR2	The information available about [X] is unclear to me.	Deleted
	UR3	I don't understand exactly how [X] works.	Deleted
	UR4	I'm not sure about how [X] would perform.	Deleted
	UR5	[X] cannot be trusted; there are just too many uncertainties.	Retained
	UR6	Using [X] entails uncertainty.	Retained

Perceived Privacy Risk	PR1	I am concerned that [X] would collect too much personal information from me.	Retained
	PR2	I am concerned that [X] would use my personal information for other purposes without my authorization.	Retained
	PR3	I am concerned that [X] would share my personal information with other entities without my authorization.	Deleted
	PR4	I worry that [X] would invade my privacy.	Retained
	PR5	I worry that [X] would intrude on my privacy.	Deleted
	PR6	I worry that [X] would compromise my privacy.	Deleted
Perceived Loss of Control Risk	LOC1	[X] does(do) not provide enough control.	Deleted
	LOC2	I worry about [X] taking full control.	Retained
	LOC3	I prefer to avoid situations where [X] would tell me what I should do.	Deleted
	LOC4	Even when I'm feeling self-confident about most things, I may still lack the ability to control [X].	Retained
	LOC5	I worry that [X] would take too much control.	Retained
	LOC6	It is important to me that I can control what [X] could do with my information.	Deleted
Brand Reliability	BR1	[Brand] meets my expectations	Deleted
	BR2	I feel confident in [X brand].	Retained
	BR3	[X brand] is a reliable company.	Retained
	BR4	I can always trust the performance of [X brand] to be good.	Retained
	BR5	I could rely on [Brand] to solve any problem.	Deleted
	BR6	I can always trust the performance of [Brand] to be good.	Deleted
Brand Benevolence	BB1	I would count on [Brand] to consider how its actions affect me.	Deleted
	BB2	I believe that [X brand] places the customers' interests first.	Retained
	BB3	[Brand] is well-meaning.	Deleted
	BB4	[X brand] cares about my needs.	Retained
	BB5	[X brand] gives me a sense of security.	Retained
Trust Disposition	DIS1	I generally trust other people.	Retained
	DIS2	I tend to count upon other people.	Retained
	DIS3	I feel that people are generally reliable.	Retained
Subjective Ambivalence	AMB1	I have strong mixed feelings both for and against using [X].	Retained
	AMB2	I feel divided between the positive and negative sides of [X].	Retained
	AMB3	I feel an inner conflict while thinking about using [X].	Retained

Perceived Ease of Use	PEOU1	Learning to use [X] would be easy for me.	Retained
	PEOU2	I would find it easy to get [X] to do what I want to do.	Retained
	PEOU3	I would find [X] easy to use.	Retained
Perceived Usefulness	PU1	Using [X] would be useful in meeting my needs.	Retained
	PU2	Using [X] would increase my effectiveness.	Retained
	PU3	I would find [X] to be useful.	Retained

