Drivers of Innovation

AN ANALYSIS OF INNOVATIVENESS ACROSS TECHNOLOGIES AND DOMAINS

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ABSTRACT

The diffusion of innovations (DOI) framework posits that there are five types of potential adopters of new innovations, based on their time of adoption—innovators, early adopters, early majority, late majority, and laggards. Understanding the characteristics of each of these five adopter-types helps in designing targeted strategies to increase the adoption. This research asked a novel question to further understanding of the DOI framework: do consumers consistently fall in the same adopter-type across various innovations? If so, what characteristics (personality, product attributes, etc.) define the "consistent consumer"?

To address these questions, the team conducted a survey on Amazon Mechanical Turk (AMT) of U.S. consumers (n=898), focusing on whether and when each consumer adopted 10 possible innovations (smartphone, DVD player, HDTV, computer, Amazon Prime, social media, e-book, digital camera, and tablet) across three technology domains (communication, entertainment, and productivity). From the survey responses, adoption curves were developed for each innovation based on when respondents adopted the innovation. The adoption curves for all 10 innovations mirrored S-shaped curves as expected in DOI. The degree of consistency (of being a certain adopter type) was measured as the number of consumers who were in the same adoption category across all innovations—a feature that would be extraordinary rare if by chance alone.

The research found almost no consistency among consumers across all 10 technologies. However, when categorized by domain, 223 consumers consistently fell in the same adoption-type in the communication domain (highly unlikely by random chance), while only 10 consumers were consistent in the productivity and entertainment domains. No consistency was observed when innovations were classified into low or high cost. Future research will explore alternative definitions of consistency, for example by not looking at exact adoption-category matches, rather looking at the range of deviations from mean adoption categories at the individual level. Another fruitful direction for research would be to explore which socio-demographic and personality traits help explain why consumers were consistent in the communication domain but not in the productivity and entertainment domains.

Introduction

Is innovativeness an inherent, static personal characteristic; or does it change based on the context and product? If a consumer adopts one new technology, how likely is he or she to adopt a different new technology? Is there variation across the different types of technology for which a person is an innovator? Beyond individual technologies, are there categories of technologies, or domain, across which a consumer is consistently an innovator?

Our research explores the nature of consumer innovativeness and considers what factors influence a consumer to be an innovator for some technologies but not for others. We define innovativeness as a consumer's willingness to adopt novel technologies at an earlier time than most consumers. We seek to determine whether consumer innovativeness is more strongly influenced by a consumer's own personal characteristics, by subjective norms and peers' opinions, or by the characteristics of the technology itself. We are specifically interested in the consistency in adoption behavior and innovativeness, as no studies have yet systematically investigated the consistency of innovativeness across new products or innovations.

To add an additional level of analysis, we also examine consumer adoption at the domain level to identify adoption trends across domains with innovative but dissimilar technologies. We use Goldsmith and Hofacker's (1991) definition of a domain of a product category that contains related technologies. Studies on consumer innovativeness often focus on the adoption of one specific technology or one domain of technology. Our study looks at innovativeness *across* domains to provide a deeper understanding of consumer innovativeness. By investigating the connections among innovativeness, personal demographics, and the exterior factors that influence consumer adoption of technology across domains, we endeavor to provide unique insights into the consumer decision-making process, specifically for novel technologies.

In this study, we use primary and secondary data to measure and explore consumer innovativeness. We developed and administered an online survey to 1,000 respondents. The survey focused on time of adoption of ten specific technologies that we classified into three different domains, the reasons for adoption or non-adoption, and personal demographics. Figure 1 shows the ten technologies and the three domains. We also classified the technologies based on cost: high-cost or low-cost. We relied on secondary data and previous research to assist us in the development of the survey and analysis of results.

Figure 1: Ten technologies and three domains in the study

	Domains		
Cost	**Communications**	**Productivity**	**Entertainment**
High	Smartphone	Digital Camera Computer	HDTV E-Book
Low	Social Media	Amazon Prime Tablet	Netflix DVD Player

In sum, the current research project has three main objectives 1) use primary survey data to create time of adoption distributions for individuals across a host of technologies and domains, 2) determine whether consumers, especially innovators, are consistent in their adoption patterns, and 3) identify what personality and demographic characteristics are common among innovators and early adopters.

Our findings indicate that consumer time of adoption for each technology in our sample mirrors the market-level time of adoption patterns among all consumers in the United States. In addition, consumers in our sample reported that a low intention to use the technology is the main reason they decided not to adopt. We also discovered that a consumer's different personality traits and demographics only moderately influence his or her decision to adopt a new technology. Ultimately, we found that the consumers in our sample were not consistent in their adoption of new technologies at any level: among the different technologies, among domains, or among different cost levels. In other words, if a consumer was an innovator for an individual technology or within a domain, he or she was not consistently an innovator for other technologies or across domains. We further address these findings in the Results and Conclusions sections below. We conclude by examining some limitations of the current research and suggestions for future research.

Literature Review

Theory of Diffusion of Innovations

Rogers' Theory of Diffusions of Innovations (1995) provides the primary theoretical framework for our study. The Theory of Diffusions of Innovations posits that adopters of new technologies can be classified into five different categories based on time of adoption. The five categories are innovators, early adopters, early majority, late majority, and laggards. While Rogers established the framework to categorize a consumer, the Theory of Diffusions of Innovations does not suggest or explore what personal characters influence a consumer to be more like to be an innovator or a laggard. Therefore, the Theory of Diffusions of Innovations provides a theoretical tool that allows us to classify consumers as innovators, early adopters, etc., but we need additional information about the consumer to fully understand the nature and consistency of his or her innovativeness. In the survey, we asked respondents if they adopted a technology, and if so, when they adopted, which allow us to classify them in Rogers' categories.

Theory of Planned Behavior (TPB)

The Theory of Planned Behavior can be operationalized to predict and explain consumer behavior. The theory posits that a consumer's behavior depends on motivation and ability. Specifically, Ajzen (1991) states that "intentions to perform behaviors of different kinds can be predicted with high accuracy from attitudes toward the behaviors, subjective norms, and perceived behavioral control; and these intentions, together with perceptions of behavioral control, account for considerable variance in actual behavior." Perceived behavioral control (PBC) captures a consumer's subjective belief about he or she can successfully acquire and use a new technology. PBC is important for analyzing consumer adoption behavior because a consumer is unlikely to adopt a new technology if he or she believes that are unable to acquire or operate an innovative technology.

So, our research adopts TPB and PBC to determine how strongly a consumer's intention to adopt, motivation to adopt, and ability to operate new technologies factor into adoption patterns. We included questions in the survey that specifically ask what factors contributed to the non-adoption of a new technology. The reasons that respondents can give are directly influenced by TPB and PBC. For example, a respondent can report that they did not adopt a new technology because he or she did not have the intention to use the technology, he or she would not be able to successfully operate the technology, or someone changed his or her mind about the technology.

Domain-Specific Innovativeness (DSI)

DSI measures an individual's innovativeness across a domain. Robertson (1971) first introduced the notion that consumers are able to innovate among products within certain domains of goods. An individual can innovate across domains, as well. Midgley and Dowling further clarified the distinction between product specific innovativeness and cross product innovativeness. They argue that cross product innovativeness more accurately captures innovativeness as a generalized personality trait, as personal innovativeness is measured across products and categories of products. DSI measures personal innovativeness and treats innovativeness as a personality trait yet allows for differences in innovativeness levels according to domain. For example, an individual may be highly innovative in the domain of smart home technology but less innovative in the domain of transportation technology.

In the survey, we grouped the ten technologies into three different domains. The three domains that we used are Communications, Entertainment, and Productivity. The ten technologies that we selected to investigate fall into one of the three domains. For example, smartphone is categorized in the Communications domain, HDTV in the Entertainment domain, and tablet in the Productivity domain. By classifying technologies into different domains, we are able to observe adoption trends not only across technologies but also across domains. Therefore, we are able to classify a respondent as an early adopter or laggard across the domain levels.

