2013

Moving toward a small-screen culture: examining the relationship between computer and smartphone user characteristics and online participation and creation

Amanda Bradford Cortright

Louisiana State University and Agricultural and Mechanical College

MOVING TOWARD A SMALL-SCREEN CULTURE:
EXAMINING THE RELATIONSHIP BETWEEN COMPUTER AND SMARTPHONE USER CHARACTERISTICS AND ONLINE PARTICIPATION AND CREATION

A Thesis

Submitted to the Graduate Faculty of the
Louisiana State University and
Agricultural and Mechanical College
in partial fulfillment of the
requirements for the degree of
Master of Mass Communication

in

The Manship School of Mass Communication

by
Amanda Bradford Cortright
B.A., Drake University, 1999
December 2013

I dedicate this thesis to my husband and son. While one offered the figurative kick to keep me focused throughout this process, the other provided the literal kick during my writing days. Both Harry and my thesis grew together, and his kicks reminded me that regardless of best laid plans, everything can come together in the end in a pretty cool way. I adore you both, Law and Harry.

ACKNOWLEDGEMENTS

I would like to thank, first, my committee chair Dr. Lance Porter. Thank you for allowing me to work with you for the past three semesters, and for the chat that one day in the summer of 2011 that helped me decide to give going back to school a try. I truly appreciate your guidance throughout this scholarly process and look forward to working with you on a publication or two in the future.

Also, to my other committee members, Dr. Amy Reynolds and Dr. Meghan Sanders: thank you for being so supportive of me during this year. Being pregnant and in graduate school isn't the easiest thing, and your willingness to reschedule meetings and advise via e-mail meant a great deal to me. Thank you both for your advice and great senses of humor throughout my tenure in the Manship School. It is faculty members like this committee that makes me wish I could stick around Manship a little longer.

TABLE OF CONTENTS

ABSTRACT

This study investigates the relationship between smartphone and desktop or laptop computer users' characteristics and online content creation and participation. A survey collected demographic information as well as detailed information on which devices were preferred by the participants in various circumstances. Results showed age and income were the two primary demographic factors in determining a user's degree of comfort with technology as well as their likelihood to participate with or create online content.

Employing the Diffusion of Innovations theory, this research found support for the idea that home computers have seen to fruition the diffusion process, and are not factors in participant's self-reporting of their level of online expertise. Looking at the use of technology through the Technology Acceptance Model lens, this research indicates that the usefulness a generation once saw in the proliferation of the home computer now has been more perceived and adopted in the area of smartphone use. This fairly widespread view of smartphone usefulness, except in the oldest age categories, indicates that like the computer becoming ubiquitous, soon too will the smartphone follow the same path.

Interesting findings include the disconnect between a user's self-concept and their actions; the *Content consumers* group, who generally consumes rather than creates or interacts with content, seems to rate themselves higher as influencers and experts online than the group who actually creates the content. And interestingly, those that are *Smartphone averse* will actually use their smartphones more in certain instances than *Content consumers*.

Why participants' self-concept differed from their self-reported usage patterns, in my view, is attributable to the fact that as the comfort level with technology rises, the awareness of that technology ebbs. This illustrates the power of ubiquity; once a piece of technology becomes

commonplace or highly familiar, the user concentrates less on the device because it has become part of his or her daily routine. This, in turn, causes the user's self-concept about the relationship between him or her and technology to become less based on actual usage patterns and more based on perception.

CHAPTER 1
INTRODUCTION

American adults like their gadgets. With 91 percent of them owning a cell phone (Smith, 2013), and 54 percent using those cell phones to access the Internet (Pew Internet & American Life Project, November 2012), there is no doubt we are more connected now than we ever have been. As society moves away from our desktop and laptop computers and onto smaller devices, it seems logical that the lack of physical keyboard and smaller screen would turn us from our current active participatory 'Net culture into a more passive, on-looking one.

But what those opening numbers cannot show is why certain devices are adopted and what effects their adoption might bring. Will a move toward smartphones and tablet computers mean fewer new blogs or forms of self-expression online? Will the smaller screen make it more difficult to participate on social networking sites or in a public online forum like a newspaper? Will these characteristics of technology lead to us simply look at what others post more than actually posting or commenting ourselves? Do the characteristics of heavy users of smartphones differ greatly from those of the laptop/desktop user? I will employ both the diffusion of innovations theory (DIT) and the Technology Acceptance Model (TAM) to study how technology is adopted, and what affects that adoption rate.

What I hope to do with this research is to offer some insight into how these newer technologies might change the way we participate in the online world. By pairing Pew Internet project data and the trends it shows in technology adoption rates with an online survey, the purpose of this research is to study the relationship between technology and participation as well as gain a better picture of the characteristics of certain groups who have demonstrated through the survey certain preferences about how they use technology. Through the examination of the

characteristics and preferences of smartphone and computer users as well as the cultural and socio-economic factors affecting one's access to technology itself, I hope to shed some light on the motivation and reasoning for why people use technology the way they do.

In addition to looking into why people choose what they choose, we must also look at the effect of those choices. A well-known name in diffusion of innovations research, Everett Rogers, discusses the pro-innovation bias embedded in much of the research done in this field; because researchers study the spread of innovation, the bias is assuming that diffusion is a good thing:

> The pro-innovation bias, coupled with the unfortunate and overwhelming dependence on survey research designs, means that diffusion research has mostly studied "what is" instead of "what could be" about diffusion processes. (Rogers, 1976, p. 295)

In addition to the insight into "why," the social implications that Rogers suggests is a key factor into adoption rates should be addressed as well. One of the limitations Rogers outlines is this "pro-innovation" bias. Diffusion research, by design, has classically looked at innovation as a good thing and at high adoption rates as a success. What are the implications of these adoption rates? Research is just beginning to look into this idea of what I will call in this thesis the Digital Divide 2.0. With innovation adoption being closely tied to socio-economic status and education level (Schlozman, Verba, & Brady, 2012; Schradie, 2011), the idea of a new form of the original "who has access to the Internet" Digital Divide debate begins anew, with a new angle.

By looking not just at who uses which device for what purpose, but also at the social influences surrounding these decisions, we can better understand the effects of socio-economic status and social networks on our behavior. The research has already begun to indicate that preference and, ultimately, behavior is a complicated idea to unravel. Our jobs, friends, social class, and education level all have a hand in what ideas are presented to us in the first place.

These ideas help us each form our own opinion, and in the realm of technology adoption, these newly formed opinions greatly influence our likelihood of acceptance and use of a new device.

Two people in the same general demographic profile may use the same device in vastly different ways. What I hope this research can do is identify a few possible characteristics of these users to see where their opinion and preference differences originated.

CHAPTER 2
LITERATURE REVIEW

Trends in Internet Usage and Smartphones

In 2004, research by the Pew Internet and American Life Project revealed that 44 percent of U.S. Internet users had added content to the World Wide Web through blogs, file sharing, or posting to Web pages. Some posted photos to Web sites, while others posted written content. While they have fallen out of fashion today, newsgroups were also a hotspot of communication online, allowing messages to be written, files to be shared, and pictures to be posted (Lenhart, Horrigan, & Fallows, 2004). What this data shows us is that just a decade after the World Wide Web and Internet became more widely used by the American public, in 2004, Americans were sharing, communicating, and creating content online.

Fast-forward to May, 2011, when the Pew Internet Project conducted their first-ever "standalone measure of smartphone ownership" (Smith, 35% of American adults own a smartphone, 2011). This survey revealed that while 83 percent of American adults have a cellphone, 35 percent of those people consider their cellphone to be a smartphone.

In the seven years between the Internet and American Life project that showed us 44 percent of U.S. Internet users added content to the Web and the 2011 survey on smartphone ownership, we moved to a time when one-third of the U.S. adult population had the Web readily available in their pockets thanks to their smartphones. Updated data in a March 2012 report from Pew, just 10 months after the 2011 survey, showed an 11 percent increase in smartphone ownership among American adults. "Smartphone owners now outnumber users of more basic phones," the report's headline read (Smith, 2012). The numbers are rising so quickly that updates to these Pew Internet reports come at a rapid pace. More recently, a June 2013 report shows that

smartphone ownership has now increased to 91 percent of American adults, up 10 percent from the previous year’s update.

The demographics for smartphone ownership are changing just as quickly, too. Now it’s not just the “early adopters” from diffusion theory that have the new gadgets; diffusion has taken place with both younger adults as well as adults of any age who have attained either high levels of household income or education. According to Smith (2013), “every major demographic group experienced significant year-to-year growth in smartphone ownership between 2012 and 2013” (p. 3).

We’re soon approaching the 20-year mark since the Internet became widely available to Americans. In the beginning, we had computers with keyboards and mice, which allowed for a similar typing environment to the familiar typewriter. Today, we have more than half of American adults with smartphones in their pockets and purses. While our goal as humans is often to communicate and connect with one another, we must consider the implications of the vast reduction in screen-size on smartphones and the lack of keyboard. While laptops are portable, and desktop computers are now a familiar shape to most of us who use the Internet regularly, the constant availability of the Web via smartphones will likely have implications on what’s created and communicated.

When thinking about access to the Internet and the World Wide Web, the idea of egalitarianism recently has come into the picture. On the Web, everyone has an equal voice, and suddenly more marginalized portions of the population now have an outlet to air their concerns. However, when we look beyond the Internet and to the devices themselves, it is still uncertain what the effect of these “always-connected” technologies will be. Certainly it makes sense that

the more affluent a population, the easier their access to technological innovations; but what about populations who are not as affluent? Are these issues simply creating a Digital Divide 2.0?

We are uncertain of the outcome of "these changing technologies on the socio-economic stratification of participation" (Schlozman, Verba, & Brady, 2012, p. 533). As Schradie's (2011) research points out, the implications of where this participation takes place is just now being explored:

> When people are able to access a computer at multiple places, or with multiple gadgets, frequently throughout the day, they have more control over the production process, and can produce more content. One implication for these results is that access at a location over which economically disadvantaged people have no control, such as a library or school, limits their likelihood of producing online content. (Schradie, 2011, p. 166)

What Schradie describes as the digital production gap is an idea that challenges the notion that the Internet "creates an egalitarian public sphere" and, conversely, returns us to the paradigm where "elite voices still dominate in the new digital commons" (p. 145).

Diffusion of Innovations

To understand this change over time from desktop computers, to laptops, to smartphones, we can first look at the diffusion of innovations theory (DIT). Clearly our social circles influence our decisions on adoption of new products and ideas, and this matters because it is important to understand why devices like computers and smartphones continue to be so widely and quickly adopted by users.

In the well-known Iowa seed corn study by Ryan and Gross (1943), it becomes evident how much the opinion of one's peers can influence the decision-making process. While salespeople had little success in the beginning in persuading rural farmers to try a new hybrid seed corn, the researchers found that when neighbors or peers began to talk about the new product, adoption grew. "The very fact of acceptance by one or more farmers offers new

stimulus to the remaining ones," Ryan and Gross wrote (p. 23), highlighting the importance of our social networks to our decision making processes. This work spurred many academics to further research diffusion theory (Rogers, 1976, p. 291), most notably Everett Rogers.

In Rogers' work, he defines five attributes that predict adoption: relative advantage, compatibility, complexity, observability, and trialability (Zhou, 2008, p. 479)**.** Each attribute – its level of strength or weakness – affects the likelihood a new "user" will choose to adopt the product (Severin & Tankard Jr., 2001, p. 208). While many researchers have tweaked and substituted other attributes, the major foundation of diffusion research has remained fairly constant (Zhou, 2008), implying it is a reliable idea to apply to current study. The characteristics of those five attributes helps classify people, according to Rogers, into certain types of adopters through which innovation flows; innovators, early adopters, early majority, late majority, and laggards (Severin & Tankard Jr., 2001).

According to Rogers (2003), each type of adopter features certain characteristics unique to its classification. A brief summary of these characteristics here will appear later again later to show how the combination of theories and research approaches can provide insight special to the research this paper hopes to serve. The adopter categories fall on a continuum from innovator on the earliest-of-adopters end to laggard on the latest-of-adopters end. Those who are earlier adopters on this continuum differ from their later-adopter counterparts in both personality traits and communication behavior (Rogers E. M., 2003, p. 298). Generally, earlier adopters are more comfortable with the idea of change, seem to be more intelligent and rational, can cope better with risk or uncertainty, have greater self-efficacy than those on the slower-to-adopt end of the spectrum. Communication styles differ, too, with earlier adopters being more prone to participate in social settings and be more connected to those in their own social network than those who are

later to adopt innovations. These earlier adopters are also more likely to seek out information and know more about developing innovations, thus developing more opinions on these innovations than that of their slower-to-adopt counterparts (Rogers E. M., 2003, pp. 288-292).

The inclusion and study of how our social system affects our choices is the heart of diffusion research:

> Diffusion studies are particularly able to reply on “moving pictures” of behavior rather than on ‘snapshots’ because of their unique capacity to trace the sequential flow of innovation through a social system. (Rogers, 1976, p. 295)

Earlier adopters were more likely to have more formal education; were a part of larger social circles through work, community, and education connections; and possessed “a greater degree of upward social mobility” than later adopters of innovation (Rogers E. M., 2003, p. 288). With these characteristics, we can see that the more people who have as much or more education and social connectivity than we do ourselves, the more likely those connections are to influence our opinion development when it comes to new technology. In fact, Rogers states that the more homophilous our circles, the more we look to people with more education and knowledge than ourselves (i.e., the opinion leaders) to help us make decisions.

The social system is such an integral part of the diffusion of innovation theory, that it seems that Rogers identified issues also highlighted by Schradie and Schlozman, Verba, and Brady:

> Homophily can act as an invisible barrier to the rapid flow of innovations within a social system, as similar people interact in socially horizontal patterns, thus preventing a new idea from trickling down from those of higher socioeconomic status, more education, and greater technical expertise. (Rogers E. M., 2003, p. 362)

This again puts the idea of the Digital Divide 2.0 under the microscope, making the inclusion of study into why people choose certain technological devices for different purposes even more

important. Do we prefer our smartphones for a certain task because that's our own personal preference? Or is it because people in our social network have set the example for which technologies are seen as convenient and useful?

This social system takes on yet another affect when adopters are categorized into voluntary or forced adopters. The workplace, while certainly part of our social system, changes the dynamic of adoption, mostly because a job might require the adoption of a new technology regardless of how the user feels about it. In a 2008 study, Zhou began to look at both the role of social influence in diffusion theory as well as the Technology Acceptance Model (TAM), on which I will elaborate more in the next section, to study the adoption rates of the Internet among Chinese journalists. While Rogers' five attributes were again found to be strong and reliable predictors of adoption in Zhou's study, what was more significant was the finding that organizations "rely not on social pressure but on the technological environment to facilitate employees' adoption…" (Zhou, 2008, p. 492). Simply having coworkers using technology to perform their daily tasks increased their perception of favorability toward the technology and thus, the adoption. It would seem that the "technological environment" that Zhou mentions can itself act as an opinion leader – and those who work within that environment receive cues and information from this opinion leader just as they would a human expert.

TAM and Its Predecessors

In addition how to our social circles and workplace environments can affect decision-making, our inner-makeup of attitudes and opinions toward those environments and objects can be predictors (Kulviwat, Bruner II, Kumar, Nasco, & Clark, 2007). In their 1974 PAD theory, Mehrabian and Russell describe three dimensions – pleasure, arousal, and dominance – as adequate descriptors, when combined in various ways and strengths, of any emotional state. The

feelings each human experiences can, according to Mehrabian and Russell, influence behavior. The PAD theory has been used in marketing, advertising, product-consumption, and other research to explore people's response to various stimuli (Kulviwat, Bruner II, Kumar, Nasco, & Clark, 2007, p. 1062).

While Mehrabian and Russell's theory analyzes the three dimensions the PAD theory claims make up our emotions, other theories or models have taken a more utilitarian approach to analyze how those emotions form opinions, and ultimately, behavior. We can extend the emotions we have toward an object into how will ultimately interact with that object. When we choose to use a device, our opinions have affected our behavior because at some point, we have thought the device was easy or convenient to use, thus making us adopt that technology.

Davis' 1989 research into how workers adopted new software technology introduced into the workplace identified two areas that are key to predicting whether one adopts technology or not: perception of usefulness and ease of use. Davis' Technology Acceptance Model (TAM), see Figure 1, asserts that it is our perception of usefulness that most highly predicts whether we accept or decide to learn to use that device. Ease of use was significantly less likely to predict adoption, which illustrates just how much the nuances of each individual matter when trying to understand how people choose and use technology. As Davis' research supports, even if a device is seen as being easy to use, that technology might not be widely adopted *unless* it is also widely viewed as being useful. We will overcome a learning curve if we think a device will make our lives easier.