APPENDIX D: DESCRIPTION OF AVS / VIDEO TRANSCRIPTION AND IMAGES





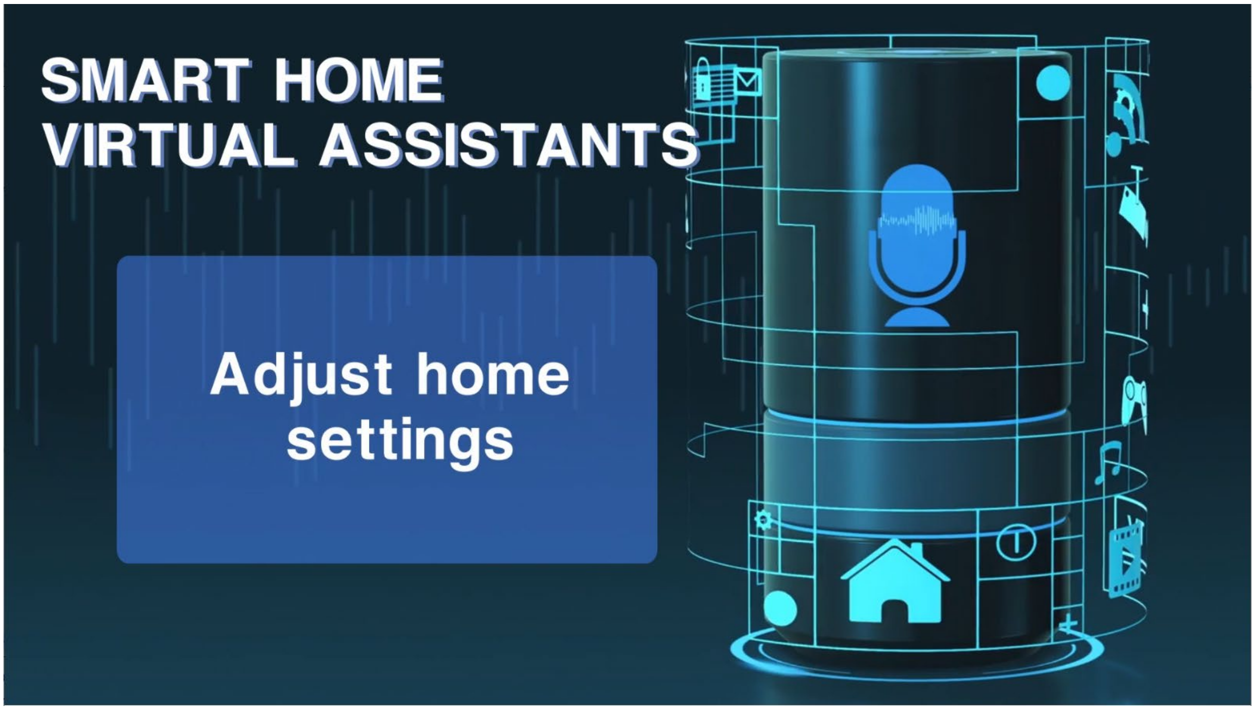
Fully automated vehicles can navigate from one location to another without any assistance from a driver. They create and maintain a map of their surroundings based on a variety of sensors.

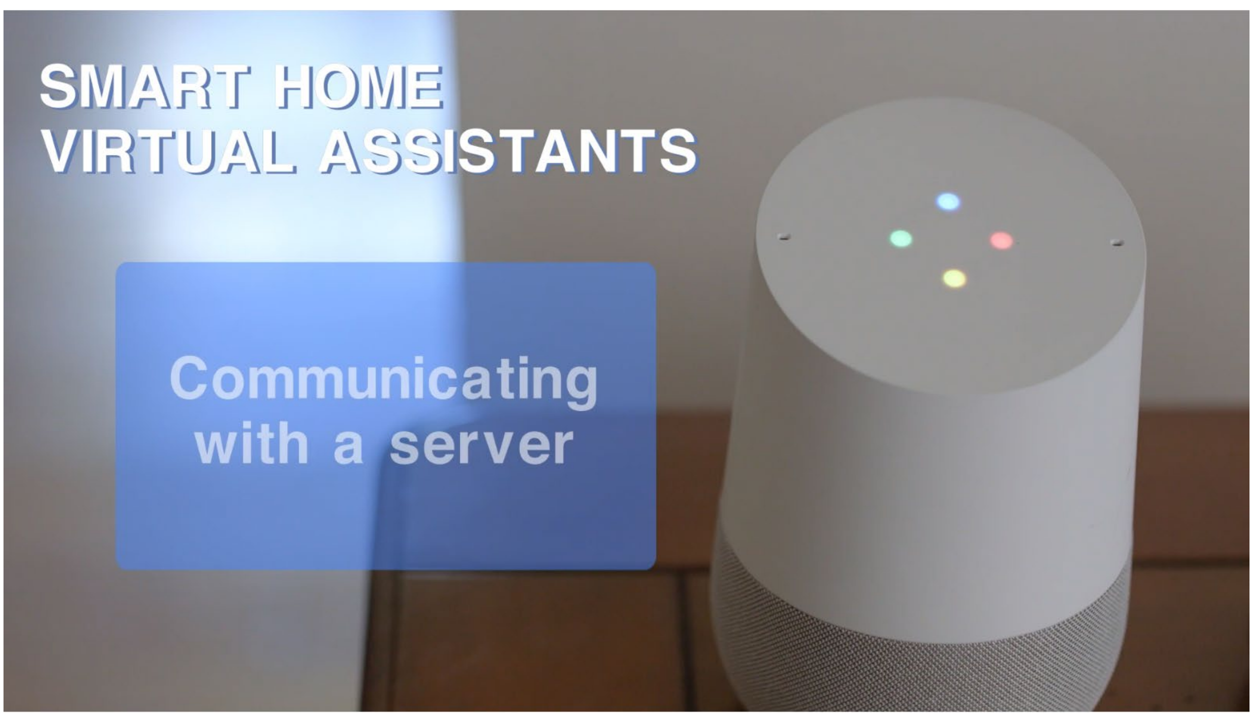
- Radar monitors the position of nearby vehicles.
- Video cameras detect other vehicles, traffic lights, read road signs and look for pedestrians.
- Light pulses bounce off the car's surroundings to measure distances, detect road edges, and identify lane markings.
- Ultrasonics in the wheels detect curbs and other vehicles when parking.

