Fashionable Technology, Fashion Waves, and Post-Adoption Regret and Satisfaction

Completed Research Paper

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Abstract

This research attempts to understand user adoption of fashionable technologies (e.g., iPhone or iPad) and the influence of fashion waves on adopters of both fashionable and non-fashionable technologies. A research model was developed based on the regret theory. We tested the model by examining 20,122 customer reviews collected from Amazon.com. A theory-driven naïve Bayes classifier was developed to analyze the regret elements of customer reviews automatically. The data largely supported the research model. Specifically, we found that adopters of non-fashionable phones experience higher levels of regret and lower satisfaction during the fashion wave, i.e., when a new fashionable phone was released. In contrast, adopters of earlier editions of fashionable phones welcomed the new fashionable phone, displaying lower levels of regret and higher satisfaction during the fashion wave period. The findings have significant implications for information systems research and practices.

Keywords: Fashionable technology, fashion wave, post-adoption regret, text-mining, naïve Bayes classifier

Introduction

> *"Once again, the iPhone goes on sale with hundreds lining up in front of Apple stores to get it the day it comes out. What motivates people to do so? Don't dismiss being fashionable as a crucial selling point."*
>
> *(Source: CNET.com [1])*

Fashions are prominent in the advances of information technologies. An IT fashion is "a transitory collective belief that an information technology is new, efficient, and at the forefront of practice" (Wang 2010, p.64). We have seen fashionable technologies gain a lot of media attention such as iPod, iPhone, Samsung Galaxy, Angry Bird©, and iPad. People adopt such fashionable technologies *en masse*.

This research is focused on two major characteristics of fashionable technology: popularity and waves. First, a fashion is characterized by popularity (Sproles et al. 1994; Watchravesringkan et al. 2010). According to the *Merriam-Webster Dictionary*, fashion is "a prevailing custom, usage, or style" or "social standing or prominence especially as signalized by dress or conduct."[2] Similarly, a fashionable technology can be viewed as a prevailing and prominent technology. Second, fashionable technology is often characterized by waves. Fashions evolve quickly and by definition are temporary (Sproles 1981). Therefore, companies are motivated to release new and improved editions of a fashionable technology to sustain the fashion. For example, Apple has released five major editions of iPhone in the past seven years. Such waves can influence adopters of earlier editions of iPhone as well as those of non-fashionable phones (e.g., Nokia and HTC phones). This research attempts to address two research questions:

- **Is it wise to adopt a fashionable technology in terms of avoiding post-adoption regret and increasing satisfaction?**
- **How does a fashion wave (the release of a new edition of a fashionable technology) influence adopters of earlier editions of this technology and adopters of non-fashionable alternative technologies?**

It is important to tackle these two research questions because they are relevant to IS practices. First, little if any IS research has studied adoption of fashionable technologies at the individual level, despite its ubiquity and importance. Second, how fashion waves influence adopters of fashionable and non-fashionable technologies is of great value, but is not yet well understood. Waves characterize fashions. A deep understanding of fashion waves can help practitioners better prepare the strategy to deal with fashion waves of own and competing technologies.

This research approaches the research questions from a regret theory perspective (Bell 1982; Inman et al. 1997; Loomes et al. 1982; Zeelenberg et al. 2000; Zeelenberg et al. 1998). The regret theory concerns about how a person reflects upon his or her *own* choice in relation to the *forgone* options. We developed a research model based on the regret theory. The model depicts how adopting a fashionable technology may be related to post-adoption regret and satisfaction, contingent upon the influence of fashion waves. A new fashion wave (e.g., the release of a new edition of iPhone) serves as an opportunity for adopters of both fashionable and non-fashionable technologies to observe forgone technologies, reflect on their adoption decisions, and adjust the level of regret and valence of the satisfaction associated with their choice. In addition, we also refer to the herd behavior literature to explain the adoption of fashionable technology. Herd behavior refers to the phenomenon that "everyone does what everyone else is doing, even when their private information suggests doing something quite different" (Banerjee 1992 p.798). Therefore, the herd behavior literature helps explain user adoption of fashionable technology because fashions are often characterized by great popularity (Sun 2013; Wang 2010).

We tested the research model in the smartphone market. In the past decade, iPhone and Samsung Galaxy phones have created multiple fashion waves, signaled by the release of new editions of each phone. We collected 20,122 customer reviews on fashionable and non-fashionable smartphones from Amazon.com. We developed a theory-driven naïve Bayes classifier to analyze these reviews. The findings largely support

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[1] Danny Suillivan, "Life in the iPhone 5 line: Fashion as a must-have 'feature'," CNET.com, September 21, 2012. http://www.cnet.com/news/life-in-the-iphone-5-line-fashion-as-a-must-have-feature/

[2] Merriam-Webster Online Dictionary. http://www.merriam-webster.com/dictionary/fashion

our model. Specifically, we found that adopters of non-fashionable phones had higher levels of regret and lower satisfaction during the fashion wave (i.e., when a new fashionable phone was released) than adopters of fashionable phones. In contrast, adopters of earlier editions of fashionable phones welcomed the new fashion wave, displaying lower levels of regret and higher satisfaction during the fashion wave period.

This research contributes to IS research in several ways. First, this research investigates fashionable technology at the individual level, an under-studied topic of apparent importance. Second, we systematically conceptualize user regret in the technology adoption context. Post-adoption regret is a relatively new concept in IS research and is different from existing concepts such as disconfirmation and satisfaction. Third, methodologically, this research demonstrates the benefits of developing theory-driven text-mining algorithms to do research on adoption and diffusion of technology. IS Researchers have called for methodological breakthroughs when studying user adoption and diffusion of technology. For example, the theme of the 2013 Pre-ICIS DIGIT Workshop sponsored by AIS SIGADIT is "Embracing Theoretical and Methodological Breakthroughs in IT Adoption and Diffusion Research." Currently, research in this area is largely survey-based. This research developed a theory-driven naïve Bayes classifier to analyze objective textual data. The algorithm allows one to automatically analyze a large amount of customer reviews. We believe using theory-driven machine learning methods can advance IS research.