Personality traits

The Big Five Factors of personality measure five dichotomous dimensions of an individual's personality: extraversion versus introversion, agreeableness versus antagonism, conscientiousness versus lack of direction, neuroticism versus emotional stability, and openness versus closed to new experiences. Each dimension is further divided into six personality facets (John and Srivastava 1999). Some of the Big Five personality traits have been found to be positively correlated with consumer stimulation and related openness to seek out and adopt new technologies (Steenkamp and Burgess 2002). Therefore, we expect that a respondent's personality traits will influence his or her innovativeness. For example, a respondent who is open to new experiences may be more likely to adopt a novel technology than a respondent who is closed to new experiences. We included questions in the survey that specifically measure each respondent's Big Five Factors of personality to determine what personality traits correspond with a high level of personal innovativeness.

Demographics

A consumer's innovativeness and likelihood to adopt new technologies can also be influenced by certain sociodemographic variables (Im, Bayus, and Mason 2003). We identified several personal demographics that we suspect most strongly influence a consumer's likelihood to adopt new technologies. Research shows that income, education, and age strongly predict innovative behavior (Dickerson and Gentry 1982; Labay and Kinnear 1981; Martinex, Polo, and Favian 1998; Midgley and Dowling 1993; Ostlund 1974; Summers 1971). We included those three demographic variables in the survey, as well as household composition, employment status, individual-level and household-level decision-making processes, and geographical location as demographic data of interest.

Expectations of Results

Based on the empirical literature, we developed a series of expectations for the results of the survey.

Expectation 1: The sample distribution of adoption times for each technology should mirror market-level diffusion. Given the tenets of Rogers' Theory of the Diffusion of Innovations, a large sample of consumers should show that the diffusion rate of technologies among random consumers should closely match the market-level rates of diffusion. We expect that 2.5 percent of survey respondents to be innovators, 13.5 percent to be early adopters, 34 percent to be early majority, an additional 34 percent to be late majority, and 16 percent to be laggards.

Expectation 2: Certain demographic characteristics will impact a respondent's willingness to adopt and time of adoption. Personal demographic variables will increase the likelihood of a respondent being an innovator or a laggard. For example, we expect that higher levels of education and income will make a consumer more likely to purchase new technologies sooner to when they are first released, thus making the consumer an innovator. We expect to see similarities and consistency across technologies for respondents with similar demographics (i.e. respondents with high incomes will consistently be innovators).

Expectation 3: Certain characteristics of the technologies themselves will impact a respondent's willingness to adopt and time of adoption. We expect that relatively low cost, easy-to-use technologies are more likely to be adopted more quickly by all consumers, thus giving those technologies a high rate of diffusion. We expect that consumers who are consistently innovators will be more likely to adopt early those technologies that are higher cost, more difficult to use, or not as useful as the other technologies.

Expectation 4: Some consumers will be more strongly persuaded by other people to adopt or not adopt than other consumers, which will affect the time of adoption of a new technology. For some technologies, we expect that peer opinion and input will make a consumer more likely to innovate, despite the consumer's personal characteristics or the features of the technologies. For example, a consumer may not normally purchase expensive entertainment technologies, but a peer's recommendation for a new HDTV may be convincing enough to make the consumer an innovator.

Methods

Survey design

The survey contained four main components: demographics, decision-making processes, self-assessed personality traits, and time of adoption. The demographics component was comprised of seven questions that required respondents to report their age, gender, education level, and employment status at the individual level. We also included questions to ascertain household income and household composition (i.e. single, married, with children, etc.). The data from this component of the survey allow us to confirm or refute Expectation 2. We expect that certain demographic characteristics will impact a consumer's level of innovativeness; therefore, by capturing demographic data in the survey, we are able to examine which demographic characteristics most strongly correspond with being an innovator or early adopter.

Then, the survey asked questions regarding decision-making at both the individual and household levels to explore how the decision-making at each level might be associated with the adoption of technologies. This component of the survey incorporated TPB and PBC to support or disprove Expectation 4. TPB and PBC suggest that consumers' motivations and intentions to behave can be predicted and influenced by norms and influence from others. So, this component allows us to determine how influential decision-making processes and exterior influence are when it comes to technology adoption. In the survey, respondents selected the statement that best describes their role when they make decisions. We asked respondents the same list of questions regarding decision-making processes, but respondents answered the questions with regard to decision-making processes at both the individual and the household levels.

➔ I am the sole decision maker

- ➔ I share decision making with others
- ➔ I give input, but someone else usually makes the final decision
- ➔ I am not usually involved in decision making

The third section of the survey included questions about personality traits. This section specifically incorporates the Big Five Factors of personality and helps us to also further explore Expectation 2, that is, which personality factors of the consumer influence innovativeness. We used the Big Five questionnaire designed by McCrae and Costa (1987). It is extensive and is mainly used to conduct studies that explore personality traits in-depth.

Since we are using these traits to complement our understanding of how individuals make decisions only about technology adoption in a larger survey, we needed a shorter instrument. Therefore, we used the Ten Item Personality Measure (TIPI). TIPI provides an instrument for effectively measuring the Big Five dimensions in a brief survey (Gosling, Rentfrow and Swan 2003). TIPI includes both a 5- and 10-item inventories for measuring personality traits across the Big Five dimensions. Although the shortened TIPI measure is slightly inferior to a full Big Five inventory, according to Gosling, Rentfrow and Swan TIPI has been shown to be reliable and valid for determining Big Five personality traits. TIPI is especially useful when personality determinations are not the primary research focus of a study, which is true for the current study. We incorporated the 10-item inventory into our survey in order to measure the Big Five personality trait dimensions in respondents. The results of the TIPI questions allow us to ascertain whether personality traits are related to the respondent's likelihood of adopting new technologies.

Finally, the fourth section of the survey included questions about whether the respondent have adopted a given technology. If respondents have adopted the given technology, the survey required them to input the year in which the technology was adopted. But, if the respondents have not adopted the technology, the survey asked a series of conditional questions regarding why they have not adopted. Respondents were required to report whether they have considered adopting the technology but ultimately decided not to adopt, or whether they have not considered adopting the technology at all. If respondents have considered but not adopted, they could indicate the reason they decided not to adopt. The reasons they could select were 1) price, 2) intention to use (respondent was not going to use the technology frequently), 3) someone made the respondent change his or her mind about adoption, or 4) learning to operate the technology would not be easy for the respondent.

This section of questions captured data about time of adoption which allows us to construct time of adoption curves for the sample for each technology. We will be able to confirm or reject Expectation 1 which states that the adoption curves for the sample should mirror market-level adoption curves for each technology that we included in the survey. Additionally, the questions in this section are grounded in TPB and PBC, which allows us to confirm or reject Expectation 3 and Expectation 4. Expectation 3 states that the characteristics of the technologies themselves impact a consumer's willingness to adopt and time of adoption. According to TPB and PBC, we can predict that a consumer will adopt a technology if he or she believes that he or she can operate the technology. The conditional questions confirm whether PBC does in fact strongly influence adoption. As mentioned above, Expectation 4 asserts that adoption can be influenced by others' opinions. The conditional questions in this component measure how strongly someone else's opinion affects the adoption of a new technology for the respondents in our survey.