Integrated software then processes all this information to control acceleration, braking, and steering, while hard-coded rules, obstacle avoidance algorithms, predictive modelling, and object recognition help the software follow traffic rules and navigate obstacles.

Video Link: https://www.youtube.com/watch?v=xsZyigzLLo8

APPENDIX E: DESCRIPTION OF SHVA / VIDEO TRANSCRIPTION AND IMAGES

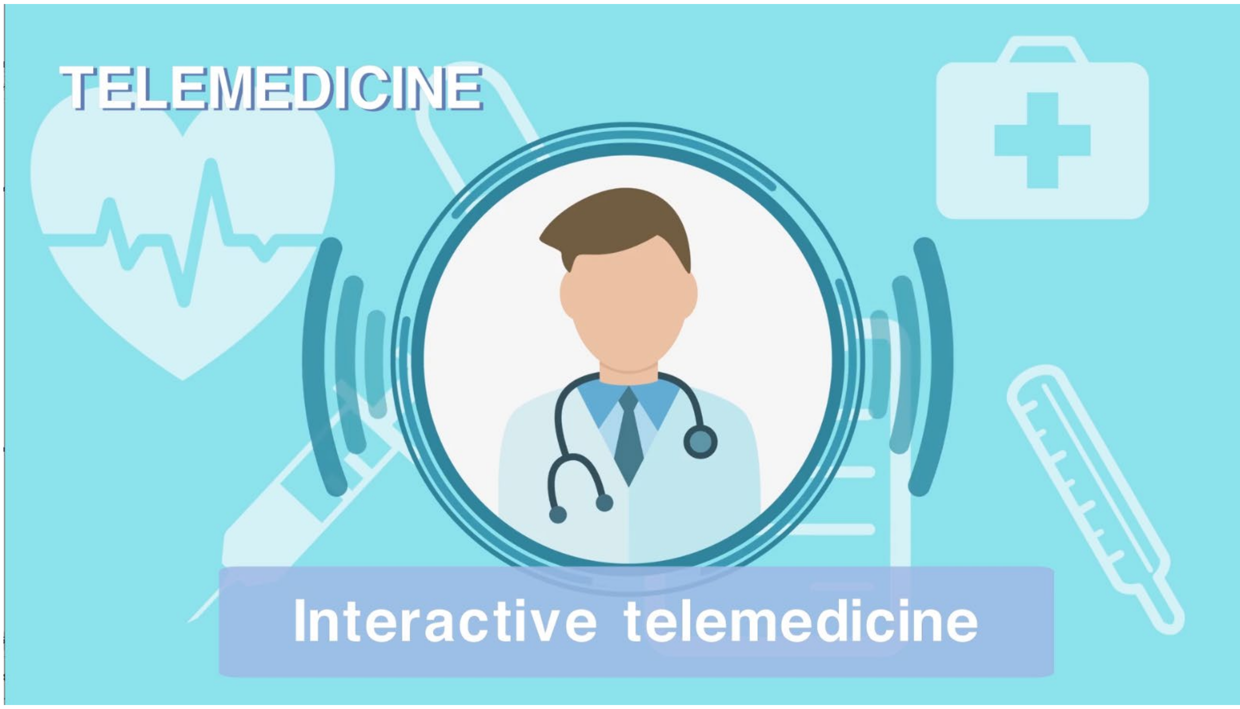




Smart home virtual assistants are internet-connected, voice-controlled devices located within the home. They can perform a variety of actions after hearing a wake word or command. Wake words rely on a special algorithm that is waiting to hear a particular word or phrase. When heard, the device activates and begins communicating with a server. The assistants communicate as a digital voice that can recognize spoken commands and then talk back. This means it can answer questions and perform certain tasks such as playing music, answering questions, and setting alarms. When linked with other available smart home technology - such as lightbulbs, thermostats, plugs, and security systems - smart home virtual assistants can adjust home settings to suit a schedule.

Video Link: https://www.youtube.com/watch?v=NNVDSUL3Lrc

APPENDIX F: DESCRIPTION OF TM / VIDEO TRANSCRIPTION AND IMAGES



Described as 'healthcare from a distance,' telemedicine uses a range of telecommunication platforms – such as apps and video conferencing - to provide the virtual delivery of healthcare without an in-person visit. Telemedicine is defined in three main categories:

- Interactive Telemedicine: This allows physicians and patients to communicate in real-time from home or a medical kiosk. An example of this would be a telephone or video consultation between patient and doctor.
- Remote patient monitoring: This allows patients to be monitored in their homes using mobile devices that collect data about temperature, blood sugar levels, blood pressure, or other vital signs.
- Store-and-forward**:** Healthcare providers can also access clinical information, such as lab results, collected at other locations.

Video Link: https://www.youtube.com/watch?v=mPNe0d5Xl_s

APPENDIX G: PRETEST EFA FOR STUDY 1