Theoretical Background

Post-Adoption Regret

Regret has been generally defined as a negative emotion as a result of decision-making under uncertainty in the presence of alternatives. When deciding among alternatives, an individual must assess the potential enjoyment or utility to be derived from each option (Kahneman et al. 1979). After selecting a course of action, an individual may feel that the situation would be better had a forgone alternative been selected. Conversely, an individual is likely to experience rejoicing (Loomes et al. 1982), euphoria or self-congratulation (Bell 1982) to the degree they assess their choice as the better or best among alternatives. As shown in Appendix A, regret has been a subject of inquiry for many fields including economics (Bell 1982; Loomes et al. 1982), psychology (Zeelenberg et al. 2007), marketing (Inman et al. 1997; Taylor 1997), and consumer behavior (Keaveney et al. 2007). Some researchers have called for more attention to it in IS research (Shih et al. 2011).

Regret has two temporal types: experiential and anticipated. Experiential or post-decision regret refers to the regret one feels having experienced the negative consequences of a made-decision, whereas anticipated regret is the negative emotion associated with the expectation of future consequences of choosing or having chosen.

Regret is similar to, yet different from existing concepts in IS research such as disconfirmation and satisfaction (Zeelenberg et al. 2000; Zeelenberg et al. 1998). They are similar in that they both are the result of counterfactual thinking. Both are based on comparisons between the actual performance of a system and a reference point. However they differ in the reference point. For disconfirmation and satisfaction, the comparison is between expected and actual performance of a system, whereas for regret the comparison is between the performance of the chosen and forgone technologies (Bhattacherjee et al. 2004; Tsiros et al. 2000; Zeelenberg et al. 2000). In other words, the reference point for disconfirmation and satisfaction is "internal" (the expectation for the chosen technology); the reference point for regret is "external" (the performance of forgone alternative technology) (Tsiros et al. 2000). Indeed, regret has been considered an antecedent of satisfaction (Inman et al. 1997; Oliver 1997).

In this research, post-adoption user regret is defined as *a painful cognitive and emotional state of feeling sorry for choosing a technology in relation to a forgone technology*. It is an experiential regret developed based on the user's own experience. User regret is in relation to the forgone technologies. Regret grows from the degree to which a customer values the forgone over the selected (Bell 1982). Hence, regret is likely to exist when a person has alternative technologies to select. For example, a person may regret choosing a Nokia phone over an iPhone.

To explain why post-adoption regret is a relevant concept for adopting fashionable technology, we refer to the herd behavior literature. The rationale is that fashionable technology is often accompanied by herd behavior: people quickly converge on fashionable technologies through imitation.

By definition, herd behavior means two things: imitating others and discounting own information (Sun 2013). Herd behavior has been observed in a variety of situations such as in the downloading of software applications (Duan et al. 2009; Walden et al. 2007) and in adoption of technology (Sun 2013). It is believed that "everyone herds somewhat, and most people herd a lot" (Prechter 1999 p. 174). It has been believed that herd behavior can cause information cascade: people defer completely to the herd, no matter what their own information suggests (Anderson et al. 1997; Bikhchandani et al. 1992; Çelen et al. 2004; Duan et al. 2009). As soon as perceived information from others becomes slightly more informative than private information, individuals tend to defer to the actions of their predecessors and a cascade begins. This leads more people to join the herd.

Regret is a frequently mentioned consequence of herd behavior (Rao et al. 2001). Herd behavior may result in negative consequences at both the individual and group level, often referred to as "the fragility of herd." When herding, a person is less responsive to his/her own private information in favor of other people's action, believing that they are better informed. Such discounted own information often includes information about own needs and local contexts (Abrahamson 1991; Fiol et al. 2003). As a result, unrealistic, less information-based expectations are formed (Rao et al. 2001). When people use the technology in their own contexts, the early discounted information may be revived and cause regret (Sun 2013).

People sometimes intentionally choose an unpopular option. This is defined as contrarian behavior. People perform contrarian behavior when they doubt the predecessors' rationality and distrust their decisions, or when they try to achieve a desired image. For example, in order to differentiate them from other organizations, some organizations reject a popular innovation because too many other organizations have adopted it (Abrahamson et al. 1993). In the technology adoption context, contrarian behavior can be viewed as a person's behavior of adopting a non-fashionable technology in front of a herd on a fashionable technology. Contrarian behavior may also be accompanied by discounting own information. A person avoids a herd because he/she doubts the rationality of the herd and mistrusts their decisions even if his/her own information suggests that the fashionable technology is a good option.

In short, facing a herd of a popular fashionable technology (e.g., iPhone), a person can choose either to join the herd (e.g., choose the fashionable technology) or be against herd (e.g., choose a unpopular alternative technology). In either case, he/she may discount his own information about the technology to be adopted. This means, both herd behavior and contrarian behavior may lead to post-decision regret.

Research Model and Hypotheses

Based on the above discussion on herd/contrarian behavior and regret, we develop a research model of adopting a fashionable technology and regret (Figure 1). The research model depicts that adopting a fashionable technology may lead to the two types of post-adoption comparisons: internal (satisfaction) and external (regret), both of which are important consequences of herd behavior (Gardial et al. 1994; Rao et al. 2001; Tsiros et al. 2000). Based on the regret literature discussed above, we include Exposure to a New Fashion Wave as a moderator in the model. As mentioned above, a necessary condition for a person to experience regret is that he/she is aware of the performance of the forgone options. A new fashion wave is an opportunity for a person to be exposed to such an influence.

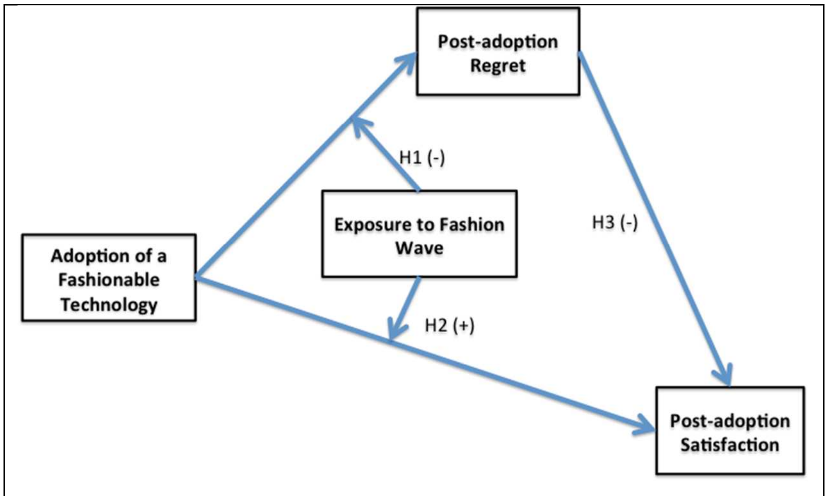

Figure 1. Research Model

Hypotheses

> ***Scenario:*** *"I wasn't even planning to buy it," said Elijah Tadj, 30, from Irvine, as we talked. But then he came out at 4 a.m. (and ended up around 25th in line) because after hearing so much about the iPhone 5, he decided he did want to upgrade. Why? The LTE speed gain? Some other feature? "It's just shinier," he said. (Source: CNET.com [1])*

The above scenario is not unfamiliar to many of us. As implied in this scenario, people hear a lot about fashionable technologies as they often attract a lot of media attention. As a result, a person may give up their own evaluations and imitate others' decision to adopt a fashionable technology rather blindly, sometimes without much investigation into its functionality.