Technologies and market diffusion

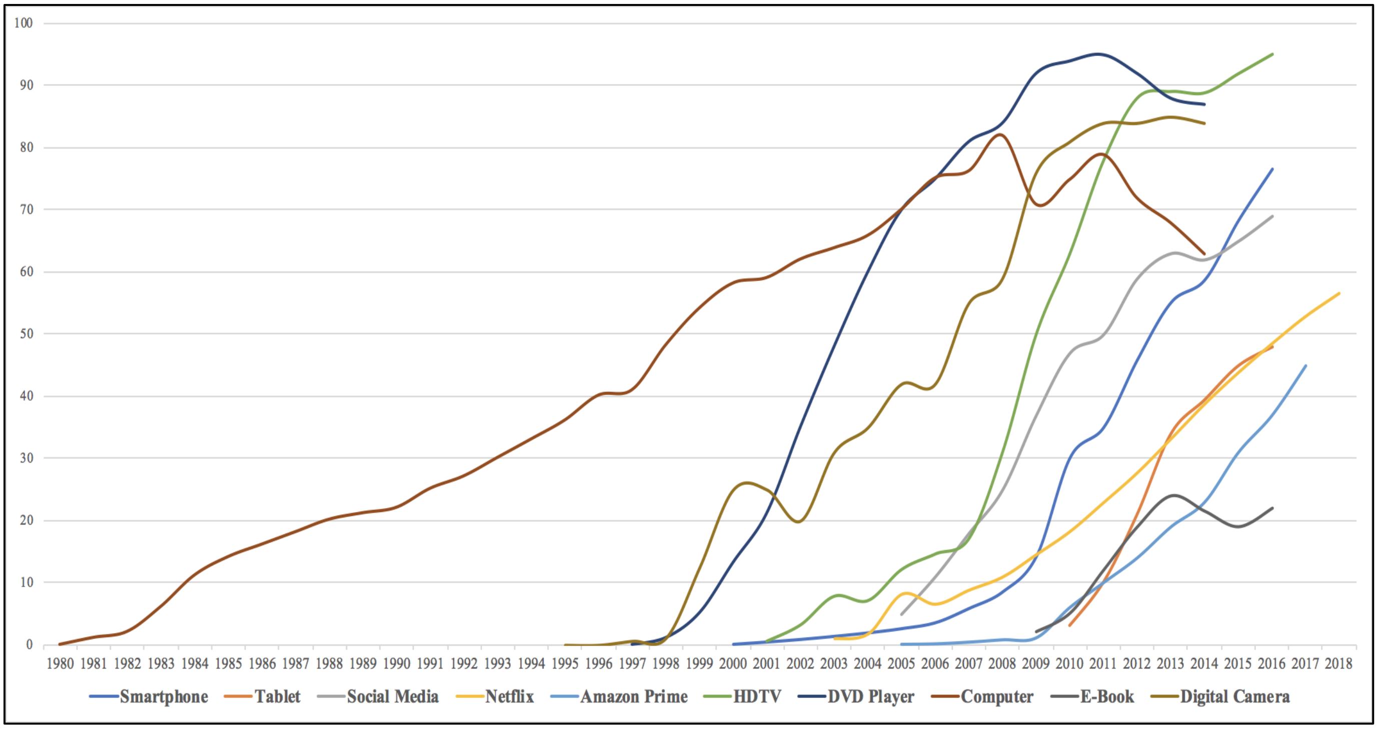
In order to include a technology in our survey and research, a market-level diffusion curve for the technology needed to exist and be publicly available. We conducted online searches for market-level diffusion curves. While many diffusions curves for various technologies are available online, we only included diffusion curves from what we determined to be reliable, valid sources. We determined that each technology must have at least late majority market penetration to be included in the research.

In addition, the technology must have been on the market long enough to be familiar to most consumers but not so old that it is irrelevant or unlikely to be considered an innovative technology. For example, a personal radio has nearly complete penetration into the U.S. consumer market; however, it is an old innovation, and new music-playing technologies, such as iPods and MP3 players, are more relevant to contemporary consumers.

After we found valid, reliable diffusion curves, we used a plot digitizer to obtain the exact year threshold for each stage of diffusion for each technology. The year of each stage of diffusion allows us to ascertain a consumer's innovativeness for each technology according to the market-level date (Figure 2 and Table 1).

As much as possible according to available data, we attempted to include a diversity of technologies according to cost. By including both high and low-cost technologies, we endeavored to capture a consumer's true innovativeness and likelihood to adopt a new technology rather than his or her ability to simply afford new technologies. Technologies that are too expensive may only be adopted by consumers who are wealthier than average consumers. To capture the widest information about technology adoption across a highly diverse sample of consumers, we needed to ensure that the technologies in the study were diverse in price of purchase and of operation.

Figure 2: The market-level of diffusion for ten technologies included in the survey.



Source: *Each curve was obtained from a different source. Please see References for citation, marked with a number.*

Table 1: Stages of technology adoption by year

Technologies	Innovators (< 2.5%)	Early Adopters (2.5 – 15.9%)	Early Majority (16 – 49.9%)	Late Majority (50 – 83.9%)	Laggards (84 – 100%)
Smartphone[1]	2000 – 2004	2005 – 2009	2010 – 2012	2013 – 2016	-
Tablet[2]	2002 – 2010	2011 – 2012	2013 – 2015	2016	-
Social Media[3]	1997 – 2004	2005 – 2006	2007 – 2010	2011 – 2016	-
Netflix[4]	1997 – 2004	2005 – 2009	2010 – 2016	2017 – 2018	-
Amazon Prime[5]	2005 – 2009	2010 – 2012	2013 – 2017	-	-
HDTV[6]	1998 – 2002	2003 – 2006	2007 – 2009	2010 – 2011	-
DVD Player[7]	1997 – 1998	1999 – 2000	2001 – 2003	2004 – 2008	2009 – 2012
Computer[8]	1980 – 1982	1983 – 1985	1986 – 1998	1999 – 2008	2009 – 2014
E-Book[9]	1998 – 2009	2010 – 2011	2012 – 2016	-	-
Digital Camera[10]	1995 – 1998	1999	2000 – 2006	2007 – 2010	2011 – 2014

Source: *Each date was obtained from a different source. Please see References for citation, marked with a number.*

Domains and classification of technologies into domains

We categorized the ten technologies into three different domains: Communications, Productivity, and Entertainment. Analysis of innovativeness at the domain level has been found to provide more reliable predictions of consumer innovativeness than analysis at the level of individual technologies (Park and Jun 2003). Investigating innovativeness at the level of an individual technology provides only one opportunity for a consumer to be innovative and ignores the wider scope of individual innovativeness. In other words, although a consumer has not adopted an HDTV, he or she may have adopted a variety of other technologies within the Entertainment domain. We miss an opportunity to understand a higher level of consumer innovativeness when the focus is on one technology rather than on a domain of related technologies.

Therefore, organized the ten individual technologies into three different domains to determine at what levels (i.e. individual technology or domain) innovativeness trends exist among survey respondents. We selected the three domains based on the chosen ten technologies for which we identified reliable market penetration curves. The three domains have shown reliability and consistency for analysis in previous research (Agarwal and Prasad 1998; Agarwal and Karahanna 2000; Grewal and Kardes 2000; Clark and Goldsmith 2006; Singh 2006; Venkatraman and Price 1990; Park 20003).

The inclusion of three different domains allows us to determine whether consumers are consistent in innovative behavior both within and across domains. We seek to understand whether innovation happens only among technologies that are similar and within the same domain (i.e. Communications) or if being an innovator in one domain increases the likelihood that a consumer will be an innovator in another domain. That is, if a consumer is innovative within the Communications domain, is he or she also an innovator in the Productivity or Entertainment domains. Cross-domain innovativeness helps us to ascertain whether innovativeness is connected to technologies or product or if innovativeness is an inherent personal characteristic that is predictably distributed among consumers.

Summary of Data

We published the survey on Amazon Mechanical Turk (MTurk) on April 11, 2018. MTurk is an online crowdsourcing platform that allows researchers to post online surveys to be completed remotely by Workers around the country. Researchers are able to prepay for a specific amount of results, or Human Intelligence Tasks (HITs). We purchased 1,000 HITs for the survey. By April 12, 2018, 1,000 HITs had been completed, and the survey was taken offline. We paid MTurk workers one dollar for a completed survey. We reviewed all HITs for completeness and validity. We rejected 96 HITs due to incompleteness or invalidity of responses.