Phase 1: Summary of Exploratory Factor Analysis Results Study 1 (N=210)

		Facilitators	Inhibitors	Brand Trust	Ambivalence
CUST2	I would enjoy having [X] tailored to my needs.	**0.932**	0.032	-0.037	0.001
CUST3	The customization enabled by [X] would be very valuable.	**0.840**	-0.055	0.028	-0.068
CUST4	I would enjoy having [X] adapted to my needs.	**0.939**	0.049	-0.012	0.015
CON3	I would value the ability to receive services from [X] wherever I am.	**0.730**	-0.074	0.170	-0.048
CON5	I would enjoy the flexibility that [X] provide.	**0.880**	-0.022	0.054	-0.050
CON7	[X] would make my life easier.	**0.904**	-0.032	-0.016	-0.008
EFF2	I would save time by using [X].	**0.820**	0.017	0.040	-0.053
EFF5	I would be more efficient thanks to [X].	**0.845**	-0.004	0.082	-0.019
EFF6	[X] would help me to do my tasks quicker and easier.	**0.862**	-0.005	0.065	-0.039
UR1	I am worried about not knowing how [X] would make decisions for me.	-0.137	**0.653**	-0.013	-0.223
UR5	[X] cannot be trusted; there are just too many uncertainties.	-0.405	**0.576**	0.014	-0.105
UR6	Using [X] entails uncertainty.	-0.187	**0.519**	-0.142	-0.200
PR1	I am concerned that [X] would collect too much personal information from me.	0.092	**0.838**	-0.054	-0.004
PR2	I am concerned that [X] would use my personal information for other purposes without my authorization.	0.159	**0.774**	0.021	0.059
PR4	I worry that [X] would invade my privacy.	0.089	**0.850**	-0.067	0.066
LOC2	I worry about [X] taking full control.	-0.172	**0.718**	0.023	-0.088
LOC4	Even when I'm feeling self-confident about most things, I may still lack the ability to control [X].	-0.184	**0.484**	0.032	-0.091
LOC5	I worry that [X] would take too much control.	-0.190	**0.739**	-0.009	-0.034
AMB1	I have strong mixed feelings both for and against using [X].	0.129	-0.007	-0.047	**-0.831**
AMB2	I feel divided between the positive and negative sides of [X].	0.098	-0.060	0.025	**-0.906**
AMB3	I feel an inner conflict while thinking about using [X].	-0.042	0.097	0.035	**-0.667**
BR2	I feel confident in [X brand].	0.070	-0.027	**0.835**	-0.018
BR3	[X brand] is a reliable company.	-0.095	-0.065	**0.963**	-0.041
BR4	I can always trust the performance of [X brand] to be good.	0.004	-0.043	**0.897**	-0.014

