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RESEARCH ARTICLE

A LONGITUDINAL STUDY OF HERD BEHAVIOR IN THE ADOPTION AND CONTINUED USE OF TECHNOLOGY[1]

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Herd literature suggests that people tend to discount their own beliefs and imitate others when making adoption decisions and that the resulting adoption decisions are fragile and can be easily reversed during the post-adoptive stage. This helps explain why the adoption of a number of new technologies—from Amazon's Kindle, to Apple's iPod, iPhone, and iPad, to various types of Web 2. 0 technologies—appears to have adoption patterns similar to those of new fashion trends (i. e., an initial en masse acquisition followed by subsequent abandonment). It is important to understand these phenomena because they are strongly related to the staying power of technology. From a herd behavior perspective, this study proposes two new concepts, namely ***discounting one's own information*** *and* ***imitating others****, to describe herd behavior in technology adoption. A research model is developed to describe the conditions under which herd behavior in technology adoption occurs, how it impacts technology adoption decision making, and how it influences post-adoptive system use. A longitudinal study is conducted to examine the research model. Findings from this research suggest that the discounting of one's own beliefs and the imitating of others when adopting a new technology are provoked primarily by the observation of prior adoptions and perceptions of uncertainty regarding the adoption of new technology. Herd behavior has a significant influence on user technology adoption; however, it does not necessarily lead to the collapse of the user base, as predicted in the herd literature. Instead, imitation can help reduce post-adoption regret and thus serve as a legitimate strategy for choosing a good enough technology, which may or may not be the best option to enhance job performance. People tend to adjust their beliefs when herding and also to revive their discounted initial beliefs to modify their beliefs about the technology at the post-adoptive stage. Findings from this study have significant research and practical implications.*

Keywords: Herd behavior, imitating, technology adoption and continued use, longitudinal study

Introduction

In recent years we have witnessed the adoption of a number of new technologies—from Amazon's Kindle, to Apple's iPod, iPhone, and iPad, to various types of Web 2.0 technologies—that appear to have adoption patterns similar to those of new fashion trends. On one hand, people often rapidly converge on certain new technologies. It took only about 10 months for Facebook to attract one million active users after its initial launch in February 2004; by mid-2009, this number had grown to 250 million.[3] Twitter's users jumped to an estimated 32.1 million from 1.6 million within

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[2]The paper was finalized when the author was Senior Visiting Scholar in the Department of Information Systems, School of Computing, at the National University of Singapore.

[3]Facebook.com (March 2012). "Timeline" (http://newsroom.fb.com/content/default. aspx?NewsAreaId=20).

1 year, from mid-2008 to mid-2009.[4] The iPhone 4S received over one million pre-orders within 24 hours after it was released in October 2011.[5] On the other hand, people may also leave a formerly popular technology *en masse*. For example, an article published by *BBC News Magazine* presented a phenomenon observed in Second Life: "[as] quickly as it [Second Life] had flared, media interest [in Second Life] ebbed away."[6] Similarly, Wikipedia. com was reported to have lost 49,000 editors (i.e., users of Wikipedia) during the first three months of 2009, compared with a loss of 4,900 over the same period in 2008.[7] Understanding this phenomenon is important because it is closely related to the staying power of these technologies.

Many factors may account for why individuals tend to converge on the same technology and later abandon it. This paper examines these phenomena from a herd behavior perspective. 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). This may explain why people quickly converge on the same form of technology by imitating each other's choices. Moreover, the equilibrium of a human herd is often fragile (Banerjee 1992; Bikhchandani et al. 1992). For this reason, when herding, people may later reexamine and reverse their initial decisions, somewhat accounting for the *en masse* abandonment of a particular technology.

To date, little information systems (IS) research has been conducted to apply herd theory to technology adoption. Duan et al. (2009) found that online users' choices of software products rise and fall dramatically when the download ranking of the software products changes. This indicates that, consistent with the predictions made in the herd literature, users tend to follow the previous adopters' choices as reflected by the downloading ranking. Li (2004) discussed and compared information cascades (i.e., people defer completely to the herd, no matter what their own information suggests) and other similar concepts such as network externality (i.e., that the value of a technology increases as the number of its users increases) and word of mouth. Walden and Browne (2009) simulated users' adoption of technology based on private information and signals inferred from observation of predecessors' actions. They found that people tend to imitate others through herding and can sometimes make incorrect adoption decisions (e.g., adopting an inferior technology). Moreover, incorrect herd decisions are more likely to be later reversed than correct herd decisions.