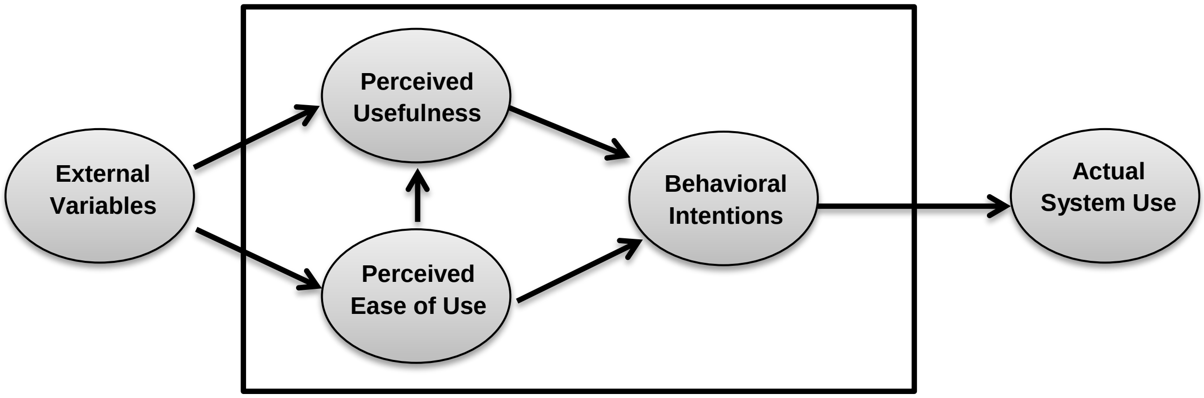

Figure 1. The TAM Model

That idea is tempered with Lai and Chang's (2011) findings that the device must also do what we expect of it. According to Lai and Chang, we have in our heads stereotypes about what we expect technology to do, how it is supposed to function, and how we are to manipulate it before we begin to use the device. While their research focused on e-book readers, the application of their research to a relatively new piece of technology in the marketplace can be considered applicable to other new devices. When a new device fits into our stereotype, that is if it does what we predicted it should and certain buttons do what we think they ought to, we're far more likely to adopt that technology into our lives (Lai & Chang, 2011).

How People Relate to Technology

If you've shoved a keyboard or mouse away from you in disgust of a computer crash, or kindly patted the top of a printer hoping your document comes out next, it should come as no surprise that humans react socially to technology. Understanding and investigating this concept, Reeves and Nass (1996) wrote *The Media Equation*, concluding that not only are media experiences also the same thing and equal to human experiences, but that "people's responses to media are fundamentally social and natural" (p. 251-253).

Through various experiments involving the programming of politeness, flattery, judgment and personality into machines, the characteristics involved in the various instances of human-computer interaction were manipulated and responses measured. Reeves and Nass also defined the five dimensions to personality, dubbed “The Big Five”: Dominance and submissiveness; friendliness; conscientiousness; emotional stability; and openness (p. 76). In each of the different types of experiments, the computers to which the participants were assigned and the work done by the participants themselves were rated more highly or favorably when the machine’s “personality” more closely matched that of the participant (p. 96). In essence, regardless of whether the computer in these experiments was programmed to be a more dominant personality or more submissive, each participant reacted socially to it; this is done unconsciously and automatically because we carry around our own “baggage of social cues” on which we instinctually rely for any interaction (p. 24). As Reeves and Nass say, “when in doubt, treat it as human” (p. 22).

People not only react to computers – and I argue to technology in general – socially, but view them as sources. Research by Sundar and Nass (2000) compared the computer-as-medium (CAM) model to the computer-as-source (CAS) model. Their investigation supported the CAS model, which claimed that individuals see the computer as an “independent source on information” (p. 683) and, consequently, apply “social rules and expectations to computers” (p. 688). In the first of two experiments, the researchers told one group of participants they would interact with computers, and another group that they would interact with programmers. Two rounds of “tutoring, testing, and evaluation” (p. 689) took place where each group began at a computer, then later moved to the computer labeled either “Computer 1” or “Programmer 1,” depending on which condition group they were assigned. At the labeled computers, the

participants would receive tutoring and feedback from their "computer" or "programmer." Participants in the "computer" condition reported the computer as being more "playful" and a generally more positive and effective experience than the "programmer" condition.

The operationalization and ecological validity limitations in this first study led the researchers to repeat the experiment with some tweaks. Participants may have had a preconceived idea of what a "programmer" was, which could have affected their evaluation in this group. Also, it is unusual to see a computer labeled as a programmer, which also may have affected the participants' perception. To control for that, the researchers designed the second experiment by telling one group, again, that they were interacting with a computer, and telling the other, this time, that they were interacting with a person in another room (p. 695).

Ultimately, this research found support for the CAS model. Humans have not "evolved to respond to 20^{th}-century technology" as pure machinery (p. 688), so when a machine replicates a human cue, we respond as if it were a human because we possess all of the cognitive shortcuts and nature to do so. This highlights not only the importance of technological development, but the importance of studying the preferences and perceptions humans have toward technology. Through social science research on this topic, researchers can offer ideas toward better design characteristics through research of the human response to these characteristics (Reeves & Nass, 1996, p. 96).

One human response already being studied is the negative side effects of technology – namely grammar. Cingel and Sundar (2012) first gave students a grammar assessment test, then followed with a take-home survey. The take-home survey asked questions about the student's average daily use of various technologies, their attitudes toward text messaging, and finally asked students to record the details of the last three received text messages. This approach

offered an opportunity to make the study more generalizable, since the last three received messages were likely from a variety of sources (parents, friends, etc.). The students were also asked to note how many forms of textual adaptation (intentional misspellings or abbreviations used for the sake of brevity in text messages, also called "techspeak") occurred in each of these text messages.

What Cingel and Sundar's found supported the Technology Acceptance Model's idea of perceived usefulness. They found that in the group of adolescents they studied, those who used text messaging more often were more likely to consider text messaging useful. In addition, they found that those who found text messaging useful would send and receive more text messages that featured "more textual adaptations" (p. 1315).

While Cingel and Sundar focused their findings' implications in terms of social cognitive theory, the findings can also back up a diffusion theory-based statement about the impact of the influence of social circles. Cingel and Sundar found a negative relationship between the number of text messages containing "techspeak," or textual adaptations, and the adolescent's score on an English grammar test. An adolescent was found to use "techspeak" more if he or she received many messages that first contained "techspeak." So, while this certainly fits the ideas of social cognitive theory, we can also see how our peers' use of an innovation affects our own.

Since users see the actual technological device as a source of information (Sundar & Nass, 2000), logically, the next step is to say that if a user trusts that source, his behavior – what he does with that source's information – might be affected. Koh and Sundar (2010) found support for the idea that credibility of a source can foster attitude and behavior change. While their research was primarily aimed at examining heuristic versus systematic processing of information, their findings indicate that "the effects of Web agent specialization," that is, the

level to which a Web site offers "expert" sources or frames itself as an expert source, can lead to changes in online behaviors, "ranging from forwarding information via e-mail to purchasing products via e-commerce Websites" (p. 121).

The more broad application of this finding is that the type of source on the Web can have a positive effect on participation online. Stories or videos from trusted sources might be shared or commented upon more often. Similar to the ideas of the user's perception in the TAM model, Kalyanaraman and Sundar (2006) looked at the processes that might mediate the relationship between customization of Web content and a user's attitude toward it. These processes included the user's perception of relevance, interactivity, involvement, community, and novelty. As each of these processes increased online (a site was seen as more relevant, interactive, or novel, for example), the user's ultimate favorability toward a Web site also increased.

In this experiment, participants handed in a pre-questionnaire that assessed their preferences for various levels of customization on the MyYahoo! site (sports, music, travel, weather) in addition to demographic information that included hometown, birthday, and their major in school. The researchers created a customized Yahoo! Portal for each participant that fell into one of three conditions: low, medium, and high. For example, a participant assigned to the "low" category would then view a portal with a low level of customization based on the participant's pre-questionnaire data.

Ultimately Kalyanaraman and Sundar found that participants were "able to discriminate between different levels of customization or personalization" and, "more importantly, exposure to personalized content translated positively into evaluation of the portal" (p. 126). This finding supports the TAM philosophy of perceived usefulness leading to more active use of a computer device. When a Web site or portal can be customized, it is then seen as more useful and

potentially easier to use. This also brings up an interesting approach to understanding the development of our own preference to use one device over another (a smartphone or a laptop/desktop computer). Are smartphones perceived to be more customizable than laptops or desktop computers, hence their widespread and rapid adoption in recent years? Or do we prefer to send an email from a device with a physical keyboard because of its perceived ease of use, or the customized address book and user display of the email client or Web site? All of these ideas could meld to create our own cognitive processes that lead to our preference.

Sundar and Marathe (2010) explored the idea that power, agency, and privacy all affect user experience online. The "power user," or the early adopter as diffusion of innovations theory calls them, had a different experience online than non-power users based on these factors. Power users reported higher-quality content when they controlled the customization process, whereas non-power users preferred content personalized based on their prior browsing behavior (p. 298)

Sundar and Marathe (2010) used an experiment similar to Kalyanaraman and Sundar's 2006 design. Participants were asked to come in and use the Google News Web site in the first round of this experiment. All participants were exposed to the same site with no variation between participants. Later, participants were asked to come back and were then assigned to one of three groups. One group again used the Google News site "as is" (p. 306), and the other group used a version that was customized for them based on their browsing in the first round, and the last were assigned to condition where they personalized the Google News site themselves. Afterward, participants filled out a questionnaire that measured "their attitudes toward news content on the site" (p. 306).

Later, in a second experiment within this research, the issue of privacy came into play. In the second study, half of the participants were told their browsing history and information from the first study might be used, the other half of the participants were told it would not be used.

After study 2, the researchers found "significant three-way interactions… for sense of control and perceived convenience" (p. 298), indicating that power users are more concerned with privacy than non-power users:

> It implies that the default assumption that users, especially power users, make is that SIP systems [system personalization based on prior usage, not user input] are low in privacy. Such a mindset could have serious implications in a number of arenas. (p. 317)

This research shows that more confident and experienced a user is with technology, the more control and power they expect to have over that technology. When convenience is factored in, power users gradually shift to preferring the SIP version of customization rather than inputting information themselves. However, non-power users in contrast "are more likely to be high self-monitors of their news consumption, perhaps limiting their exploration" (p. 318) once they are made aware of the privacy issue (the use of their information and browsing history by the Web site) when online.

How DIT and TAM Come Together

The TAM model was expanded upon by Venkatesh and Davis (2000), incorporating more of the individual characteristics of the user. With this nod to diffusion of innovations theory, this new model called TAM2 added in a look at social norms and how they affect individual decisions. If a circle of friends and coworkers find a device or piece of technology useful, that is much more likely to predict their adoption rate of that device than if they would have made a decision alone. This effect was lessened over time, though, as personal usage increased and the social influences were overtaken by personal opinion on the device.

Venkatesh and Bala (2008) further edited the TAM model by introducing 12 variables that affected user adoption. While the tweaking of the TAM model has added multiple variables, making it more complex, many researchers still rely on the original TAM model because of it being highly predictable and parsimonious (Wang, Chung, Park, McLaughlin, & Fulk, 2012).

A further adaptation or revision of TAM occurred when Stern, Royne, Stafford, and Bienstock (2008) proposed to add in one's feelings about the computer itself to the model and apply this new model to online auctions. This research took a different tack because it did not solely focus on the subject's feelings toward the technology as a predictor of use, but the subject's feeling about the device on which another task was taking place. Stern, et al. stepped beyond just looking at the device's adoption rate and began to look past the technology itself into our attitudes about the task for which we're using the technology. Their findings reinforced "TAM's historical robustness" (p. 630) and supported the idea that feelings toward the computer can affect usage intentions and experience.

The situational differences among users also occur in the technology itself. Taking a closer look at the characteristics designed into each new piece of technology is what Verkasalo, Lopez-Nicolas, Molina-Castillo, and Bouwman (2010) propose. By studying a group who used smartphone applications (apps), Verkasalo et al. looked at the behavior of the user toward the device and were able to expand upon and offer support of Davis' TAM model, noting that "technological barriers have a negative effect on behavioral control" (p. 251). Essentially, this finding shows us that while our motivation to want to learn the technology might drive us, as Davis argues, if the technological barriers are too great, our control over the device is lost. Going beyond the TAM model, Verkasalo et al. incorporated the diffusion of innovation theory as well as studied the social norms that affect our decision to adopt technology. Their research supports

the theory that if “early adopters” find the technology useful, it is more likely to become more widely adopted by the rest of society. This research also supports what Lai and Chang suggest: if the technology does what our stereotyped view says it should do, that technology is more likely to become part of the mainstream.

The user, powered by perceptions of usefulness and convenience, is the driving force behind technology now (Lichtenberg, 2011). As people become more and more familiar with new things and their capabilities, they grow to expect certain functions. The "expanding range of digital formats" (p. 106) in the publishing industry now allow for functions that books alone cannot support; the addition of the mobile web and social media have increased the opportunities for direct interaction with content, which helps explore my argument about emerging technologies possibly facilitating participation. We are in the age of digital abundance, and I believe we will seek out technology that we perceive as useful to help us wade through it all.

In addition to the qualities of usefulness and ease of use, people, more simply, use what they like. Before the release of the original iPhone in 2008, then president of Apple, Steve Jobs, was quoted saying, “people want the *real* Internet on their phone” – and he was right (West & Mace, 2010). The demand for mobile data packages has skyrocketed since the introduction of the iPhone, proving that once we had an Internet that was familiar to us and convenient to use, wide adoption happened – and quickly (p. 282).

Diffusion of innovations theory and TAM come together again in Chan-Olmsted, Rom, and Zerba’s (2012) research on the news consumption rates of young adults. Their research found support for the “perceived relative advantage of a new technology and its adoption” as well as the idea that “relative advantage perception of mobile news plays a role in how early and how much a young adult might use mobile news” (p. 139). Here, smartphones come into play

with the finding that the perception of mobile news being useful is related to how early and how young a user might be when he or she first adopts that mobile device. Another interesting conclusion from Chan-Olmsted et al. was the finding that mobile phone use does not predict adoption of a young adult's traditional media usage nearly as well as it predicts his or her mobile news adoption (p. 141). Here we have the type of media usage this younger generation will adopt being predicted not by what information they seek, but what technology they have on hand with which to seek it out.

Modifications to the technology acceptance model.

Convenience is the key predictor of adoption in the Technology Acceptance Model, and research has moved from this mostly cognitive-focused model (Nasco, Kulviwat, Kumar, & Bruner II, 2008), to tweaking the model, to even calls for its replacement. In their 2007 research, Kulviwat, et al. (2007) proposed replacing TAM with CAT: the Consumer Acceptance of Technology model.

The CAT model combines some of the cognitive elements of TAM (relative advantage, perceived usefulness, and perceived ease of use – see Figure 1) with those of Mehrabian and Russell's dimensions of emotion (pleasure, arousal, and dominance). A combination of these six factors all lead to attitude toward adoption, which predicts adoption intention (see Figure 2). This model sought to combine elements of TAM with "multidimensional operationalization of affect as well as the addition of relative advantage" (Kulviwat, Bruner II, Kumar, Nasco, & Clark, 2007, p. 1069) to see if the model would improve the prediction of adoption intention. When testing whether CAT would outperform TAM, the researchers found the CAT model explained 53 percent of the variance in behavioral intention. When relative advantage and affective

components were removed, the explained variance dropped to 38 percent, supporting the idea that inclusion of affect was important to the model's predictive capabilities.

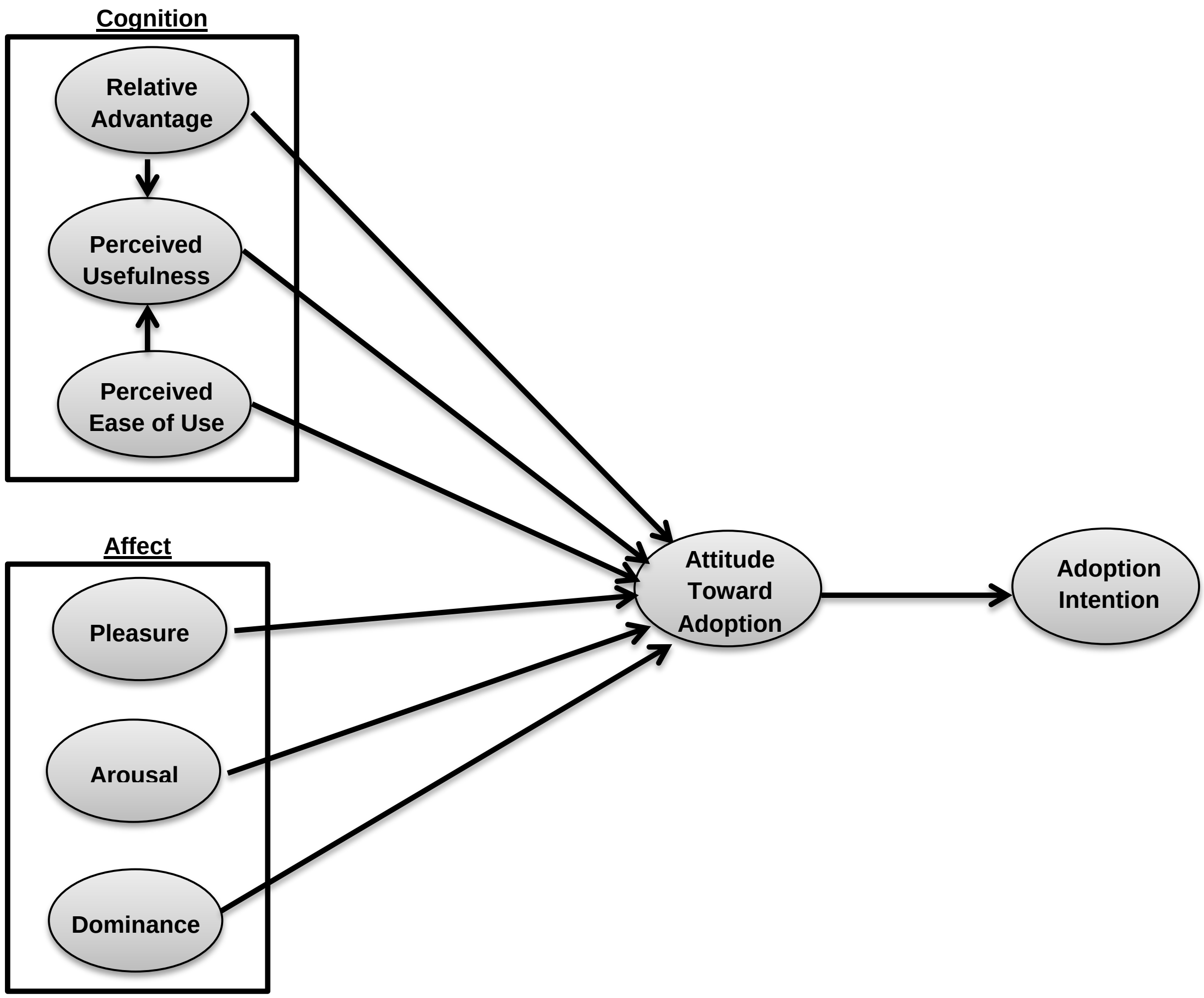

Figure 2, The Proposed Consumer Acceptance of Technology (CAT) model.

