

AN EXPLORATORY STUDY ON THE DETERMINANTS OF PURCHASE INTENTION
FOR INTERNET OF THINGS PRODUCTS

by

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The digital age has been defined by new technologies that have revolutionized the way people communicate with each other and with brands. Sprouting from radio-frequency identification (RFID) technology in the 1990s, the Internet of Things (IoT) has taken on a significant role in providing the constant connectivity and customization that consumers demand. Defined by industry leader Richard Yonck as “interconnected physical objects, capable of sharing data about their state or the state of their environment” (Yonck, 2013, p.17), IoT includes technologies like the Apple Watch, Amazon Echo, and Hello Barbie. These technologies are not limited to toys and gadgets and can be found across a variety of sectors including “environmental monitoring, health care, inventory and product management, smart home and workplace, [and] security and surveillance” (Atzori, Iera, & Morabito, 2014, p. 97).

While these devices are evolving faster than strategic communication practices and the law can adjust, what stays the same is that these technologies collect data at all times to further customize the end user’s experience. They represent a significant shift in technology and the mindset of the consumer that is becoming the new norm. Consumers interact with brands in a more personal way, and companies have access to increasing amounts of personal data from each customer. However, this data collection creates a potential problem. Most IoT devices use unencrypted networks and do not require users to set complex passwords (Nelson & Simek, 2015). Therefore, these devices can become gateways for hacking and theft of personal information if improperly managed. High profile hacks of these devices make the news and may dissuade consumers from purchasing IoT devices,

but a trustworthy brand can build on its brand identity to overcome these barriers to adoption.

This research will seek to discern how IoT companies can use brand trust, self-efficacy, and factors influencing technology acceptance in messaging to consumers. In addition, this study will look at how reducing anxiety and privacy concerns may increase purchase intention of IoT technologies. The goal of this study is to provide theoretical and practical insights for advertising IoT technologies. This study was conducted in three parts with online surveys. The rest of this paper will review key literature, explain the method, report results, discuss potential implications, limitations, and provide direction for future study.

Literature Review

Although IoT is a new and revolutionary type of technology, it is the result of a trend toward interactivity that has influenced marketing communication for over a decade. Literature on the history of the web and new technology development identifies barriers to adoption of IoT products. Additional literature about branding, technology adoption, self-efficacy, anxiety, privacy concerns, and purchase intention offers a roadmap for understanding how companies may increase IoT adoption. Each of these areas is examined below.

Web 2.0 to Web 3.0

Web 2.0 was a term coined in 2004 by Tom O'Reilly and Dale Dougherty as a way to explain their observations after the dot com crash (O'Reilly, 2007; Barassi & Treré, 2012). They observed that even after the crash the Internet was still as important as ever, and that

companies that survived shared the ability to “harness collective intelligence” (O’Reilly, 2007, p. 22). Web 2.0 technologies were interactive websites that allowed the user to participate in a way that had not been possible on the web before. In essence, Web 2.0 applications harnessed the power of their users, who were highly participatory, and ideas and knowledge flowed both directions (Constantinides & Fountain, 2008). While social media is a hallmark of Web 2.0 technology (the terms are sometimes used interchangeably), sites like Wikipedia are also examples of how user interaction changes content creation (O’Reilly, 2007). Constantinides & Fountain (2008) defined five main categories of Web 2.0 technologies: blogs, social networks, content communities (where information is organized and shared), forums, and content aggregators (e.g., RSS feeds). The key similarity across these technologies is not just interactivity, but that they “automatically get better the more people use [them]” (O’Reilly, 2007, p. 22).

Web 2.0 allowed users to share a portion of themselves across a global platform and interact with other *people*, not just a computer. For the first time, there was an opportunity for the web to become democratized as users gained the power. With Web 2.0 mass data collection increased as personal information flowed across the Internet (Constantinides & Fountain, 2008; Barassi & Treré, 2012). With so much personal information shared on the Internet, users were able to surveil each other and build a shared economy, while marketers could start to commodify users’ time, behavior and personal data (Barassi & Treré, 2012). Nothing about the technology of Web 2.0 was radically new to the software industry; what changed was how marketers used the technology to build engagement into their core marketing strategies (Constantinides & Fountain, 2008). Instead of broader

marketing campaigns, the interactivity of Web 2.0 created a space where marketers could target a very segmented population with specific “low-volume, customized products and services” (Constantinides & Fountain, 2008, p. 237). A prime example of this is Netflix, which built its company on fulfilling specific movie requests quickly and one at a time.

There is not a neat divide between Web 2.0 and Web 3.0, but this new stage of web development transitioned from user participation to user *cooperation* by using personal data to “create new meaning” (Barassi & Treré, 2012, p. 1270). Rather than users continuously posting information on the web, this new stage of web development allows technology to interact with users and create custom content. Not only is technology evolving, but so are users’ attitudes towards its uses. The potential for Web 3.0 was recognized by the World Wide Web’s founder Sir Tim Berners-Lee in 1999, even before the realization of Web 2.0. He saw the potential for his creation to allow “machines to talk to one another” (Barassi & Treré, 2012, p. 1272).

Web 3.0 technologies have two main properties: they “offer users the possibility to cooperate in the creation of Web data, whilst at the same time searching the Web in an intelligent way” (Barassi & Treré, 2012, p. 1273). This is different from Web 2.0 because while the older technologies allowed users to interact with existing information, Web 3.0 engages users in creating a new shared meaning, often through the use of their personal data. An example of this in marketing is the global clothing chain Zara. Through the use of Web 3.0, Zara is able to anticipate customer demands based on the information it collects from its customers, resulting in a quicker turnaround from ideas to production and improving demand forecast (Garrigos-Simon, Lapiedra Alcamí, & Barberá Ribera, 2012).

These new technologies use customers' input (personal data like shopping habits) to more accurately predict patterns of behavior for an entire market. They also demonstrate that Web 3.0 is more interdependent than its predecessors. While Web 2.0 shifted the power to users, machines hold power in Web 3.0 to provide the customization consumers want. In response to this new environment, Garrigos-Simon et al. (2012) have recommended that companies work to build trust with customers through social networks and to increase customers' participation in the personalization of marketing initiatives (i.e. crowdsourcing). The brands that are the most successful at transitioning from Web 2.0 to Web 3.0 are those that combine data manipulation with user interaction. In order for this to occur, the Internet has become larger and smarter.

Internet of Things

In response to user demands for more growth and customization of the Internet, new technology developed with the power of Web 3.0 called Internet of Things. These IoT devices are capable of meeting the demands of customization and expanding quickly as technology develops. IoT devices are still primarily used by innovators and early adopters of technology, who are only a small percentage of consumers.

Definition. While, Yonck provides a working definition for IoT, a more extensive academic definition adds further insight. Miorandi, Sicari, De Pellegrini, and Chlamtac, (2012) define IoT as devices that can communicate and interact "either among themselves building networks of interconnected objects, or with end-users or other entities in the network" (p. 1498). This interaction is unique to IoT devices. For example, users interact with Google Nest technology (a smart thermostat) by managing temperature preferences

through an app. In addition to the user's ability to manually set the temperature, Nest will interact with local weather forecasts to adapt to weather changes. With the greater ownership of smart devices, these technologies are given further opportunity to communicate with each other. For example, a Nest owner that also owns Amazon Echo (a smart speaker) can pair the two devices and control the Nest by speaking to the Echo.

The most important aspect of this definition of IoT is the ability to respond to users' needs in real time and to react to the users' physical world (Miorandi et al., 2012; Skaržauskienė & Kalinauskas, 2012). IoT technologies link the real world and virtual worlds, allowing consumers to have connectivity anytime and anywhere (Skaržauskienė & Kalinauskas, 2012).

The innovation of these technologies is directly tied to the proliferation of smart phones, because almost all IoT technologies come with a smart phone app to control them (Want, Schilit, & Jenson, 2015). A 2015 Global Attitudes Survey conducted by the Pew Research Center found that 72% of adults in the United States and 43% of adults worldwide reported having a smart phone (Poushter, 2016). Smart phone owners who can connect more devices to their phones represent a significant share of the market. One million new devices connect every single day, and up to 50 billion devices will be connected by 2020 (Bojanova, Hurlburt, & Voas, 2014). With devices on the Internet outnumbering humans, people will have less direct control and involvement in most online communication, which instead will be dominated by "machine-to-machine" or machine-to-cloud communication (Yonck, 2013, p. 16).

Due to their highly technical nature, IoT devices are black boxes. While consumers may understand what is input into IoT devices (personal data) and what is output (customization), they do not understand the mechanics of how these technologies collect, store, and process data. Because of the sheer amount of data being collected and shared by these devices, security and privacy concerns necessitate effective marketing communication and trust between brands and consumers.

Privacy and security. Most of the current literature on IoT is based in computer science or other technology based disciplines. There is a distinct lack of literature in strategic communication research addressing the Internet of Things, perhaps because of its newness and technological complexity. The problematic nature of data breaches is acknowledged in the literature, and while multiple solutions to data privacy are considered, new ways to hack are developed as quickly as solutions are implemented. Security and privacy concerns are fundamental because IoT technologies can collect data anytime, anywhere, and about anything (Hernández-Ramos, Bernal Bernabe, Moreno, & Skarmeta, 2015). The most common uses of IoT technology are in the home security and health sectors, and the data being collected is highly sensitive, creating concerns about identity and privacy in addition to security (Hernández-Ramos et al., 2015). Miorandi et al. (2012) go so far as to suggest that solving privacy and data security issues is the key to wider adoption of IoT technology.

Internet privacy differs from traditional privacy. Internet users do not expect to be free from observation, as the Miriam Webster dictionary defines privacy. Instead, Internet users want to be able to determine what private information is shared and how it can be

used (Barrajón, 2013). In the case of IoT, privacy is not the absence of data collection, but rather a sliding scale of permission given by the user. In a trade publication for lawyers, Nelson and Simek (2015) pointed out that most users employ unencrypted networks, simple passwords, and other short cuts to increase their ease of use. In many cases, users only think about security and how much privacy they have surrendered after a data breach. A fundamental part of Barrajón's definition of Internet privacy is that users are allowed to reevaluate their privacy concerns continuously. However, since IoT technologies initially ask permission to collect data and then continue doing so without renewing permission, reevaluating privacy requires consumer knowledge and effort.