The studies mentioned above have contributed greatly to IS research. However, they are limited in two ways that hinder our understanding of herd behavior in technology adoption and its continued use. First, existing IS studies on herd behavior were conducted primarily at the herd level based on simulated or observed data about the behavior of a herd and, accordingly, have yielded little insight into the cognitive process of individuals with respect to herd behavior. This limitation blurs the line between true (intentional) herding and spurious (unintentional) herding. The term *spurious herding* suggests that when people arrive at the same decision it does not necessarily mean that they are herding; such a clustering of behavior may simply be the result of commonly shared information (Bernhardt et al. 2009; Bikhchandani and Sharma 2000; Cipriani and Guarino 2005; Grinblatt et al. 1995). One way to distinguish herd behavior from spurious herding is to analyze how individuals make the decision to herd cognitively (Drehmann et al. 2005; Fiol and O'Connor 2003). Second, existing IS research on herd behavior is focused primarily on technology adoption; the distal effect of herd behavior on post-adoptive system use has received little attention to date. This fact, combined with the first limitation, results in a lack of understanding of the impact of herd behavior on post-adoptive user beliefs and behavior, which is crucial to understanding the continuance of system use. In order to address these limitations and thereby to enrich our understanding of herd behavior with respect to technology adoption and its continued use, this research develops two research questions:

1. How do people make decisions about adopting an IS through herding?
   a. Under what conditions does herd behavior occur in the context of technology adoption?
   b. How does herd behavior influence technology adoption (the cognitive process of herd behavior in technology adoption)?

2. How does herd behavior influence continued system use at the post-adoptive stage?

[4]Jessica E. Vascellaro (May 26, 2009), "Twitter Trips on Its Rapid Growth," *Wall Street Journal* (http://online.wsj.com/article/SB124329188281552341.html).

[5]Apple Press (October 10, 2011), "iPhone 4S Pre-Orders Top One Million in First 24 Hours" (http://www. apple. com/pr/library/2011/10/10iPhone-4S-Pre-Orders-Top-One-Million-in-First-24-Hours. html).

[6]Lauren Hansen (November 2009), "What Happened to Second Life?," *BBC News Magazine* (http://news.bbc.co.uk/2/hi/uk_news/magazine/8367957.stm).

[7]Julia Angwin, and Geoffery A. Fowler (November 27, 2009), "Volunteers Log Off as Wikipedia Ages," *Wall Street Journal* (http://online.wsj.com/article/SB125893981183759969.html).

To approach these research questions, this paper will present a research model based on the herd literature. The model integrates two herd factors, namely *discounting own information* (the degree to which one disregards his/her own beliefs about a technology when making an adoption decision) and *imitating others* (the degree to which one follows previous adopters to adopt a particular form of technology), into a simplified cognition change model (CCM) (Bhattacherjee and Premkumar 2004). This model delineates the cognitive process typical of individuals when herding to adopt a technology and the impact of such herd behavior on their post-adoptive system use. An empirical longitudinal study has been conducted to examine the research model.

Theoretical Development

Herd Behavior

> *When people are free to do as they please, they usually imitate each other.*
> — Eric Hoffer (1902–1983), writer/philosopher

We have all been witness to, and participated in, innumerable situations where decision making was influenced strongly by what others around us were doing. Herd behavior, for example, has been observed in a variety of situations such as in the choosing of retirement investments (Choi et al. 2003), the opening of new bank branches (Chang et al. 1997), the developing of prime-time television programs (Kennedy 2002), and the downloading of software applications (Duan et al. 2009; Walden and Browne 2009). (For a summary of the relevant literature on herd behavior, see Appendix A.) "Everyone herds somewhat, and most people herd a lot" (Prechter 1999, p. 174). Let us use a scenario to illustrate the key points of herd behavior.

[Scenario 1] Two technologies, Alpha and Beta, have similar functionalities and qualities. Three people need to choose one of them. The first person, Alice, prefers Alpha and chooses it. The second person, Barbara, based on her own limited information about these two technologies, thinks that Beta is slightly better. Nevertheless, she does not really know much about either of these two technologies. Therefore, she discounts her own opinion and follows Alice's choice, believing, rightly or wrongly, that Alice knows better. Observing that both Alice and Barbara have chosen Alpha, a third person, Carol, is likely to choose Alpha as well. Hence, a herd is formed: all of the herd members chose Alpha, even though not all of them preferred it over Beta.