We distinguish two types of adoption: adoption of a fashionable technology and adoption of a non-fashionable technology. The findings from herd/contrarian behavior render mixed suggestions regarding the consequences of adopting a fashionable technology. On the one hand, when adopting a fashionable technology, a person is inevitably influenced by the popularity of the fashionable technology and thus more or less engages in herd behavior. Fashions are often adopted through "mass conformity" (Sproles 1981, p.116). It is worth noting that herd behavior is a continuous factor: people can vary in their degree of herding (Sun 2013). That is, facing a herd, a person may not totally give up his/her own information, but only discount it to a certain degree. A consequence of this discounting own information is that one may ignore or under-estimate information about local contexts and own needs. Subsequently, he/she may later find out this technology may not be the best fit to his needs and local contexts and accordingly regret the adoption decision.

On the other hand, adopting a fashionable technology may be a good strategy to choose a "good enough" technology (Kahneman et al. 1979; Thaler et al. 1997; Tversky et al. 1974). People may follow a "correct" herd and adopt a sound technology (Walden et al. 2007; Walden et al. 2009). Herding can help a person to achieve acceptable or above-average technical advantages (Sun 2013). In addition, herding can have intangible benefits. It may help avoid damages to one's reputation and image, e.g., being considered not in fashion (Anderson et al. 1997; Chevalier et al. 1999; Graham 1999).

The mixed findings regarding adopting fashionable technologies are likely to co-exist in the smartphone market. In other words, we do not expect to see adopting a fashionable phone or a non-fashionable phone to be different in post-adoption regret and satisfaction. The rationale is that probability of adopting a "wrong" smartphone is low. First, smartphones are in general easy-to-use so that users are unlikely to have major problems using a smartphone after adoption. Second, smartphones are similar in functionalities. They all have the ability to place phone calls, send/receive emails, text message, take photos, download apps, and play games, among others. Third, smartphones are usually produced by large well-known companies and an expectation of reasonable quality is often warranted. In short, the risk of adopting an "inferior technology" (Abrahamson 1991) —which is a major reason for post-decision regret— is low. It makes sense for a person to adopt a fashionable smartphone since it is unlikely to be a bad phone (Sun 2013). "There is no wrong phone," as said by a CNET columnist, "whatever works for you, works for you."[3] So we believe that adopting a fashionable technology will not be significantly different from adopting a non-fashionable technology.

Nevertheless, we argue that fashion waves, defined *as the release of a new edition of a fashionable technology*, will result in different experience for adopters of both fashionable technologies and non-fashionable alternative technologies. A necessary condition for regret is realization of the forgone options (Zeelenberg et al. 2007). Hence, when a new edition of a fashionable technology is released, a person who chose an earlier edition of this technology will rejoice a renewed sense of fashion. He/she also thinks that the chosen technology is a sound one because otherwise there would not be a new edition of it. One reason for a person to regret is that the fashion leaders discredit a technology; this new information may cause its popularity to dissipate rapidly (Abrahamson et al. 1993). The release of a new edition of a fashionable technology helps reinforce the fashion trend and thus prevents adopters of this technology from regretting their choice. In contrast, seeing the release of a new edition of a fashionable smartphone (e.g., iPhone) drives an adopter of a non-fashionable technology (e.g., Nokia Phone) to reflect upon his/her own choice. The newly released phone serves as the reference point for a comparison between the chosen technology and forgone alternatives and likely provokes regret.

Hypothesis 1: The relationship between adopting a fashionable technology and regret is moderated by exposure to a new fashion wave so that adopters of a non-fashionable technology are more likely to experience regret when seeing a new fashion wave.

The relationship between adopting fashionable technology and post-adoption user satisfaction can be better explained through the expectation-confirmation process (Bhattacherjee et al. 2004). After adoption, the user will have direct experience with the technology and will form new evaluations of it based on realized performance. When the discrepancies between the actual and expected performance are observed, people disconfirm their early expectations. If the disconfirmation is negative —i.e., that actual performance is worse than expected— people develop low user satisfaction (Bhattacherjee et al. 2004; Parthasarathy et al. 1998). When a new edition of the adopted fashionable technology is released, the user of an earlier edition of this fashionable technology is likely to revive his/her early expectations about how fashionable the technology is. Such a positive confirmation can enhance his/her satisfaction. Conversely, seeing the release of a new fashionable technology, adopters of a non-fashionable technology may feel that their choice did not bring a sense of fashion, and thus lower satisfaction (Tsiros et al. 2000).

Hypothesis 2: The relationship between adopting a fashionable technology and post-adoption satisfaction is moderated by exposure to a new fashion wave so that adopters of a non-fashionable technology are more likely to have low satisfaction when seeing a new fashion wave.

Post-adoption regret has a negative influence on satisfaction. The rationale is that a person adjusts his/her satisfaction based on comparisons with other forgone options. Regret implies a perceived loss and can be viewed as a "*should expectation*" (Inman et al. 1997). If the chosen technology is believed to be better than forgone alternatives (low regret), the user may feel more satisfied, even if it does not meet earlier expectations (Tsiros et al. 2000). On the other hand, if the technology is worse than forgone technologies, he/she may feel that the technology "should" perform better and accordingly feel unsatisfied with it. Such *should* expectations make the shortcomings of the chosen technology even more salient and thus can reduce satisfaction (Inman et al. 1997; Taylor 1997).

Hypothesis 3: Post-adoption regret will have a significant negative effect on satisfaction.