Our goal was to obtain a sample size of one thousand respondents or HITs (n=1,000). To obtain an accurate measurement of innovativeness for consumers around the United States, we obtained a sample that was representative of five regions of the U.S.: Southwest (135 respondents), Southeast (197 respondents), Midwest (200 respondents), West (167 respondents), and Northeast (199 respondents). Respondents who live outside of the U.S. were prohibited from completing the survey. We determined that in order to obtain a power analysis of 0.9, we needed at least 132 respondents per geographic region of the U.S. In some regions we collected up to 200 responses in anticipation of responses that could not be used in the analysis (e.g. incompleteness, illegitimate or inaccurate responses, etc.).

All the incomplete survey responses were excluded of the analysis, which resulted in the removal of 102 observations from the final dataset. In total, the sample size of this study was 898 respondents.

Analysis of Results

Demographics analysis

We collected information from survey respondents about a variety of personal demographics, including age, gender, income, education level, and employment. The average age of respondents was 35.3 years old. The youngest respondent was 18 years old, and the oldest respondent was 74 years old. Regarding household composition, on average, there were 2.1 adults and 0.68 children in respondents' households. Four hundred and eighty respondents identified as male, 413 identified as female, and 5 identified as "Other." These data closely mirror national data. The median age of U.S. citizens is 37.9 years, the average household is 2.64 people, and 51 percent of the U.S. population is female (U.S. Bureau of the Census 2017).

The majority of respondents (63 percent) were employed full-time. Eleven percent of respondents were employed part-time, and 5 percent were students. Only 4 percent of respondents were unemployed, 2 percent were retired, and 10 percent were self-employed.

Overall, respondents were highly educated. Fifty-five percent of respondents had a bachelor's degree, and about one quarter (24 percent) had some college but no degree. Eleven percent of respondents had a master's degree, and 3 percent had a doctor's degree. Seven percent of respondents were a high school graduate or GED equivalent. Less than 1 percent of respondents had not completed high school. The respondents in the survey were more highly educated than the U.S. populace. For example, only 44 percent of people in the U.S. have completed a bachelor's degree or higher (Ryan and Bauman 2016).

Respondents were fairly evenly distributed across income levels. A quarter of respondents reported an annual income of $50,000 to $74,999. Fifteen percent of respondents reported annual incomes of less than $25,000 and of $25,000 to $34,999. Sixteen percent earned an annual income of $35,000 to $49,999. Twelve percent of respondents reported an annual income of $75,000 to $99,999, and 11 percent reported an income of $100,000 to $149,999. Only 5 percent of respondents reported an annual income of over $150,000 (Table 2). Given that the current median household income in the U.S. is $59,039, the income distribution of respondents in our sample seem to represent households in the U.S. in terms of income (U.S. Bureau of the Census 2018).

Table 2: Tabular distribution of respondents according to various demographic variables.

	Southwest	Southeast	Midwest	West	Northeast	Total
Gender						
Male	73	97	105	93	112	**480**
Female	62	98	93	73	87	**413**
Other	0	2	2	1	0	**5**
Employment Status						
Employed full time	78	132	120	99	139	**568**
Employed part-time	14	22	28	17	17	**98**
Student	8	6	16	6	10	**46**
Unemployed	10	5	7	16	7	**45**
Retired	3	7	2	6	4	**22**
Self-employed	18	20	21	16	13	**88**
Homemaker	4	5	6	7	9	**31**
Education						
< High School	0	0	1	0	2	**3**
High School Graduate	6	19	16	10	12	**63**
Some College	71	74	72	53	50	**320**
Bachelor's Degree	49	68	84	89	101	**391**
Master's Degree	9	25	22	12	27	**95**
Doctorate Degree	0	11	5	3	7	**26**
Income						
<$25,000	26	34	29	26	20	**135**
$25,000 to $34,999	25	31	35	24	21	**136**
$35,000 to $49,999	21	26	33	30	32	**142**
$50,000 to $74,999	38	49	46	45	53	**231**
$75,000 to $99,999	16	23	29	17	25	**110**
$100,000 to $149,999	6	20	21	17	34	**98**
$150,000 or above	3	14	7	8	14	**46**

Source: Authors calculation based on survey responses.

Decision-making at the household and individual levels

We asked our respondents about their decision-making behavior at the individual and household levels with regard to technology adoption. At the household level, only 41 percent of respondents reported that they are the sole decision-makers in their households, while over half of respondents (53 percent) reported that they share decision-making responsibilities with other members of the household. At the individual level, more than three-fourths (76 percent) of respondents claim that they are the sole decision-makers. On the other hand, almost a quarter of respondents (23 percent) stated they share their decision-making responsibilities with others. Few respondents reported that someone else completely makes decisions about adoption of new technologies for them at both the household and individual levels (Table 3).

Table 3: Tabular distribution of respondents' decision-making practices

	Female	Male	Other	Total	Percentage
Decision-making for the household					
I am the sole decision-maker	210	159	3	372	41%
I share decision-making with others	240	233	2	475	53%
Someone else makes the decisions	30	21	0	51	6%
Decision-making for myself					
I am the sole decision-maker	366	317	3	686	76%
I share decision-making with others	109	92	2	203	23%
Someone else makes the decisions	5	4	0	9	1%

Source: Authors' calculation based on survey responses.

Personality traits

Using the TIPI 10-item inventory instrument, we determined each respondent's reported level of extraversion, agreeableness, conscientiousness, emotional stability, and openness to experience. Each personality trait is measured on a scale of 1 to 10 with 5 being an intermediate level for each specific personality trait. If the average score for a respondent is above 5, we can conclude that the respondent is highly characterized by that specific personality. If the score is below 5, the person is not characterized by that particular personality trait. For example, if a respondent is measured at a level of 7 for openness to experience, the score strongly suggests that the respondent identifies with this personality trait and is constantly open to new experiences.

Previous studies have found that extraversion, agreeableness, and openness to experience are positively correlated with consumer stimulation and related openness to seek out and adopt new technologies (Steenkamp and Burgess 2002). Table 3 summarizes the average scores for each personality trait of the 898 respondents.

Table 4: Tabular distribution of respondents' Big Five personality traits

	Extraversion	Agreeableness	Conscientiousness	Emotional Stability	Openness to Experience
Female	3.7	5.6	5.6	4.6	5.2
Male	3.6	5.0	5.4	5.0	5.0
Other	4.8	4.9	6.0	4.8	5.1
Total	3.6	5.3	5.5	4.8	5.1