BB2	I believe that [X brand] places the customers' interests first.	-0.005	0.037	**0.905**	-0.005
BB4	[X brand] cares about my needs.	0.071	0.085	**0.887**	0.070
BB5	[X brand] gives me a sense of security.	0.049	-0.001	**0.909**	0.006
	Eigenvalues	**12.593**	**4.888**	**2.844**	**1.341**
	% 0f variance	**44.768**	**17.850**	**9.723**	**4.962**
	α	**0.973**	**0.927**	**0.965**	**0.852**

Extraction Method: Principal Axis Factoring.
Rotation Method: Oblimin with Kaiser Normalization.

APPENDIX H: PRETEST EFA FOR STUDY 2

Phase 1: Summary of Exploratory Factor Analysis Results Study 2 (N=169)

		Facilitators	Inhibitors	Brand Trust	Ambivalence
CUST2	I would enjoy having [X] tailored to my needs.	**0.908**	-0.037	-0.068	-0.020
CUST3	The customization enabled by [X] would be very valuable.	**0.887**	-0.027	-0.046	-0.087
CUST4	I would enjoy having [X] adapted to my needs.	**0.887**	-0.111	-0.004	-0.028
CON3	I would value the ability to receive services from [X] wherever I am.	**0.835**	-0.071	0.015	0.015
CON5	I would enjoy the flexibility that [X] provide.	**0.862**	-0.073	0.063	-0.024
CON7	[X] would make my life easier.	**0.876**	0.045	0.087	0.023
EFF2	I would save time by using [X].	**0.831**	0.056	0.080	-0.008
EFF5	I would be more efficient thanks to [X].	**0.767**	0.057	0.163	0.060
EFF6	[X] would help me to do my tasks quicker and easier.	**0.798**	0.138	0.110	0.014
UR1	I am worried about not knowing how [X] would make decisions for me.	-0.050	**0.575**	0.062	-0.231
UR5	[X] cannot be trusted; there are just too many uncertainties.	-0.346	**0.490**	-0.054	-0.143
UR6	Using [X] entails uncertainty.	-0.195	**0.457**	-0.017	-0.107
PR1	I am concerned that [X] would collect too much personal information from me.	-0.049	**0.688**	-0.157	-0.197
PR2	I am concerned that [X] would use my personal information for other purposes without my authorization.	0.024	**0.589**	-0.178	-0.290
PR4	I worry that [X] would invade my privacy.	-0.011	**0.733**	-0.276	-0.107
LOC2	I worry about [X] taking full control.	-0.063	**0.907**	0.030	0.069
LOC4	Even when I'm feeling self-confident about most things, I may still lack the ability to control [X].	0.159	**0.653**	-0.005	0.048
LOC5	I worry that [X] would take too much control.	-0.086	**0.941**	0.028	0.083
AMB1	I have strong mixed feelings both for and against using [X].	-0.099	-0.059	0.060	**-0.858**
AMB2	I feel divided between the positive and negative sides of [X].	0.207	0.020	-0.070	**-0.881**
AMB3	I feel an inner conflict while thinking about using [X].	0.025	0.297	0.027	**-0.658**
BR2	I feel confident in [X brand].	0.014	-0.132	**0.838**	0.020
BR3	[X brand] is a reliable company.	-0.018	-0.108	**0.850**	-0.125
BR4	I can always trust the performance of [X brand] to be good.	0.031	-0.044	**0.814**	0.027