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[3] Danny Sullivan, "No one likes a fanboy. How about more perspective about tech?" CNET, March 13, 2012. http://www.cnet.com/news/no-one-likes-a-fanboy-how-about-more-perspective-about-tech/

Methodology

Data

We tested the research model in the smartphone markets. Smartphone sales have soared to over 717 million units in 2012 (IDC 2012). In this market, iPhone and Samsung Galaxy have been fashion leaders for the past several years. Samsung's Galaxy phones have challenged iPhone fashion for years. "Samsung is the only Android OEM that can stand on its own against the Apple juggernaut." [4] iPhone and Galaxy have released multiple editions and created multiple fashion waves. Table 1 lists the major editions and release dates of iPhone and Galaxy phones, collected from Apple and Samsung websites (Table 1).

Table 1. Major Fashion Waves of Smartphone

Phone Edition	Release Data
iPhone 1 (2G)	6/29/07
iPhone 3G	7/11/08
iPhone 3GS	6/19/09
iPhone 4	6/24/10
iPhone 4s	10/14/11
iPhone 5	9/21/12
iPhone 5s	9/20/13
Samsung Galaxy S2	5/2/11
Samsung Galaxy S3	5/29/12
Samsung Galaxy S4	4/26/13
Samsung Galaxy S5	4/11/14

We collected the reviews of different models of cell phones from Amazon.com. We first searched each cell phone on Amazon.com and recorded the URLs of the "Customer Reviews" web pages in the search result. A Java program was written to directly retrieve the "Customer Reviews" web pages using these URLs. Then, we parsed retrieved HTML pages and extracted information of all customer reviews of each cell phone. We stored the reviews in a MySQL database table. We stored such attributes of each review as review creation time, phone type, star (1-5), and review content (text), among others. In total, we collected 20,122 reviews for 53 models of seven major phone brands, as summarized in Table 2.

Table 2. Summary of the Sample

	Total	Brands	Number of Reviews
Fashionable Phone	10,035	iPhone	4,215
		Samsung Galaxy	5,820
Non-Fashionable Phones	10,087	Blackberry	3,372
		Google Nexus	936
		HTC	2,235
		LG	189
		Nokia	2,225

[4] Ryan Whitwam, "Samsung Galaxy S5 vs. iPhone 5S: Which smartphone should you pay?" ExtremeTech. February 27, 2014. http://www.extremetech.com/mobile/177455-samsung-galaxy-s5-vs-iphone-5s-which-smartphone-should-you-buy

Measures

Table 3 summarizes the measures of the variables. *Adoption of Fashionable Technology* is a binary variable, with a value of 1 for adoption of a fashionable technology and 0 for adoption of a non-fashionable technology. When a review is on a fashionable phone, i.e., an iPhone or a Samsung Galaxy, we consider this review as adopting a fashionable technology. On the other hand, if a review is about a non-fashionable phone, we label this review as adopting a non-fashionable technology.

Table 3. Operational Definitions of Variables

	Measures	Source
Adopting Fashionable Technology	1: Posting a review on a fashionable phone. 0: Posting a review on a non-fashionable phone.	Self-developed
Exposure to Fashion Wave	1: The review was posted within 60 days after a major iPhone or Galaxy phone was released (Table 1). 0: The review was posted outside the 60-day window after a major iPhone or Galaxy phone was released.	Self-developed
Satisfaction	The star rating: 1 (I hate it); 2 (I don't like it); 3 (It's ok); 4 (I like it); 5 (I love it).	Amazon.com
Regret	Text-mining result: 1: Regret 0: Non-regret	Self-developed text-mining algorithm to analyze customer reviews.

Exposure to Fashion Wave is also a binary variable, with a value of 1 for exposure to a fashion wave and 0 for non-exposure to a fashionable wave. When a review was created within 60 days [5] after a major fashion wave began, i.e., that a new edition of a fashionable phone was released (Table 1), we consider the review to have been posted under the strong influence of the fashion wave. In contrast, when a review was posted out of the 60-day window, we believe the author of the review was not exposed to the strong influence of a fashion wave. A fashion wave influences adopters of both an old edition fashionable phone and a non-fashionable phone. For example, if a person posted a review on Nokia Lumia 521 phone within 60 days after iPhone 5 was released, we give this review a value of 1 for Exposure to Fashion Wave because his/her review was subject to the influence of the release of the new iPhone 5.

Amazon's Star Rating was utilized to measure *satisfaction*, with 1 for "I hate it," 2 for "I don't like it," 3 for "it's ok," 4 for "I like it," and 5 for "I love it" (Amazon.com). The star rating indicates reviewers' attitudinal reaction to the product being reviewed. It is consistent with the definition of satisfaction as "the attitude that a user has toward an information system" (Wixom et al. 2005, p.87).

To measure *regret*, we analyzed customer textual reviews using a naïve Bayes classifier we developed guided by Zeelenberg et al.'s (2000; 2007; 1998) conceptualization of regret. Specifically, we used the words and categories of regret as proposed by Zeelenberg and colleagues to develop the training set and verify the results of the different versions of the classifiers. Appendix B presents the details of the development process. The classifier gives each review a score of either "1" if it reflects the customer's regret or "0" if it does not. The classifier has 124 feature words with an accuracy of 81.76%, sensitivity of 73.33%, and specificity of 82.58%, all of which are higher than the suggested thresholds. Some sample feature words that have the strongest weights in representing the Regret category include "refund," "return," "regret," "back," "reorder," among others. An examination of these features indicates that they

[5] We also tried 15-day, 30-day, 45-day, 75-day, and 90-day windows and found the 60-day window had the highest level of heterogeneity. Specifically, we followed the same algorithm as that of cluster analysis. Well-formed clusters are characterized by small intra-cluster distance and larger inter-cluster distance (Bapna et al. 2004). We thus attempted to identify the window that was relatively heterogeneous in and outside of it, on the basis of post-adoption regret and satisfaction. The 60-day window has the highest level of heterogeneity.

are consistent with the conceptualization of regret (e.g., Zeelenberg et al. 2000), indicating the face validity of the classifier. Below are two examples of customer reviews from the Regret category.

- "My experience with <a smartphone brand> is a never ending daily struggle and I regret the fateful decision of ordering a <the smartphone brand> in December last year."
- "this phone was confusing to use after using android system, also the phone got hot when using it. returned for a refund."