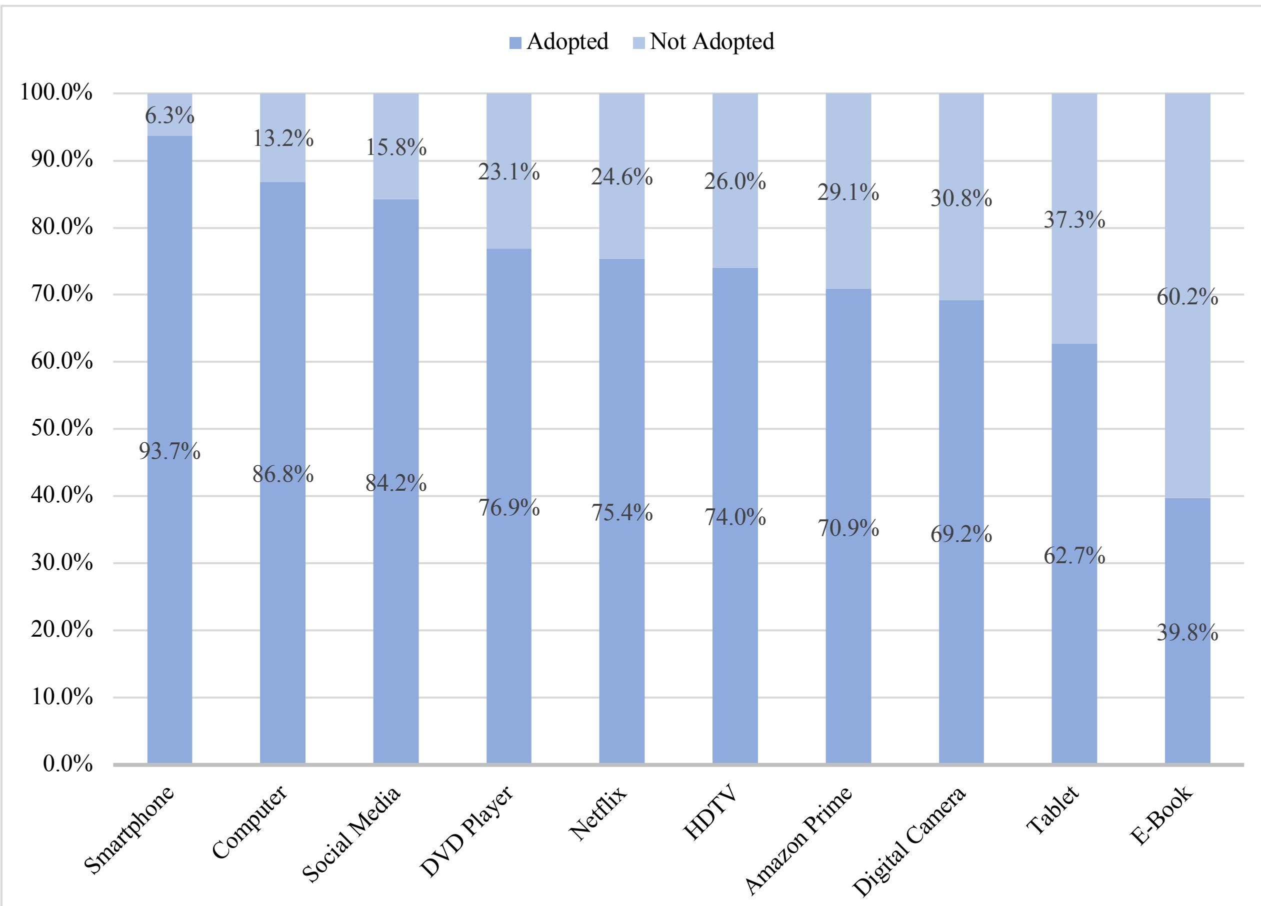
Source: Authors' calculation based on survey responses.

Table 4 shows the reported average levels of the Big Five personality traits of our sample. We observe that reported averages of personality traits like agreeableness, conscientiousness, and openness to experience are slightly over 5. In other words, on average our respondents have an *intermediate level* of agreeableness, conscientiousness, and openness to experience which, based on findings of previous research, might lead us to expect a low number of innovators or early adopters among our respondents. Instead, we might find more adopters of technology at the majority level stages. It is worth to mention that on average our sample has a level of 3.6 for extraversion. Extraversion is another personality trait that has been identified as characteristic of innovators consumers.

Adoption behavior: mirroring market-level diffusion

With the aim of determining the adoption rate of the ten technologies among our respondents, we asked them to report whether or not they had adopted the technologies. We found that three quarters of respondents have adopted smartphone, computer, social media, DVD player, Netflix, and HDTV (Figure 3). At least, 673 respondents have bought these products.

Figure 3: Distribution of adopted and non-adopted technologies among respondents



Source: Authors' calculation based on survey responses.

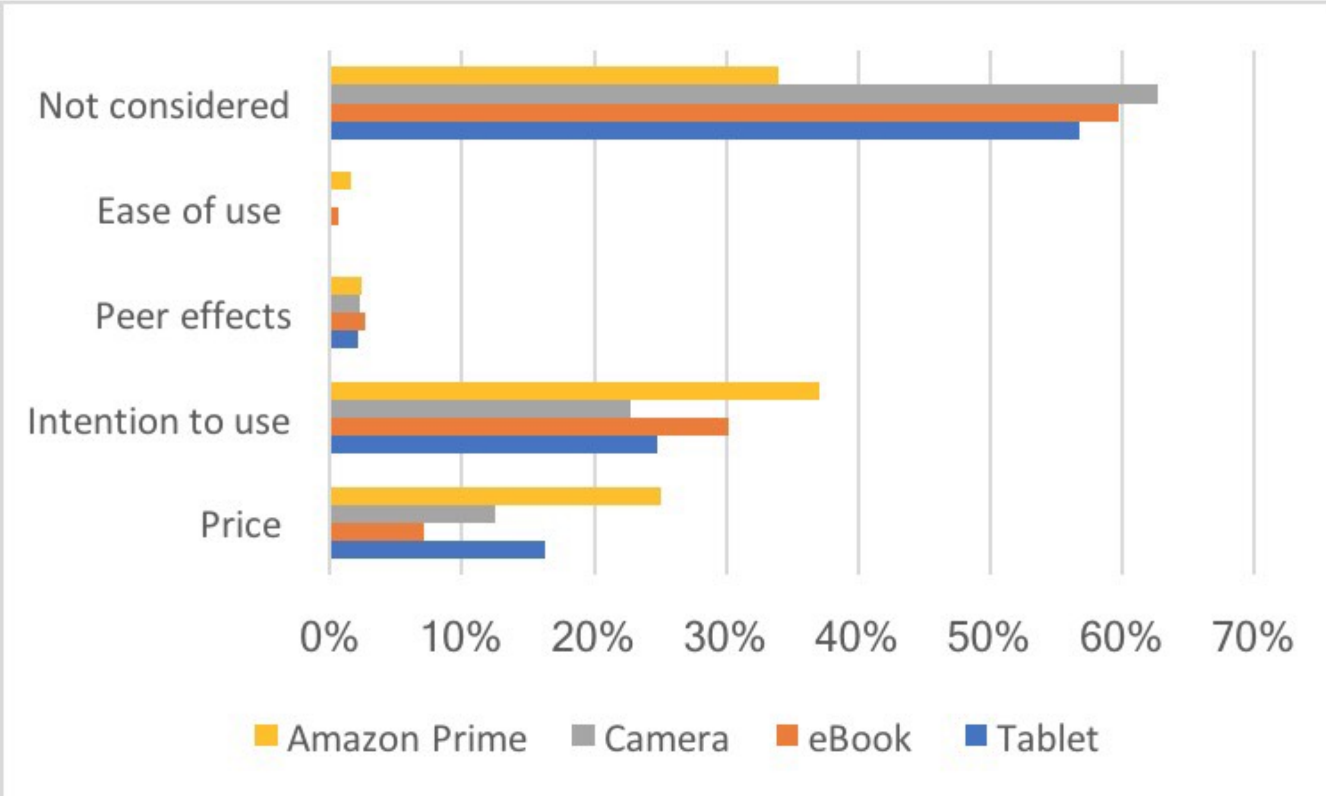
Amazon Prime, digital camera, tablet, and e-book had a lower adoption rate and disperse distribution in our sample. Some 261 respondents reported that they have not adopted Amazon Prime, while 538 respondents said that they have not adopted e-book technology.

Non-adoption behavior

For the purpose of this research it is also important to identify the rationale behind non-adoption decisions. Therefore, we included some questions that explore the reasons why non-adopters decide not to adopt specific technologies. We framed the questions based on the tenets of TPB theory, that is, intention to use, attitude (price, usefulness) and PBC. We expected that respondents would not adopt new technologies if the intention to use the technology is low, if the price is too high, or if the consumer believes the product is not useful or he or she would be unable to operate it.

In the first place, we aimed to identify whether a non-adopter had at least considered buying the technologies. We found that for some technologies, like camera, e-book, and tablet, 60 percent of the non-adopters had not even considered adopting. In the case of Amazon Prime, about 35 percent of the non-adopters indicated that they did not consider to adoption it, and approximately another 40 percent did have not a real intention to use the technology (Figure 4).