Through various adaptations, revisions, and additions to TAM over the years, it seems that when adding elements of social context and affective components to TAM's cognitive-focused model, predictive power rises. However, I believe for simplicity's sake that we can rely on the core components of TAM as Wang, et al. (2012) have stated; the simple elements of perceived usefulness and perceived ease of use toward technology make TAM a parsimonious

and consistently predictable model. Whether we look at the more streamlined Technology Acceptance Model or the more robust Consumer Acceptance Model, it's clear both models discuss technology in a general terms. My research aims to investigate specifically smartphones and computers to see if these models still fit the way Americans use technology. As these technologies became more prevalent, the literature responded with research that began to look into these specifics.

Wei et al. (2012), in a uses and gratifications approach, looked not just at smartphones, but the apps that resided on those devices. The focus of the study investigated which apps college students used and why. Their findings boiled the "why" down to entertainment, followed closely by convenience, once again a core component of TAM. Apps are most convenient when they are available with a tap of the finger; when they are ready for use at a moment's notice, apps are perceived as more gratifying (Wei, Karlis, & Haught, 2012). Another facet of this research that supports the purpose of this thesis was their finding of a negative predictor between the idea of convenience and use of the Gmail app. The researchers concluded that while participants liked the constant availability of their email, they preferred a traditional computer with a keyboard when it came to sending emails. This naturally leads me to wonder if those students would send fewer emails with increased smartphone use.

Why Participation and Creation Matter

Few could argue that the evolution of the Internet to the interactive and ubiquitous force that it is today has not affected and will not continue to affect its users. In the U.S. and many parts of the world, the Internet has provided a platform on which anyone can stand to share their voice and opinion. While the jury may still be out on how revolutionary the Internet and its

power to lend a voice truly may be (Papacharissi, 2002), the audience it gathers has been shown to mean a great deal to the speaker (Marwick & Boyd, 2010).

Conversely, just as there are many reasons to embrace technology wholeheartedly for its ability to broadcast citizen voices, research must also look at the reasons why people choose not to take part in that participatory environment that are unrelated to usefulness or capabilities we may see in technology. In Liu's 2010 proposal of yet another adaptation to TAM, the issue of self-efficacy and its relationship to anxiety comes up. This study explored wikis (online, community-generated sources of collective knowledge) in educational environments and noted that although there have been many studies that show a negative correlation between self-efficacy and anxiety, there are reasons to suspect that online-posting anxiety (the fear of the ramifications of posting content online) is a result of that user's computer/Internet self-efficacy (Liu, 2010, p. 57). This idea of understanding what user thinks of his or her ability about technology may affect the ultimate outcome of his or her online experience shows that while there is power in understanding and becoming comfortable with technology, there is that important first step of the TAM model of perceiving those actions to be useful and ourselves capable of doing them.

Technology has been adopted and assimilated into the lives of many adults today, essentially becoming part of our culture. In his editorial in *Convergence*, Henry Jenkins (2008) stated that these consumers armed with this new technology are using it to "assert their own control over cultural flows" (p. 9). This idea of power is a most interesting aspect to investigate. If these new technologies and their capabilities lend us the opportunity to even appear to have control over "cultural flows," it is important to understand the motivations of the user behind this technology (Jenkins, 2008, p. 11). Merely studying the rates of adoption, or the trends in

technological advancement is not enough; we must seek out the whys and hows of this adoption and subsequent use, so we can better understand the larger picture into which these pieces fit.

In viewing this issue from another perspective, we can ask not just what comes of our use of technology, but for what purpose can and *should* the technology be invented in the first place? Tacchi (2011) explores the idea of information and communication technology (ICT), but expands it to information and communication technology for development (ICT4D). The "for development" aspect takes this field of study from a process of creating technologies and devices, to the technology's "social consequences for social life" (p. 664). Tacchi argues that having a "voice" should be an end, not a means, of technological development, and that development not merely could, but *should* promote advocacy and agency within communities.

Participation and creation are more than just an end to well-designed technology; they can be viewed as a means to be a force of change or community-building around larger social issues. If we can understand why people choose certain technologies and why they use them in the manner they do, we can use both Jenkins' and Tachhi's perspectives to understand both the power of the technology over us, and the power within ourselves to utilize aspects of technology.

Schradie's research into the digital production gap offers a new angle by which we can study online participation by asking, "Who is making the content?" If, as Schradie indicates, the "haves" produce much more online content than the "have nots," the idea of the new Digital Divide 2.0 resurfaces. The question is no longer "who is participating?" but becomes "why is that segment of the population participating so much more than another?"

A relatively new aspect to online content creation is the ability to create or participate online via a smartphone. The widespread adoption of smartphones and the mobile Web places

the ability to contribute online content into the hands of 54 percent of the American adult population (Smith, 2013) with these numbers rising each year.

Nuances of digital communication.

But mobile communication differs than the more traditional face-to-face encounters of every day (Campbell & Kwak, 2011). The size of our social circles and networks as well as the amount of agreement between the user and that circle can determine how effectively communication takes place. Campbell and Kwak found that the level of online participation via mobile technology would rise with the degree of agreement between the mobile user and the network within which he or she was communicating (pp. 1016-1018). In essence, users are more likely to participate and create content in an environment where they feel supported and accepted. A more negative aspect to this research is that the effect of smaller networks and the level of social connectedness have on participation; the less socially connected a user is, the less incentive or motivation she has to participate online (p. 1019). The researchers suggest that the "effects of mobile communication on political life are more profound for younger users..." (p. 1020); while they focus on the effects on political participation, I argue that these findings are applicable to any type of online participation.

While Schradie's digital production gap highlights the importance of studying who is creating the content, we can look to areas like Brazil where access to the Internet via computer is certainly affected by socioeconomic status, but access to smartphones is not (Pedrozo, 2013). Pedrozo states that mobile phones have "changed the notion of time and space" (p. 145), allowing the "have nots" to have access where they would not have before. However, she also notes how social networks and identification are changing – especially for youth – who "enthusiastically adopt, shape, and appropriate new media in their different forms" (p. 147).

However Pedrozo's argument aligns with Schradie's when it comes to the factor of socioeconomic status. While Schradie mainly argues about the implications of the "haves" creating the majority of the online content, Pedrozo suggests that the inclusion of mobile devices broadens the scope of who these online or mobile content creators are while agreeing that the content they create still relies on social, economic and cultural frameworks (p. 147).

Pedrozo also looks into what I call the Digital Divide 2.0, suggesting there are multiple digital divides in technology set into motion by differing social, economic, political and technological issues (p. 149). While she acknowledges that these are fairly technologically determinist arguments, she goes on to say that initially, this Digital Divide 2.0 begins and is caused by the "haves" having the ability to adopt technology quickly and first. However, as in the cases of Brazil and Italy, mobile phone technology and its ability to facilitate online participation and content creation, "widely spread across all social classes" (p. 150). What this means is that the digital divide comes as our societies move from a culture of "instant gratification to one of constant gratification"; while the quick spread of mobile technology can usher in a democratizing effect, it cannot completely make up for the gap left in regard to socioeconomic status or complete digital literacy (p. 154).

The assumption of youth as creators.

But before we can better understand these lofty goals of technology's role in creating agency, identity, or as a tool for social change, we first have to understand a more basic premise of how technology users act and think. Before we can try to understand intent or motivation behind uses of technology, we first must look at who tends to use this technology and why.

Humans are creatures of habit, and consequently, using a very broad brush, many are resistant to change in some form or another. Humans have read books for hundreds of years, yet

the adoption of e-book readers has been on the rise, hitting 19 percent of American adults in 2011 (Zickuhr, October 2012). If society in general is resistant to change, how have these devices steadily gained popularity? The answer lies in another human quality: laziness. The perception of convenience can trump the hesitation to learn how to use a new device; if that new device enhances a daily routine, the user becomes more apt to try it.

As Lai and Chang (2011) found, users adopted e-books with enthusiasm because e-readers allowed them to use the devices as they would a traditional book (bookmarks, making notes in margins, highlighting important passages), along with the added conveniences provided by the technology (light weight, multiple books on one device, etc.). We have a stereotype of what we think and hope a piece of technology can and should do; if that stereotype holds true when we use it, we're far more likely to adopt that technology into our daily lives because it is convenient to do so (Lai & Chang, 2011).

Applying this idea to the concept of the Internet, most of the spirit of the argument holds true. As Papacharissi (2002) notes, Internet users will "mold" the power of this seemingly cavernous platform to fit their needs. Though we may feel more empowered through anonymity online, and while the political sphere may grow because of this inclusion, the character and nature of the sphere has not changed because of the Internet. The political process has always had gadflies and naysayers; the Internet has just made it easier to remain anonymous or to deliver our opinion directly. These authors show that our intentions – either to communicate or to take part in a hobby – have not changed with the introduction of new technology, but it has modified how we carry out those tasks.

More than just our human nature affects what technology we choose and why, our age and socioeconomic status also play a clear role. Simply having access to the Internet does not

mean we will participate. In fact, Bergstrom (2008) found that in the realm of online newspapers, most people were reluctant to participate online. The exception to this was a “small group of young, well-educated, frequent Internet users” (p. 76) whose desire to participate (by leaving comments on news stories) was “above all.” It is this group, too, she found, who are most comfortable with new technology and thus, more than any other demographic group most likely to offer feedback on content provided by others.

Correa (2010), too, defines a group most likely to participate online. In the group she calls “online experts,” college students between the ages of 18 and 24 were most likley to participate and create online content the more they thought they could actually achieve the task. In Correa’s study, which noted “perceived competence” as a measure largely correlated to the likelihood of content creation, slightly more men than women would create content, but when perceived competence, motivation, and level of online skills were taken into consideration, this gender gap disappeared. Even more interesting was the finding that, when controlling for all other variables, white students were less likely than African-American students to create content online – particularly in a civic or political conversation/setting. While this study is particulary interesting to look at the roles age and social factors may play in our likelihood of participation, the larger picture indicates, at least in the case of young adults who are most familiar with technology in general, that motivation and ability to create and participate seems to trump other factors that, on their own, might lessen one’s rate of participation. As Correa finds, “at equal levels of motivation, the education difference in Internet usage wanes” (p. 74).

As we delve deeper into the individual characteristics that affects why a person might or might not want to participate online, understanding the attitudes toward technology is important, too. Page et al., (2010) found that among a group of “Digital Natives,” identified as those born

after 1983, attitudes about how the Internet made them feel changed with age even within that group. This shows that simply being familiar with technology, or being of a socioeconomic class privileged with access, does not account for the entire likelihood of adoption or acceptance. Overall, 56 percent of youth reported positive feelings toward the Internet, but there was a difference in that level of positive feeling among ages 13 to 19, and older than 19 (p. 1354-1356). Page el al.'s research supports the idea that the stereotype of being technologically oriented applied to a younger generation "fail to acknowledge" situational and cultural variations among individuals (p. 1359).

Since each user will relate or react to technology in different ways based on individual characteristics, it is logical that everyday routines also define the choices that user makes for himself. Like Lai and Chang (2011) found with e-book readers, convenience also represents a big reason of the shift to smartphone adoption. As Anderson (2010) argues, users have not necessarily adopted smartphones because they're inherently better at providing us the Internet, they just fit more easily into busy everyday lives. As Pew data supports, society now is past the point in diffusion theory where the younger generation or the early adopters are the only ones with the new gadgets; *every* demographic group saw "significant year-to-year growth in smartphone ownership" (Smith, 2013).

But as diffusion theory states, the early adopters set the tone for the innovation's diffusion. It's fairly clear in the literature that when it comes to technology, those early adopters are far more often than not the youth (Zemmels, 2012). Since it is assumed, in most cases, that "young people can serve as excellent indicators of future trends in new media" (Zemmels, 2012, p. 4), the consequences of this should briefly be discussed. As previously mentioned, Cingel and Sundar's research points out the effect of mobile technology and "techspeak" on youth grammar

test performance. Privacy is another concern. Because the social circles and networks of today's youth affect their perception and ultimate decision on technology adoption, Zemmels notes that these early adopters dismiss the importance of privacy – even if their privacy had been challenged in the past – because the "social benefits so prevail in their minds" (p. 17). With more media channels and the nature of the media landscape challenging "traditional notions of media research," Zemmels calls upon researchers to focus more on these early adopters.

Rationale and Research Questions

Can the widespread adoption of convenient technology ultimately change what users do online? Based on the research from Wei et al. (2012) and Correa (2010), the group of young people considered "online experts" (ages 18-24) should be more apt to embrace technology, thus behaving differently online than groups with lower adoption rates. My research seeks to look at the relationship between specific devices and behavior:

> H1: Participants who use their smartphone as a primary means of accessing the Internet will create less content online than participants who primarily use computers.

As the technology acceptance model indicates, perceived usefulness plays a big part in our likelihood of adopting technology (Davis, 1989). With online experts feeling more comfortable with technology and its features (Correa, 2010), my second hypothesis marks the line this research aims to address – the different affect smartphone use has on online creation and online participation:

> H2: Participants who use their smartphone as a primary means of accessing the Internet will participate online more than participants who primarily use computers.

As a challenge to researchers, Wheaton (2010) in an editorial in *Advertising Age* states, "Our obsession with mobile should not be about technology or tactics; rather it's the ability to change the way we work, plan, communicate and buy" (p. 27). Studying a diverse group on Internet users, especially the wider range of demographics available by using Amazon's Mechanical Turk feature, should help shed light on if, in fact, technology can change people's behavior, as Wheaton asserts. This leads to my next set of hypotheses:

> <u>H3:</u> As an individual's level of comfort with technology rises, so too will the rate of online participation.
>
> <u>H4:</u> As an individual's level of comfort with technology rises, so too will the rate of online creation.
>
> <u>H5:</u> Online experts will create online content more than non-experts.
>
> <u>H6:</u> Online experts will participate online more than non-experts.

Also, to what extent does the influence of our social circles or our demographics affect our preference and ultimate behavior with technology? Diffusion theory and research by Sundar et al. (2010) and Reeves and Nass (1996) suggest that it is the combination of preferences, our circles of influence, individual characteristics, and the ubiquity of the technology that affects our choices. These ideas lead to my last set of research questions:

> <u>RQ1:</u> How does socio-economic status affect technology use?
>
> <u>RQ2:</u> How does socio-economic status affect one's level of comfort with technology?
>
> <u>RQ3:</u> How does socio-economic status affect one's likelihood of being an "online expert?"

The next chapter will discuss the process of building the survey used in this research, the use of Amazon.com's Mechanical Turk system to distribute the survey, and the methodology, measures, and procedure employed during this process.

CHAPTER 3
METHODOLOGY

The Survey

I used an online survey to measure participant demographic data as well as determine which type of devices they own. To qualify for this survey, the respondent agreed that they own or use both a laptop/desktop computer and a smartphone. This survey included questions about Internet usage, if and how the participant uses Facebook and Twitter, whether they follow blogs or online news stories, and whether they currently write a blog.

Questions regarding frequency of use, importance of being able to post content online, and the frequency of content contribution online came from the Pew Internet and American Life project (November 2012), which frequently asks users about their Internet and mobile phone usage. Questions discussing the control a user has over a situation, the importance of being an influencer and the participant's idea of "community" came from Sanders and Song's (2012) Blogalicious Multicultural Influencer survey.