Hernández-Ramos et al. (2015) address the communication that is missing between the technology industry and users of smart technology. Different companies developed IoT technologies in silos without sharing standards or maintaining similar processes for data privacy, and most of these technologies are still focused on single applications (Skaržauskienė & Kalinauskas, 2012; Miorandi et al., 2012). One of the most popular strategies in literature for improving IoT data security is for computer scientists to essentially open-source solutions and problem solve together. However, this practice is impossible if IoT companies remain in their silos. While academia openly acknowledges privacy concerns and works toward a security system that can overcome data breaches, consumers have little understanding of these issues. As Kounelis et al. (2014) point out, this ignorance could lead to a loss of trust that could, in turn, threaten the survival of the technology. This privacy and customization exchange is a fundamental dilemma for IoT companies, since they have to balance demands for more customized experiences with

sensitivity to data security. The literature suggests companies should address these privacy issues by pushing for the adoption of regulations, minimizing data collection wherever possible, and improving transparency with the public (Weber, 2015). This third solution requires IoT companies to make an effort to open up these black boxes through their marketing communication.

In light of Web 3.0's capabilities and consumers' demands for interactivity, marketers have an increasing amount of big data available to target messages to specific consumers. *Big data* refers to extremely large data sets that, because of their size, offer new opportunities to study previously challenging research questions. With the inherent data collecting capabilities of IoT and creation of big data sets, privacy literature has already been discussed as a fundamental part of IoT (Eastin, Brinson, Doorey, & Wilcox, 2016; Miorandi et al., 2012). Privacy literature argues that consumers concerned with privacy should understand they must sacrifice some privacy for the greater good that big data can provide for society (i.e., large data sets and better understanding of issues) (Eastin et al., 2016). IoT literature lacks a discussion of how users' ability to control settings could factor into their adoption of IoT technologies. The Communication Privacy Management Theory states that people believe their privacy is protected by boundaries that are determined by social norms and constantly negotiated (Eastin et al., 2016). One of the central variables in determining these privacy barriers is control (Eastin et al., 2016). Control helps consumers cope with the loss of their privacy, and must be considered in the context of IoT.

Users' privacy and security concerns about these devices are not unfounded, despite the amount of computer science literature seeking to improve security. A hack of these

technologies creates real problems for consumers and a public relations crisis for IoT companies. One example is the denial of service hack on October 21, 2016. Dyn, an Internet performance management company, was hacked through thousands of IoT devices, shutting down the sites of clients like Twitter, Amazon, Netflix, Paypal, and *The New York Times*. Hackers were able to infect this large network with malware through IoT devices, which after being breached were used as a door to take websites offline (Simon, 2016; Johnson, 2016). This is the sort of worst case scenario being discussed in the literature, and there were two waves of attacks before Dyn got the problem under control. After the attack, experts advised users to change passwords, a seemingly simple solution to a greater problem of security discussed in the literature (Simon, 2016). Notably, this was probably the first time the term “Internet of Things” was being used broadly and consciously by the general public. Previously, mentions of these technologies had largely been limited to tech forums. Now, however, media outlets like NPR, Fortune, and the *New York Times* were discussing IoT technologies by name. Internet of Things even trended as a topic on Facebook. This coverage dramatically highlighted the features and vulnerabilities of these devices.

This crisis illustrates why brand trust and communication are so important for IoT technology companies. Since these devices are black boxes, the consumer has a hard time understanding the security features and potential risks of a device. When marketing these items, companies must find ways to describe IoT features clearly and empower customers to use IoT devices securely. Doing so will help companies build brand trust and reduce customers’ anxiety about data privacy.

Risk and future. Perspectives on the future of these technologies fall into two main camps: those who believe IoT will become just another part of the Internet and those who see it as a revolutionary means of communication. Edwards (2015) falls into the first camp and postulates that in the next few years the term Internet of Things will stop being used and the technology will just become another taken-for-granted aspect of the Internet. This is the path other new technologies have taken, and he argues that the hype surrounding the Internet of Things has largely faded. Most of the literature, including Saint (2014) and Atzori et al. (2014) falls into the second category, and predicts that not only is IoT the defining technology of Web 3.0, but that these smart technologies will become social technologies, consuming information as well as collaborating with each other to create the best customization. These technologies will become less physical as communication and data collection is increasingly conducted via remote data centers, or *clouds* (Bojanova, Hurlburt, & Voas, 2014). No matter what the technical future of IoT is, the data collection and personalization these devices are capable of are changing customer expectations of technology.

The Internet of Things was developed with marketing considerations in mind, and was used early on as a way to connect a product to an interactive advertising experience. The original IoT technology, RFID, was developed to ease collection of health data, improve product inventory reports, and simplify entry for consumers into attractions. With the broader use of Web 3.0, participative marketing is the answer to a world that demands more interactivity and personalization from smart devices (Jara, Parra, & Skarmeta, 2014).

Based on the literature and the future of the Internet of Things, why would companies that use and develop these technologies want to make the security issue more public through their marketing communication? The answer is that consumers are already catching on. In 2014 the Federal Trade Commission issued a report “warning of the lack of transparency and potential dominance” of these Internet of Things companies (Edwards, 2015, p. 39). At the time this report went mostly ignored because most of the companies selling IoT products were small and obscure, but higher profile companies have now moved into the IoT market. There is also growing pressure to regulate how data is stored, secured, and used. With information on how data is used becoming more public, IoT companies need to develop communication plans that bolster relationships with consumers, establish themselves as trustworthy sources of information, and persuade the general public to adopt these otherwise niche technologies. Consumers communicate with brands in nuanced ways, and developing strong brand relationships is key to building trust.

Branding and Consumers

A brand is an identity associated with a company that differentiates it from its competition. A brand’s identity is shaped by every consumer interaction, either positively or negatively. In the digital age, consumers are engaging more frequently with brands over a variety of platforms. This engagement is sustained even after purchasing when consumers review a product, thus shaping the brand’s perception among other consumers (Edelman, 2010). Because modern “consumers no longer accept the role of passive recipients of marketing communication,” brands must “interact with individual customers quickly, openly, and continuously” (Acar & Punton, 2016, p. 4). Several attempts have been made to

model this new relationship between brands and consumers. Recent examples include the Consumer Decision Journey and Customer Purchase Journey models (Edelman, 2010; Cundari, 2015). These models recognize that the customer's journey is not a straight line ending with a purchase, but rather a loop in which customers continue to research a product or advocate for the brand (Edelman, 2010; Cundari, 2015). These models respond to two shifts in marketing, the Zero Moment of Truth (ZMOT) and earned media. Zero Moment of Truth, a concept developed by Google, is the point *before* purchase where consumers research a product (Lecinski, 2011). Shoppers use a multitude of sources online to make decisions about products, and the most powerful sources are other consumers' endorsements (Lecinski, 2011). Companies must now monitor their earned media, or "consumer-created channels," as frequently as their owned media, because of the importance of consumer-to-consumer opinions in the purchase process (Edelman, 2010, p. 3). This changing priority away from company-created channels is a product of consumers trusting brands less, and relying on their peers more.

How will these evolving relationships between consumers and brands affect consumer enthusiasm for Web 3.0? Cundari (2015) argued that with the adoption of social media, marketing entered the Age of the Consumer, an era defined by empowered consumers seeking to take control of marketing and interact more personally with brands. The environment in which these consumers exist has also changed. Empirical evidence finds that consumers perceive peer-generated advertising, or earned media, as more trustworthy and persuasive (Acar & Punton, 2016). Empowered consumers (i.e., those who are loyal to the brand and see themselves as brand ambassadors) would be enthusiastic about the

capabilities of Web 3.0 because they would be given the power to shape a brand's meaning. This is why campaigns like Lay's Do Us A Flavor and Choose Your Flavor Experience are so successful. Successful campaigns like Lay's are driven by consumers and initiate dialog between the brand and consumer, which successful brands turn into empowerment and greater customer loyalty (Acar & Punton, 2016). Empowered customers champion brands within their peer networks, building trust, relationships, and customer bases for those brands.

Brand Trust

Brand trust is important because with the proliferation of marketing messages, trust helps consumers streamline their purchasing decisions (Moorman, Zaltman, & Deshpande, 1992). Cultivating brand trust is key in developing repeat customers. Brand trust is defined as "the willingness of the average consumer to rely on the ability of the brand to perform its stated function" (Chaudhuri & Holbrook, 2001, p. 82). Brands can build trust through their reputation, closeness to consumers, performance, and accountability (Morrison & Firmstone, 2000). It is the key to moving a consumer from a one-time buyer to a loyal customer (Chiu, Hsu, Lai, & Chang, 2012). There are several types of brand trust, but this study focuses on "identity-based trust" that is built on "shared values, goals, interests" and other qualities rather than "through perceived quality or prestige" (Yi, Batra, & Siqing, 2015, p. 56-57). This is the same kind of trust that develops in interpersonal relationships. Most of the literature about trust focuses on interpersonal trust, and can be cross-applied to consumer-brand relationships. According to Mayer, Davis, and Schoorman's (1995) theory of trust in interpersonal relationships, the antecedents to trust are ability, benevolence, and

integrity. These antecedents are characteristics that the trustor seeks in the trustee. Ability refers to competency in technical tasks; benevolence is the belief that someone is good (and worth trusting) and suggests a relationship between the two parties; and integrity is the existence of morality in the trustor (Mayer et al., 1995). These variables were derived from previous studies of personal qualities such as competence, loyalty, reputation, and expertise.

Brand trust is a strong predictor of brand loyalty (behavioral and attitudinal), which contributes positively to a brand's market share and drives up the product price (Chaudhuri & Holbrook, 2001). Trust is also indirectly related to purchase intention through relationship building factors like quality of interactions with a brand and the level of involvement a brand has with the consumer (Moorman et al., 1992). Morgan & Hunt's (1994) seminal study on relationship marketing concluded that trust is developed when companies provide a superior product or service; maintain their values; communicate effectively; and avoid taking advantage of customers. Their Commitment-Trust Theory postulates that while there are a host of factors that build relationships between consumers and brands, commitment and trust are the most important.

Building brand trust is especially vital in online shopping, because of the "spatial and temporal distance between buyers and online sellers" (Chiu et al., 2012, p. 835). Online shopping dominates purchase behavior, accounting for 51% of total purchases in the United States in 2016 (Stevens, 2016). Brand trust supersedes a lack of knowledge and reduces risk and anxiety for consumers (Morrison & Firmstone, 2000; Mayer et al., 1995). With the majority of purchases happening online, IoT companies not only need to build brand trust

to overcome anxieties about the new technology, but to overcome the weaknesses of the medium through which consumers will most likely purchase IoT products.