By definition, herd behavior can be conceived of as having two aspects: imitating others and discounting one's own information. Imitating others means that a person who is herding observes others and makes the same decisions or choices that the others have made. In Scenario 1, Barbara decided to imitate Alice and chose Alpha. Discounting one's own information, means that when herding, one may be less responsive to his/her own private information and favor a predecessor's action, believing that that person is better informed. This often occurs when others have made a different choice than what one's own information suggests, similar to Barbara's actions (Banerjee 1992; Bikhchandani et al. 1992).

Prior research has identified two primary conditions under which herd behavior can occur: *uncertainty about the decision* and *observation of others' actions*. On the one hand, people are more likely to herd when they are uncertain about the decision to be made, as a result of having either incomplete or asymmetric private information (Bikhchandani and Sharma 2000; Fiol and O'Connor 2003; Lieberman and Asaba 2006; Walden and Browne 2009). On the other hand, observing that many people have made the same decision is a necessary condition for herd behavior to occur. First, the number of previous adopters matters: "The adoption of one alternative becomes more likely the more others have made the same choice" (Rao et al. 2001, p. 504). Second, the identity of predecessors may also matter. People may follow members of the general public or of a specific group who are believed to have better information and who are more likely to have made the *right* decision such as that of successful others (Bandura 1986), reputational early adopters (Abrahamson 1991), and fashion leaders (Bikhchandani et al. 1992).

An essential characteristic of a herd is an information cascade. In an information cascade, people defer completely to the herd, no matter what their own information suggests (Anderson and Holt 1997; Bikhchandani et al. 1992; Çelen and Kariv 2004; Duan et al. 2009). As soon as perceived information becomes even 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. "The probability that a cascade starts after the first few individuals is very high" (Bikhchandani et al. 2000, p. 286).

An information cascade provides an information-based explanation for herd behavior. In an information cascade, signals and actions are often passed throughout the herd from leaders to followers, often without much new information being added. This transfer suggests that herd behavior is often characterized by *low informativeness*: a herd does not carry all of the information/preferences of herd members (Banerjee 1992; Bikhchandani et al. 1992; Bikhchandani and Sharma 2000; Lieberman and Asaba 2006). In Scenario 1, Barbara discounts her own preference and follows Alice's choice. Accordingly, the knowledge base of this herd member does not faithfully reflect Barbara's preferences and is of low informativeness with respect to its followers. Here an information cascade begins. The third person, Carol, may mistakenly believe that both Alice and Barbara prefer Alpha and mistakenly discount her own preferences as well, further decreasing the collective informativeness of the herd. Hence, Alice's preference has cascaded to her followers. Accordingly, a herd may not carry as much information as might be expected; consequently, even though many people choose a specific technology, it does not necessarily mean that every adopter prefers it over all other options.

Prior research on herd behavior has emphasized the fragility of herd behavior resulting from low informativeness, at both the individual and the herd levels. At the individual level, limited previous research argued that people who make decisions by herding may experience "post decision regret" (Rao et al. 2001). By following other people's decisions, a person may overlook his or her own needs and thus may mistakenly adopt a technology that is not suitable for use in his/her own contexts (Abrahamson 1991). For example, in Scenario 1, although Alpha meets Alice's needs and fits into her local use context, it may not be the best choice for Barbara. A new piece of information made available later (e.g., from Barbara's own experience with Alpha) may change Barbara's mind and cause her to leave the herd.

At the herd level, the fragility of the herd means that some people's abandonment of a particular herd may cause others to leave the herd as well, starting "a herd in the opposite direction" (Bikhchandani and Sharma 2000, p. 281). So a herd as a whole can be flighty: rapidly achieving conformity and then dissolving as people abandon the herd. Such a "negative diffusion" runs the risk of collapsing the status quo of the herd (Rao et al. 2001). A prominent example is the collapse of the Internet bubble in the middle of 2000: some pessimistic assessments of the then-expanding Internet bubble began to appear and then grew rapidly, causing the collapse of the Internet market (Lieberman and Asaba 2006). In some cases, people may even follow the herd and make decisions that they know to be incorrect. As vividly put by Prechter (1999), pp. 174-175),

> when panic ensues, those less prone to panic know that if they do not act, they may be driven to bankruptcy by those who do. This knowledge creates a chain reaction as otherwise calm people succumb to the fear that the panic will ruin them.