The survey for this research used standard "yes or no" responses as well as five-point Likert-type scale questions (from strongly disagree to strongly agree) about each type of device (smartphone and laptop/desktop computers) as well as the Internet usage areas mentioned above. The entire questionnaire can be found in Appendix A.

I built the survey in Qualtrics and used Amazon.com's Mechanical Turk to distribute the survey link to its users, or "workers," who received 50 cents upon completion. The survey was restricted to be available only to U.S. workers within Amazon.com's Mechanical Turk system. Before being allowed to take part in the survey, each user verified they did indeed have or use

both a laptop/desktop computer as well as a smartphone. Only participants who agreed they possess both technologies were allowed to continue and receive compensation.

About Mechanical Turk

I used Amazon.com's Mechanical Turk service to distribute the survey in hopes of gaining a wider audience with varied demographic data. Mechanical Turk is a website and service where the user decides whether he is a "worker" or a "requester." A requester is a company, organization, or independent researcher who pays a worker to complete a Human Intelligence Task, or HIT. HIT examples include sorting images into categories, answering surveys, collecting and inputting data, rating sentiment of various phrases, or transcribing a video or static image. A requester inputs the type of HIT to be completed, the pay rate, the time period it should take an average person to complete, and a deadline. A worker logs on and is able to look at an available list of HITs and decides which she wants to pursue. Requesters can set how many responses they want (or tasks to be completed) as well as limit who sees their tasks by country, value of Mechanical Turk worker approval rating, and various other forms of inclusion and exclusion. A requester also is able to review the quality of the completed task before approving payment for that worker. Before a requester can publish a job on Mechanical Turk, they must first deposit money to cover the entirety of the job into their amazon.com account; essentially the requester must prepay for his research. Amazon's fee for Mechanical Turk is 10 percent of the prepaid deposit. For this research, I set the pretest to limit the number of HITs to 25. For the full run of the survey, I set the limit at 425.

Pretest of the Survey

On June 30, 2013 at roughly midnight, I ran a pretest of the survey to ensure Mechanical Turk was set up correctly and that workers were able to access the survey link and complete it.

As Buhrmester (2012) advises, making a survey "live" late in the evening takes advantage of the time at which most survey-takers are online. In roughly 30 minutes, I had 30 respondents. After cleaning the data, a total of 18 usable responses remained. I omitted eleven participants for obvious unusable responses and one response self-reported as not qualifying for the survey. The quality of the 18 responses left assured me the survey link to Qualtrics and the details of Mechanical Turk were ready to be made available for a longer period of time for the majority of my data collection.

The Full Run of the Survey

For two days, beginning on the morning of July 13, 2013, I re-activated the survey on Mechanical Turk, again offering a reward of 50 cents to each user who qualified to participate. I kept the same settings and questionnaire link from the pretest. The pretest and this survey instance were identical, save for the time period each was opened to the Mechanical Turk workforce. At the end of this two-day period, I collected 443 responses. Forty-two responses were omitted because of self-reported non-qualification and one response was removed for obvious unusable answers.

Since the pretest was identical to the main run of this survey, the usable datasets were combined for a total of 418 respondents (N=418) who were used in the analysis for this thesis.

Demographic Breakdown of Participants

The majority of participants were age 25-41 (N=220 or 52.6 percent) and reported their race as Caucasian (N=301 or 72 percent). The next two largest age groups were found on either side of the 25-41 range: 18-24 year-olds were the next largest group (N = 96, or 23 percent), followed by 42-55 (N = 72, or 17.2 percent), 55-64 (N = 26, or 6.2 percent), and 65-plus and prefer not to answer (N-4, or 0.9 percent).

The majority had either some university or college education (N=128 or 30.1 percent) or were a college or university graduate (N=157 or 37.6 percent). Both ends of the educational spectrum seemed to balance out, too: a total of 16.8 percent of participants reporting either a high school education or less (N=53 or 12.7 percent) or reported graduating from a technical college or trade school (N=17 or 4.1 percent), while 15.5 percent reported having some post-graduate education (N=19 or 4.5 percent) or reported graduating with a Master's or Doctoral degree (N=46 or 11 percent).

The majority of respondents reported their race as Caucasian (N=301 or 72 percent), with the remaining participants choosing Asian/Asian Pacific Islander (N=35 or 8.4 percent); African American (N=34 or 8.1 percent); Hispanic (N=22 or 5.3 percent); Mixed Ethnicity (N=10 or 2.4 percent); or Native American (N=8 or 1.9 percent). A combined 1.9 percent (N=8) chose either Other (N=3) or Prefer Not to Answer (N=5).

Demographic characteristics where the distribution was more evenly spaced include income and gender. Gender was fairly evenly represented with 47.6 percent identifying as male (N=199) and 51.9 percent identifying as female (N=217). Only 2 respondents (or one-half of a percent) preferred not to answer. Income included eight levels to self-report and a chart appears below for easier reading. The chart illustrates that the majority (N=325 or 77.6 percent) reported household earnings at less than $74,999.

Participants used the Android operating system (N=206, or 49.3 percent) more than iOS/iPhone (N=182, or 43.5 percent). Blackberry (N=17, or 4.1 percent), Windows OS (N=10, or 2.4 percent), or participants with more than one of these devices (N=3, or 0.7 percent) had much smaller numbers. The majority reported using a tradition PC running the Windows operating system (N=328, or 78.5 percent), followed by Mac users (N=54, or 12.9 percent), and

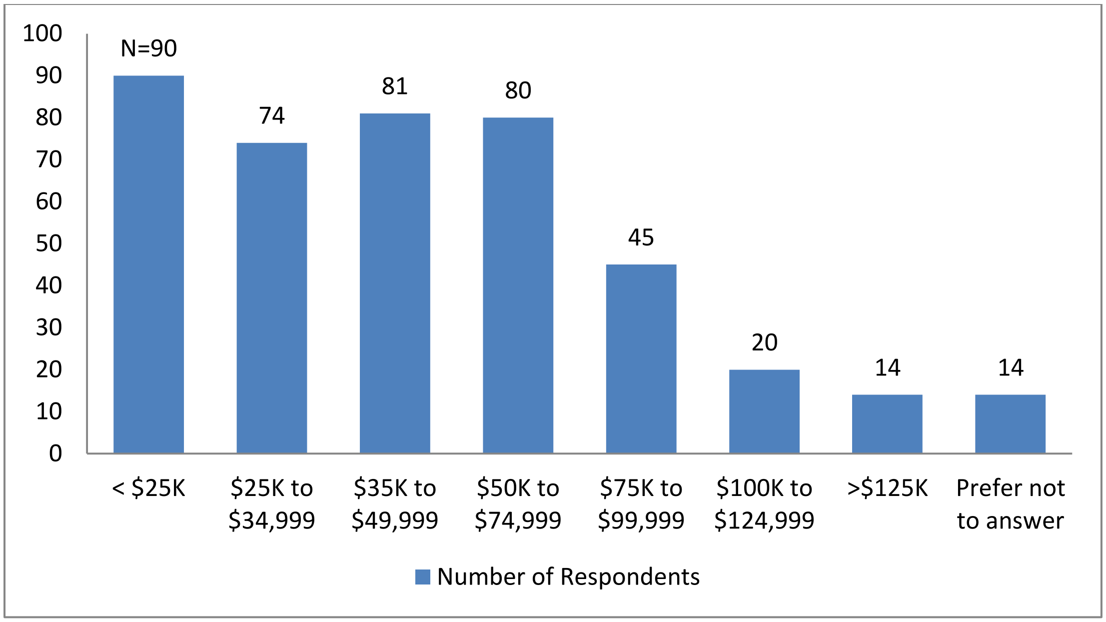

Figure 3: Self-Reported Income

users reporting to have more than one computer at home with varying operating systems (N=30, or 7.2 percent). Lastly, users who reported either using a Linux or Unix operating system at home and those who reported “other” had the same frequencies: (N=3, or 0.7 percent).

Measures

From the questionnaire, I developed 12 measures for analysis. The demographic information consisted of standard elements, such as age, gender, education, income, and race. Next, the two main areas of this research, online participation and online creation, were separated into two measures. The *Online Participation* measure was made up of content participation activities in which participants indicated they took part (for example, liking content on Facebook, retweeting on Twitter, commenting on social media or blogs, sharing stories or photos on social media, repinning on Pinterest, etc.). The *Online Creation* measure was made up of content creation activities in which participants indicated they take part (for example, blogging, writing new status updates or tweets, etc.).

Next, this research aims to focus on what might affect online participation and creation. I created six more measures from the survey research. The *Comfort with Technology* measure explored the degree to which the participant felt comfortable with technology in general. The *Online Experts* measure reported the level of self-reported level of expertise with technology and the Internet. The *Smartphone Use* measure reported the degree to which the participant indicated they used a smartphone for accessing online content, content participation, or content creation. The *Computer Use* measure reported the degree to which the participant indicated they used a computer (either laptop or desktop) for accessing online content, content participation, or content creation. The *Perceived Usefulness* measure asked users how they believed a smartphone or computer affected their ability to create or participate online. Finally, the *Influencers* measure reported the degree to which the participant thought of him or herself as an influencer of others.

Constructing the Measures

The main questions in the survey that illustrated the primary measures listed above each had multiple parts. First I ran a Chronbach's α on the items that made up each question to determine if any items affected the internal reliability of the question. Next, I ran a factor analysis on each question to see if any relationships or groups were present among the items that made up the question as a whole.

The Demographics indices were not put to these tests as their components are from a single question and are categorical data. The remaining eight indices were constructed as follows:

Smartphone use.

A factor analysis using varimax rotation on 28 items that measured preference for smartphone use for various tasks resulted in the loading of five factors. The first factor explained

17.8 percent of the variance, the second explained 16.4 percent, the third 13.6 percent, the fourth explained 13.3 percent and the fifth 11.2 percent.

The first component, entitled Social Media Participation, was made up of eight items that measure participants' smartphone use for social media tasks (Chronbach's $\alpha = .94$).

The second component, entitled Contributing and Finding Content, was made up of six items that measure participants' smartphone use for creating and sharing videos and online content, as well as seeking out information online and participating with content online (Chronbach's $\alpha = .88$).

The third component, entitled Utilitarian Tasks: Browsing and Email, was made up of six items that measure participants' smartphone use for checking, sending, and reading email; searching Google; and reading blogs and news stories (Chronbach's $\alpha = .85$).

The fourth component, entitled Creation and Participation: Twitter and Blogs, was made up of five items that measure participants' smartphone use for using Twitter and writing their own blogs, and commenting on others' blogs (Chronbach's $\alpha = .93$).

The last component, entitled Pinterest, was made up of three items that measure participants' smartphone use for using the Pinterest website (Chronbach's $\alpha = .97$).

Computer use.

I ran a factor analysis using varimax rotation on the 28 items that measured participant preference to use a laptop or desktop computer for various tasks. This resulted in the loading of six factors. The first factor explained 21.8 percent of the variance, the second explained 12.9 percent, the third 12.2 percent, the fourth explained 10.6 percent, the fifth 10.4 percent, and the sixth 9.4 percent.

The first component, Social Media Participation, comprised eight items that measure participants' preference to use a laptop or desktop for social media tasks (Chronbach's α = .96).

The second component, entitled Creation and Participation: Twitter and Blogs, was made up of five items that measure participants' preference to use a laptop or desktop for using Twitter, writing their own blogs, or commenting on others' blogs (Chronbach's α = .92).

The third component, entitled Participation While Browsing, was made up of five items that measure participants' preference to use a laptop or desktop for using general Internet browsing the participation that takes place while doing so (Chronbach's α = .85).

The fourth component, entitled Utilitarian Tasks: Read/Write Email and Google, was made up of four items that measure participants' preference to use a laptop or desktop for the general tasks of checking and sending email as well as searching Google (Chronbach's α = .84).

The fifth component, Pinterest, was made up of three items that measure participants' preference to use a laptop or desktop for using the Pinterest website (Chronbach's α = .99).

The sixth component, entitled Video, was made up of three items that measure participants' preference to use a laptop or desktop for using sharing and creating videos (Chronbach's α = .90).

Online participation.

A factor analysis using varimax rotation on the six items that measured the frequency of online participation resulted in the loading of two factors. The first factor explained 36.1 percent of the variance, and the second explained 28.3 percent.

The first component, entitled Online Participation: Sites, was made up of three items that measure how often respondents participate on online sites such as UrbanSpoon, news sites, and organizations to which they belong (Chronbach's α = .75).

The second component, entitled Online Participation: Social Media and Blogs, was made up of three items that measure how often respondents participate on social media sites or blogs they follow (Chronbach's $\alpha = .65$).

Online creation.

A factor analysis using varimax rotation on the four items that measured the frequency of online participation resulted in the loading of two factors. The first factor explained 41 percent of the variance, and the second explained 35.6 percent.

The first component, entitled Online Creation: Owned Content, was made up of two items that measure how often a participant adds new content to sites they own, such as their own web site or their own blog (Chronbach's $\alpha = .76$).

The second component, entitled Online Creation: Social Media, comprises two items that measure how often respondents create content on social media sites (Chronbach's $\alpha = .60$).

Comfort with technology.

This index comprises the six items that measure a participant's self-reported level of comfort with technology. After running a Chronbach's Alpha test, two items were marked as affecting the internal reliability of this measure and were consequently removed. I ran a factor analysis using varimax rotation on the remaining four items and one factor loaded. This became my Comfort with Technology index (Chronbach's $\alpha = .90$).

Online experts.

This index comprises three items asked participants to self-report their level of expertise in smartphones, computers, and general Internet use. I ran a factor analysis using varimax rotation and one factor loaded. This became my Online Experts index (Chronbach's $\alpha = .82$).

Perceived usefulness.

Four questions in my survey measured participants' perceived usefulness of smartphones and computers to affect online participation and creation. Since all four of these questions were identical in design (a five-point Likert scale), they were paired up to create a separate Perceived Usefulness index each for smartphone use and for computer use.

I ran a factor analysis using varimax rotation on the two items that measured the perceived usefulness of smartphones and one factor loaded. This became my Smartphone – Perceived Usefulness index (Chronbach's $\alpha = .79$).

Next, I ran another factor analysis using varimax rotation on the remaining two items that measured the perceived usefulness of computers and one factor loaded. This became my Computer – Perceived Usefulness index (Chronbach's $\alpha = .79$).

Influencers.

Two questions in my survey measured participants' perceived level of being an influential person online and the importance of being able to post content online. I ran a factor analysis using varimax rotation on these two items and one factor loaded. This became my Influencer index (Chronbach's $\alpha = .62$).

The next chapter will discuss the results of the survey, its participant demographic characteristics, the reliability of the measures, and the testing of my hypotheses and research questions.

CHAPTER 4
RESULTS

Cluster Analysis

To see which combinations of factors might distinguish how various groups were using technology, I used the factors from the following indices in a cluster analysis: Smartphone use, Computer use, Online experts, Comfort with technology, Perceived usefulness, and Influencers. The three-factor solution was the best fit, with convergence occurring after 27 iterations. Euclidean distances indicated that this three-factor solution provided cluster groups that were different from one another (see Table 1). F-ratios were the largest in the three-factor solutions, indicating that the variables used in the analysis played a large part in determining groups (see Table 2). I ran a cluster analysis because this statistical test uses the data itself to identify groups. With the data, rather than the researcher, producing the groups present within that data, the study of that group and its characteristics is more reliable. The distances between the final cluster centers can be found in Table 4.

The first cluster comprised 134 *Smartphone averse*, who scored low on use of smartphones in social media, on Twitter and blogs, the online experts, comfort with technology, and the perceived usefulness of smartphone dimensions that resulted from the factor analysis. This group scored more highly on tasks involving the computer and low on the self-reported level of influence they felt they had online. The second cluster comprised 146 *Content consumers*, who scored lowly on both indices that measured smartphone and computer use on various online platforms. This group scored higher on the influencers and online experts dimensions and view smartphones to be slightly less useful than computers.

Table 1
Cluster Analysis

Final Cluster Centers	Smartphone Averse (N = 134)	Content Consumers (N = 146)	Content Creators (N = 135)
S – Social Media Participation	-.64**	.23**	.40**
S – Contributing/Finding Content	.03*	-.30*	.24
S – Utilitarian Tasks/Email/Browsing	-.50**	-.03**	.54**
S – C&P: Twitter & Blogs	.08**	-.30**	.26
S – Pinterest Use	.13**	-.62**	.53**
C – Social Media Participation	.29	.19	-.50**
C – C&P: Twitter & Blogs	.25**	-.37**	.15
C – Participation While Browsing	.23**	-.30**	.08
C – Utilitarian Tasks/Email/Browsing	.19	.34	-.56**
C – Pinterest Use	.22**	-.38**	.19
C – Video Creation	.20*	-.13*	-.07^
Online Expert Index	-.67**	.36**	.27**
Comfort With Technology	-.60**	.12**	.47**
S - Perceived Usefulness	-.84**	.24**	.58**
C - Perceived Usefulness	.12	.33	-.49**
Influencer Index	-.72**	.41**	.26**

S = user preference for a smartphone for that task
C = user preference for a computer for that task
C&P = Creation and Participation
* = significant from other cluster groups at the .05 level
** = significant from other cluster groups at the .01 level
^ = approached significance; p = .057

The third cluster comprised 135 *content creators*, who scored highly in the smartphone online content and creation dimensions as well as the comfort with technology and smartphone perceived usefulness dimensions. This group scores the lowest of the three on the use of a computer for social media participation and for utilitarian tasks such as email checking and Internet browsing. This group uses their smartphone for most of their online tasks and uses their computer more than *content consumers*, but far less than the *smartphone averse* group.