Results

Descriptive Statistics

Table 4 shows the basic descriptive statistics. The correlation between regret and satisfaction (-0.433) confirms that they are conceptually different.

Table 4. Descriptive Statistics

	Mean	Std. Dev.	Correlations			
			1	2	3	4
1. Adopting Fashionable Technology	0.50	0.50				
2. Satisfaction	3.67	1.60	.029**			
3. Regret	0.08	0.28	-.006	-.433**		
4. Exposure to Fashion Wave	0.27	0.45	.033**	-.009	.006	

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

Tables 5 and 6 show the descriptive statistics of regret and satisfaction for the fashionable and non-fashionable phone adopters within or outside of the 60-day window. There is no big difference on regret and satisfaction scores between fashionable phone adopters and non-fashionable phone adopters outside of 60-day window. Within the 60-day window, however, a much larger difference in both regret and satisfaction between adopters of fashionable and non-fashionable phones can be observed.

Table 5. Descriptive Statistics: Regret

Exposure to Fashion Wave	Adoption a Fashionable Phone	Mean	Std. Dev	N
.00	.0	.082	.2744	7462
	1.0	.083	.2762	7129
	Total	.083	.2753	14591
1.00	.0	.095	.2931	2625
	1.0	.078	.2689	2906
	Total	.086	.2807	5531
Total	.0	.085	.2794	10087
	1.0	.082	.2741	10035
	Total	.084	.2768	20122

Table 6. Descriptive Statistics: Satisfaction				
Exposure to Fashion Wave	**Adoption a Fashionable Phone**	**Mean**	**Std. Dev**	**N**
.00	.0	3.656	1.5784	7462
	1.0	3.694	1.6105	7129
	Total	3.675	1.5942	14591
1.00	.0	3.515	1.6277	2625
	1.0	3.758	1.5875	2906
	Total	3.643	1.6111	5531
Total	.0	3.620	1.5925	10087
	1.0	3.713	1.6040	10035
	Total	3.666	1.5989	20122

Hypothesis Testing

To test the hypotheses, we used different analytical methods in light of the fact that the dependent variables are either dichotomous (Regret) or interval (Satisfaction). For the former, we use logistic regression, which is appropriate for dichotomous dependent variables (Hosmer et al. 2000). For the latter, we use linear regression. Table 7 shows the results in detail. Figure 2 illustrates the structure model. All the three hypotheses were confirmed form the empirical study.

Figures 3a and 3b illustrated the interaction effects of exposure to fashion wave more clearly. In the window of 60 days after a new edition of a fashionable phone was released, those who adopted an earlier edition of a fashionable phone enjoyed a lower level of regret and increased satisfaction. Out of the 60-day window, there is no significant difference in regret and satisfaction between adopters of fashionable and non-fashionable technologies.

Table 7. Results of Logistic and Linear Regressions				
IV	**DV: Regret #**		**DV: Satisfaction**	
	Step 1	**Step 2**	**Step 1**	**Step 2**
Constant	-2.385 (0.057)	-2.415 (0.042) **	3.833 (0.015) **	3.861 (0.017) *
Adoption of Fashionable Technology	-0.048 (0.051)	0.015 (0.060)	0.085 (0.020) **	0.041 (0.034)
Exposure to a New Fashion Wave	0.049 (0.057)	0.160 (0.079) *	-0.026 (0.023)	-0.109 (0.033) **
Interaction: Adoption of Fashionable Technology X Exposure to a New Fashion wave		-0.223 (0.113)*		0.161 (0.046) **
Regret			-2.498 (0.037) **	-2.496 (0.037) **

Note: Robust standard errors are in parentheses.
Logistic regression is used because the DV is a dichotomous variable.
* Significant at the 0.05 level. ** Significant at the 0.01 level.