BB2	I believe that [X brand] places the customers' interests first.	0.060	0.110	**0.881**	0.041
BB4	[X brand] cares about my needs.	0.008	0.086	**0.894**	-0.037
BB5	[X brand] gives me a sense of security.	0.134	-0.004	**0.763**	0.061
	Eigenvalues	**12.008**	**5.294**	**1.923**	**1.413**
	% 0f variance	**44.474**	**19.606**	**7.123**	**5.233**
	α	**0.968**	**0.927**	**0.948**	**0.875**

Extraction Method: Principal Axis Factoring.
Rotation Method: Oblimin with Kaiser Normalization.

APPENDIX I: PRETEST EFA FOR STUDY 3

Phase 1: Summary of Exploratory Factor Analysis Results Study 3 (N=178)

		Facilitators	Inhibitors	Brand Trust	Ambivalence
CUST2	I would enjoy having [X] tailored to my needs.	**0.892**	-0.032	0.027	-0.002
CUST3	The customization enabled by [X] would be very valuable.	**0.807**	-0.060	-0.024	-0.048
CUST4	I would enjoy having [X] adapted to my needs.	**0.893**	-0.027	0.056	-0.028
CON3	I would value the ability to receive services from [X] wherever I am.	**0.865**	-0.077	-0.032	-0.059
CON5	I would enjoy the flexibility that [X] provide.	**0.907**	-0.053	0.035	0.003
CON7	[X] would make my life easier.	**0.907**	0.082	-0.057	0.077
EFF2	I would save time by using [X].	**0.864**	0.020	-0.052	-0.015
EFF5	I would be more efficient thanks to [X].	**0.847**	0.026	-0.070	0.029
EFF6	[X] would help me to do my tasks quicker and easier.	**0.868**	0.013	-0.036	0.042
UR1	I am worried about not knowing how [X] would make decisions for me.	0.034	**0.731**	0.126	0.021
UR5	[X] cannot be trusted; there are just too many uncertainties.	-0.222	**0.633**	0.072	0.014
UR6	Using [X] entails uncertainty.	-0.095	**0.567**	0.106	-0.026
PR1	I am concerned that [X] would collect too much personal information from me.	0.006	**0.854**	-0.023	-0.054
PR2	I am concerned that [X] would use my personal information for other purposes without my authorization.	0.089	**0.950**	-0.094	0.085
PR4	I worry that [X] would invade my privacy.	-0.063	**0.861**	-0.051	0.015
LOC2	I worry about [X] taking full control.	-0.036	**0.775**	0.011	-0.039
LOC4	Even when I'm feeling self-confident about most things, I may still lack the ability to control [X].	0.001	**0.592**	0.003	-0.173
LOC5	I worry that [X] would take too much control.	-0.039	**0.780**	-0.004	-0.090
AMB1	I have strong mixed feelings both for and against using [X].	0.015	0.123	-0.055	**-0.722**
AMB2	I feel divided between the positive and negative sides of [X].	-0.081	-0.098	-0.105	**-1.010**
AMB3	I feel an inner conflict while thinking about using [X].	0.082	0.113	0.172	**-0.691**
BR2	I feel confident in [X brand].	0.050	-0.034	**-0.835**	0.001
BR3	[X brand] is a reliable company.	-0.061	-0.034	**-0.964**	-0.004
BR4	I can always trust the performance of [X brand] to be good.	-0.043	-0.003	**-0.949**	-0.012