Herd Behavior in Technology Adoption

Consistent with prior herd literature, this research defines **herding in technology adoption** as *the phenomenon that a person follows others when adopting a technology, even when his/her private information suggests doing something else.* While it can be used as a means to make a decision about which technology to adopt, herding can also include making a choice between the adoption and rejection of a particular technology. Similar decisions have been studied in existing herd literature. Bikhchandani et al. (1992) investigated how a person decides "whether to adopt and reject" some behavior based on his/her observations of the adoption and rejection decisions of predecessors. Rao et al. (2001) argued that research on herd behavior has been focused on decisions that are discrete, such as "to invest or not to invest, to adopt or to reject" (p. 504). Similarly, Bikhchandani and Sharma (2000) studied the decision of financial analysts "to invest" and "not to invest." Therefore, the decision to adopt or reject a technology effectively represents a situation where herd behavior may occur.

Herding involves both one's own private information and one's observations of the actions of others. The situation presented in Scenario 1—that all people end up making the same choice—is somewhat unrealistic because not everyone completely disregards his/her private information when imitating others. More often, people depend on a combination of their own information as well as their observations of the behavior of others. As a result, herd behavior is "observed but is somewhat less widespread than is predicted by the respective theories, with agents following their own signals more than the theory predicts" (Hey and Morone 2004, p. 639). Avery and Zemsky (1998) also showed that financial agents often trade on the differences between their own information and that which is publicly available.

Some explanations exist for why people take into account both the observations of others and their own information. First of all, other people's actions may be considered less relevant (Bikhchandani et al. 1992). Observations of others' behavior often carry information different from one's own information. That many people have adopted a particular form of technology may indicate that the technology is popular and that it has been *useful to others*. On the other hand, a person's own information indicates how this technology can *meet his/her own needs*. Second, predecessors may send mixed signals (e.g., some adoptions and some rejections), which indicate their disparate views regarding the technology and may trigger one to question the value of the technology by leveraging his/her own information (Banerjee 1992). Third, people may not *trust* predecessors' decisions (Hey and Morone 2004).

Table 1. Differences Between Herd Behavior, Network Externality, and Subjective Norm

	Herd Behavior	Network Externality	Subjective Norm
Definition	A person follows others when adopting a technology.	The value of a technology increases as the number of its users increases.	A person's perception that most people who are important to him/her think he/she should or should not perform the behavior in question.
Information source	Prior adopters.	Those who can benefit from the new adoption of the technology.	People in an adopter's reference group (important to the adopter) who may or may not have adopted the technology.
What information is inferred from others	Estimated value of the technology.	Benefits from more adopters of the technology.	Others' opinions/norms about the adoption.
How information is inferred from others	Observation.	Observation and direct communications.	Perceptions of how others would think about the behavior.
The impact of the number of others	The more, the stronger influence of others. However, the informativeness of predecessors may be low.	In general, the more prior adopters, the stronger the influence of others, and the higher perceived value of the technology. However, network externality is subject to the chilling effect and network congestion.	No strong relationship. Limited to those who are important to the adopters.
Motivations	To overcome uncertainty and to avoid costs or blame for choice.	To enjoy the increased value associated with the enlarged user base.	To avoid being judged unfavorably or in the hope of being judged favorably.
Long-term impact	Herds are often fragile and later reversals of herd practices are expected. On the other hand, herding practice may also have reasonable staying power if the true value of the adopted practice is ultimately revealed.	Network externality can strengthen the perceived value of a technology and can thus reinforce the user base.	Subjective norms do not matter much after the technology is adopted.

The above discussions lead to two preliminary arguments: (1) that people consider *both* their private information and the observations of others' actions when making a decision, and (2) that people subjectively determine to what extent they can prudently base their decisions on the actions/decisions of other people. Accordingly, this research proposes two new concepts—**imitating others (IMI)** and **discounting own information (DOI)**—to describe herding behavior in technology adoption. IMI concerns the degree to which a person will follow others' decisions when adopting a technology; DOI concerns the degree to which a person disregards his/her own beliefs about a particular technology when making an adoption decision.