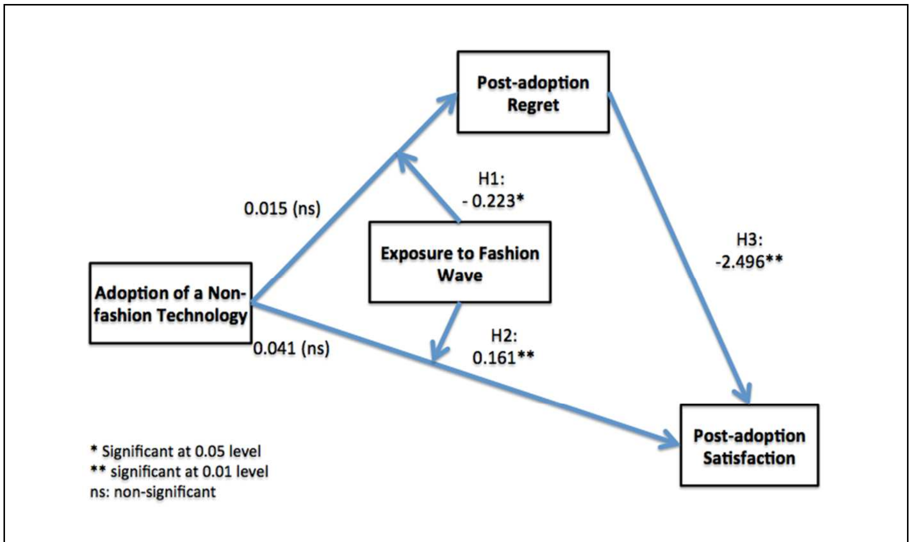

Figure 2. Results of Hypothesis Testing

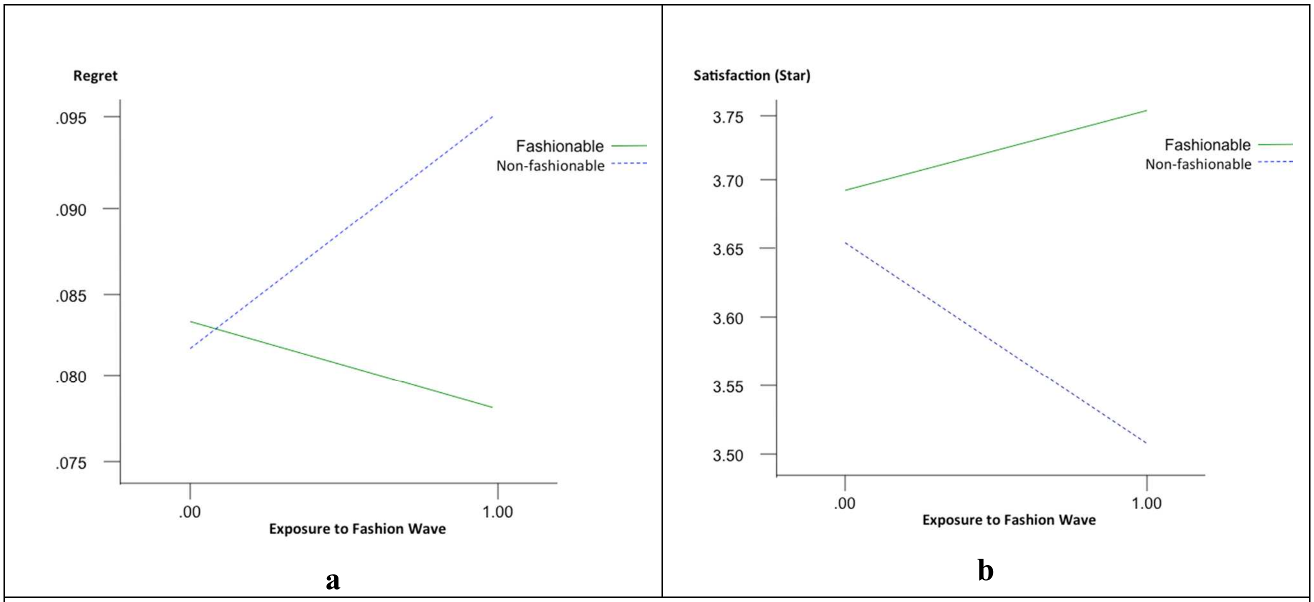

Figure 3. Interaction Effects of Exposure to Fashion Wave and Adoption of Fashionable Technology on Regret and Satisfaction

Post Hoc Analysis

Insofar, we have treated the two fashionable phones equally: we have assumed that users of fashionable technologies react identically to fashion waves of their own technology and those of opposing fashionable technologies. Nevertheless, users of a fashionable technology (e.g., iPhone) may react differently to the release of a new edition of this technology and to that of an opposing fashionable technology (e.g., Samsung Phone). We thus conducted a *post hoc* analysis on within-fashion comparison, focusing on customer reviews on the two fashionable smartphones. Specifically, we examined how owners of fashionable technology react to own fashion waves (i.e., the release of a new edition of the fashionable technology a person owns) and to opposing fashion waves (i.e., the release of a new edition of the opposing fashionable technology). We added two dummy variables: During Own Wave and During Opposing Waves.

During Own Wave =

"1" when a customer review on a fashionable technology was posted within 60 days of a new edition of the same technology was released,

"0" when a customer review on a fashionable technology was posted out of the 60 days of a new edition of the same technology was released.

During Opposing Wave =

"1" when a customer review on a fashionable technology was posted within 60 days of a new edition of the opposing technology was released,

"0" when a customer review on a fashionable technology was posted out of 60 days of a new edition of the opposing technology was released.

Table 8 summarizes the results. The results suggest that fashionable technology owners are more sensitive to fashion waves of their own technology than those of opposing technologies. Specifically, when a new edition of the technology a person owns is released, he or she is more likely to experience reduced regret and enhanced satisfaction.

Table 8. Results of Logistic and Linear Regressions

	Regret	**Satisfaction**
Constant	-2.382 (0.027) **	3.862 (0.011) **
During Own Wave	-0.234 (0.108) *	0.129 (0.039) **
During Opposing Wave	0.041 (0.099)	0.056 (0.040)
Regret		-2.498 (0.037) **

Note: Robust standard errors are in parentheses.
Logistic regression is used because the DV is a dichotomous variable.
* Significant at the 0.05 level. ** Significant at the 0.01 level.

Discussion

Major Findings

Given the ubiquity of fashionable technologies for individual users, this research investigates how owners of fashionable and non-fashionable technologies behave differently in terms of post-adoption regret and satisfaction and how they react differently to fashion waves. A research model was developed based primarily on the regret theory. An examination of 20,122 Amazon.com customer reviews on both fashionable and non-fashionable smartphones were examined to test the research model. The findings support all our three hypotheses. In general, adopting fashionable technology can lead to good enough choices: those who adopted fashionable smartphones have the same level of post-adoption regret and satisfaction with those who adopted non-fashionable phones. Nevertheless, during a fashion wave, adopting a fashionable technology can lead a person to experience less post-adoption regret (H1) and higher satisfaction (H2). At the same time, the results also confirmed the significant negative influence of post-adoption regret on satisfaction (H3).

Overall, the findings suggest that adopting a fashionable smartphone is a good idea. It does not lead to higher regret or lower satisfaction. In addition, it helps the user enjoy less regret and higher satisfaction during the fashion waves. Furthermore, the *post hoc* analysis suggests that people are more sensitive to their own fashion waves. When a new edition of a fashionable technology is released, the owners of this fashionable technology enjoy a lower level of regret and increased level of satisfaction. In contrast, they do not change their regret and satisfaction levels in front of the fashion waves of the opposing technology.

Our findings seem to suggest that herding is a good strategy for technology adoption, consistent with an early study (Sun 2013). However, we have to state that our findings are limited to fashionable technology. Although fashions are characterized by herd behavior, herd behavior does not exist only in fashions. Herds may form on many non-fashions. For example, people tend to download the software applications that have been downloaded by a lot of people (Duan et al. 2009). Following a herd on other non-fashion technologies may still run the risk of making wrong decisions as has been suggested in prior research (Abrahamson 1991; Sun 2013; Walden et al. 2009).

Limitations

This research has limitations. First, our data was limited to posted reviews. There may be self-selection bias if customers who post reviews are different from those who do not. Second, we focused on smartphones, which are in general easy to use and share a lot of common functions. Also, smartphones are often produced by large manufactures with well-known brands. Future research can study other types of products. Third, aiming at analyzing a large amount of objective data from Amazon data, we sacrificed subjectivity. After all, concepts such as regret and satisfaction are subjective feelings. One thing future research can do is to develop survey measures for regret and triangulate the findings from this research. Fourth, we used review posting as the proxy for adoption. A person may review a smartphone without owning it. We do not see this happen often though based on a quick scanning of some reviews. This issue can be clarified in future research.