Example: Hello Barbie

One case that demonstrates the pitfalls when a brand lacks trust and open communication with consumers is the Hello Barbie case. Hello Barbie is a new Barbie doll, introduced by Mattel in 2015, that connects to Wi-Fi and collects data based on what a child tells it in order to provide increasingly personalized responses to the child. These conversations are also stored for parents to access and share on social media (Jones, 2016). Hello Barbie has three major characteristics of an Internet of Things technology: it connects to the Internet autonomously, stores data in a cloud, and is customizable.

The Campaign for a Commercial Free Childhood and other concerned parent groups have opposed Hello Barbie. The group has spoken extensively to the media and even begun the social media hashtag “#HellNoBarbie” in order to fight the toy’s release (Weisbaum, 2015). The organization’s platform is that any type of data collection on children is wrong, since children are uneducated and vulnerable users. Mattel received complaints that Hello Barbie is a severe invasion of privacy, even though the Barbie only listens when its belt buckle is pressed. The Barbie connects automatically to any available Wi-Fi network, and therefore can be very vulnerable to hackers. (This is the same vulnerability that was exploited in the previously mentioned denial of service hack on Dyn.) Preliminary literature on this case also expresses concern that users are not fully informed about how data is collected, and since these toys can be used in communal settings like daycares, not all data collection is done with permission (Jones, 2016). Consumers who purchased the product

followed up with “star” reviews on websites that sell the toy like Amazon and Target. Some of these reviewers expressed concern with the Barbie’s data collection and anger that Mattel is not listening to these concerns. On the other hand, positive reviewers pointed out that data collection is a fact of life and the interactivity of the toy is fun and exciting.

Mattel’s primary messages addressing consumer concerns were that the company was “committed to safety and security” and “products conform with applicable laws” (Weisbaum, 2015, para 5). This is incredibly vague, and there are hardly any laws or regulations that specifically regulate IoT. However, Mattel did make an attempt to communicate with its potential customers with a “Privacy Policy” and Q&A document on its website. Despite this effort to communicate, the Q&A was loaded with technical specifications and did not answer the questions parents were asking in a way that was direct or easy to find. This reaction in the media and among concerned parents shows that Mattel failed to communicate effectively with many of its consumers. It was operating on a one-way, outdated model of marketing communication.

Theories of Technology Adoption

In order for brands to effectively communicate with consumers, they have to understand why consumers adopt new technologies. Everett Rogers’s Diffusion of Innovations theory is the seminal work on understanding how a new technology is adopted. Diffusion of Innovations divides consumers into five groups: innovators, early adopters, early majority, late majority, and laggards (Rogers, 1982). However, this study focuses primarily on the characteristics of the technology rather than the characteristics of the adopters.

The Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) are influential models in the adoption of technology literature. These models seek to identify what psychological variables lead individuals to adopt new technologies. The Technology Acceptance Model posited that the most important variables influencing the adoption of technology were perceived ease of use and usefulness of that technology (Davis, 1989). Building on TAM, UTAUT compared the works of eight different models related to the psychology of technology acceptance, and narrowed the most important variables down to performance expectancy, effort expectancy, social influence, and facilitating conditions. Performance expectancy is defined as how users believe adopting a technology will affect their work (Venkatesh et al., 2003). The dimensions of performance expectancy include perceived usefulness, outcome advantage, intrinsic motivation, and relative advantage. Effort expectancy is best described as the ease of use of a particular technology (Venkatesh et al., 2003). Its dimensions include perceived ease of use, actual ease of use, and complexity. Social influence is defined as the influence peers have on the adoption of a new technology (Venkatesh et al., 2003). The dimensions of social influence include subjective norms (the social pressure a person feels to behave a certain way), image (status), and social factors (how an individual interprets culture and relationships). In marketing literature, Lecinski (2011) noted that in the ZMOT consumers trust their peers' opinions more than a company's messaging. With the widespread use of social media, marketers now have a way to monitor social influence (Risselada, Verhoef, & Bijmolt, 2014). The power of social influence one person has over another on social media can be measured by how strong their connection is and how similar they are (Risselada et

al., 2014). Social influence encompasses the importance peer groups have over purchase decisions. Facilitating conditions are defined as whether surrounding infrastructure is ready to adopt the system (Venkatesh et al., 2003). This includes how much support and compatibility an innovation finds in the workplace.

Research demonstrated that performance expectancy, social influence, and effort expectancy were directly related to behavioral intention, and facilitating conditions were directly related to behavior change (Venkatesh, Morris, Davis, & Davis, 2003). Originally, self-efficacy and anxiety were also identified as factors in adoption of new technologies, but they were not direct predictors of behavioral change in the UTAUT model. Venkatesh et al. (2003) predicted that although self-efficacy and anxiety were distinct variables, they were being mediated through effort expectancy. UTAUT has been shown to be a very accurate predictor of new technology acceptance and is adaptable to various new technologies (Maruping, Bala, Venkatesh, & Brown, 2017; Ukbapi & Karjaluo, in press; Martins, Oliveira, & Popovič, 2014). UTAUT faces challenges since it is difficult for researchers to monitor people while making real decisions (Venkatesh et al., 2003). Most studies can only ask questions retrospectively after the subject has already adopted the new technology. Despite this limitation, UTAUT is a reliable predictor of behavior. Each of the UTAUT variables tied directly to behavioral intention (performance expectancy, effort expectancy, and social influence) potentially influence what messages are most effective when persuading a consumer to purchase a new technology.

Self-Efficacy

While UTAUT is derived from psychology, it is a management/information systems theory that still relies heavily on physical processes that make technology more adoptable in the workplace. UTAUT focuses on the aspects of a technology that make it adoptable. In order for adoption of a technology to be permanent, users must be persuaded to change their beliefs and behavior. Self-efficacy is a key to permanent behavior change. A part of social cognitive theory, self-efficacy is defined as “the conviction that one can successfully execute the behavior required to produce the outcomes” (Bandura, 1977, p. 193). Bandura (1977) explained that self-efficacy differs from outcome expectancy because of the contributing factor of motivation. People can have high outcome expectancy if they believe a behavior will lead to a certain outcome, but unless they have motivation, they do not have the self-efficacy to engage in the behavior. Self-efficacy is directly tied to behavioral change and can lead to purchase intention.

Morton, Rabinovich, Marshall, and Bretschneider (2011) found that uncertainty, mediated through efficacy, was the deciding factor in how messages were received. When faced with uncertainty about the effects of climate change, participants showed attitudes of denial, by responding “if we don’t know what will happen in the future, why should I take action now” (Morton et al., 2011, p. 4-5). This suggests that uncertainty (especially uncertainty rooted in a lack of self-efficacy) can inhibit action. Messages containing self-efficacy could help mitigate uncertainty and lead to behavior change.

Self-efficacy also has a connection to control. In a study about technology adoption in the workplace, Morris and Venkatesh (2000) found that for older workers—regardless of

income, occupation, or education—the ability to control a technology influenced their short-term and long-term decision to adopt it. Self-efficacy has the ability to convince consumers that despite a lack of understanding about how IoT works, they still have the ability to control sensitive data collection and security settings. In seminal literature on computer self-efficacy, Compeau and Higgins (1995) found that higher self-efficacy decreased anxiety and indirectly increased usage of computers. Their research highlighted the importance of self-efficacy in the adoption of new technologies. Their findings inform this study because if an advertising message convinces potential customers that they have the ability to use a new technology, then those consumers should be more likely to adopt the new technology. An important step in translating trust and self-efficacy into purchase intention is reducing uncertainties. Self-efficacy reduces uncertainties users have about their own capabilities, but uncertainties may still remain about the technology itself.

Anxiety

Computer and website anxiety are terms that have been developed to explain why people avoid using these new technologies. These terms encompass the fear of losing data as well as apprehension about the features of these technologies (Xu, 2016; Celik & Yesilyurt, 2013). Xu (2016) found that virtual customer service chat reduced customers' website anxiety. Similar to the development of trust, technology-facilitated chat provides a two-way communication channel that builds relationships. Just as computer anxiety gave way to website anxiety, Internet of Things anxiety is a logical progression. As established in IoT literature, users' primary concerns are the safety, security, and the usability of these devices. IoT anxiety could lead customers to avoid these products. Celik and Yesilyurt (2013)

found that improved attitudes about technology, like the reduction of anxieties, increased adoption. Porto Bellini, Isoni Filho, de Moura Junior, and de Cássia de Faria Pereira (2016), on the other hand, found that digital natives, or the upcoming generation that does not remember life without technology, can have low anxiety and still choose not to use new technologies. Thus, reduction of anxiety alone will not automatically lead to the adoption of a new technology. Other factors must be considered as well.

Privacy Concerns

Typically, privacy is defined as “the right to be let alone,” but in the terms of interaction with the Internet, it refers to the moderation of “collection, disclosure, or other use of personal information” (Wang, Lee, & Wang, 1998, p. 64). People’s concern for their privacy develops from a variety of different factors, including their gender, familiarity with technology, and culture (Taddicken, 2014; Angst & Agarwal, 2009). With so many factors involved in the development of a person’s privacy concerns, it is a complex trait. Previous research in e-tourism has shown success in manipulating an online user’s privacy concerns through privacy assurance in messaging (Ukbapi & Karjaluto, in press).

Privacy concerns have always been a concern with Internet use because of the amount of data that is shared (Solove & Hartzog, 2014). Early literature on Internet adoption was skeptical of the spread of Internet technologies due to the issue of privacy (Wang et al., 1998). The invasion of privacy that comes with data collection has to be carefully balanced by showing the benefits of personalization (Angst & Agarwal, 2009). Companies responded to consumer insecurities by including privacy policies on their websites to explain how consumer data was secured, used, and shared (Solove & Hartzog,

2014). In fact, the concern for privacy is a common reason people are reluctant to use the Internet (Dinev & Hart, 2005). However, a study of Web 2.0 users found that once they adopted the new technology, privacy concerns no longer impacted how they interacted online (Taddicken, 2014). The waning power of privacy was supported by previous literature that showed that as users became more familiar with the Internet, they were more comfortable with their privacy being invaded (Dinev & Hart, 2005). Dinev and Hart concluded that the decreasing importance of privacy was not because users had changed their perception towards the importance of guarding their privacy, but rather because they felt more control over the technology. Nevertheless, IoT technologies represent a new area that may raise new concerns over privacy, and such concerns may affect purchase intentions.