Distinguishing Herding from Similar Concepts

The influence of other people on one's adoption of a technology has been studied from various angles in IS research. It is thus necessary to distinguish herd behavior from other similar concepts. This section focuses on how herd behavior differs from two similar concepts that have been studied in prior IS research: network externality and subjective norm. The differences between these concepts and herd behavior are summarized in Table 1.

Network externality refers to the phenomenon that "the value of a technology increases as the number of its users increases"

(Li 2004, p. 94). It differs from herding in several ways. First, network externality is closely tied to the increasing value of a technology resulting from new users. A potential user may know that his/her adoption can increase the value of a particular technology to those who are using it (e.g., friends connected through Facebook). Herd behavior does not have this type of value-adding mechanism. Instead, the motivations behind herding are to overcome uncertainty and to avoid information search costs or being blamed for making a particular choice. Second, when herding, people infer information through observing others' actions. Network externality, on the other hand, is often the result of frequent information sharing among new and existing users. Third, while herding means that information is inferred from the general public or from well-informed predecessors, network externality is focussed more on the information inferred from those who can benefit most from one's adoption of this technology. Fourth, an adoption decision made via herding is fairly volatile and is prone to reversal. In contrast, network externality can serve to reinforce the value of a technology and make the user base less fragile (Li 2004). Finally, network externality—contrary to herd behavior, which often means that there is a dramatic burst of adopters—can actually have a chilling effect: people may delay their initial adoption, waiting for more early adopters to provide them with more network externality utility (Goldenberg et al. 2009).

Another similar concept is the subjective norm (SN) (Davis et al. 1989; Thompson et al. 1991; Venkatesh et al. 2003). An SN is defined as "a person's perception that most people who are important to him think he should or should not perform the behavior in question" (Fishbein and Ajzen 1975, p. 320). Thompson et al. (1991) proposed a concept of a social norm and acknowledged its similarity to SN. Both concepts capture the element of social influence and explain how a person believes those important to him/her will view him/her as a result of adopting a technology (Venkatesh et al. 2003).

Herd behavior is essentially different from SN in several ways. First, herding and SN differ in their information sources. SN usually comes from one's reference group, which consists of those who are important to him/her. For example, Thompson et al. (1991) studied the social norms of coworkers, supervisors, and managers. People in a person's reference group do not necessarily use the technology themselves. Herd behavior, on the other hand, usually has a much broader information source (e.g., prior iPhone purchasers). Also, while herding, one follows those predecessors who actually have adopted the technology. Second, herding and SN differ about what information is obtained and the motivations behind its acquisition. For example, a person often obtains information about the *norms* through being aware of SN. Such norms are "self-instructions to do what is perceived to be correct and appropriate by members of a culture in certain situations" (Triandis 1980, p. 126). An SN means that there is an expectation that the adoption decision may later be judged by the reference group: people care how the use of a certain technology will affect their image in their personal social systems (Moore and Benbasat 1991). Through herding, a person obtains such information about the perceived value of the technology and attempts to avoid costs or blame for an incorrect choice. He/she does not care about how the people he/she follows view him/her as a result of using a particular technology. Third, herding and SN differ in how information is obtained. An SN depends primarily on *messages received* from others (Thompson et al. 1991; Triandis 1980). Herd behavior depends on *observations* of other people's behavior.

Research Models and Hypotheses

Research Model

To build a research model of herd behavior in technology adoption and its continued use (Figure 1), this paper refers to Bhattacherjee and Premkumar's (2004) work on cognition change in technology adoption and continuance. Built primarily upon the expectancy–confirmation theory, the cognition change model (CCM) describes how people adopt and later continue to use an IS. According to the CCM, a person's initial beliefs about a technology determine his/her intention to use a technology. Later, the initial beliefs can be disconfirmed due to the availability of new information and personal experience with the technology. Such a disconfirmation influences his/her level of satisfaction and modifies that person's beliefs about the technology, which in turn influences his/her intention to continue to use the technology.

The CCM was chosen as the theoretical lens for two primary reasons. First, CCM addresses both the adoptive and the post-adoptive stages. This helps us to understand simultaneously the impact of herd behavior at the adoptive stage and the fragility of herd behavior at the post-adoptive stage. Second, CCM has constructs that can be easily tailored to study herd behavior. For instance, an understanding of initial beliefs and the intention to use is needed to study the impact of herd behavior on one's decision making. Post-adoptive factors such as disconfirmation, satisfaction, and intention to continue are necessary for examining the fragility of herd behavior. The disconfirmation construct is highlighted here because it is related to similar concepts, such as post-decision regret (Rao et al. 2001), that have been studied in prior herd research.