Table 2
ANOVA Table Representing F Ratios

	Cluster Mean Square	d.f.	Mean Square	Error d.f.	F	Sig
S – Social Media Participation	41.7	2	.80	412	52.1	.00
S – Contributing/Finding Content	9.0	2	1.0	412	9.4	.00
S – Utilitarian Tasks/Email/Browsing	36.4	2	.82	412	44.3	.00
S – C&P: Twitter & Blogs	11.6	2	.95	412	12.2	.00
S – Pinterest Use	48.0	2	.76	412	61.6	.00
C – Social Media Participation	25.2	2	.90	412	28.3	.00
C – C&P: Twitter & Blogs	15.1	2	.93	412	16.1	.00
C – Participation While Browsing	10.1	2	1.0	412	11.0	.00
C – Utilitarian Tasks/Email/Browsing	32.0	2	.90	412	37.6	.00
C – Pinterest Use	16.3	2	.93	412	17.4	.00
C – Video Creation	4.4	2	1.0	412	4.5	.00
Online Expert Index	44.5	2	.80	412	56.4	.00
Comfort With Technology	40.0	2	.81	412	49.0	.00
S - Perceived Usefulness	74.5	2	.67	412	115.1	.00
C - Perceived Usefulness	25.3	2	.90	412	28.6	.00
Influencer Index	52.2	2	.80	412	69.3	.00

S = user preference for a smartphone for that task
C = user preference for a computer for that task
C&P = Creation and Participation

Testing Hypotheses

H1: Participants who use their smartphone as a primary means of accessing the Internet will create less content online than participants who primarily use computers.

Results show support for H1. A one-way analysis of variance revealed that respondents who used their smartphones more on social media sites create more social media content ($M = .22$, $s = .07$) than participants who less frequently used their smartphones in the same capacity ($M = -.20$, $s = .06$, $F(1, 416) = 18.8$, $p < .001$).

Table 3
Attributes of Groups

	Smartphone Averse	Content Consumers	Content Creators
S – Social Media Participation	--	+	+
S – Contributing/Finding Content	+	--	+
S – Utilitarian Tasks/Email/Browsing	--	--	+
S – C&P: Twitter & Blogs	+	--	+
S – Pinterest Use	+	--	+
C – Social Media Participation	+	+	--
C – C&P: Twitter & Blogs	+	--	+
C – Participation While Browsing	+	--	+
C – Utilitarian Tasks/Email/Browsing	+	+	--
C – Pinterest Use	+	--	+
C – Video Creation	+	--	--
Online Expert Index	--	+	+
Comfort With Technology	--	+	+
S - Perceived Usefulness	--	+	+
C - Perceived Usefulness	+	+	--
Influencer Index	--	+	+

S = user preference for a smartphone for that task
C = user preference for a computer for that task
C&P = Creation and Participation
- - = two dashes represent a negative sign and were used for easier reading

A one-way analysis of variance revealed that respondents who used their smartphones more for utilitarian tasks such as checking email and browsing create more social media content ($M = .10$, $s = .07$) than participants who less frequently used their smartphones in the same capacity ($M = -.10$, $s = .07$, $F(1, 416) = 4$, $p < .05$). A one-way ANOVA also revealed that respondents who used their smartphones more for utilitarian tasks such as checking email and browsing create more of their own content ($M = .16$, $s = .08$), including their own web sites or blogs, than participants who less frequently used their smartphones in the same capacity ($M = -.17$, $s = .06$, $F(1, 416) = 11.9$, $p < .01$).

Table 4
Distances Between Final Cluster Centers

Cluster:	Smartphone averse	Content consumers	Content creators
Smartphone averse	—	2.642	3.012
Content consumers	2.642	—	2.278
Content creators	3.012	2.278	—

A one-way ANOVA showed that respondents who used their smartphones more to navigate the Pinterest website (M = -.12, s = .06) created less of their own online content, such as their own web sites or blogs, than participants who less often used their smartphones to navigate Pinterest (M = .1, s = .07, F (1, 416) = 4.8, p = .03).

The *Content consumer* group that emerged from the cluster analysis scored low on smartphone use for online content creation on blogs or social media and on video creation (see Table 3). However, a one-way analysis of variance found a significant relationship between participants' use of a smartphone for social media purposes and the three groups that emerged from the cluster analysis. A Tukey Post Hoc analysis revealed that *Content creators* (M = .40, s = .07) and *Content consumers* (M = .23, s = .09) were much more likely to use their smartphones for social media purposes than the *Smartphone averse* (M= -.64, s = .07, F (2, 412) = 52.1, p < .01). Also, another ANOVA found a significant relationship between participants' who use a smartphone for utilitarian tasks, such as browsing and checking email, and the three groups that emerged from the cluster analysis. A Tukey Post Hoc analysis revealed *Content creators* were most likely to use smartphones for these purposes (M = .54, s = .07) than *Content consumers* (M = -.03, s = .07) or the *Smartphone averse* (M= -.5, s = .08, F (2, 412) = 44.3 p < .01).

A one-way analysis of variance found a significant relationship between participants' who use a smartphone for online content creation and participation on Twitter and blogs and the three groups that emerged from the cluster analysis. A Tukey Post Hoc analysis revealed that

Content consumers were least likely to use their smartphones for these purposes (M = -.30, s = .08) than *Content creators* (M = .30, s = .07) or the *Smartphone averse* (M= .08, s = .10, F (2, 412) = 12.2, p < .01).

A one-way analysis of variance found a significant relationship between participants' who use a desktop or laptop computer to create or participate online with Twitter or on blogs and the three groups that emerged from the cluster analysis. A Tukey Post Hoc analysis revealed that the *Content consumers* were least likely to use their computer for these purposes (M = -.36, s = .08) than *the Smartphone Averse* (M = .25, s = .08) or the *Content creators* (M= .15, s = .10, F (2, 412) = 16.1, p < .01).

Another one-way analysis of variance found a significant relationship between participants' who use a desktop or laptop computer for utilitarian tasks, such as browsing or checking email, and the three groups that emerged from the cluster analysis. A Tukey Post Hoc analysis revealed that the *Content creators* were least likely to use their computer for these purposes (M = -.60, s = .10) than *the Smartphone Averse* (M = .19, s = .07) or the *Content consumers* (M= .34, s = .07, F (2, 412) = 37.3, p < .01). An ANOVA found a significant relationship between participants' who use a desktop or laptop computer for video viewing and production and two of the three groups that emerged from the cluster analysis. A Tukey Post Hoc analysis revealed that the *Smartphone averse* were more likely to use their computer for these purposes (M = .20, s = .09) than *Content consumers* (M= -.13, s = .07, F (2, 412) = 4.5, p = .01). There was no significant relationship between this type of computer use and the *Content creator* group.

Another ANOVA found a significant relationship between participants' who created content for their own websites or blogs and the three groups that emerged from the cluster

analysis. A Tukey Post Hoc analysis revealed that *Smartphone averse* were least likely to create this online content for themselves ($M = -.21$, $s = .05$) than *Content creators* ($M = -.12$, $s = .08$) or the *Content consumers* ($M= .31$, $s = .10$, $F (2, 412) = 11.4$ $p < .001$). Similarly, an ANOVA found a significant relationship between participants' who created content on social media and the three groups that emerged from the cluster analysis. A Tukey Post Hoc analysis revealed that *Smartphone averse* were again the least likely to use their smartphones to create this online content ($M = -.45$, $s = .07$) than *Content creators* ($M = .26$, $s = .09$) or the *Content consumers* ($M= .18$, $s = .09$, $F (2, 412) = 22.6$ $p < .001$).

> <u>H2</u>: Participants who use their smartphone as a primary means of accessing the Internet will participate online more than participants who primarily use computers.

Results show support for H2. A one-way analysis of variance revealed that respondents who used their smartphones more for utilitarian tasks such as checking email and browsing participate more on websites ($M = .12$, $s = .08$), such as leaving comments or reviews, than participants who less frequently used their smartphones in the same capacity ($M = -.13$, $s = .06$, $F (1, 416) = 6.4$, $p < .05$). A one-way ANOVA also revealed that respondents who used their smartphones more for utilitarian tasks such as checking email and browsing participate more on social media sites or blogs they follow ($M = .12$, $s = .07$) than participants who less frequently used their smartphones in the same capacity ($M = -.13$, $s = .07$, $F (1, 416) = 6.3$, $p < .05$).

A one-way ANOVA showed that respondents who used their smartphones more for to navigate the Pinterest website ($M = -.16$ $s = .06$) participated less on websites, such as leaving comments or reviews, than participants who less often used their smartphones to navigate Pinterest ($M = .13$, $s = .07$, $F (1, 416) = 8.8$, $p < .01$).

The *Content creator* group that emerged from the cluster analysis scores highly on smartphone use for social media participation as well as participation on blogs, Twitter and

Pinterest (see Table 3) as compared to the other two groups. A one-way ANOVA found a significant relationship between participants' who use a smartphone for finding and contributing content and the three groups that emerged from the cluster analysis. A Tukey Post Hoc analysis revealed that *Content consumers* were least likely to use their smartphones for these purposes ($M = -.30$, $s = .08$) than *Content creators* ($M = .24$, $s = .08$) or the *Smartphone averse* ($M = .03$, $s = .10$, $F(2, 412) = 9.4$, $p < .01$).

A one-way analysis of variance found a significant relationship between participants' who use a smartphone to use the Pinterest website and the three groups that emerged from the cluster analysis. A Tukey Post Hoc analysis revealed that the *Content creators* were more likely to use their smartphones for these purposes ($M = .53$, $s = .07$) than *the Smartphone Averse* ($M = .13$, $s = .10$) or the *Content consumers* ($M = -.61$, $s = .06$, $F(2, 412) = 61.6$, $p < .01$).

Another one-way analysis of variance found a significant relationship between participants' who use a desktop or laptop computer for social media participation and the three groups that emerged from the cluster analysis. A Tukey Post Hoc analysis revealed that the *Content creators* were least likely to use their computer for these purposes ($M = -.50$, $s = .09$) than *the Smartphone Averse* ($M = .29$, $s = .08$) or the *Content consumers* ($M = .20$, $s = .08$, $F(2, 412) = 28.3$, $p < .01$). An ANOVA also found a significant relationship between participants' who use a desktop or laptop computer to participate with online content while browsing and the three groups that emerged from the cluster analysis. A Tukey Post Hoc analysis revealed that again, the *Content creators* were least likely to use their computer for these purposes ($M = .08$, $s = .8$) than *the Smartphone Averse* ($M = .23$, $s = .07$) or the *Content consumers* ($M = -.30$, $s = .08$, $F(2, 412) = 11$, $p < .01$).

Another ANOVA found a significant relationship between participants' who use a desktop or laptop computer to interact with the Pinterest website and the three groups that emerged from the cluster analysis. A Tukey Post Hoc analysis revealed that the *Smartphone Averse* were most likely to use a computer for these purposes (M = .22, s = .07) than *the Content creators* (M = .20, s = .10) or *Content consumers* (M= -.40, s = .07, $F (2, 412) = 17.4$, $p < .01$).

Another ANOVA found a significant relationship between participants' who participated with content for their own websites or blogs and the three groups that emerged from the cluster analysis. A Tukey Post Hoc analysis revealed that *Smartphone averse* were least likely to participate with this online content (M = -.23, s = .06) than *Content creators* (M = -.23, s = .06) or the *Content consumers* (M= .22, s = .10, $F (2, 412) = 8.0$ $p < .001$). Similarly, an ANOVA found a significant relationship between participants' who participated with content on social media and blogs and the three groups that emerged from the cluster analysis. A Tukey Post Hoc analysis revealed that *Smartphone averse* were again the least likely to participate with this online content (M = -.43, s = .07) than *Content creators* (M = .24, s = .09) or the *Content consumers* (M= .19, s = .08, $F (2, 412) = 20.3$ $p < .001$).

.

<u>H3</u>: As an individual's level of comfort with technology rises, so too will the rate of online participation.

Results show support for H3. A one-way analysis of variance revealed that respondents who used their smartphones to participate more in social media were more comfortable with technology (M = .22, s = .06) than those who participated less (M = -.22, s = .08, $F (1, 416) = 21.1$, $p < .001$). Also, respondents who used their smartphones in a utilitarian fashion to search for information and send email were more comfortable with technology (M = .12 s = .06) than those who used their smartphones less (M= -.13, s = .07, $F (1, 416) = 6.9$, $p < .01$). Finally,

another ANOVA revealed that participants who use their smartphones more for using the Pinterest website were more comfortable with technology (M = .19, s = .07) than those who participated less via smartphone (M = -.15, s = .07, F (1, 416) = 11.7, p < .01).

A one-way analysis of variance showed that participants who used a laptop or desktop computers more to participate on social media were less comfortable with technology (M = -.10, s = .07) than those who participated less via laptop or desktop computer (M = .13, s = .07, F (1, 416) = 4.934, p < .05).

The result of an ANOVA approached significance, revealing that participants who primarily use the computer for utilitarian tasks, such as browsing the Internet and checking or sending email are less comfortable with technology (M = -.09, s = .07) than participants who participate less via laptop or desktop (M = .10, s = .07, F (1, 416) = 3.7, p = .055).

The *Content consumer* and *Content creator* groups that emerged from the cluster analysis are characterized by increasing levels of comfort with technology respectively (see Table 1) as well as higher scores of using a smartphone for participation online (see Table 3). A one-way analysis of variance found a significant relationship between participants' self-reported level of comfort with technology and the three groups that emerged from the cluster analysis. A Tukey Post Hoc analysis revealed that the *Content creators* were most likely to be comfortable with technology (M = .47, s = .07) than *the Smartphone Averse* (M = -.60, s = .10) or the *Content consumers* (M= .18, s = .07, F (2, 412) = 49, p < .01).

H4: As an individual's level of comfort with technology rises, so too will the rate of online creation.

H4 was not supported. A one-way ANOVA revealed no significant relationship between a participant's level of comfort with technology and the heavier use of smartphones to create

content online. However, The *Content creator* group that emerged from the cluster analysis is characterized by more smartphone use than computer use, and scored highly on the comfort with technology dimension (see Table 3).

The *Content consumer* and *Content creator* groups are characterized by increasing levels of comfort with technology respectively (see Table 1) as well as higher scores of using a smartphone for online content creation (see Table 3). A one-way analysis of variance found a significant relationship between participants' self-reported level of comfort with technology and the three groups that emerged from the cluster analysis. A Tukey Post Hoc analysis revealed that the *Content creators* ($M = .47$, $s = .07$) and *Content consumers* ($M = .18$, $s = .07$) were more likely to be comfortable with technology than *the Smartphone Averse* ($M = -.60$, $s = .10$, $F(2, 412) = 49$, $p < .01$).

<u>H5</u>: Online experts will create online content more than non-experts.

H5 was not supported. There was no significant relationship between a participant's self-reported level of online expertise and the heavier use of smartphones to create content online. However, a one-way analysis of variance found a significant relationship between participants' perception of smartphone usefulness and the three groups that emerged from the cluster analysis. A Tukey Post Hoc analysis revealed that *Content creators* were most likely to consider smartphones useful ($M = .60$, $s = .06$) compared to *Content consumers* ($M = .24$, $s = .07$) and the *Smartphone averse* ($M = -.84$, $s = .07$, $F(2, 412) = 115.1$ $p < .001$). Similarly, an ANOVA found a significant relationship between participants' perception of laptop/desktop usefulness and the three groups that emerged from the cluster analysis. A Tukey Post Hoc analysis revealed that *Content creators* were least likely to consider computers useful ($M = -.50$, $s = .10$) compared to

Content consumers (M = .33, s = .06) and the *Smartphone averse* (M = .12, s = .09, F (2, 412) = 28.6, p < .001).

H6: Online experts will participate online more than non-experts.

Results show support for H6. A one-way analysis of variance found that participants who use their smartphones more to participate on social media are more likely to consider themselves Online Experts (M = .17, s = .07) than those who participate less (M= -.16, s = .07, F (1, 413) = 11.7, P < .01). Also, participants who used their smartphones more for utilitarian tasks such as browsing or checking email were also more likely to consider themselves Online Experts (M =.13) than those who use their smartphones less for those purposes (M = -.14, F = 8, p < .01).

Another ANOVA found a significant relationship between participants' self-reported level of online expertise and the three groups that emerged from the cluster analysis. A Tukey Post Hoc analysis revealed that the *Content consumers* (M = .40, s = .07) and *Content creators* (M = .30, s = .08) were more likely to consider themselves online experts than *the Smartphone Averse* (M = -.70, s = .08, F (2, 412) = 56.4, p < .01).