Purchase Intention

Behavioral and attitude change has been discussed as a result of brand trust, self-efficacy, and technology anxiety (Moorman et al., 1992, Bandura, 1977; Celik & Yesilurt, 2013). In marketing, the outcome of this behavior change is commonly to purchase a product. Purchase intention is an effective way to track attitude changes that lead to behavioral changes. Purchase intention is defined as “an individual’s conscious plan to make an effort to purchase a brand” (Spears & Singh, 2004, p. 56). It is a specific intention to act on an attitude toward a brand (Spears & Singh, 2004; Ostrom 1969). While purchase behavior reflects the outcome of persuasion, purchase intention reflects the success in changing attitudes and is seen as the best predictor of purchase behavior (Kalwani & Silk, 1982). In order to persuade a consumer to purchase a product or service, brands have to

overcome any objections and change negative attitudes that a consumer may have. These attitudes are typically related to issues like price, perceived quality, usefulness, and ease of use. The significance and influence of attitudes toward behavioral intention varies by study, but seems to correlate most strongly in the case of purchase intention (Bagozzi, 1981; Spears & Singh, 2004; Venkatesh et al., 2003). Purchase intention is a frequent and easily measurable way to test reactions to marketing messages.

IoT technologies are growing rapidly, and the literature focuses on consumer concerns and potential barriers to adoption. Chief in these barriers are privacy concerns and technology anxieties. Companies interested in selling IoT technologies will have to use marketing messages to persuade consumers to overcome their concerns about IoT and purchase these products. Technology adoption theories posit that overcoming these barriers is a matter of convincing consumers of the social and physical benefits of new technologies, while traditional communication theory emphasizes the importance of developing brand trust. All of these variables have been tested in other contexts, and this study will translate these relationships to IoT adoption. The results will help guide the creation of effective marketing messages for IoT products.

Research Question and Hypotheses

This study explores how technology acceptance variables, self-efficacy, anxiety, privacy concerns, and brand trust in advertising messages relate to purchase intention. The relationships between these variables are defined in literature and map out a model for how trust, self-efficacy, use of the product, and social factors can be used to overcome challenges inherent in IoT technologies that inhibit their adoption. The unique challenges of

new technologies make this topic salient for traditional technology companies, as well as other companies looking to add IoT capabilities to their products. The objective of this study is to explore what factors affect the adoption of Internet of Things products so that more effective marketing messages can be designed.

Based on the preceding literature review, this study tests seven hypotheses:

H1: Performance expectancy will be a positive predictor of IoT purchase intention.

H2: Effort expectancy will be a positive predictor of IoT purchase intention.

H3: Self-efficacy will be a positive predictor of IoT purchase intention.

H4: Anxiety will be a negative predictor of IoT purchase intention.

H5: Privacy concerns will be a negative predictor of IoT purchase intention.

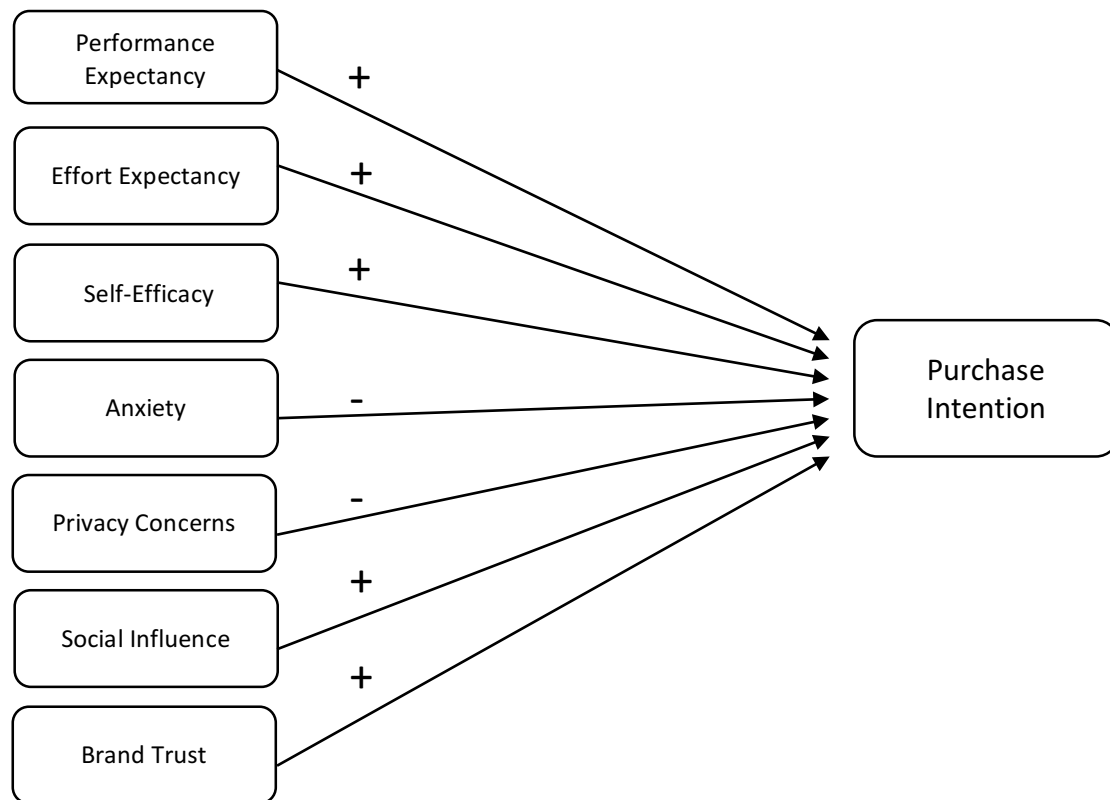
H6: Social influence will be a positive predictor of IoT purchase intention.

H7: Brand trust will be a positive predictor of IoT purchase intention.

These seven hypotheses are reflected in Figure 1. Performance expectancy, effort expectancy, and social influence (UTAUT variables) were predicted to have a positive effect on purchase intention. Self-efficacy and brand trust were also predicted to have a positive effect on purchase intention. Anxiety and privacy concerns were predicted to have a negative effect on purchase intention. These hypotheses are based on the existing literature, but do not explain whether brand trust affects the salience of the other independent variables. Therefore, in addition to the seven hypotheses, the following research questions is posed:

RQ1: Are there any differences in the variables that predict purchase intention when trust is high instead of low?

Figure 1. *Proposed Model of Variables Predicting Purchase Intention of IoT Products*



Methods

The purpose of this study was to explore factors that influence customer's intentions to purchase IoT technologies. The hypotheses were tested using an online survey that exposed participants to product information about a smart speaker (a common IoT product currently on the market) and tested their resulting performance expectancy, effort expectancy, self-efficacy, anxiety, privacy concerns, social influence, brand trust, and purchase intention. This study was conducted in three parts. Measures for each of the components of the proposed model were derived from previous literature. This section describes the procedures and measures used.

Part 1 Procedure

Part 1 was an online survey to determine which well-known technology brand had the highest and lowest brand trust. Part 1 used a snowball sample of 66 respondents. This sample was mostly comprised of university students, and was more likely to be young and highly educated based on the researcher's network. A copy of the questionnaire is included in Appendix A.

Subjects were asked to evaluate brand trust for 10 brands on a 100-point rating scale (1 = low trust; 100 = high trust). The purpose of these questions was to gauge the subjects' trust of technology brands. The two brands with the highest and lowest brand trust scores were then used as examples in Part 2 and Part 3. Next, participants were exposed to product information about an Internet of Things product (a smart speaker) and given 48 questions to evaluate their performance expectancy, effort expectancy, self-efficacy, anxiety, privacy concerns, social influence, and purchase intention (see Appendix A for questionnaire items). This served as a reliability check. All of the survey questions were reliable, based on Cronbach's alpha, and therefore did not need to be altered prior to Part 2 and Part 3.

Measures

Through the independent variables of performance expectancy, effort expectancy, self-efficacy, anxiety, privacy concerns, social influence, and brand trust, this study examined which factors advertiser should emphasize in order to increase purchase intention (the dependent variable). These variables were measured using questionnaires in response to one of two example advertisements. Each measure was developed from the

literature with an emphasis on the nuances of technology. All measures were reliable, with Cronbach's alphas between .76 or greater (see Table 1 for all reliability statistics). The questionnaire items used for each variable were the same in Part 1, Part 2, and Part 3.

Table 1.

Reliability for Variables in Exploratory Study of IoT Purchase Intention

Variable Name	Cronbach's α		
	Part 1	Part 2	Part 3
Brand Trust	.90	.91	.88
Performance Expectancy	.92	.92	.91
Effort Expectancy	.91	.91	.92
Self-Efficacy	.85	.85	.90
Anxiety	.77	.76	.77
Privacy Concerns	.95	.86	.85
Social Influence	.85	.89	.88
Purchase Intention	.95	.91	.90

Performance Expectancy. Derived from UTAUT, performance expectancy is made up of perceived usefulness, outcome advantage, intrinsic motivation, and relative advantage. Typically, this variable applies to job related activities, but for this study it was adapted to reflect the social and productivity uses of a smart speaker. This scale included eight items adapted from Venkatesh et al. (2003) (see Table 2) measured on a seven-point Likert scale (1 = strongly disagree; 7 = strongly agree). Items included "If I use this product, I will be able to more easily entertain at home" and "This product is better than the speaker I already have." The Cronbach's alpha for performance expectancy ranged from .91 to .92.

Effort Expectancy. Effort expectancy is another variable derived from UTAUT, and is comprised of ease of use and complexity. Effort expectancy is distinctive because it does not include motivation, a key element to self-efficacy. Also, this variable focuses on the features inherent in the product, rather than an evaluation of the user's motivation or skills.

This variable had 10 items (see Table 2) from Venkatesh et al. (2003), and was measured on a seven-point Likert scale (1 = strongly disagree; 7 = strongly agree). Higher scores for effort expectancy indicate that participants are more comfortable with the effort they expect a technology to require (i.e., higher scores mean the product seems easier to use). Items included, "I would find the product to be flexible to interact with" and "My interaction with this product would be clear and understandable." The Cronbach's alpha of effort expectancy ranged from .91 to .92.