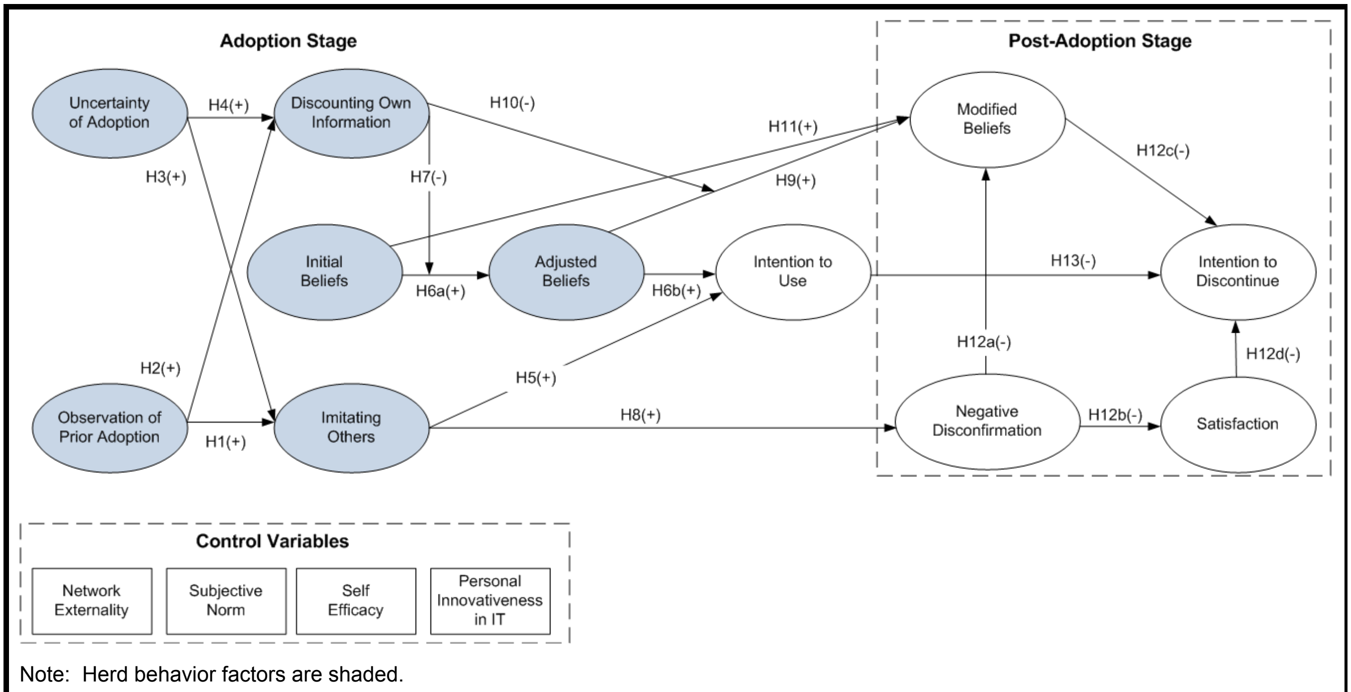

Figure 1. The Research Model

CCM was revised in two ways in this study to build the research model. First, herd behavior-related factors including IMI, DOI, and their antecedents (i.e., uncertainty and observation of others' adoptions) were integrated into the CCM. Second, to study the fragility of the herd, the disconfirmation construct was modified to focus solely on the negative disconfirmation; similarly, the intention to continue with the CCM was replaced with intention to discontinue.

Hypotheses

Antecedents of Herding

As mentioned above, the herd literature has suggested two conditions for herd behavior to occur: observation of others' action and uncertainty regarding the decision to be made. Both conditions abound in the context of technology adoption and make herd behavior commonplace in technology adoption.

The Internet and other digital channels provide people with easy access to observing other people's decisions pertaining to technology adoption (Duan et al. 2009). Society has paid considerable attention to the advances in information technology. For example, newspapers have been keen to keep their readers updated on the latest developments in information technology (e.g., *The New York Times* has a section focusing exclusively on information technologies). Also, numerous websites have been able to provide information on such aspects as product popularity, which summarizes the history of previous adoptions. For example, Download. com ranks products by "total downloads (by previous adopters)." Amazon. com provides information regarding what similar products other people have chosen and their popularity in terms of the number of previous purchases. In addition, the high level of availability of IT products in local stores allows people to observe others' adoption of a technology in their daily lives. For example, the observation provided through the wide press coverage by digital and traditional news channels that people waited in line to purchase the first-released iPad in April 2010 might have stimulated a large number of people to follow the trend and purchase an iPad themselves. The ubiquity of information technology in the workplace also makes it easy for one to observe the adoption of various information technologies by others. In summary, people have many opportunities to observe others' adoption of information technology through many channels.