Figure 4: Reasons for non-adoption of selected technologies

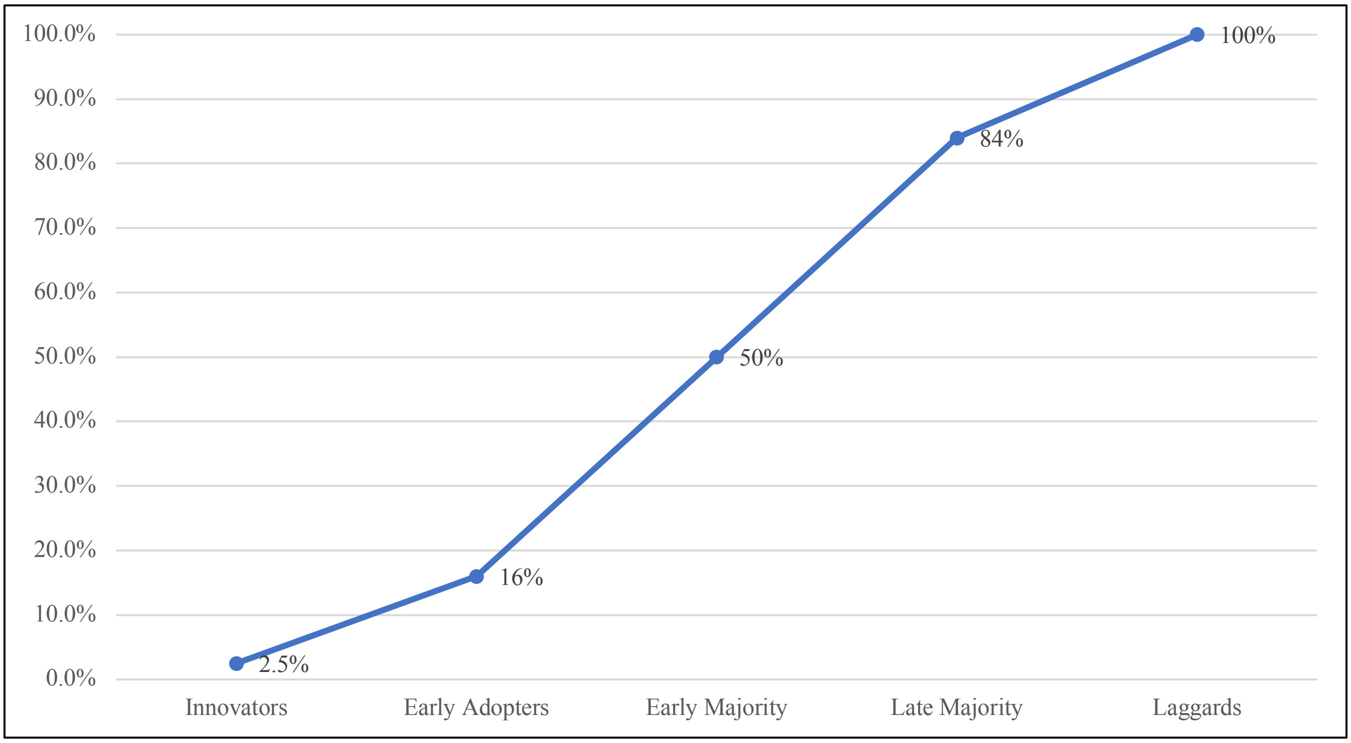


Source: Authors' calculation based on survey responses.

Adoption curves among respondents

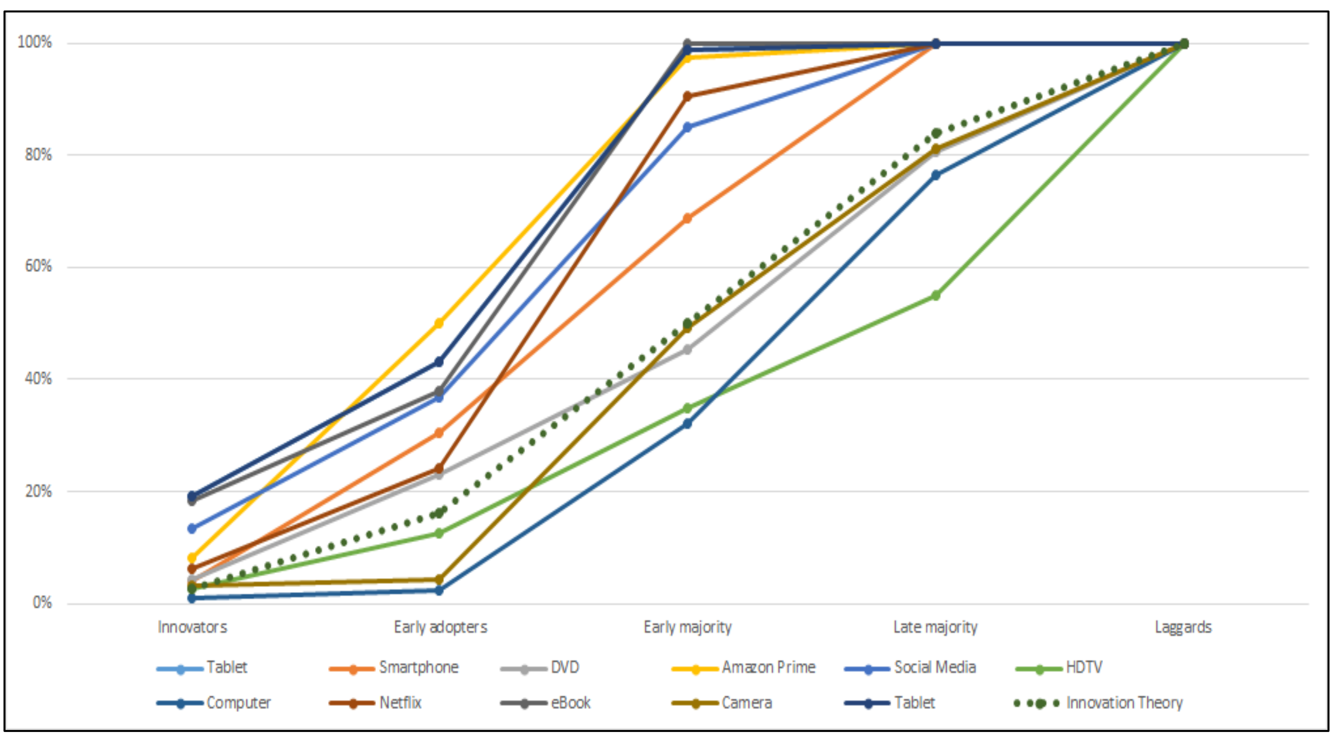
The survey required adopters of technologies to enter the years in which they purchased the technologies. Once we captured this information, we processed it in a way that allows us to identify if those curves matched with the diffusion of innovation theorized by Rogers. Figure 5 shows the S-curve that Rogers identified as being the market-level penetration rate of new technologies. In comparison, Figure 6 shows the adoption curves among our respondents. We find that all the adoption curves follow the S-distribution posited by Rogers. The only exception is for HDTV. We suspect this is because sales of HDTVs may have decreased after other technologies with similar characteristics were released on the market (i.e. smart televisions).

Figure 5: Rogers's' S-curve of market-level diffusion



Source: Rogers (1995).