Self-efficacy. In this study, a specific measure for computer self-efficacy was used, since it takes into account how to effectively use computer technologies that often require unique skills (Porto Bellini et al., 2016). These questions were from Porto Bellini et al.'s (2016) study of self-efficacy in computer mediated interaction, with the only modification being the substitution of "Internet of Things" where the previous study referred to "computer" and "system." The scale included seven items (see Table 2) measured on a seven-point Likert scale (1 = strongly disagree; 7 = strongly agree). Items included statements like "I am motivated to use new technologies." The Cronbach's alpha for self-efficacy ranged from .85 to .90.

Anxiety. While trust is important in building a relationship and self-efficacy is important in building confidence, a consumer's anxiety about security or privacy concerns could lead to avoiding the new technology. Therefore, reduced anxiety about a new technology should increase purchase intention. The anxiety items came from Porto Bellini et al.'s (2016) study of the relationship between self-efficacy and anxiety and Xu's (2016) computer anxiety work. There were six anxiety items (see Table 2), with the only

modifications from their original text being the insertion of “Internet of Things” to bring clarity to the question. Items included, “I feel anxious about using new technologies,” and “I am afraid of using this new technology incorrectly.” Each item was measured on a seven-point Likert scale (1 = strongly disagree; 7 = strongly agree). The Cronbach’s alpha for anxiety ranged from .76 to .77.

Privacy Concerns. The scale for privacy had five items adapted from Dinev and Hart’s (2004) study of Internet privacy (see Table 2). Each item was measured on a seven-point Likert scale (1 = strongly disagree; 7 = strongly agree). The original items used scenarios to assess privacy use, asking questions like “when I shop online, I am concerned that the credit card information can be stolen while being transferred on the Internet” and “when I am online, I have the feeling that all my clicks and actions are being tracked and monitored” (Dinev & Hart, 2004, p. 418). In this study, the questions were adapted to be shorter, directly mention privacy, and targeted towards IoT instead of general Internet use. For example, “privacy is important to me” and “I am concerned about the personal data this device collects could be misused by [brand].” The Cronbach’s alpha for privacy concerns ranged from .85 to .95.

Social Influence. Social influence is a variable included in the UTAUT model, and is comprised of subjective norms, image, and social factors. The scale for social influence included seven items from Venkatesh et al. (2003) (see Table 2) measured on a seven-point Likert scale (1 = strongly disagree; 7 = strongly agree). Since the original article tested the adoption of new technologies in the workplace, the questions measured the influences of coworkers and for this study were adapted to friends. Items included, “my friends would

enjoy using this product in a social setting,” and “Having this product would be a status symbol in my social network.” The Cronbach’s alpha for social influence ranged from .85 to .89.

Brand Trust. Brand trust in this study is identity-based brand trust, which develops from “shared values, goals, interests” and other identity-based similarities (Yi et al., 2015, p. 57). The reason for measuring this specific type of trust is because, as shown with the development of Web 3.0, consumers feel real connections over computer-mediated communication. This type of trust is also negatively affected during a crisis, or if a brand acts out of character (Yi et al., 2015). As previously discussed, a major concern about IoT technologies is their black box nature and potential safety and security issues. If consumers do not believe a company’s privacy policy and security settings match up with their beliefs about privacy, then the consumers and brand have misaligned values. These contrasting beliefs are negatively reflected in identity-based brand trust. The items for brand trust were from Yi et al. (2015)’s comprehensive study of brand identity and trust. They included items like “I trust this brand” and “this is an honest brand.” There were four brand trust items (see Table 2), each measured on a 100-point rating scale for Part 1, and seven-point Likert scale for Part 2 (1 = strongly disagree; 7 = strongly agree). The Cronbach’s alpha for brand trust ranged from .88 to .91. The 100-point scale was used in Part 1 because the researcher was trying to identify two brands out of 10 with the highest and lowest brand trust and needed as much variance as possible in the scores. In Parts 2 and 3, brand trust was measured on a seven-point Likert scale to coincide with other measures.

Table 2.

Measures for Variables in Exploratory Study of IoT Purchase Intention

Variable Name	Measure	Reference
Performance Expectancy	1. Using this product would improve the quality of my life.	Venkatesh et al (2003)*
	2. Using this product would increase my productivity at home.	Venkatesh et al (2003)*
	3. Using this product would make my life easier.	Venkatesh et al (2003)*
	4. I would find this product useful at home.	Venkatesh et al (2003)*
	5. This product is better than the speaker I already have.	Venkatesh et al (2003)*
	6. This product has features that are more exciting than other speakers.	Venkatesh et al (2003)*
	7. If I use this product, I will improve my productivity at home.	Venkatesh et al (2003)*
	8. If I use this product, I will be able to more easily entertain at home.	Venkatesh et al (2003)*
Effort Expectancy	1. Learning to use this product would be easy for me.	Venkatesh et al (2003)
	2. I would find it easy to get this product to do what I want it to.	Venkatesh et al (2003)
	3. My interaction with this product would be clear and understandable.	Venkatesh et al (2003)
	4. I would find the product to be flexible to interact with.	Venkatesh et al (2003)
	5. It would be easy for me to become skillful at using the system.	Venkatesh et al (2003)
	6. I would find this product easy to use.	Venkatesh et al (2003)
	7. Using this product would take too much time from my normal activity (reversed).	Venkatesh et al (2003)
	8. It takes too long to learn how to use the product to make it worth the effort (reversed).	Venkatesh et al (2003)
	9. I believe it is easy to get this product to do what I want it to do.	Venkatesh et al (2003)*
	10. This product would be easy to set up.	Venkatesh et al (2003)*
Self-Efficacy	1. I have the skills needed to use [product name].	Porto Bellini et al (2016)
	2. I am motivated to use new technologies.	Porto Bellini et al (2016)
	3. I can operate effectively the functionalities of [product name].	Porto Bellini et al (2016)
	4. I am confident about how to use the tools of [product name].	Porto Bellini et al (2016)
	5. I am able to use the [product name].	Porto Bellini et al (2016)
	6. I know what the features of this technology look like.	Porto Bellini et al (2016)
	7. I am curious about exploring new technologies.	Porto Bellini et al (2016)
Anxiety	1. I feel anxious about using new technologies.	Xu (2016)
	2. This technology is intimidating to me.	Xu (2016)
	3. I am uncomfortable with the fact this technology will be really used.	Porto Bellini et al (2016)

	4. I am afraid of using this new technology incorrectly.	Porto Bellini et al (2016)
	5. I question why I will need to use this technology.	Porto Bellini et al (2016)
	6. I am hesitant to use [product name].	
Privacy Concerns	1. Privacy is very important to me.	Dinev & Hart (2004)*
	2. Privacy concerns affect the way I use technology.	Dinev & Hart (2004)*
	3. When using new technology, I think about how it will affect my privacy.	Dinev & Hart (2004)*
	4. I am concerned with the amount of information that is collected on me.	Dinev & Hart (2004)*
	5. I am concerned the personal information this device collects could be misused by [brand].	Dinev & Hart (2004)*
Social Influence	1. People who influence my behavior think that I should use this product.	Venkatesh et al (2003)
	2. People who are important to me think that I should use this product.	Venkatesh et al (2003)
	3. I would use this product if many of my friends used it.	Venkatesh et al (2003)
	4. My friends would enjoy using this product in a social setting.	Venkatesh et al (2003)*
	5. In general, my friends are interested in using smart speakers.	Venkatesh et al (2003)*
	6. If someone in my social network owned this product, they would have higher prestige than those who did not.	Venkatesh et al (2003)*
	7. Having this product would be a status symbol in my social network.	Venkatesh et al (2003)*
Brand Trust	1. I trust this brand.	Yi et al (2015)
	2. [Brand] is reliable.	Yi et al (2015)
	3. This is an honest brand.	Yi et al (2015)
	4. [Brand] is dependable.	Yi et al (2015)
Purchase Intention	1. I will never buy this product (reversed).	Spears & Singh (2004)
	2. I definitely intend to buy this product.	Spears & Singh (2004)
	3. I am interested in purchasing this product.	Spears & Singh (2004)
	4. I will definitely not buy this product (reversed).	Spears & Singh (2004)
	5. I will probably buy this product.	Spears & Singh (2004)

* Adapted from

Purchase Intention. Purchase intention is a common way of assessing purchase behavior (i.e., behavior change). In many studies it is measured on a single item scale, which can lead to oversimplified results (Spears & Singh, 2004; Chang & Wildt, 1994; Kalwani & Silk, 1982). Spears and Singh (2004) developed a seven-point semantic differential scale to evaluate purchase intention in more detail. This scale was adapted into a seven-point Likert scale (1 = strongly disagree; 7 = strongly agree) to fit with other questionnaire items (see Table 2). Items were both positively and negatively oriented, including “I will never buy this product” and “I am interested in purchasing this product.” The Cronbach’s alpha for purchase intention ranged from .90 to .95.

Part 1 Insights

The primary purpose of Part 1 was to determine which of 10 brands had the highest and lowest brand trust. A cursory glance at the means of all 10 brands (see Table 3) shows that Amazon had the highest brand trust score ($M = 85.11, SD = 12.77$) and Baidu had the lowest brand trust score ($M = 45.18, SD = 22.29$). To determine if the means were significantly different, a repeated measures ANOVA was conducted. There was a significant difference between at least two of the means, $F(9, 26) = 12.66, p < .001, \text{Wilks' Lambda} = .19$. Pairwise comparisons between each brand showed that Amazon and Baidu had the largest difference in means at 39.94 and this difference was statistically significant ($p < .001$). Therefore, the Amazon Echo, a smart speaker on the market, was used in Part 2 as the example for high brand trust. Baidu was used in Part 3 as the low brand trust example. Baidu, a Chinese brand, is in the process of creating a smart speaker called Xiaoyu Zaijia or “Little Fish.” In an effort to avoid extraneous variables, the researcher chose not to identify

Baidu's product as Xiaoyu Zaijia. The product needed to be believable, so Little Fish could not be used since it would be confusing without context. Instead, the product featured in the advertisement was named Baidu Home Robot, based on some of Baidu's descriptions of the product.