Research Implications and Future Directions

Adopting a fashionable technology is more than its functional features. Therefore, existing user acceptance research that heavily emphasizes usefulness of technology may not be sufficient to understanding user acceptance of fashionable technology. Therefore, new theories are needed to study fashionable technology. This research leveraged the herd behavior literature to study fashionable technology. In addition, the findings show that people can be influenced by the release of fashionable technology. This cross-technology influence on users should receive more attention.

One thing we should be aware of is that fashionable technology has a transitory nature. Actually, prior research has included the transitory nature as part of the definition of fashionable technology (Abrahamson 1991; Wang 2010). That is, a fashionable technology may become non-fashionable later. In this case of smartphones, BlackBerry was a fashionable technology around 2000; yet it is not any more after iPhone and Samsung phones became fashionable smartphones. The transitory nature of fashionable technology warrants further investigation.

The *post hoc* analysis on within-fashion comparisons merits more attention in future research. Our results suggest that people do perform different differently toward their own fashionable technologies and toward opposing fashionable technologies. Therefore, more acute understanding of how people perceive fashionable technology and the consequences is necessary in light of the fact that we are witnessing the intense competition among fashionable technologies (e.g., the ongoing law suits between iPhone and Samsung phones.)

Studying regret has implications for research on making sound adoption decisions (Sun 2011). How people choose a technology that fits their own contexts and meets their needs is apparently a topic of great values since making incorrect adoption decisions may lead to a waste of money, time and opportunity costs (Abrahamson 1991). It has been argued that we do not yet have a systematic conceptualization of soundness of technology adoption (Sun 2011). Regret can be used as an indicator of soundness of technology adoption decisions.

Studying regret can enrich our understanding of post-adoption user behavior. This research reveals two types of post-adoption comparisons people may perform: internal comparison (satisfaction) and external comparisons (regret). While the former has received a considerable amount of attention in IS research, especially in the stream of expectation-confirmation studies (Bhattacherjee 2001; Bhattacherjee et al. 2004; McKinney et al. 2002; Sun 2013; Venkatesh et al. 2010), the latter has not yet received sufficient attention. Given that regret can have a strong and direct impact on repurchase intention (Tsiros et al. 2000), more attention is needed to investigate this important concept. In addition, as mentioned earlier, regret is relevant to today's IT practices in that people have more and more alternative technologies to choose from. Regret can help study cross-technology comparisons. A topic of immediate need is to develop measures for regret. In addition, regret has been studied primarily at the individual level. Future research can explore group or organizational level regret as IS research has done with mindfulness (Butler et al. 2006; Fichman 2004; Swanson et al. 2004).

The naïve Bayes classifier developed in this research can be used by future research to measure user regret using objective data. Indeed, we believe that developing similar classifiers can be beneficial for studying user behavior and IS because they allow researchers to analyze a larger amount of textual information, e.g., the Big Data. To do so, a researcher should keep in mind that developing a robust classifier needs a solid understanding of the concept. For example, in this research, Zeelenberg et al.'s (2007; 1998) conceptualization of regret guided the development of our classifier. Future research can also attempt to employ different machine learning algorithms such as deep neural network (Hinton et al. 2006) and SVM (support vector machine, Vapnik 2000) when studying user behavior in IS research.

Practical Implications

Developing fashionable technologies has always been a goal for many companies. However, practitioners have questioned how the users of the earlier editions of a fashionable technology may react to the release of a new edition of this technology. Findings from this research deliver an encouraging answer to this question. Specifically, those who adopted earlier editions of a fashionable technology actually rejoice the release of a new edition of this technology.

Findings from this research also suggest that adopters of non-fashionable technologies have negative reactions to the release of a new edition of fashionable technologies. When a new fashionable technology is released, producers of non-fashionable technologies should pay attention to how to alleviate customers' regret and prevent potential product returns. The enlarged gaps in regret and satisfaction between owners of fashionable and non-fashionable technologies may means product returns and negative words of mouth. Therefore, the changes in regret and satisfaction scores should receive practitioners' sufficient attention. The enlarged gap of user satisfaction (i.e., from 0.04 to 0.22 on a five-point scale) during the fashion waves between owners of fashionable and non-fashionable phones could have substantial economic implications for companies that sell and provide customer services to those phones.

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Appendix A: A Literature Review on Regret

Article	Context	Definition of Regret	Measures	Major Findings
(Inman, et al., 1997)	Marketing	A consumer would experience regret if the actual performance of a chose product is worse than the actual performance of a forgone product	Experienced Regret	Information about the forgone alternative, whether primary, third-party, or word-of-mouth, influenced subjects' valuation of the chosen alternative.
(Kang et al. 2009)	IS	Resultant judgment of comparing one's outcome with a better…outcome, which would have occurred had a different alternative been selected	Experienced Regret	Regret had a significant negative influence on continuance behavior in online service usage, and the effect was greater than that of perceived usefulness, perceived enjoyment or past use.
(Loomes and Sugden, 1982)	Economics	Resultant condition one may experience if, upon reflection, an individual identifies the alternative as more desirable than the "chosen outcome and then becomes aware of how much better his position would have been, had he chosen differently	Anticipated Regret	An individual's ability to anticipate regret exerts significant influence over choice patterns.
(Shih and Schau, 2011)	Technology	Expectation of discontent if choice outcomes were to be revealed	Anticipated Regret	Anticipated regret is greater under conditions of high perceived rate of innovation, or when the technology is perceived to be developing rapidly.
(Tsiros and Mittal, 2000)	Consumer Behavior	Consequence of decision making under risk [which] may arise when individuals appear, after the fact, to have made the wrong decision even if the decision appeared to be the right one at the time it was made	Experienced Regret	Regret may be activated by information on the forgone outcome or counterfactual thinking. Regret negatively influences repurchase intentions directly, and complaint intentions indirectly through satisfaction.
(Zeelenberg 1999)	Psychology	Negative, cognitively based emotion that we experience when realizing or imagining that our present situation would have been better had we acted differently	Experienced and Anticipated Regret	Anticipated regret is rational to the extent that it protects people from the adverse consequences of their decisions. Experienced regret may help people learn from their mistakes.