BB2	I believe that [X brand] places the customers' interests first.	0.020	-0.044	**-0.893**	-0.064
BB4	[X brand] cares about my needs.	0.134	0.059	**-0.842**	0.023
BB5	[X brand] gives me a sense of security.	0.089	0.046	**-0.865**	0.044
	Eigenvalues	**12.934**	**4.856**	**1.814**	**1.432**
	% 0f variance	**47.903**	**17.986**	**6.719**	**5.305**
	α	**0.971**	**0.936**	**0.986**	**0.862**

Extraction Method: Principal Axis Factoring.
Rotation Method: Oblimin with Kaiser Normalization.

APPENDIX J: PRETEST EFA FOR STUDY 4A

Phase 1: Summary of Exploratory Factor Analysis Results Study 4a (N=77)

		Facilitators	Inhibitors	Brand Trust	Ambivalence
CUST2	I would enjoy having [X] tailored to my needs.	**0.767**	0.115	0.292	-0.020
CUST3	The customization enabled by [X] would be very valuable.	**0.799**	0.186	0.090	-0.162
CUST4	I would enjoy having [X] adapted to my needs.	**0.759**	0.172	0.217	0.141
CON3	I would value the ability to receive services from [X] wherever I am.	**0.707**	0.103	0.247	-0.020
CON5	I would enjoy the flexibility that [X] provide.	**0.762**	0.119	0.225	0.154
CON7	[X] would make my life easier.	**0.815**	-0.032	0.250	0.024
EFF2	I would save time by using [X].	**0.779**	0.074	0.141	-0.025
EFF5	I would be more efficient thanks to [X].	**0.611**	0.263	0.085	-0.187
EFF6	[X] would help me to do my tasks quicker and easier.	**0.790**	0.221	0.023	-0.124
UR1	I am worried about not knowing how [X] would make decisions for me.	-0.316	**0.521**	0.016	-0.041
UR5	[X] cannot be trusted; there are just too many uncertainties.	-0.393	**0.802**	0.070	-0.056
UR6	Using [X] entails uncertainty.	-0.196	**0.717**	0.113	0.064
PR1	I am concerned that [X] would collect too much personal information from me.	-0.169	**0.736**	0.095	-0.172
PR2	I am concerned that [X] would use my personal information for other purposes without my authorization.	-0.276	**0.796**	0.138	-0.105
PR4	I worry that [X] would invade my privacy.	-0.261	**0.759**	0.081	0.083
LOC2	I worry about [X] taking full control.	-0.285	**0.786**	-0.056	-0.114
LOC4	Even when I'm feeling self-confident about most things, I may still lack the ability to control [X].	-0.163	**0.762**	-0.155	-0.232
LOC5	I worry that [X] would take too much control.	-0.311	**0.815**	0.095	-0.181
AMB1	I have strong mixed feelings both for and against using [X].	0.001	0.667	-0.072	**0.555**
AMB2	I feel divided between the positive and negative sides of [X].	-0.009	0.648	-0.045	**0.456**
AMB3	I feel an inner conflict while thinking about using [X].	0.035	0.677	-0.128	-0.004
BR2	I feel confident in [X brand].	0.756	0.222	**0.012**	0.021
BR3	[X brand] is a reliable company.	0.683	0.091	**0.027**	0.083
BR4	I can always trust the performance of [X brand] to be good.	0.811	0.160	**-0.144**	-0.073

BB2	I believe that [X brand] places the customers' interests first.	0.781	0.212	**-0.526**	-0.054
BB4	[X brand] cares about my needs.	0.662	0.238	**-0.531**	0.032
BB5	[X brand] gives me a sense of security.	0.825	0.197	**-0.263**	-0.034
	Eigenvalues	**9.561**	**7.145**	**1.345**	**1.130**
	% 0f variance	**35.411**	**26.463**	**4.980**	**4.186**
	α	**0.929**	**0.939**	**0.913**	**0.778**

Extraction Method: Principal Axis Factoring.
Rotation Method: Oblimin with Kaiser Normalization.