Table 3.
Descriptive Statistics for Brand Trust in Part 1

Brand Name	M (SD)
Apple	79.35 (20.94)
Google	83.70 (11.32)
Microsoft	75.96 (15.95)
Amazon	85.11 (12.77)
Sony	75.00 (11.22)
Logitech	62.75 (22.99)
Bose	79.10 (14.64)
SK Telecom	45.83 (22.12)
Baidu	45.18 (22.29)
Mycroft AI	47.13 (23.09)

Part 2 and Part 3 Procedure

Part 2 and Part 3 were online surveys using samples from Amazon's Mechanical Turk (MTurk) and hosted on Qualtrics. Parts 2 and 3 utilized MTurk because it is a cost efficient and reliable method of conducting online studies (Berinsky, Huber, & Lenz, 2012). In a study of MTurk respondents, researchers found that the pool tended to be young, well-educated, and racially diverse (Berinsky et al., 2012). For new technology and online brand interaction, a younger and more educated set of respondents is appropriate. Cross-contamination and survey fatigue are potential problems of these online survey services, but most respondents

reported they took two or fewer surveys in a specific category in one month (Berinsky et al., 2012).

To ensure participants understood the product, and to explore differences related to brand trust, participants were shown sample advertisements. In Part 2, participants saw an ad for the Amazon Echo (see Figure 2), and in Part 3 they saw an ad for the Baidu Home

Figure 2. *Product Advertisement with High Brand Trust*

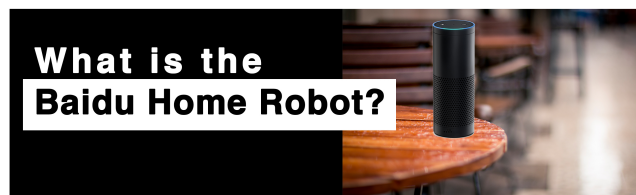


Amazon Echo is an easy-to-use speaker you control without the need to touch a button. It connects to your music library, other devices, and adapts to your preferences. Easily choose when and how Amazon Echo is connected to you. Adjust privacy settings with the press of a button. The Amazon Echo is built to listen to you, and can even hear your commands from across the room while music is playing. **Experience hands-free high quality sound to free up your life.**

Product features:

- Easily control your Apple Music, Pandora, Spotify, and iHeartRadio accounts
- Equipped with voice recognition technology that will easily pick up your voice
- Don't change the way you speak: your Echo adapts to your speech patterns and vocabulary for convenient operation
- Use the customizable Amazon Echo app to connect other smart devices in your home and set privacy preferences
- Convenient on/off button and sleep mode

Figure 3. *Product Advertisement with Low Brand Trust*



The Baidu Home Robot is an easy-to-use speaker you control without the need to touch a button. It connects to your music library, other devices, and adapts to your preferences. Easily choose when and how Baidu Home Robot is connected to you. Adjust privacy settings with the press of a button. The Baidu Home Robot is built to listen to you, and can even hear your commands from across the room while music is playing. **Experience hands-free high quality sound to free up your life.**

Product features:

- Easily control your Apple Music, Pandora, Spotify, and iHeartRadio accounts
- Equipped with voice recognition technology that will easily pick up your voice
- Don't change the way you speak: your Home Robot adapts to your speech patterns and vocabulary for convenient operation
- Use the customizable Home Robot app to connect other smart devices in your home and set privacy preferences

Robot (see Figure 3). Based on these ads, subjects in each part were asked 52 questions to evaluate their performance expectancy, effort expectancy, self-efficacy, anxiety, privacy

concerns, social influence, brand trust, and purchase intention (see Appendix B for questionnaire items). There was a slight variance in wording of the survey questions from Part 1, since Part 2 and Part 3 questions referenced specific brands and product names, while Part 1 was vague. In addition, brand trust was measured on a seven-point Likert scale for consistency with the other variables. Questions were randomized to prevent order effects. Part 2 had a total of 99 respondents and the reliability for all scales was .76 or higher (see Table 1). Part 3 had a total of 102 respondents and the reliability for all scales was .77 or higher (see Table 1).

Data from both parts were analyzed using SPSS 23. While Qualtrics automatically deleted unfinished responses, listwise deletion was used to address missing data in the completed responses (no item had more than 2% missing data). Also, four reversed items were recoded (see Table 2). After checking reliability scores, the researcher used SPSS to compute new variables. The descriptive statistics for variables from each part (defined by which brand advertisement people saw) are reflected in Table 4. To determine which factors were significant predictors of purchase intention, linear regression analyses were performed for Part 2 and Part 3. The results of these analyses are discussed in the next section.

Table 4.

Means and t-tests for Variables Used to Predict Purchase Intention of IoT Smart Speaker (N= 201)

Variable Name	<i>M (SD)</i> Amazon	<i>M (SD)</i> Baidu	<i>t</i>	<i>p</i>
Brand Trust	5.81 (.96)	4.52 (.91)	9.70	< .001
Performance Expectancy	4.77 (1.18)	4.75 (1.10)	-.14	.89
Effort Expectancy	5.55 (.86)	5.29 (.92)	1.90	.059
Self-Efficacy	5.56 (.84)	5.40 (.94)	1.23	.22
Anxiety	3.12 (1.13)	3.09 (1.11)	.49	.63
Privacy Concerns	5.06 (1.21)	5.14 (1.21)	-.14	.89
Social Influence	3.95 (1.19)	4.03 (1.14)	-.73	.47
Purchase Intention	4.63 (1.42)	4.38 (1.33)	1.01	.32

Results

The purpose of this research was to determine how brand trust and technology acceptance variables could be used in advertising to increase purchase intention of IoT technologies. In order to conduct this exploratory study, the researcher showed participants an advertisement for a smart speaker and asked questions about seven independent variables (brand trust, performance expectancy, effort expectancy, self-efficacy, anxiety, privacy concerns, and social influence) as well as one dependent variable (purchase intention). In Part 2, participants saw an advertisement for Amazon Echo (Amazon scored the highest for brand trust in Part 1). In Part 2, participants saw an advertisement for Baidu Home Robot (Baidu scored the lowest for brand trust in Part 1). Linear regression models were created to test the seven hypotheses. The results of each regression analysis as well as a comparison of Part 2 and Part 3 are discussed below.

Part 2 Results

As the literature review established, many of the independent variables in this study are theoretically linked, not only to the dependent variable, but to each other. In order to make sure multicollinearity was not a severe problem in the regression, a correlation matrix was generated. This matrix showed high correlation between performance expectancy and social influence ($r = .73, n = 99, p < .001$) and effort expectancy and self-efficacy ($r = .82, n = 99, p < .001$). High correlations merit further investigation for multicollinearity, so a regression was run including all seven independent variables and one dependent variable with collinearity diagnostics. In addition to not being statistically significant ($p = .65$), self-efficacy had a tolerance of .23 and a VIF of 4.38. Effort expectancy had a tolerance of .21 and a VIF of 4.80. These statistics showed multicollinearity issues. Effort expectancy had a larger regression coefficient and higher reliability. Several regression models were tested removing each variable, and self-efficacy was a non-significant predictor in every model. Therefore, it was removed from the model on the basis of multicollinearity, effort expectancy was retained, and the regression was rerun.

Table 5.

Regression Analysis Predicting Purchase Intention of Amazon Echo (N = 99)

Variable Name	β	t	p
Brand Trust	.08	1.15	.25
Performance Expectancy	.75	9.03	< .001
Effort Expectancy	-.17	-2.30	.024
Anxiety	-.22	-3.12	.002
Privacy Concerns	-.043	-.71	.48
Social Influence	.046	.62	.54
$R^2 = .78$			
Adjusted $R^2 = .77$			

The results of the final Part 2 regression model are presented in Table 5. Performance expectancy ($\beta = .75, p < .001$), effort expectancy ($\beta = -.17, p = .024$), and anxiety ($\beta = -.22, p = .002$) were statistically significant predictors of purchase intention. However, effort expectancy showed a regression coefficient in the opposite direction of the prediction. These results suggest that participants who believed the technology would take more effort to adopt, were more likely to show increased purchase intention. Brand trust, privacy concerns, and social influence were statistically insignificant. The Part 2 regression model explained 77% of the variance in purchase intention.

Part 3 Results

Similar to Part 2, the first step was to see if multicollinearity was an issue for any independent variables. A correlation matrix was generated, showing a high correlation between effort expectancy and self-efficacy ($r = .89, n = 101, p < .001$), and performance expectancy and social influence ($r = .76, n = 100, p < .001$). Based on this high correlation, a regression model was run with collinearity diagnostics. Self-efficacy had a tolerance of .14 and a VIF of 7.33. Effort expectancy had a tolerance of .17 and a VIF of 5.95. These statistics showed collinearity. Similar to Part 2, effort expectancy had a larger regression coefficient and higher reliability. When various models were tested with different variable removed, self-efficacy was non-significant each time.

The results of the final Part 3 regression model are presented in Table 6. Brand trust ($\beta = .32, p < .001$), performance expectancy ($\beta = .39, p < .001$), and anxiety ($\beta = -.27, p = .002$) were statistically significant predictors of purchase intention. Effort expectancy,

privacy concerns, and social influence were statistically insignificant. The Part 3 regression model explained 68% of the variance in purchase intention.

Table 6.

<i>Regression Analysis Predicting Purchase Intention of Baidu Home Robot (N = 102)</i>			
Variable Name	β	t	p
Brand Trust	.32	3.64	< .001
Performance Expectancy	.39	3.88	< .001
Effort Expectancy	-.15	-1.82	.073
Anxiety	-.27	-3.19	.002
Privacy Concerns	-.057	-.81	.42
Social Influence	.15	1.56	.12
$R^2 = .70$			
Adjusted $R^2 = .68$			

Evaluation of Hypotheses

Out of the seven proposed hypotheses, two were supported, one was partially supported, and four were rejected. Hypothesis 1, *performance expectancy will be a positive predictor of IoT purchase intention*, was supported. Both the Amazon and Baidu regression models showed performance expectancy to be a statistically significant positive predictor of purchase intention. Hypothesis 2, *effort expectancy will be a positive predictor of IoT purchase intention*, was rejected. In the Amazon regression model, effort expectancy was a negative predictor of purchase intention. On the other hand, in the Baidu regression model, effort expectancy was not a significant predictor of purchase intention. Hypothesis 3, *self-efficacy will be a positive predictor of IoT purchase intention*, was rejected. In both the Amazon and Baidu models, self-efficacy had to be eliminated due to multicollinearity, and

was not part of the final model. Hypothesis 4, *anxiety will be a negative predictor of IoT purchase intention*, was supported. In both the Amazon and Baidu models, anxiety had a negative regression coefficient and was statistically significant. Hypothesis 5, *privacy concerns will be a negative predictor of IoT purchase intention*, was rejected. Neither regression model found privacy concerns to be a significant predictor of purchase intention. Hypothesis 6, *social influence will be a positive predictor of IoT purchase intention*, was rejected. Neither regression model found social influence to be a significant predictor of purchase intention. Hypothesis 7, *brand trust will be a positive predictor of IoT purchase intention*, was partially supported. In the Amazon regression model, brand trust was not a statistically significant predictor of brand trust. However, in the Baidu regression model, brand trust was a significant positive predictor of purchase intention.