Research Questions: Demographic Relationships

RQ1 asked if socio-economic status affected technology use. A one-way analysis of variance found a significant difference between participants' age how useful they considered a smartphone. A Tukey Post Hoc analysis revealed that participants ages 56 and older less likely to consider a smartphone useful (M = -.60, s = .20) than those ages 18-24 (M = -.00, s = .10) or ages 25-41 (M = .15, s = .10). Those ages 42-55 were significantly less likely to consider a smartphone useful (M = -.22, s = .12) than ages 25-41 (M = .15, s = .10). Those ages 18-24 (M = -.00, s = .10) were less likely to see a smartphone as being useful than those ages 25-41 (M = .15, s = .10, F (3, 414) = 6.8, p < .001). Also, a one-way analysis approached significance in the

relationship between participants' age and how useful they considered a computer. Those ages 18-24 ($M = -.2$, $s = .12$) were less likely to consider a laptop or desktop to be useful computer to be useful than those ages 25-41 ($M = .00$, $s = .06$), ages 42-55 ($M = .16$, $s = .12$) or those who are older than 56 ($M = .3$, $s = .14$, $F(3, 413) = 2.5$, $p = .057$).

A crosstabulation test on the groups that resulted from the cluster analysis (*Smartphone averse*, *Content consumers and Content creators*) found a significant relationship between these groups and age ($\chi^2 = 37.6$, $p < .001$). As groups aged, they were more likely to be categorized into the *Smartphone averse* group (see Figure 4). This group characterized by more computer use than smartphone use as well as a higher perception of computer usefulness than smartphone usefulness (see Table 3).

A crosstabulation test on the groups that resulted from the cluster analysis (*Smartphone averse*, *Content consumers and Content creators*) also found a significant relationship between these groups and level of education ($\chi^2 = 13.1$, $p = .01$). The mid-level of education comprised the majority of the three groups from the cluster analysis (see Figure 4). This group characterized by more computer use than smartphone use as well as a higher perception of computer usefulness than smartphone usefulness (see Table 3).

<u>RQ2</u> asked if socio-economic status affected one's level of comfort with technology. A one-way analysis of variance found a significant relationship between participants' age and their likelihood of considering themselves comfortable with technology. A Tukey Post Hoc analysis revealed that participants ages 56 and older were significantly less likely to be comfortable with technology ($M = -.66$, $s = .22$) than those ages 42-55 ($M =-.03$, $s = .10$), ages 25-41 ($M = .02$ $s = .07$) or ages 18-24 ($M= .18$, $s = .10$, F 3, 411) = 5.6, $P < .01$).

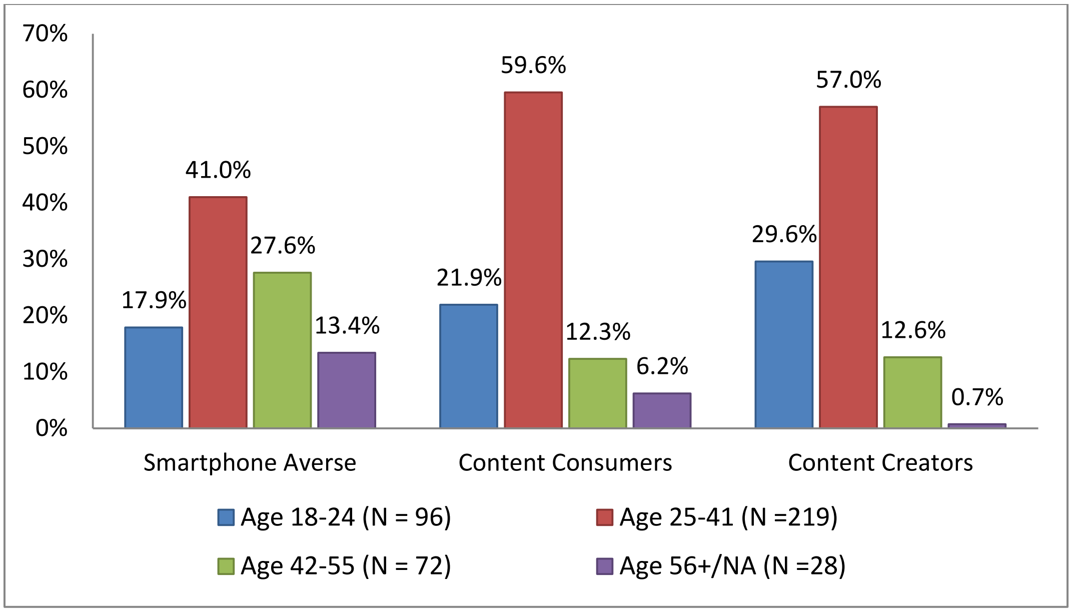

Figure 4: Age and the Cluster Groups

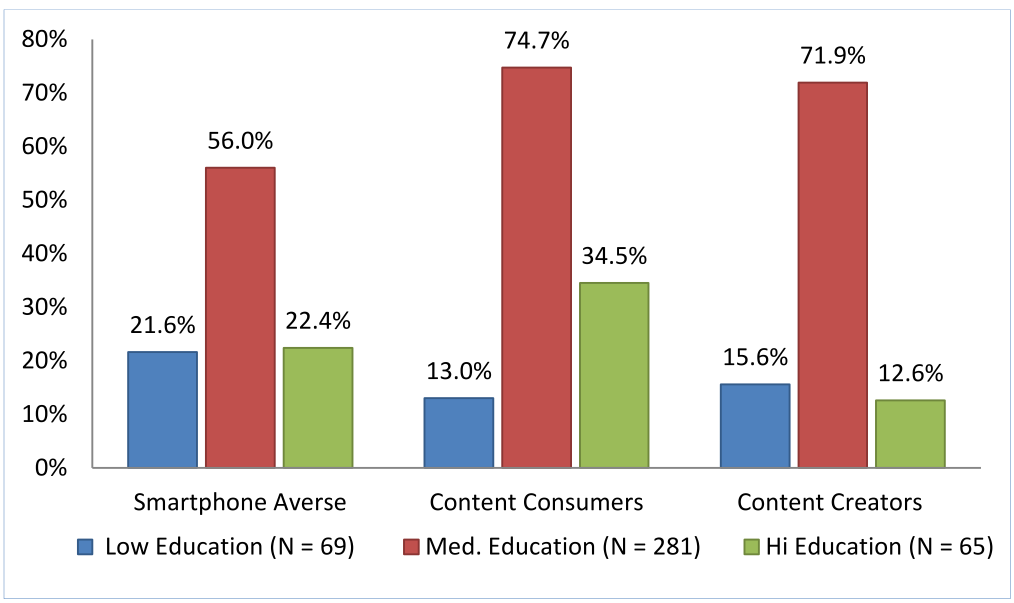

Figure 5: Level of Education and the Cluster Groups

The youngest two age groups, ages 18-24 and 25-41, were the least likely groups to be among the *Smartphone averse* group that emerged from the cluster analysis (see Figure 4). The

oldest age group, ages 56+, were the most likely group to be *Smartphone averse*, which features a much lower level of comfort with technology than the other two groups that emerged from the cluster analysis (see Table 3).

RQ3 asked if socio-economic status affected one's likelihood of being an "online expert." A one-way analysis of variance found a significant relationship between participants considering themselves online experts and age. A Tukey Post Hoc analysis revealed that participants ages 18-24 were significantly more likely to classify themselves as Online Experts ($M = .04$, $s = .09$) than those ages 56 and older ($M = -.53$, $s = .20$, $F(3, 411) = 4.3$, $P < .01$).

A one-way analysis of variance found a relationship between low- and mid-levels of education and a participant's likelihood to classify themselves as an Online Expert. A Tukey post hoc analysis revealed that participants with low levels of education ($M= -.23$) were less likely to classify themselves as an Online Expert than those with medium levels of education ($M = .08$, $F = 3$, $p = .05$).

A one-way ANOVA found a significant relationship between participants who would classify themselves as an Online Expert and gender. A Tukey post hoc analysis revealed that women ($M = -.13$, $s = .07$) were less likely to classify themselves as an Online Expert than men ($M = .14$, $s = .06$, $F(2, 412) = 4.5$, $p = .011$>.

The youngest two age groups, ages 18-24 and 25-41, were the least likely groups to be among the *Smartphone averse* group that emerged from the cluster analysis (see Figure 4). The oldest age group, ages 56+, were the most likely group to be *Smartphone averse*, which features a much lower likelihood of self-reporting as an online expert the other two groups that emerged from the cluster analysis (see Table 3).

Online experts and comfort with technology.

A one-way ANOVA found significant differences in whether participants would classify themselves as online experts and their level of comfort with technology. A Tukey post hoc analysis revealed that those who self-reported a low comfort with technology ($M = -.72$, $s = .11$) were significantly less likely than those with a medium level of comfort with technology ($M = -.12$, $s = .08$, $F(2, 360) = 61.82$, $p < .001$) to classify themselves as Online Experts. Participants who had a high level of comfort with technology were significantly more likely than the other two groups to classify themselves as Online Experts ($M = .62$, $s = .06$, $F(2, 360) = 61.82$, $p < .001$).

CHAPTER 5
DISCUSSION

The role technology plays in our everyday lives, for most, increases as innovations appear. Do we not feel lost if we forget our cellphone? Have watches become obsolete because we now use that phone also to tell time? Subtly, technology and its constant state of innovation changes the way we do things. Most forms of media have adapted to the online and mobile age; we can check sports scores on our phones as well as be alerted to breaking news, and we can be instant detectives through search engine apps. So, naturally the field of mass communication should embrace the study of technology and its effects because it is not just the latest version of Candy Crush for which we rely on our mobile devices; it is a mixture of all the other tasks we once reserved for libraries or, more recently, computer- and Internet-based searches.

It is the constant change of technology that brings uncertainty about many media outlets, but if the American public is using the smartphone as frequently as the statistics tell us, the contribution to and participation with online content will continue – just possibly in a form we are not used to. This study showed that desktop and laptop computers are past the point of being seen as innovations, and are seen as common-place items in each home. The smartphone is almost to that stage, too, but its use for everyday tasks has increased as the use of the computer for those same tasks is on the decline.

What was most interesting was the discovery of the disconnect between a user's self concept and their actions; the *Content consumers* group, who generally consume rather than create or interact with content, seems to rate themselves higher as influencers and experts online than the group who actually creates the content. Those that are *Smartphone averse* will actually use their smartphones more in certain instances than *Content consumers*. While it was not the

intent of this research to assess participants' self-concept, it does point out that simply studying a user's self-reported actions doesn't tell the whole story. This research reveals that those who rate themselves as the most comfortable with technology use that technology to its full capacity far less than users who have only a moderate level of comfort. Similarly, those who considered themselves *Online Experts* participated more with, but created far less content than those who self-reported lower levels of expertise.

Why participants' self-concept differed from their self-reported usage patterns, in my view, is attributable to the fact that as the comfort level with technology rises, the awareness of that technology ebbs. High comfort levels cause the technology and the usage of it to fall more into the background of one's thoughts and daily routine, causing users to overestimate their actual usage. Conversely, those with a lower or more moderate level of comfort are likely more aware of their interactions with technology as they require more of a cognitive load to navigate through each task. This illustrates the power of ubiquity; once a piece of technology becomes commonplace or highly familiar, the user concentrates less on the device because it has become part of his or her daily routine. This, in turn, causes the user's self-concept about the relationship between him or her and technology to become less based on actual usage patterns and more based on perception.

The Ubiquity of Computers and Smartphones

The purpose of this research was to examine the relationship between smartphone and computer use and online content creation and participation. Looking at it through a Diffusion of Innovation lens, the results show that, indeed, the diffusion of computer use among across the American population has reached the point where it is no longer considered an innovation. The smartphone is the new frontier, but even still, this technology has diffused from the earliest of

adopters, the innovators, practically to the laggards. This research supports the idea that smartphones have reached "critical mass" (Rogers E. M., 2003), and in Rogers' words himself, "When enough adoptions have occurred that many individuals in a system perceive that 'everybody's doing it,' the rate of adoption speeds up… and the critical mass occurs" (p. 350).

The process of the smartphone becoming a mainstream piece of technology (Smith, 2013), took much less time to go from innovator to late majority than the home computer did (Zitz, n.d.). This fact supports the Technology Acceptance Model's idea of perceived usefulness leading to adoption as well as diffusion theory's idea of diffusion and critical mass. The home computer proved its usefulness to the majority of the American population. Armed with that information, the American public much more quickly saw the advantages – the usefulness – of the smartphone, thus the faster adoption rate.

This research goes beyond supporting that the theoretical perspectives of perception of usefulness and diffusion theory hold true. These results offer a look at the end-stage of diffusion, that is, the current state where computers are seen as rather common place, and offer new avenues to study the effect of diffusion theory, that is, what comes next after the wave of smartphones reaches the same common-place stature as computers. It also speaks to the robust nature of the Technology Acceptance model (Stern, Royne, Stafford, & Bienstock, 2008) by indicating how the perception of usefulness might affect one's choices for technology and its subsequent use.

Comfort with Technology, Online Expertise, and Online Creation and Participation

Overall, this study revealed a distinct difference in the use of technology by people who consume content and those who create content. Creators see technology in a different light than consumers, but consumers seem to rate themselves higher as influencers and online experts than

the group who actually creates content. And interestingly, those that are smartphone averse will actually use their smartphones more in certain instances than consumers will (see Chapter 4, Table 1).

This study showed us that heavy computer use did not pose a significant factor in affecting the likelihood of participating with or creating content online. The analyses discussed in Chapter 4 show tasks traditionally involving more typing or more content creation – tasks typically done from a home computer with a traditional keyboard or mouse – had no significant relationship to a participant's level of comfort with technology. The computer is already ubiquitous and it seems heavy users don't consider this technology a factor when self-reporting their level of online expertise.

While the smartphone is on the verge of ubiquity, the amount of time one uses his or her phone is the telling factor; heavy users were more likely to participate and create than non-heavy users. The analysis discussed in Chapter 4 among the *Smartphone Use* and the *Comfort With Technology* indices, however, did show a significant relationship between a participant's level of comfort with technology and heavy use of smartphones for utilitarian tasks, such as checking email and tasks requiring fewer characters or finger taps to type or tap on screen.

Heavy smartphone users were more comfortable with technology in general than light users, and their likelihood of considering themselves online experts were higher than non-light users. This research did not support what Bergstrom (2008) found, and I believe the reason is attributable simply to the time-frame in which the studies were conducted. In Bergstrom's 2008 study, the iPhone had been on the market less than a year (Apple Inc., 2007). My study took place five years later, giving the diffusion process more time to seep from early majority down to the late majority and laggards. While the impact the iPhone had on smartphone adoption can't be

understated, the majority of participants in this research used the Android operating system (49.3 percent), with the iPhone being a close second (43.5 percent). This is yet another indication of the smartphone reaching its critical mass within society and its perceived usefulness becoming an assumption of everyday use.

Much like Bergstrom (2008) and Wei et al. (2012) found, there is indeed a group of younger people who consider themselves online experts. However, unlike Bergstrom and Wei et al., this research indicates that the generation who has grown up in a more digital environment, those ages 18 to 24, has already been affected by the diffusion process and is looking for the next innovation. It is in the age group who saw smartphones emerge as an innovative technology – those ages 25 to 41 – that exists the largest perception of usefulness. It is interesting to note that *Content Consumers* report the highest levels of online expertise even though they merely consumer and do not contribute content to the online world. Considering oneself an online expert might indicate one's frequency of use, but this research shows it has no bearing on whether one will participate or create online content with that technology.

Those who were most comfortable with technology were no more likely to participate more via smartphone than they would any other device. They were contributing online, yes, but the device did not seem to play an important role. Again, I attribute this to the diffusion process; the youngest of participants are more likely to consider themselves online experts, and these are the same group to not see smartphones emerge as an innovative technology. This is also classic example of the Technology Acceptance Model; the higher the perception of usefulness and utility leads to higher adoption and use of a technology.

What's interesting, however, is not the somewhat logical conclusion that those in the *Smartphone averse* group would obviously be less likely to use their smartphones in various

situations than the other two groups that emerged from the cluster analysis, but that that in some cases, the *Content consumer* group was even less likely to use their smartphone than the *Smartphone averse*. When it came to using a smartphone to contribute and find content online, to create and participate on Twitter and online blogs, or to navigate the Pinterest website, the *Content consumer* group was the least likely group to choose to use a smartphone to do so.

What this indicates is that there is a distinct difference between being *Smartphone averse* and being a sole *Content consumer*. It appears that those who solely consume what the Internet has to offer are much more likely to do so via computer. Even with the capabilities on their smartphone, these participants made a distinct choice not to use it for this capacity, and in fact, rated their perception of a computer's usefulness higher than that of their smartphone.

Another interesting distinction is how different the views of the perceived usefulness of a computer differ between the *Content consumer* and *Content creator* groups. *Content creators* are much less likely to find a computer useful (and, conversely, much more likely to find a smartphone useful) than the *Content consumer* group. This shows that *Content creators* appear to favor the convenience, portability, and instant-gratification of smartphone use, as computers offer more robust features typically.