Appendix B: Developing a Naïve Bayes Classifier For Measuring Regret

Data Pre-processing

We first screened the 20,122 reviews collected from Aamzon.com. Each word may exist in reviews with different forms. Hence, we performed the following pre-process steps to reduce the variation of a word. First, we converted all letters to lower case. This made the instance of a word at the beginning of a sentence to match the instance of a word in the middle of a sentence. Second, we removed common words such as "and", "a", and "an" often referred to as "stop words." Finally, we transformed different grammatical forms of a word into a common base, using the Porter Stemmer Algorithm (Porter 2001). We used unigram language model (Manning et al. 2008) to describe reviews, which assumed that words in the reviews are independent. We scanned all reviews in the training data set and create a feature vector space V of words w1, w2, w3 ...:

V={w1, w2, w3....}

Classification of Reviews

We identified 7,054 unsatisfied reviews, i.e., those with 1 to 3 stars, believing that regret is more likely to exist in unsatisfied reviews. Then, we would like to identify reviews that expressed regretting in the text content. It is very time-consuming to manually read all 7,054 reviews. Thus, we employed a text classification process as our pre-filtering step. We first manually identified 282 "Regret" reviews from 1,194 reviews based on Zeelenberg et al.'s (2000; 2007; 1998) conceptualization of regret. Specifically, Zeelenbert et al.'s terms and words (e.g., "switch to" "regret" "should have chosen") were used to identify potential customer reviews that indicated regret feeling. We then went through them to select 282 reviews that actually meant regret. We used the 282 reviews as positive data and sampled the same number of "Not-Regret" reviews as negative data to train a naïve Bayes classifier (Maron et al. 1960). Then, we used the classifier to predict the rest 5,860 unlabeled reviews. For those classified as "Regret" reviews, we again manually checked if they belong to "Regret" or not based on Zeelenberg et al.'s definition of regret. Then, we add newly identified "Regret" reviews into our positive training data and refine the classifier to classify the rest reviews. These steps were repeated several times until no more review were classified as "Regret" by classifier. Eventually, we identified 1,682 "Regret" reviews.

Naïve Bayes Classifier

We built a review classifier by learning a classification function f that maps reviews R to two classes C: {"Regret", "Not-Regret"}.

f: R →C

We used the naïve Bayes classifier, which is simple but works well on text classification problems. It is based on Bayes rules (Bayes et al. 1763). Assuming features are independent, the probability that a review r belong to class c, P(c|r) is

$$P(c|r) = P(c) \prod_{1 \le k \le N_w} P(w_k|c)$$

where $P(w_k|c)$ is the conditional probability that a word w_k occurs in review of class c, $P(c)$ is the prior probability of class c, w_k is the k_{th} word in this review and N_w is the total number of words in the feature vector space.

The best class of a review is the maximum a posteriori (MAP) class:

$$c_{map} = argmax_{c \in C} P(c|r) = argmax_{c \in C} P(c) \prod_{1 \le k \le N_w} P(w_k|c)$$

Since same word may occurs several times in one review, we used multinomial Bayes model, which counts occurrences of features in each review. Hence, for each review, the entry for each word in the feature space is the number of occurrences of the word in this review. Then, the conditional probability $P(w_k|c)$ is the relative frequency of word w_k in reviews of class c:

$$P(w_k|c) = \frac{T_{cw}}{\sum_{w' \in V} T_{cw'}}$$

where T_{cw} is the number of occurrences of word w in reviews of class c.

Because the training data are not large enough to cover all terms in test data, Laplace smoothing is utilized to estimate conditional probabilities of unseen words.

$$P(w|c) = \frac{T_{cw} + 1}{\sum_{w' \in V}(T_{cw'} + 1)} = \frac{T_{cw} + 1}{(\sum_{w' \in V} T_{cw'}) + |V|}$$

where |V| is the size of feature collection V. We implemented the Naïve Bayes classifier using Java.

Classifier Evaluation

We used 5-fold cross validation method to evaluate the performance of regret classification of the naïve Bayes classifier. Two classes of training data are imbalanced. The ratio between negative (non-regret) data and positive data is about 4:1. Therefore, the overall accuracy can be quite misleading as the classifier can classify all the samples belonging to the majority class and have a high accuracy. For a better evaluation of our classifier under such circumstances, we choose three metrics: sensitivity, specificity and balanced accuracy, for our evaluation.

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN+FP}$$

$$Balanced\ Accuracy = \frac{Sensitivity + Specificity}{2}$$

where TP, TN, FP, FN indicate true positive, true negative, false positive and false negative, respectively.

χ² Feature Selection

We initially construct our naïve Bayes classifier on 564 train dataset including 282 "Regret" reviews and 282 "Not-regret" reviews. There are 10486 terms total in these 564 reviews. We were only able to achieve a balanced accuracy of 74.9%. We hypothesized that the low performance may be due to too many noise features. We then used χ2 test (Fisher 1925) to select related features. The χ2 test measured whether the occurrence of a specific term and the occurrence of a specific class are independent. The χ^2 score of each feature (word) w according to training reviews D can be calculated by:

$$X^2(D,w,c) = \sum_{t\epsilon\{1,0\}} \sum_{c\epsilon\{1,0\}} \frac{(N_{c,t} - E_{c,t})^2}{E_{c,t}}$$

where t =1 indicates the word w occurs a review and t=0 otherwise; c=1 indicates the positive class of this review and c=0 otherwise. $N_{c,t}$ is the number of reviews that have values of t and c. $E_{c,t}$ is the expected number of reviews with c and t together. Here, we assumed that word and class are independent.

We ranked the features with respected to their χ^2 score. We trained the naïve Bayes classifier using different numbers of features on same training dataset. The result is shown in Table B2. When we reduced the number of features from 10486 to 877, the performances (balanced accuracy) of the classifier were also decreased. When we reduce the number of features to 225, 181, 124, the balanced accuracy of the classifier were improved to about 78%. We got the best balanced accuracy with 225 features, which include words, such as "return", "regret", "refund", representing the customers' regret feeling. However, if we further reduce the number of features, the performances of classifiers were decreased dramatically.

Table B2. Performances of naïve Bayes classifier using different number of features [#]

Number of Features	Sensitivity	Specificity	Balanced Accuracy
10486	65.24%	84.55%	74.90%
2728	56.82%	87.21%	72.02%
877	60.91%	85.16%	73.04%
225	74.91%	82.11%	78.51%
181	74.73%	82.22%	78.48%
124	73.33%	82.58%	77.96%
51	74.50%	77.08%	75.79%
27	82.09%	50.31%	66.2%

[#] The values are the average of five-fold cross validation.