Evaluation of Research Question

The research question considered in this study was: *Are there any differences in the variables that predict purchase intention when trust is high instead of low?* To determine whether there were significant differences in performance expectancy, effort expectancy, anxiety, privacy concerns, and social influence between the participants that saw the advertisement for the high trust brand (Amazon) versus the low trust brand (Baidu), the researcher ran an independent samples t-test for each variable. The results of these t-tests are in Table 4. There was a statistically significant difference in brand trust between participants who saw the Amazon advertisement and those that saw the Baidu advertisement ($t(196) = 9.70, p < .001$). This was consistent with expectations, since the Amazon had the highest brand trust score and Baidu had the lowest brand trust score in

Part 1. There was no statistically significant difference between any of the other variables between Part 2 and Part 3 of the study. If there had been significant differences between the means of the two parts, this might have suggested an interaction effect between brand trust and other independent variables. While interaction cannot be ruled out, the results of the t-tests suggest that brand trust does not affect customer's evaluations of other variables. The implications of these results are discussed next.

Discussion

This study sought to improve the advertising of IoT products by exploring the factors that influence consumers' purchase of IoT technologies. In addition to traditional technology adoption variables, this study also tested the importance of brand trust, self-efficacy, anxiety, and privacy concerns. Performance expectancy and anxiety were consistently significant predictors of purchase intention for IoT products. Brand trust was only a significant predictor of purchase intention in Part 3 of the study, when participants were shown an advertisement for a brand with low brand trust (Baidu). Self-efficacy was excluded from the final regression models due to collinearity with effort expectancy. This result was similar to Venkatesh et al. (2003) where self-efficacy was excluded and treated as a potential mediating variable for effort expectancy. Privacy concerns and social influence were not statistically significant in either regression model. Effort expectancy was a negative predictor of purchase intention in the high brand trust survey, and insignificant for low brand trust. The discussion of theoretical and practical implications of these results follows.

Theoretical Implications

Current literature posits two potential futures for IoT. One is that IoT will become a normal part of Internet as we know it. The features that make IoT “unique” will eventually just become features of every technology. The other perspective says that IoT is a revolutionary and unique technology. While this study is limited to one IoT product, it lends support to the idea that IoT technology is not fundamentally different from any new technology that came before it, at least in terms of consumer adoption. While IoT products have unique data processing capabilities that introduce anxieties communicators should address, this study suggests IoT is predictable rather than revolutionary. This is a positive implication for marketing communications professionals, because it means models of technology adoption can be applied to the IoT adoption.

When participants were given an advertisement for a brand with low trust (Baidu), brand trust was a significant predictor of IoT purchase intention. However, when the brand had high trust (Amazon), brand trust was insignificant. The ceiling effect is a likely explanation of brand trust’s insignificance for a highly trusted brand. The ceiling effect is the concept that at a certain point an independent variable no longer has an effect on the dependent variable. In this case, when brand trust is high enough, it stops influencing purchase intention. Amazon was a highly trusted brand in Part 2 ($M = 5.81$). On the seven-point Likert scale used to evaluate brand trust, this means most participants rated somewhat agreed or agreed that Amazon was a trustworthy brand. Another factor influencing Amazon’s brand trust over Baidu’s is the participants’ familiarity with both Amazon and the Echo. Since participants were recruited from the U.S. they were likely

much more familiar with Amazon than with Baidu, especially since the Baidu smart speaker had not been released yet.

While the UTAUT framework was generally effective at predicting IoT purchase intention, this study found evidence that additional variables are also relevant. Anxiety and self-efficacy were considered in the original UTAUT model, but they were thrown out as not directly causing behavioral intention (Venkatesh et al., 2003). The results of this study suggest otherwise for anxiety. While anxiety was not a direct predictor of behavioral intention in the past, the increasing concerns related to big data and security of cloud technologies might have altered this relationship. More research needs to be done to validate anxiety's direct link to behavioral intention for new technologies.

The collinearity between self-efficacy and effort expectancy was not surprising. In the literature, self-efficacy and effort expectancy are similar. Both are variables that explain one's ability to use new technologies. The difference between the two, noted in Bandura (1977), is motivation. Similar to Venkatesh et al. (2003)'s belief that self-efficacy moderated effort expectancy's relationship with behavioral intention, this study's results could indicate the two variables share an extraneous relationship.

Interestingly, the findings for effort expectancy challenged the theoretical assumptions of UTAUT. Davis (1989) found that usefulness was a stronger predictor of technology use than ease of use, but ease of use was still a significant variable. There is no theoretical reason why effort expectancy is a negative predictor of purchase intention, and this finding might have been influenced by one of the limitations of this study. Effort expectancy was not a significant predictor of purchase intention for participants who were

shown a low-trust brand. Furthermore, it was a *negative* significant predictor when participants were shown a high-trust brand. Referring back to Roger's Diffusion of Innovations theory, certain types of people adopt new technologies. It is a reasonable assumption that innovators and early adopters might enjoy or seek out a challenge when adopting a new technology. Berinsky et al. (2012) determined that MTurk audiences tended to be more technologically advanced and more educated than the average consumer. Perhaps consumers who seek out new technologies expect or want a challenge when adopting a new technology. It is unlikely that the average consumer who is adopting a new technology to fulfill a specific need (like fitting in or performing a task) would want a challenge in figuring out how to use it.

Another possible explanation for this finding is that participants who are more knowledgeable about IoT products in general are also more aware of certain difficulties using them. If this is the case, participants who were more interested in smart speakers and more likely to buy them may have had different expectations about the effort necessary to use an Amazon Echo. In order to understand these expectations, more research would have to be done about consumers' knowledge of these products.

IoT literature focuses a great deal on the technical, legal, and reputational challenges of protecting consumers' privacy. Relying on current literature, brands selling IoT products would assume they would need to put a great deal of effort into convincing potential customers that their privacy is safe. This study contradicts that theoretical assumption. Instead, privacy concerns were not important.

While social influence was not significant, previous research showed that consumers

trust the opinions of their peers more than a brand's messaging. Therefore, the conception of social influence as a variable could be different than Venkatesh et al. (2003) theorized. It is also possible that since peer reviewers give advice about how well a product works, social influence is indirectly affecting purchase intention through perceived usefulness. The smart speaker is not an IoT product that is used frequently in groups, nor can it be worn or carried as a status symbol. If a different IoT product had been tested, social influence could have been a significant variable.

Finally, another theoretical implication of this study is that theories of technology acceptance can be used to guide strategic communication. The Customer Purchase Journey and other models of consumer behavior predict the process through which a consumer makes a decision. A key step prior to purchase is the evaluation of the product. Theories of technology acceptance provide further insight into how consumers evaluate and consider a product. Each of the factors identified in this study as a significant predictor of purchase intention could be addressed through strategic communication.

Practical Implications

This study provides some important practical implications for strategic communication of IoT technologies. The positive predictor of purchase intention, performance expectancy, should always be addressed to strengthen the marketing of IoT products. The usefulness or comparative advantage of IoT products is the most significant factor in influencing a consumer's purchase intentions. This suggests that advertising messages need to highlight what differentiates IoT technologies from other products, and how these differences make the consumer's life better.

In cases where brands are aware consumers do not trust them, building this brand trust is key to increasing purchase intention. This trust, like an interpersonal relationship between the company and consumer, can be built through communication. Consumers care whether brands share their values, so corporate social responsibility is one effective way to build similarity and improve trust (Tingchi Liu et al., 2014). However, for brands that have a high levels of trust already, due to the ceiling effect, incremental increases in that brand trust may not translate to increased purchase intention.

Aside from including variables that increase purchase intention, companies also need to proactively dispel anxieties surrounding the adoption of IoT technologies. There is, however, a fine line between decreasing a potential customer's anxieties and introducing new anxieties. This is the case with privacy. While some products might invoke stronger privacy concerns than a smart speaker, brands that discuss privacy in their advertising risk raising issues that the customer is not already considering. Addressing anxiety is a delicate balance for each IoT product.

This study informs companies selling IoT products what issues their marketing messages ought to address or highlight. Brand trust is important for companies with low brand trust to address, while effort expectancy negatively influenced purchase intention for products with high brand trust. This may mean that when consumers trust a brand, they are more likely to seek a challenging technology to adopt. Performance expectancy and technology anxiety are variables that consistently influenced the purchase intention of IoT products.

Limitations

This study only tested one specific product, a smart speaker, and other IoT products might have different motivators. Also, the sample was small for all three parts. More statistical power with a larger sample might have found more significant variables.

Previous studies including Morris and Venkatesh (2000) and Venkatesh et al. (2003) found that characteristics like age, gender, and experience with technology also influenced an individual's adoption of technology. This study was anonymous and did not collect any demographic data on participants, and therefore could not estimate the potential interaction effect of these other factors.

Finally, by providing participants with a fake advertisement about real products, the researcher risked the possibility that participants who had knowledge of these products would be influenced by additional knowledge they had of the product that was not being controlled by the researcher.

Future Research

As an exploratory study, this research cast a wide net across a group of variables influencing how consumers process their decision to purchase a new product. Further research can explore the significant variables from this study in more depth. One variable that might be considered in future study is whether a consumer's knowledge or familiarity with an IoT device influences the likelihood of adoption. The consumer's decision to purchase a new technology is more complex than the variables explored in this study. The literature suggests that a more complicated relationship exists between many of the variables included in this study, and future research should include mediating variables.

Future research could also use the results of this study to design and test advertising messages for IoT products.

Conclusion

The purpose of the study was to explore what variables influence a consumer's decision to adopt IoT technology. Participants were exposed to two smart speaker ads and asked questions about what influenced and impeded their adoption of the product. The results showed that performance expectancy influenced participants to express higher purchase intention for the IoT product. For a less trusted brand, brand trust was a positive predictor of purchase intention. Higher levels of anxiety led to decreased purchase intention. Effort expectancy was a negative predictor of purchase intention for a highly trusted brand. And contrary to predictions, social influence, privacy concerns, and self-efficacy were not influential in determining purchase intention. These results provide a guide for strategic communications professionals when marketing IoT products.