APPENDIX K: PRETEST EFA FOR STUDY 4B

Phase 1: Summary of Exploratory Factor Analysis Results Study 4b (N=75)

		Facilitators	Inhibitors	Brand Trust	Factor 4	Ambivalence
CUST2	I would enjoy having [X] tailored to my needs.	**0.879**	-0.016	-0.103	-0.075	-0.172
CUST3	The customization enabled by [X] would be very valuable.	**0.392**	0.139	-0.075	0.474	0.178
CUST4	I would enjoy having [X] adapted to my needs.	**0.867**	0.134	0.113	0.012	-0.106
CON3	I would value the ability to receive services from [X] wherever I am.	**0.401**	-0.096	-0.071	0.244	0.290
CON5	I would enjoy the flexibility that [X] provide.	**0.763**	-0.013	-0.076	0.002	-0.218
CON7	[X] would make my life easier.	**0.703**	-0.022	-0.270	0.069	-0.011
EFF2	I would save time by using [X].	**0.535**	-0.116	-0.214	0.135	0.070
EFF5	I would be more efficient thanks to [X].	**0.718**	-0.091	-0.129	-0.006	0.306
EFF6	[X] would help me to do my tasks quicker and easier.	**0.469**	-0.091	-0.268	-0.007	0.208
UR1	I am worried about not knowing how [X] would make decisions for me.	-0.040	-0.019	-0.044	**-0.821**	-0.058
UR5	[X] cannot be trusted; there are just too many uncertainties.	0.019	0.211	0.082	**-0.729**	0.003
UR6	Using [X] entails uncertainty.	0.109	0.272	0.011	**-0.638**	0.084
PR1	I am concerned that [X] would collect too much personal information from me.	0.076	**0.905**	0.001	-0.014	-0.051
PR2	I am concerned that [X] would use my personal information for other purposes without my authorization.	-0.005	**0.881**	-0.033	-0.069	-0.110
PR4	I worry that [X] would invade my privacy.	0.036	**0.890**	0.005	-0.072	-0.049
LOC2	I worry about [X] taking full control.	-0.164	**0.721**	-0.089	0.141	0.458
LOC4	Even when I'm feeling self-confident about most things, I may still lack the ability to control [X].	0.172	**0.340**	0.038	-0.612	0.134
LOC5	I worry that [X] would take too much control.	-0.024	**0.658**	-0.035	-0.252	0.136
AMB1	I have strong mixed feelings both for and against using [X].	-0.107	0.226	-0.033	-0.382	**0.503**
AMB2	I feel divided between the positive and negative sides of [X].	-0.224	0.193	0.061	-0.184	**0.671**
AMB3	I feel an inner conflict while thinking about using [X].	-0.114	0.003	-0.049	-0.685	**0.426**
BR2	I feel confident in [X brand].	-0.096	-0.004	**-0.954**	0.052	-0.054
BR3	[X brand] is a reliable company.	-0.035	0.111	**-0.944**	0.025	-0.186

BR4	I can always trust the performance of [X brand] to be good.	-0.060	0.014	**-0.935**	-0.005	0.004
BB2	I believe that [X brand] places the customers' interests first.	0.233	-0.056	**-0.597**	0.018	0.329
BB4	[X brand] cares about my needs.	0.230	0.026	**-0.706**	-0.106	0.099
BB5	[X brand] gives me a sense of security.	0.258	-0.068	**-0.722**	-0.087	0.053
	Eigenvalues	**9.285**	**6.948**	**1.93**	**1.503**	**1.231**
	% 0f variance	**34.39**	**25.733**	**7.148**	**5.565**	**4.561**
	α	**0.916**	**0.932**	**0.947**		**0.869**

Extraction Method: Principal Axis Factoring.
Rotation Method: Oblimin with Kaiser Normalization.