Effect of Demographics

Age and education levels were the only demographic characteristics to affect one's likelihood of adopting technology and feeling comfortable with it. It was surprising to see not the youngest age group in this study – the 18 to 24-year-olds as Correa (2010) finds – but the second tier – ages 25 to 41 – most likely to perceive smartphones as useful. The oldest age group – ages 56 and older – was most likely to find a computer useful; much more so than the youngest age group. This could illustrate a shift in thinking about technology, too; for older adults, computers

and cellphones might be seen as tools, but for younger age groups, the cellphone or smartphone may be more of a lifestyle necessity.

Worth noting is the absence of income in this discussion. In none of the tests did income hold a significant relationship with technology or task preference. This may indicate that the wide availability of technology allows for lower prices and more access by diverse demographic groups. However, the design of this survey itself might explain the absence of significance, and could be noted as a limitation in this research. More investigation into this demographic characteristic and its effect is needed, as Schradie (2011) and even Rogers (2003) suggest.

Having at least some college education seemed to be the mark at which the participants in this study formed their opinions on technology (see Chapter 4, Figure 5). This mid-education level, which included some college education or graduation from a college or university, marked the point at which more people were more likely to be *Content consumers* or *Content creators* more than any other education level. The implications of this for higher education settings are fairly large. It is at the moment where a student decides to continue his or her education past high school that the opportunity exists to change that student's opinion and comfort level with emerging technologies. Of course higher education has already adopted this thought and has placed an importance on the use of technology in its classrooms, but this research highlights the fact that the youngest of participants in this study see computers as a "given," and are ready for the next step in the innovation process.

When thinking about online content creation and participation, we see that the youngest of the groups doesn't contribute or participate nearly as much as the next higher age group (ages 25-41). As the younger group uses their smartphones as an everyday lifestyle tool, the next older age group remembers what it was like to have one big desktop in the house with a dial-up

Internet connection and still finds it incredibly useful to have that same functionality in their pockets or purses. While the age of blogs and personal websites might see an ebb as this youngest generation contributes less, the growth of Vine, Instagram, and other picture and video-sharing applications may just move content creation to a different plane than what researchers are accustomed to investigating. This youngest age group is looking for the next innovation and it's up to the researchers to watch these emerging technologies to see where their use might lead.

What I call the Digital Divide 2.0 takes these standard demographics less into consideration; no longer does the digital divide exist strictly on the basis of Internet access – the divide has become more complicated. In addition to education and income's effects on technology use, the Digital Divide 2.0 widens its scope beyond access and to identifying the characteristics and effects of the content creators. The implications of identifying who creates the majority of online are vast when one considers that affect on minority groups or voices online. If one demographic group creates the majority of the online content, the popular view of the Internet being an egalitarian space with room for everyone's voice comes under fire. This is an area ripe for future research.

Limitations and Suggestions for Future Research

This study, through its use of a survey, was not able to forecast the fate of online creation and participation; it can only speak to what relationships exist and what affects those relationships. While this research has supported the idea of the household computer as a ubiquitous device, a limitation must be mentioned that the use of Mechanical Turk was indeed an online-only source. Participants in this study were required to have both a smartphone and a home computer, so the assumption of at least a base level of comfort with technology is inherent in this research. Future research could benefit from the study of the true laggards – possibly

characterized by those without home Internet connections, computers or smartphones to see at what point demographics affect this portion of society.

As Rogers (2003) suggests, survey research might not be the correct way to go about studying the implications phase of diffusions research. Future research would benefit from in-depth case studies or longitudinal observation on both the youngest generation's opinions and tendencies toward technology as well as the laggards' aversion to it. Setting aside the non-generalizability that comes with some in-depth interviews, the next phase of research on diffusion theory must go beyond watching the phenomenon take place, and instead look at what the consequences might be (Rogers E. M., 2003, pp. 440-442). In addition, future research should, as Schradie's research suggests, investigate who is creating the content. While my research did not show support for the effect of income or race on online content and participation, future research could benefit from looking at how income, access, and education factor more deeply into the creation of content those with lower education levels consume.

Conclusion

This research offers an insight into the age groups and their likelihood of being comfortable with technology and their self-reported evaluation of their level of expertise online. Surprisingly, the youngest age groups don't rate themselves as comfortable with technology or as highly on the online expert scale as the age group directly above them. This shows that simply growing up with some technologies doesn't increase one's general knowledge of technology. The age group that had to learn a little programming, or go through lengthy software and hardware installation processes seems to see the usefulness, and put to use for the purpose of creation and participation, more new forms of technology than the generation who grew up with plug-and-play interfaces.

This brings up the question that as technology becomes more accessible, will the user and his or her behavior online be beholden to the design and scope of future devices? As technology becomes more and more sophisticated and all the while simpler to use, will the ability to freely express one's ideas be limited to whether there's an "app for that?" These questions reinforce the importance for mass communication's study of technology effects. Our voices are heard on the open Web now, in forums, in comments left on stories, on our own personal blogs or websites. It is in the next technological wave that these opportunities should be monitored. As technology moves more from the ebb stage to a free-flow, researchers can become prepared for the consequences and as a discipline, adapt.

REFERENCES

Anderson, C., & Wolff, M. (2010, August 17). *The web is dead. Long live the Internet.* Retrieved from Wired.com: http://www.wired.com/magazine/2010/08/ff_webrip/all/1

Apple Inc. (2007, January 9). *Apple reinvents the phone with iPhone.* Retrieved from apple.com: http://www.apple.com/pr/library/2007/01/09Apple-Reinvents-the-Phone-with-iPhone.html

Bergstrom, A. (2008). The reluctant audience: Online participation in the Swedish journalistic context. *Westminster Papers in Communication and Culture, 5*(2), 60-80.

Buhrmester, M. (2012, January 18). *Amazon Mechanical Turk Guide for Social Scientists.* Retrieved June 28, 2013, from http://homepage.psy.utexas.edu/homepage/students/buhrmester/MTurk%20Guide.htm

Campbell, S. W., & Kwak, N. (2011). Political involvement in 'mobilized' society: The interactive relationships among mobile communication, network characteristics, and political participation. *Journal of Communication, 61*(2011), 1005-1024.

Chan-Olmsted, S., Rom, H., & Zerba, A. (2012). Mobile News Adoption among Young Adults: Examining the Roles and Perceptions, News Consumption, and Media Usage. *Journalism & Mass Communication Quarterly, 90*(1), 126-147.

Cingel, D. P., & Sundar, S. S. (2012, May 11). Texting, techspeak, and tweens: The relationship between text messaging and English grammar skills. *New Media & Society, 14*(8), 1304-1320. doi:10.1177/1461444812442927

Correa, T. (2010). The participation divide among 'online experts': Experience, skills and psychological factors as predictors of college students' Web content creation. *Journal of Computer-Mediated Communication, 16*(1), 71-92. doi:10.1111/j.1083-6101.201

Davis, F. D. (1989, September). Perceived usefulness, perceived ease of use and user acceptance of information technology. *MIS Quarterly*, 319-340.

Jenkins, H., & Deuze, M. (2008). Editorial. *Convergence, 14*(1), 5-12. doi:10.1177/1354856507084415

Kalyanaraman, S., & Sundar, S. S. (2006). The psychological appeal of personalized content in web portals: Does customization affect attitudes and behavior? *Journal of Communication, 56*(2006), 110-132. doi:10.1111/j.1460-2466.2006.00006.x

Koh, Y. J., & Sundar, S. S. (2010). Heuristic versus systematic processing of specialist versus generalist sources in online media. *Human Communication Research, 36*, 103-124. doi:doi:10.1111/j.1468-2958.2010.01370.x

Kulviwat, S., Bruner II, G. C., Kumar, A., Nasco, S. A., & Clark, T. (2007, December). Toward a Unified Theory of Consumer Acceptance Technology. *Psychology & Marketing, 24*(12), 1059-1084. doi:10.1002/mar.20196

Lai, J., & Chang, C. (2011). User attitudes toward dedicated e-book readers for reading: The effects of convenience, compatibility and media richness. *Online Information Review, 35*(4), 558-580. doi:10.1108/14684521111161936

Lenhart, A., Horrigan, J., & Fallows, D. (2004). *Content Creation Online.* Pew Internet & American Life Project. Retrieved from http://www.pewinternet.org/Reports/2004/Content-Creation-Online.aspx

Lichtenberg, J. (2011). In from the edge: The progressive evolution of publishing in the age of digital abundance. *Pub Res Q, 27*, 101-112.

Liu, X. (2010, January). Empirical Testing of a Theoretical Extension of the Technology Acceptance Model: An Exploratory Study of Education Wikis. *Communication Education, 59*(1), 52-69.

Marwick, A. E., & Boyd, D. (2010, July 7). I tweet honestly, I tweet passionately: Twitter users, context collapse, and the imagined audience. *New Media & Society*, 1-20. doi:DOI: 10.1177/1461444810365313

Nasco, S. A., Kulviwat, S., Kumar, A., & Bruner II, G. C. (2008, October). The CAT Model: Extenstions and Moderators of Dominance in Technology Acceptance. *Psychology & Marketing, 25*(10), 987-1005.

Page, K., DK, & Mapstone, M. (2010, December). How does the web make youth feel? Exploring the positive digital native rhetoric. *Journal of Marketing Management, 26*(13-14), 1345-1366.

Papacharissi, Z. (2002). The virtual sphere: The internet as a public sphere. *New Media & Society, 4*(1), 9-27. doi:10.1177/14614440222226244

Pedrozo, S. (2013, January). New media use in Brazil: Digital inclusion or digital divide? *Online Journal of Communication and Media Technologies, 3*(1), 144-162.

Pew Internet & American Life Project. (November 2012). *Cell Phone Activities 2012.*

Reeves, B., & Nass, C. (1996). *The Media Equation: How people Treat Computers, Television, and New Media Like Real People and Places.* Cambridge University Press.

Rogers, E. (1976, March). New Product Adoption and Diffusion. *Journal of Consumer Research, 2*, 290-301.

Rogers, E. M. (2003). *Diffusion of Innovations* (5th ed.). New york, NY: Free Press.

Ryan, B., & Gross, N. (1943). The Diffusion of Hybrid Seed Corn in Two Iowa Communities. *Rural Sociology, 8*(1), 15-24.

Sanders, M. S., & Song, F. (2012). *Women of color in social media survey.* Retrieved from BeBlogalicious: http://beblogalicious.com/multicultisurvey/

Schlozman, K. L., Verba, S., & Brady, H. E. (2012). *The Unheavenly Chorus: Unequal Political Voice and the Broken Promise of American Democracy.* Princeton, NJ, USA: Princeton University Press.

Schradie, J. (2011). The digital production gap: The digital divide and Web 2.0 collide. *Poetics, 39*, 145-168.

Severin, W., & Tankard Jr., J. W. (2001). *Communication Theories: Origins, Methods, and Uses in the Mass Media* (Fifth ed.). Addison Wesley Longman, Inc.

Smith, A. (2011). *35% of American adults own a smartphone.* Pew Internet & American Life Project. Retrieved from http://www.pewinternet.org/~/media/Files/Reports/2011/PIP_Smartphones.pdf

Smith, A. (2012). *46% of American adults are smartphone owners.* Pew Internet & American Life Project. Retrieved from http://www.pewinternet.org/~/media/Files/Reports/2012/Smartphone%20ownership%202012.pdf

Smith, A. (2013, June 5). *Smartphone Ownership - 2013 Update.* Retrieved June 19, 2013, from pewinternet.org: http://www.pewinternet.org/Reports/2013/Smartphone-Ownership-2013/Findings.aspx

Stern, B. B., Royne, M. B., Stafford, T. F., & Bienstock, C. C. (2008, July). Consumer Acceptance of Online Auctions: An Extension and Revision of the TAM. *Psychology & Marketing, 25*(7), 619-636.

Sudar, S. S., & Sampada, S. M. (2010). Personalization versus customization: The importance of agency, privacy, and power usage. *Human Communication Research, 36*, 298-322. doi:10.1111/j.1468-2958.2010.01377.x

Sundar, S. S., & Nass, C. (2000, December 1). Source orientation in human-computer interaction: Programmer, networker, or independent social actor? *Communication Research, December 2000,* 683-703. doi:10.1177/009365000027006001

Tacchi, J. (2011). Open content creation: The issues of voice and the challenges of listening. *New Media & Society, 14*(4), 652-668.

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences, 39*, 274-315.

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

Verkasalo, H., Lopez-Nicolas, C., Molina-Castillo, F. J., & Bouwman, H. (2010). Analysis of users and non-users of smartphone applications. *Telematics and Informatics, 27*(2010), 242-255. doi:10.1016/j.tele.2009.11.001

Wang, H., Chung, J., Park, N., McLaughlin, M. L., & Fulk, J. (2012). Understanding Online Community Participation: A Technology Acceptance Perspective. *Communication Research, 39*(6), 781-801.

Wei, R., Karlis, J., & Haught, J. (2012). Apps, apps, and more apps: A uses and gratifications study of app use. *Annual Meeting of the International Communications Association.* Phoenix.

West, J., & Mace, M. (2010). Browsing as the killer app: Explaining the rapid success of Apple's iPhone. *Telecommunications Policy, 34*, 270-286.

Wheaton, K. (2010, Sept. 13). It's not the phone or the app, it's the shift in behavior. *Advertsing Age*, p. 27.

Zemmels, D. R. (2012). Youth and new media: Studying identity and meaning in an evolving media environment. . *Communication Research Trends, 31*(2012), 4-22.

Zhou, Y. (2008). Voluntary adopters versus forced adopters: Integrating the diffusion of innovation theory and the technology acceptance model to study intra-organizational adoption. *New Media & Society, 10*(3), 475-496. doi:10.1177/1461444807085382

Zickuhr, K. (October 2012). *The rise of e-reading.* Pew Research Center’s Internet & American Life Project presentation, Florida Public Library Directors' meeting, Tallahassee, Fla.

Zitz, M. (n.d.). *Diffusion of Personal Computers for Home Use*. Retrieved from SUNY IT: http://people.sunyit.edu/~zitzm/presentation4.html

APPENDIX A:
SURVEY

2) To qualify for this survey, you indicated at sign-up that you own both a smartphone (Android, iPhone, Blackberry etc…) as well as a laptop or desktop computer. Is this correct?
() Yes, I own/use both a smartphone and a laptop/desktop computer.
() No, I do not own/use both of these kinds of technology. I have one or the other, or neither.

(if no, the survey will not continue)

3) You've indicated you own or use a smartphone on a regular basis. What kind do you have?

iPhone
Android
Blackberry
Windows Phone
I have more than one smartphone
Other (what kind? _______)

4) You've indicated you have either a desktop computer or a laptop. Which do you have?

Laptop, Desktop, Both
Other (_________)

5) Is your computer:
Mac
PC
Linux/Unix
I have a combination of these
Other (_______)

6) What is your age?
18-24
25-41
42-55
56-64
65 or older
Prefer not to answer

7) What gender do you identify with?
Male, Female

8) Which description best fits your level of expertise when it comes to:
Newbie *Basic User* *Competent User* *Advanced User* *Seasoned Expert*

Internet use
Smartphone use
Laptop/desktop computer use

11) How often do you use your smartphone or laptop/desktop (for any purpose, calls, texting, games, etc...?

Not every day; 1 hour or less each day; 1-3 hours each day; 3-6 hours each day; 6-10 hours each day; More than 10 hours each day

Smartphone

Laptop/desktop computer

13) Do you:

Write a blog?	***Yes***	***No***
Have a Pinterest account?		
Read the news online?		
Read blogs/follow Tumblrs online?		
Have Facebook account?		
Have a Twitter account?		
Have a personal Web site?		

14) Have you ever contributed material (text, photos, comments, videos, etc…) to:

Yes ***No***

A Web site for yourself

A business Web site (Yelp, Urbanspoon, local newspaper online, etc…)

A Web site for an organization you belong to, such as a charge, club or professional group?

Another person's personal Web site or blog?

15) The Internet, Social Media especially, has a lot to do with networks of people sharing and sharing and shaping the conversation. How much of an influencer do you consider yourself to be? *(5-pt likert scale)*

Not influential at all *Somewhat influential* *Extremely Influential*

16) How often do you update or post comments on:

Never/NA *Seldom/every few months* *Monthly* *Weekly* *Daily/almost daily*

Your blog

Your personal Web site

A business Web site (Yelp, Urbanspoon, local newspaper online, etc…)

A Web site for an organization you belong to, such as a charge, club or professional group?

News sites or news articles online

A blog or Tumblr you follow

Facebook status

Comment on Facebook

Retweet something on Twitter

17) Overall, when you use the Internet, do you do that mostly using your:

Cellphone

Laptop/desktop

A combination of both devices

18) Why?