Appendix A
Part 1 Survey

CONSENT TO PARTICIPATE IN RESEARCH

Title of Research: An exploratory study on the determinants of purchase intention for Internet of Things products – Part 1

Funding Agency/Sponsor: n/a

Study Investigators: Maggie Holman & Dr. Joshua Bentley

What is the purpose of the research? The purpose of this project is to explore what factors make people more likely to buy Internet of Things products (e.g., smart speaker, learning thermostats).

How many people will participate in this study? Approximately 60 people will participate in Part 1 of this study.

What is my involvement for participating in this study? You will be asked to evaluate 10 different brands. Then you will be given product attributes for an Internet of Things technology (a smart speaker). Based on these product attributes you will answer 48 questions, including questions about how useful you feel this technology is, how easy this technology would be to use, and how likely you would be to purchase it.

How long am I expected to be in this study for and how much of my time is required? This survey takes approximately 15 minutes to complete. There are a total of 54 questions.

What are the risks of participating in this study and how will they be minimized? You might become bored or fatigued reading product information and answering 54 questions. Please do not complete this survey if you do not feel comfortable sitting and answering questions for approximately 15 minutes. While smart speakers are real products, please note the attributes that are listed are not specific to any brand or product on the market.

What are the benefits for participating in this study? Although there are no direct benefits to you for participating, you will be providing valuable information to academics and professionals about how to communicate with consumers about new technologies.

Will I be compensated for participating in this study?

For students of Dr. O’Neil’s Research Methods class: You will receive up to two points on one of your exams. All you need to do is click on the link at the end of your survey and fill out your student I.D. and click “submit.”

For other participants: There is no compensation.

What is an alternate procedure(s) that I can choose instead of participating in this study?

For students of Dr. O'Neil's Research Methods class: You may write a two-page paper on a topic approved by Dr. O'Neil.

For other participants: n/a

How will my confidentiality be protected? This study is confidential and no information collected will identify you personally.

Is my participation voluntary? Yes. Your participation is completely voluntary.

Can I stop taking part in this research? Yes. You may choose not to complete the survey at any time.

What are the procedures for withdrawal? To stop taking part, simply close the browser window where the online survey is displayed. In doing this, your survey session will end and you will not be required to participate any further. Your answers to any survey items will not be included in the study.

Will I be given a copy of the consent document to keep? You may print off this page for your records.

Who should I contact if I have questions regarding the study? Maggie Holman, Texas Christian University Strategic Communication Master's Student, m.holman@tcu.edu. You may also contact the faculty advisor for this study, Dr. Josh Bentley, j.bentley@tcu.edu.

Who should I contact if I have concerns regarding my rights as a study participant?

Dr. Dennis Cheek, Chair, TCU Institutional Review Board, Phone 817 257-6741.

Dr. Bonnie Melhart, TCU Research Integrity Office, Telephone 817-257-7104.

By clicking the button below, you indicate that you have read or been read the information provided above, you have received answers to all of your questions and have been told who to call if you have any more questions, you have freely decided to participate in this research, and you understand that you are not giving up any of your legal rights. You also indicate you are an adult (18 years or older).

Q1 Please select all of the following brands you currently own:

- Apple (1)
- Google (2)
- Microsoft (3)
- Amazon (4)
- Sony (5)
- Logitech (6)

- Bose (7)
- SK Telecom (8)
- Baidu (9)
- Mycroft AI (10)

Q2 Please rate the following brands based on how trustworthy they are (0= not trustworthy, 100= trustworthy):

_____ Apple (1)	_____ Logitech (6)
_____ Google (2)	_____ Bose (7)
_____ Microsoft (3)	_____ SK Telecom (8)
_____ Amazon (4)	_____ Baidu (9)
_____ Sony (5)	_____ Mycroft AI (10)

Q3 Please rate the following brands based on how reliable they are (0= not reliable, 100= reliable):

_____ Apple (1)	_____ Logitech (6)
_____ Google (2)	_____ Bose (7)
_____ Microsoft (3)	_____ SK Telecom (8)
_____ Amazon (4)	_____ Baidu (9)
_____ Sony (5)	_____ Mycroft AI (10)

Q4 Please rate the following brands based on how dependable they are (0= not dependable, 100= dependable):

_____ Apple (1)	_____ Logitech (6)
_____ Google (2)	_____ Bose (7)
_____ Microsoft (3)	_____ SK Telecom (8)
_____ Amazon (4)	_____ Baidu (9)
_____ Sony (5)	_____ Mycroft AI (10)

Q5 Please rate the following brands based on how honest they are (0= not honest, 100= honest):

_____ Apple (1)	_____ Logitech (6)
_____ Google (2)	_____ Bose (7)
_____ Microsoft (3)	_____ SK Telecom (8)
_____ Amazon (4)	_____ Baidu (9)
_____ Sony (5)	_____ Mycroft AI (10)

Q6 Please rate how likely the following brands would be to make sound equipment (i.e. speakers, headphones, etc.):

	Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely
Apple (1)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Google (2)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Microsoft (3)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Amazon (4)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Sony (5)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Logitech (6)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Bose (7)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
SK Telecom (8)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Baidu (9)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Mycroft AI (10)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

You are interested in purchasing a smart speaker for your household. There are several brands on the market, so you are doing research to compare features. You come across the following product information. Please look at the product information and answer the following questions.

Product description:

This product is an easy-to-use speaker you control without the need to touch a button. It connects to your music library, other devices, and adapts to your preferences. It's easy to choose when and how it is connected to you. You can adjust privacy settings with the press of a button. This product is built to listen to you, and can even hear your commands from across the room while music is playing. Experience hands-free high quality sound to free up your life.

Product features:

- Easily control your Apple Music, Pandora, Spotify, and iHeartRadio accounts
- Equipped with voice recognition technology that will easily pick up your voice
- Don't change the way you speak: this product adapts to your speech patterns and vocabulary for convenient operation
- Use the customizable app to other smart devices in your home and set privacy preferences
- Convenient on/off button and sleep mode

Appendix B
Part 2 Survey

CONSENT TO PARTICIPATE IN RESEARCH

Title of Research: An exploratory study on the determinants of purchase intention for Internet of Things products – Part 2

Funding Agency/Sponsor: n/a

Study Investigators: Maggie Holman & Dr. Joshua Bentley

What is the purpose of the research? The purpose of this project is to explore what factors make people more likely to buy Internet of Things products (e.g., smart speaker, learning thermostats).

How many people will participate in this study? Approximately 200 people will participate in Part 2 of this study.

What is my involvement for participating in this study? You will be shown an advertisement for an Internet of Things technology (a smart speaker) along with a list of product attributes. Based on this information as well as your feelings about new technologies you will answer 52 questions, including questions about how useful you feel this technology is, how much you trust the brand that makes this technology, and how likely you would be to purchase it.

How long am I expected to be in this study for and how much of my time is required? This survey takes approximately 15 minutes to complete. There are a total of 52 questions.

What are the risks of participating in this study and how will they be minimized? You might become bored or fatigued reading product information and answering 52 questions. Please do not complete this survey if you do not feel comfortable sitting and answering questions for approximately 15 minutes. While the product reflected is a real product, please note this is not a real advertisement and product details may not be true.

What are the benefits for participating in this study? Although there are no direct benefits to you for participating, you will be providing valuable information to academics and professionals about how to communicate with consumers about new technologies.

Will I be compensated for participating in this study? Yes. You will receive \$1.25 through MTurk for participating in this study. Once you reach the end of the questionnaire, you will receive a code you can enter on MTurk.com. Once the researcher verifies your participation, payment will be approved.

How will my confidentiality be protected? This study is confidential and no information collected will identify you personally. Your MTurk user ID will be used to approve payment and will then be deleted.

Is my participation voluntary? Yes. Your participation is completely voluntary.

Can I stop taking part in this research? Yes. You may choose not to complete the survey at any time. However, if you do choose not to complete the survey, you will not receive the code for your MTurk payment.

What are the procedures for withdrawal? To stop taking part, simply close the browser window where the online survey is displayed. In doing this, your survey session will end and you will not be required to participate any further. Your answers to any survey items will not be included in the study.

Will I be given a copy of the consent document to keep? You may print off this page for your records.

Who should I contact if I have questions regarding the study? Maggie Holman, Texas Christian University Strategic Communication Master's Student, m.holman@tcu.edu. You may also contact the faculty advisor for this study, Dr. Josh Bentley, j.bentley@tcu.edu.

Who should I contact if I have concerns regarding my rights as a study participant?
Dr. Dennis Cheek, Chair, TCU Institutional Review Board, Phone 817 257-6741.
Dr. Bonnie Melhart, TCU Research Integrity Office, Telephone 817-257-7104.

By clicking the button below, you indicate that you have read or been read the information provided above, you have received answers to all of your questions and have been told who to call if you have any more questions, you have freely decided to participate in this research, and you understand that you are not giving up any of your legal rights. You also indicate you are an adult (18 years or older).

Q2 Please select all of the following brands you currently own:

- Apple (1)
- Google (2)
- Microsoft (3)
- Amazon (4)
- Sony (5)
- Logitech (6)
- Bose (7)
- SK Telecom (8)
- Baidu (9)
- Mycroft AI (10)

Having this product would be a status symbol in my social network.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I will never buy this product.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I definitely intend to buy this product.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I am interested in purchasing this product.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I will definitely not buy this product.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I will probably buy this product.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Thank you for completing this survey. Here is your code to enter in MTurk for your payment: **RzXd9EA3**
Please make sure to copy this code before clicking next.

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Abstract

AN EXPLORATORY STUDY ON THE DETERMINANTS OF PURCHASE INTENTION FOR INTERNET OF THINGS PRODUCTS

by Margaret Holman, 2017 Department of Strategic Communication Texas Christian University

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The purpose of this study was to explore factors that influence customer's intentions to purchase Internet of Things (IoT) technologies. Intended as an exploratory study to expand on technology acceptance variables, this study tested the effects of brand trust, performance expectancy, effort expectancy, social influence, self-efficacy, anxiety, and privacy concerns on purchase intention for IoT products. Using three surveys, the researcher found that performance expectancy had a positive effect on purchase intention. Anxiety had a negative effect on purchase intention, while privacy concerns, social influence and self-efficacy were not significant. Brand trust and effort expectancy had varying influences on purchase intention depending on whether the participant was responding to an advertisement for a product with high brand trust or low brand trust. This study has implications for what issues companies should address or avoid in their marketing communication to increase adoption of IoT products.