Figure 6: Consumers' S-curves for adoption of ten technologies

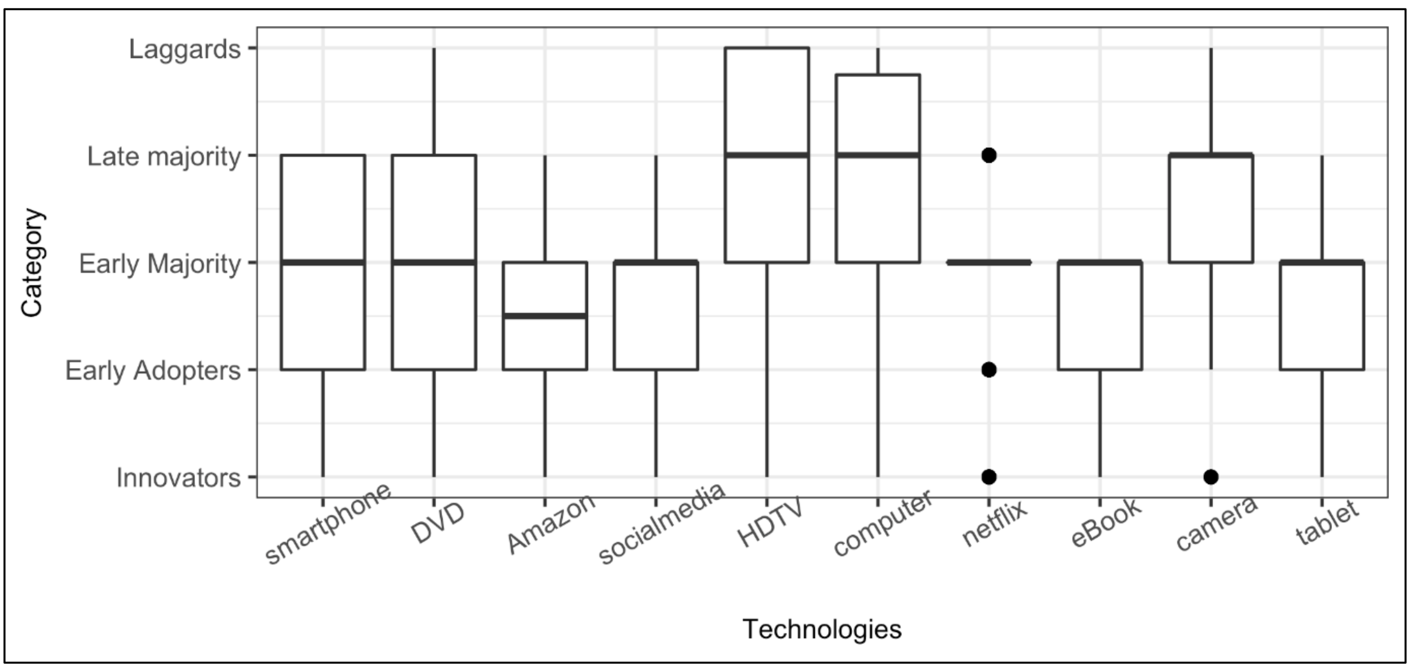


Source: Authors' calculation based on survey responses.

Consistency of adoption behavior across technologies

Figure 7 shows the median of adoption phase for each of the technologies included in this study. Most of the median values correspond to late majority and later phases of Rogers' diffusion theory. Thus, we conclude from the graph that the distribution of the adoption phases is spread across technologies like smartphone, DVD player, HDTV, and computer. While other technologies, like Amazon, social media, e-book, digital camera, and tablet, are concentrated. However, to take a deeper look at the data, we analyzed the mode values for smartphone, Amazon Prime, social media, Netflix, and digital camera, which are in the early majority phase. The results indicates that most of our respondents adopted these technologies at the same time that majority of the consumer in the U.S. did it. In other words, the rate of adoption of the technologies among respondents in our survey supports Rogers' diffusion of innovation theory.

Figure 7: Consistency of adoption across technologies



Source: Authors' calculation based on survey responses.

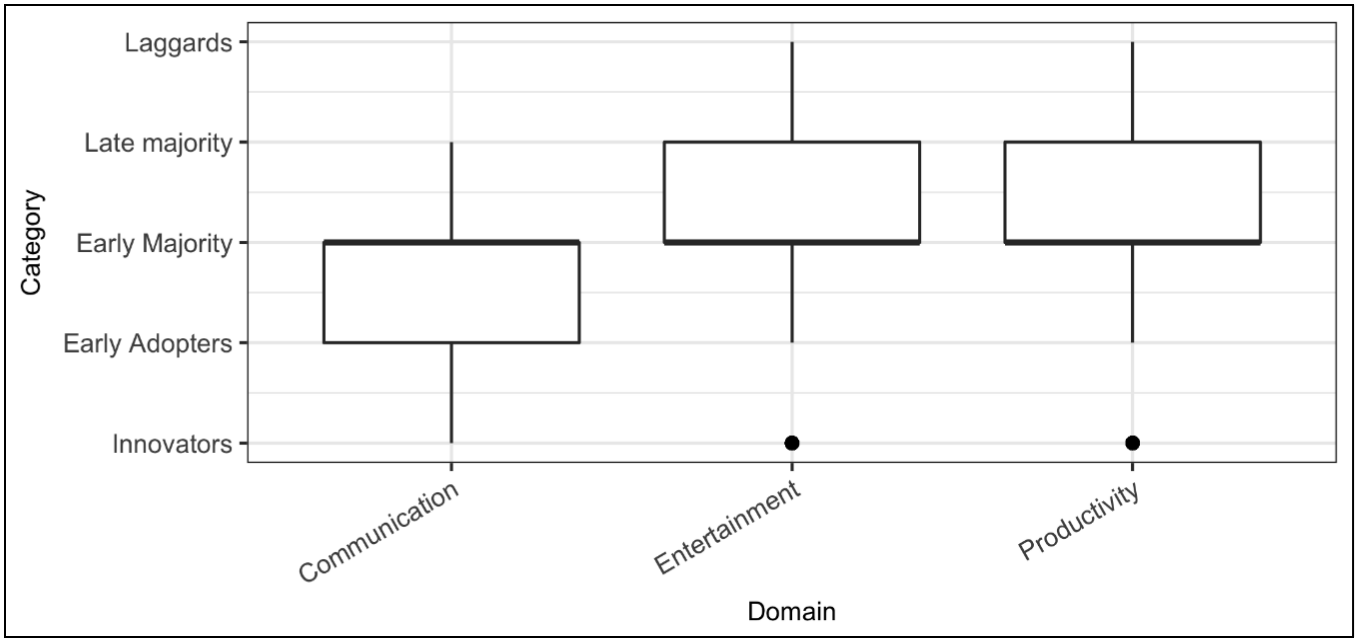
We did not find that any consumer is consistent in their adoption patterns at any stage of diffusion: innovator, early adopter, early majority, late majority, or laggards. In other words, the time of adoption of new technologies among respondents is inconsistent regardless of the relative age of the technology. Hence, these results allow us to conclude that respondents in our sample are not consistent in their adoption of new technologies.

Consistency of adoption behavior across domains

Given this finding, we next explored whether respondents showed consistency in adoption behavior across domains. Again, our findings indicate that consumers are not consistent in their adoption decisions, even at the domain level.

Figure 8 shows the median values of adoption phase for each domain. We find there is a tendency among our respondents to adopt products in the communication, entertainment, and productivity domains at the early majority phase. But, overall, there is no consistency of adoption behavior across domains. Instead, our findings suggest that non-adopters increase significantly in the productivity domain. We found that 240 respondents have not adopted any of the products in the productivity domain.