19) Thinking now about how you get information and communicate with others using a laptop/desktop or cell phone, how important is it that…you can share or post content online:
very important, *somewhat important,* *not too important* *or not at all important?*

20) When you write or send an email, do you **prefer** use:
Desktop/ laptop computer
Smartphone

21) *why? ________________________

22) When you read or check email, do you **prefer** use:
Desktop/ laptop computer
Smartphone

23) *why? ________________________

24) When writing a blog or a lengthy post online, do you **prefer** use:
Desktop/ laptop computer
Smartphone

25) *why? ________________________

26) **The purpose of this survey is to see how you <u>prefer</u> to use your smartphone for, and what activities you <u>prefer</u> to do on your laptop/desktop computer. In the questions that follow, please choose the option that ***best fits*** your personal preference.**

(continued)

27) I prefer to use my <u>smartphone</u> for the following tasks
Strongly Disagree Disagree Neutral Agree Strongly Agree N/A

Writing a new an email
Reading email
Checking Pinterest
Repinning pins in Pinterest
Adding new/original pins to Pinterest
|Searching Google
Reading blogs
Reading news stories
Finding sports scores
Commenting on news stories
Commenting on a business site (Yelp, Urbanspoon, etc)
Checking in (on Facebook, FourSquare etc)
Sharing my stories on social media
Sharing others' stories on social media
Sharing my pictures on social media
Sharing others' pictures on social media
Checking email
Reading email
Checking Facebook
Commenting/"liking" on Facebook
Updating my Facebook status
Commenting on blogs or Tumblrs I follow
Checking Twitter
Retweeting a tweet
Writing a new tweet
Writing a blog
Creating a video
Sharing videos I made (Facebook, Vine, YouTube, etc)
Sharing a video someone else made (Facebook, Vine, YouTube, etc)

28) I will <u>check</u> email on my smartphone if I have to, but I prefer my laptop/desktop computer:
Strongly Disagree Disagree Neutral Agree Strongly Agree N/A

(continued)

29) I prefer to use my desktop/laptop for the following tasks

Strongly Disagree Disagree Neutral Agree Strongly Agree
N/A

Writing a new an email
Reading email
Checking Pinterest
Repinning pins in Pinterest
Adding new/original pins to Pinterest
Searching Google
Reading blogs
Reading news stories
Finding sports scores
Commenting on news stories
Commenting on a business site (Yelp, Urbanspoon, etc)
Checking in (on Facebook, FourSquare, etc)
Sharing my stories on social media
Sharing others' stories on social media
Sharing my pictures on social media
Sharing others' pictures on social media
Checking email
Reading email
Checking Facebook
Commenting/"liking" on Facebook
Updating my Facebook status
Commenting on blogs or Tumblrs I follow
Checking Twitter
Retweeting a tweet
Writing a new tweet
Writing a blog
Creating a video
Sharing videos I made (Facebook, Vine, YouTube, etc)
Sharing a video someone else made (Facebook, Vine, YouTube, etc)

30) I will write/send an email on my smartphone if I have to, but I prefer my laptop/desktop computer:

Strongly Disagree Disagree Neutral Agree Strongly Agree
N/A

31) I will update a status or tweet on social media using my smartphone if I have to, but I prefer my laptop/desktop computer:

Strongly Disagree Disagree Neutral Agree Strongly Agree
N/A

32) On tasks that you indicated you prefer a desktop or laptop computer, please explain why:

33) On tasks where you prefer to use your smartphone, please explain why:

34) Imagine you're sitting at your breakfast table and you have both your laptop/desktop computer and your smartphone in front of you. Which one do you choose for each of these tasks?

	Laptop/Desktop	Smartphone
Writing a new an email		
Reading email		
Checking Pinterest		
Repinning pins in Pinterest		
Adding new/original pins to Pinterest		
|Searching Google		
Reading blogs		
Reading news stories		
Finding sports scores		
Commenting on news stories		
Commenting on a business site (Yelp, Urbanspoon, etc)		
Checking in (on Facebook, FourSquare etc)		
Sharing my stories on social media		
Sharing others' stories on social media		
Sharing my pictures on social media		
Sharing others' pictures on social media		
Checking email		
Reading email		
Checking Facebook		
Commenting/"liking" on Facebook		
Updating my Facebook status		
Commenting on blogs or Tumblrs I follow		
Checking Twitter		
Retweeting a tweet		
Writing a new tweet		
Writing a blog		
Creating a video		
Sharing videos I made (Facebook, Vine, YouTube, etc)		
Sharing a video someone else made (Facebook, Vine, YouTube, etc)		

(continued)

35) Please indicate which sentiment best describes your feeling toward technology in general:
Strongly Disagree *Disagree* *Neutral* *Agree* *Strongly Agree*

I find it intimidating
I don’t like learning technology, but eventually get used to it.
I’m excited to try out new gadgets.
I generally understand technology and learn to use new things quickly.
I generally enjoy technology and learn to use new things quickly.
Once I learn how to use it, I love it.

36) How important is the idea of community to you?
Not important at all *Somewhat Important* *Moderately important* *Important* *Very Important*

37) How important is it for you to feel like you have control over your environment?
Not important at all *Somewhat Important* *Moderately important* *Important* *Very Important*

38) At about what age (approximate is OK if you don’t remember exactly) did you first begin using a laptop/desktop regularly?

39) How well do each of these rationales match what influenced you to begin using that laptop/desktop?
Strongly Disagree *Disagree* *Neutral* *Agree* *Strongly Agree*

I asked for the laptop/desktop.
My parents bought it for me, so I began using it.
I saw my friends or coworkers using one and thought I might like one, too.
I asked for the laptop/desktop after my friends got one first.
I saw an advertisement and thought I should have one, too.
I saw the laptop/desktop being used on TV or in the movies and thought I might like one, too.
None of these describe me. My explanation is:______________________

40) At about what age (approximate is OK if you don't remember exactly) did you first begin using a smartphone regularly?

41) How well do each of these rationales match what influenced you to begin using that smartphone?
Strongly Disagree *Disagree* *Neutral* *Agree* *Strongly Agree*

I asked for the smartphone.
My parents bought it for me, so I began using it.
I saw my friends or coworkers using one and thought I might like one, too.
I asked for the smartphone after my friends got one first.
I saw an advertisement and thought I should have one, too.
I saw the phone being used on TV or in the movies and thought I might like one, too.
None of these describe me. My explanation is:______________________

42) How much do you think your <u>smartphone</u> affects your ability to participate online?
No affect *It's moderately important* *I couldn't participate without it*

43) How much do you think your <u>laptop/desktop</u> computer affects your ability to participate online?
No affect *It's moderately important* *I couldn't participate without it*

44) How much do you think your <u>smartphone</u> affects your ability to create content online?
No affect *It's moderately important* *I couldn't create without it*

45) How much do you think your <u>laptop/desktop</u> affects your ability to create content online?
No affect *It's moderately important* *I couldn't create without it*

46) Are you currently employed?
Yes, No, I prefer not to answer

47) Does your job provide you with technology, such as a work laptop, cellphone, or desktop computer?
Yes
No
I work at home or for myself, so I have provided the technology
Other:____________________

48) What is your job title?
(fill in the blank)

49) Do you use your work-provided technology for personal use?
Yes
No

<u>(continued)</u>

50) <u>While at work</u>, I prefer to use my <u>desktop/laptop</u> for the following tasks

Strongly Disagree *Disagree* *Neutral* *Agree* *Strongly Agree* *N/A*

Writing a new an email
Reading email
Checking Pinterest
Repinning pins in Pinterest
Adding new/original pins to Pinterest
|Searching Google
Reading blogs
Reading news stories
Finding sports scores
Commenting on news stories
Commenting on a business site (Yelp, Urbanspoon, etc)
Checking in (on Facebook, FourSquare etc)
Sharing my stories on social media
Sharing others' stories on social media
Sharing my pictures on social media
Sharing others' pictures on social media
Checking email
Reading email
Checking Facebook
Commenting/"liking" on Facebook
Updating my Facebook status
Commenting on blogs or Tumblrs I follow
Checking Twitter
Retweeting a tweet
Writing a new tweet
Writing a blog
Creating a video
Sharing videos I made (Facebook, Vine, YouTube, etc)
Sharing a video someone else made (Facebook, Vine, YouTube, etc)

(continued)

51) <u>While at work</u>, I prefer to use my <u>cellphone</u> for the following tasks
Strongly Disagree *Disagree* *Neutral* *Agree* *Strongly Agree* *N/A*

Writing a new an email
Reading email
Checking Pinterest
Repinning pins in Pinterest
Adding new/original pins to Pinterest
|Searching Google
Reading blogs
Reading news stories
Finding sports scores
Commenting on news stories
Commenting on a business site (Yelp, Urbanspoon, etc)
Checking in (on Facebook, FourSquare etc)
Sharing my stories on social media
Sharing others' stories on social media
Sharing my pictures on social media
Sharing others' pictures on social media
Checking email
Reading email
Checking Facebook
Commenting/"liking" on Facebook
Updating my Facebook status
Commenting on blogs or Tumblrs I follow
Checking Twitter
Retweeting a tweet
Writing a new tweet
Writing a blog
Creating a video
Sharing videos I made (Facebook, Vine, YouTube, etc)
Sharing a video someone else made (Facebook, Vine, YouTube, etc)

52) <u>While at work</u>, how often do you use your smartphone (for any purpose, calls, texting, games, etc...?
Not every day
1 hour or less each day
1-3 hours each day
3-6 hours each day
6-10 hours each day
More than 10 hours each day

53) While at work, how often do you use your laptop/desktop?
Not every day
1 hour or less each day
1-3 hours each day
3-6 hours each day
6-10 hours each day
More than 10 hours each day

54) While at work, have you ever contributed material (text, photos, comments, videos, etc…) to:

	Yes	No
A Web site for yourself		
A business Web site (Yelp, Urbanspoon, local newspaper online, etc…)		
A Web site for an organization you belong to, such as a charge, club or professional group?		
Another person's personal Web site or blog?		

55) While at work, how often do you update or post comments on:

	Never/NA	*Seldom/every few months*	*Monthly*	*Weekly*	*Daily/almost daily*
Your blog					
Your personal Web site					
A business Web site (Yelp, Urbanspoon, local newspaper online, etc…)					
A Web site for an organization you belong to, such as a charge, club or professional group?					
News sites or news articles online					
A blog or Tumblr you follow					
Facebook status					
Comment on Facebook					
Retweet something on Twitter					

56) Overall, when you use the Internet while at work, do you do that mostly using your:
Cellphone
Laptop/desktop
A combination of both devices

57) Why?

58) When you write or send an email for work purposes, do you **prefer** use:
Desktop/ laptop computer
Smartphone

59) why? _________________________

60) When you read or check work email, do you **prefer** use:
Desktop/ laptop computer
Smartphone

61) why? ________________________

62) Please indicate your household income:
Less than $25,000
$25,000-$34,999
$35,000-$49,999
$50,000-$74,999
$75,000-$99,999
$100,000-$124,999
More than $125,000

63) Please indicate your highest level of education attained:
High school graduate or less
Technical or trade school graduate
Some college/university
College/university graduate
Some post-graduate work
Master’s or doctorate degree

64) Please indicate your ethnicity:
Asian/Asian Pacific Islander
Hispanic
Mixed ethnicity
Native American
Caucasian
African American
Other: __________________

65) In what state do you currently reside?
<enter two-letter state abbreviation>

APPENDIX B:
IRB APPROVAL FORMS

Application for Exemption from Institutional Oversight

LSU

Institutional Review Board
Dr. Robert Mathews, Chair
131 David Boyd Hall
Baton Rouge, LA 70803
P: 225.578.8692
F: 225.578.5983
irb@lsu.edu
lsu.edu/irb

Unless qualified as meeting the specific criteria for exemption from Institutional Review Board (IRB) oversight, ALL LSU research/ projects using living humans as subjects, or samples, or data obtained from humans, directly or indirectly, with or without their consent, must be approved or exempted in advance by the LSU IRB. This Form helps the PI determine if a project may be exempted, and is used to request an exemption.

-- Applicant, Please fill out the application in its entirety and include the completed application as well as parts A-F, listed below, when submitting to the IRB. Once the application is completed, please the completed application to the IRB Office or to a member of the Human Subjects Screening Committee. Members of this committee can be found at http://research.lsu.edu/CompliancePoliciesProcedures/InstitutionalReviewBoard%28IRB%29/item24737.html

-- A Complete Application Includes All of the Following:
- **(A)** A copy of this completed form and a copy of parts B thru F.
- **(B)** A brief project description (adequate to evaluate risks to subjects and to explain your responses to Parts 1&2)
- **(C)** Copies of all instruments to be used.
  - *If this proposal is part of a grant proposal, include a copy of the proposal and all recruitment material.
- **(D)** The consent form that you will use in the study (see part 3 for more information.)
- **(E)** Certificate of Completion of Human Subjects Protection Training for all personnel involved in the project, including students who are involved with testing or handling data, unless already on file with the IRB. Training link: (http://phrp.nihtraining.com/users/login.php)
- **(F)** IRB Security of Data Agreement: (http://research.lsu.edu/files/item26774.pdf)

1) Principal Investigator: Amanda Cortright **Rank:** graduate student

Dept: Mass Communication **Ph:** 386-852-7091 **E-mail:** acortr2@tigers.lsu.edu

2) Co Investigator(s): please include department, rank, phone and e-mail for each
*If student, please identify and name supervising professor in this space

Lance Porter, Assistant Professor, 225-578-7377, lporter@lsu.edu

3) Project Title: Online Participation and Content Creation

4) Proposal? (yes or no) no **If Yes, LSU Proposal Number**

Also, if YES, either ◯ **This application completely matches the scope of work in the grant**
OR ◯ **More IRB Applications will be filed later**

5) Subject pool (e.g. Psychology students) computer users on Amazon's Mechanical Turk

*Circle any **"vulnerable populations" to be used**: (children <18; the mentally impaired, pregnant women, the ages, other). Projects with incarcerated persons cannot be exempted.

6) PI Signature A B Cortright **Date** 5/15/13 (no per signatures)

**** I certify my responses are accurate and complete.** If the project scope or design is later changes, I will resubmit for review. I will obtain written approval from the Authorized Representative of all non-LSU institutions in which the study is conducted. I also understand that it is my responsibility to maintain copies of all consent forms at LSU for three years after completion of the study. If I leave LSU before that time the consent forms should be preserved in the Departmental Office.

IRB# E8334 LSU Proposal #
- ✓ Complete Application
- ✓ Human Subjects Training
- ✓ IRB Security of Data Agreement

Study Exempted By:
Dr. Robert C. Mathews, Chairman
Institutional Review Board
Louisiana State University
203 B-1 David Boyd Hall
225-578-8692 | www.lsu.edu/irb
Exemption Expires: 6/5/2016

Screening Committee Action: Exempted X Not Exempted ____ Category/Paragraph 2
Signed Consent Waived?: Yes / No
Reviewer Meghan Sanders **Signature** [signature] **Date** 6/6/13
RCM

Amanda Cortright -- IRB Exemption Application – acortr2@tigers.lsu.edu

Consent Statement –Part D

The survey will feature this Consent Statement on the opening screen:

Thank you for taking the time to take this survey. The purpose of this survey is to gauge your preference of technology when performing various tasks online. If you agree to take part in this research, you will be asked to answer a series of questions about your use of the Internet when using smartphones, laptop computers, and desktop computers. Your participation is:

- completely voluntary and can be withdrawn at any time during the survey if you choose without penalty.
- anonymous (your identity is unknown to the researchers)
- greatly appreciated and would help the researchers gather important data on how users relate and feel about technology and how those feelings might affect one's general use of technology.
-

Please note:

- All data collected from this survey is held securely and confidentially.
- There are no right or wrong answers to the questions, so please answer them as honestly as possible.
- This survey has been approved by the Louisiana State University Institutional Review Board.
- This survey is being conducted as part of academic research toward Master's degree completion. For any questions or concerns, please contact: acortr2@tigers.lsu.edu or lporter@lsu.edu. You may also contact the Institutional Review Board in the Office of Research and Economic Development at Louisiana State University with concerns at (225) 578-5833 or research@lsu.edu.
- By participating in this study, participants will help contribute to research that seeks to understand how users relate and feel about technology and how those feelings might affect one's general use of technology.
- Participants who meet the criteria outlined on the first screen of the survey will be compensated 50 cents for completing this online survey.
- This survey has been approved by the LSU Institutional Review Board. IRB approval number: ________ *(to come)*.

- By clicking "Next," you acknowledge that you have agreed to the terms stated above.

Study Exempted By:
Dr. Robert C. Mathews, Chairman
Institutional Review Board
Louisiana State University
203 B-1 David Boyd Hall
225-578-8692 | www.lsu.edu/irb
Exemption Expires: 6/5/2016

VITA

Amanda Cortright graduated from Drake University in Des Moines, Iowa in 1999 with a Bachelor's degree in Journalism and Mass Communication, majoring in magazine journalism and minoring in graphic design. After 10 years of working as a copy editor, section editor, and assistant features editor in the newspaper industry, she took a buyout when the industry became strained in 2009 and moved to Baton Rouge, Louisiana, where she acted as a freelance editor for two years. In 2011, she enrolled in Louisiana State University's Manship School of Mass Communication to earn her Master's in Mass Communication. After graduation in December 2013, Amanda will take some time off the academic and industry fronts and embark on the adventure of parenthood. Someday she would like to return to the media landscape, helping to shape the new direction of communication avenues in a media organization, educational environment, or non-profit organization.