Figure 8: Consistency of adoption across domains

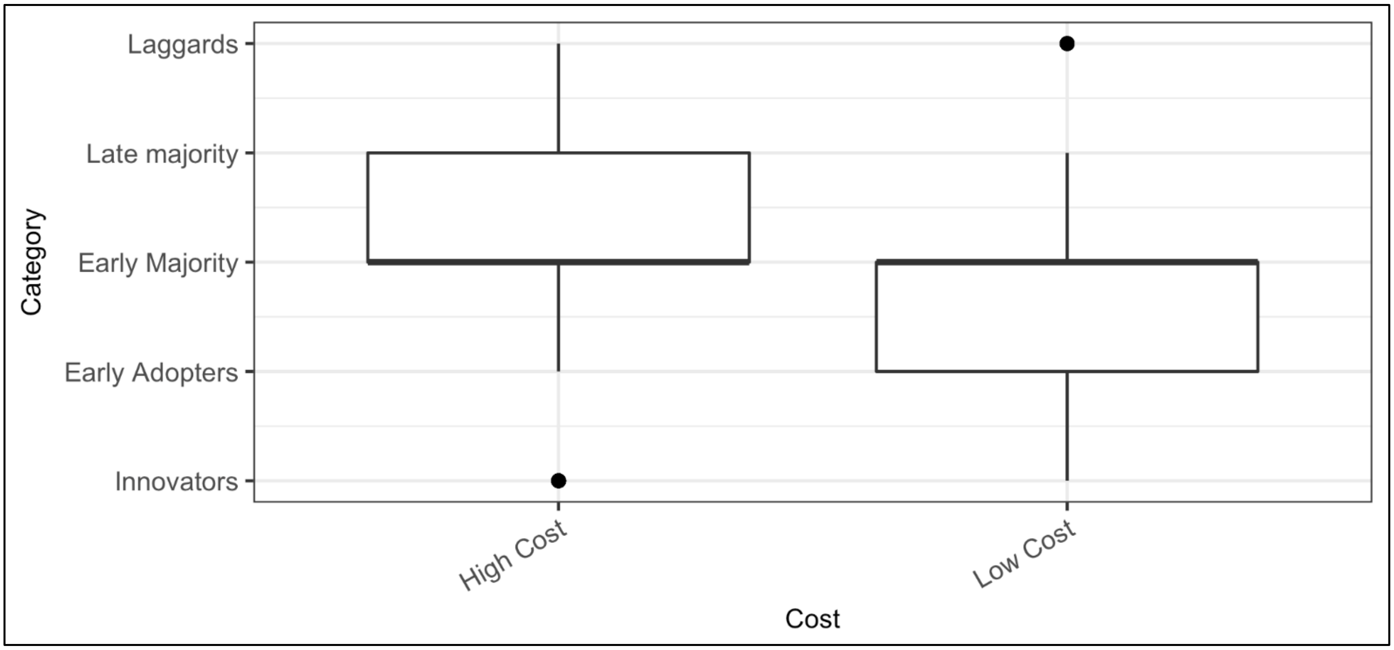


Source: Authors' calculation based on survey responses.

Consistency of adoption behavior across costs

At the cost level, we found that there is only one respondent who was consistent in adopting all high-cost technologies at the early majority phase. Nine respondents did not adopt any of the high-cost technologies, and eighteen respondents did not adopt any of the low-cost technologies. We also found three respondents were consistent in their adoption of low-cost technologies once the technologies had reached an early majority phase at the market-level. However, none of these findings are robust enough to further explore what individual characteristic might be associated with their consumption decisions. We can, however, infer based on Figure 9 that the high-cost technologies were adopted with more frequency once those technologies reached the early majority phase. Low-cost technologies seem to be adopted more consistently at the early adopters and early majority levels.

Figure 9: Consistency of adoption across costs



Source: Authors' calculation based on survey responses.

Discussion

We approached this project with three objectives and four expectations of results based on existing research regarding consumer adoption of new technologies. The three objectives were to 1) use primary data from the survey to create time of adoption distributions for all respondents across a ten technologies and three domains, 2) determine whether consumers, especially innovators, are consistent in their adoption patterns, and 3) identify what personality and demographic characteristics are common among innovators and early adopters.

The four expectations of results were: 1) the sample distribution of adoption times for each technology should mirror market-level diffusion; 2): certain demographic characteristics will impact a respondent's willingness to adopt and time of adoption; 3) certain characteristics of the technologies themselves will impact a respondent's willingness to adopt and time of adoption; and 4) some consumers will be more strongly persuaded by other people to adopt or not adopt than other consumers, which will affect the time of adoption of a new technology.

We met objective 1 and found support for expectation 1. In the survey, we asked respondents whether they have adopted each technology, and if so, the year at which they adopted. Using this data, we constructed diffusion curves for the respondents in our survey. We found that the times of adopt for each technology for respondents in the survey match the market-level diffusion timeline, as theorized by Rogers.

We also met objectives 2 and 3; however, the data show inconclusive results that cause us to refute or rethink our expectations. We found that, overall, the respondents in our survey were not consistent in their adoption patterns. Some respondents were innovators for certain technologies but not for all ten technologies or all technologies within a single domain. We also did not find consistency in innovator or early adopter adoption patterns across domains.

Additionally, we cannot definitely conclude that a respondent's personality traits or demographic characteristics strongly influence his or her adoption habits (expectation 3). The data show that respondents in our sample exhibited only a moderate level of the personality types that are correlated with a heightened willingness to be an innovator (i.e. extraversion, agreeableness, and openness to new experiences). A different sample with respondents who more strongly exhibited these characteristics may show more consistency in personal innovativeness across technologies and domains.

Finally, we did not find evidence to support expectations 3 and 4. Our data do not show that the characteristics of the technologies themselves impacted a respondent's willingness to adopt. Most of the respondents in the sample did not consider adopting the technology, if they had not already adopted. Respondents reported that their intention to use the technology rather than the characteristics of the technology itself (i.e. cost) was the main reason for non-adoption. Also, we did not find that respondents in the survey were strongly persuaded by others to adopt or not adopt.

Conclusions

Ultimately, our research findings support the theory that the diffusion of technologies occurs in incremental phases. For the ten technologies that we included in our study, the time of adoption for each technology by respondents closely mirrors the market-level diffusion rate. However, we are not able to conclude that respondents in our survey are consistent in their adoption habits at either the technology or the domain level. We also cannot conclude that a person's personality traits, demographics, or susceptibility to others' opinions influence individual adoption habits. The characteristics of the technologies themselves also appear to have minimal to no influence on adoption. In sum, the results from our representative sample to do lend support to the postulate that innovativeness is a static, inherent personal characteristic that show consistency across technologies and domains. Personal innovativeness among our respondents appears to be dependent on the product or technology.

Limitations & Recommendations for Further Research

As with any research study, several limitations impact the data, the analysis of the data, and the results and conclusions. We recognize that we may have introduced bias in our sample by using Amazon MTurk to collect data. While we aimed to obtain a balanced representation from respondents in all five regions of the U.S., the MTurk workers who completed the survey may not accurately represent the U.S. consumer market. For instance, given that an MTurk worker must have access to a computer and the internet, the worker may be more technologically advanced than the average consumer. We obtained a larger sample than we needed to attempt to overcome issues of bias, but bias still may be present in our sample.

Give the time limitations of the project, we were unable to complete a full statistical analysis of the data. We were able to analyze descriptive statistics, but we did not complete an inferential statistical analysis. Ideally, we would have completed regression or similar analyses to determine the strength of relationships and causality among variables.

The technologies that we included in the survey were limited due to the availability of market-level diffusion data. Without a market-level diffusion curve for a technology, we could not include the technology in the survey. This excluded several technologies that could have been more relevant to the contemporary consumer or technologies that demonstrated better consistency in adoption among consumers.

The results from our project offer exciting next steps and possibilities for future research. Specifically, future research could more specifically explore the connection between personality traits and adoption. Existing research has found that certain characteristics, like extraversion, agreeableness, and openness to new experiences, are strongly related to innovators and early adopters; however, additional research is needed to understand the personality traits of early majority, late majority, and laggard adopters.

We measured ‘consistency’ as the measured number of consumers who were in the same adoption category across all innovations. This measure is crude and future research could identify alternative ways of defining consistency.

Furthermore, future research could further explore the possible relationship between the characteristics of the technology and adoption. Our study primarily focused on the connection between cost (high cost and low cost) and adoption. Future research could investigate adoption patterns for technologies that show a wider diversity of characteristics. For example, a study could focus on technologies that have varying degrees of visibility, usefulness, time-saving or productivity components, or ease of use. We believe that further research can provide great insight into consumer innovativeness and deepen our understanding of the factors that influence consistent innovation.

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