When observing, people may pay attention to both the *number* and *identity* of technology adoption predecessors. On one hand, the number of such predecessors who made the same decision has a strong influence on followers' decisions. In general, the higher the number of predecessors making the same decision, the more likely one is to herd and to make the same decision (Banerjee 1992; Bikhchandani et al. 1992; Rao et al. 2001). For example, one may see a report that the iPhone has been accepted by "millions of users" and accordingly be driven to adopt an iPhone. On the other hand, the identity of previous adopters may also matter (Bikhchandani et al. 1992). People often follow the general choice trends of previous adopters, believing in the "wisdom of the crowd." Sometimes, however, they may follow a specific group of people, such as IT experts or fashion leaders, believing that they are more likely to have more accurate information than the general public (Bandura 1986). For instance, Boudreau and Robey (2005) have shown that people learn from "power users," who have more extensive experience with an information system.

The easy access to predecessors' decisions would make potential users more prone to imitate others' decisions and to discount their own information. It has been found that organizations learn from other organizations by following their actions, as in adopting innovations (Abrahamson 1991; Abrahamson and Rosenkopf 1993; Kraatz et al. 2001). The benefits of a particular type of technology may not become evident until it has been used for some time. Hence, skeptical adopters learn from observing the results of others' adoption and by doing so, infer more information with regard to the value of adoption (Bikhchandani et al. 1992; Kraatz and Zajac 2001). Such an inference regarding the value of a technology serves as a heuristic of social proof and may lead one to imitate the choice of another user and to question his/her own information if it is conflicting with others' information (Rao et al. 2001).

By following others, people may also attempt to save costs associated with information searching and experimentation (Rao et al. 2001). Information searching is a strategy people perform to deal with asymmetric information (Akerlof 1970; Fiol and O'Connor 2003; Langer 1989; Stiglitz 1975). It is often accompanied by an investment of time and energy, and probably a monetary investment as well. Also, information searching could be risky in that one may decide to give up the search and maintain the status quo, resulting in a waste of the personal investment that has been made (i.e., sunk costs). Moreover, even with the needed information in hand, one may still need to experiment with the technology being considered before making the decision to adopt it, which, again, is time- and energy-consuming. Therefore, a reasonable strategy to save the cost of information searching and experimentation is to follow others' actions and to take a free ride while giving up one's own beliefs, assuming that predecessors have gone through the necessary search and experimentation.

H1: Observation of other people's adoption is positively associated with IMI.

H2: Observation of other people's adoption is positively associated with DOI.

Another factor that makes herd behavior more common in technology adoption is the related uncertainty of technology adoption. Uncertainty in general refers to a person's perceived inability to predict something accurately due to having imperfect information (Milliken 1987; Pfeffer and Salancik 1978). Uncertainty is present when "a framework for interpreting a message is available, but there is a lack of information to process" (Dennis and Valacich 1999, p. 1). Thus, uncertainty of technology adoption can be viewed as *the degree to which one is unable to accurately predict the issues related to the adoption of a technology due to imperfect information.* Milliken (1987) identified three types of uncertainties: state uncertainty, effect uncertainty, and response uncertainty. State uncertainty is one's perception that the environment or a particular component of that environment is unpredictable. Effect uncertainty refers to one's inability to predict the nature of the impact of a future state of the environment or of a particular environmental change on the organization. Response uncertainty is one's lack of knowledge of response options and/or an inability to predict the likely consequences of a particular response choice. Each of the three types of uncertainty can occur in the context of technology adoption (Sun and Fang 2010). For example, one may be unclear about what a technology is for (state uncertainty). He/she may be uncertain about what a technology can do for him/her (effect uncertainty) and whether or not he/she is able to deal with potential changes of the technology, such as upgrades or requirements to download software to support it following adoption (response uncertainty).

The complexity of information technology and the imperfections in the related information lead to much uncertainty regarding technology adoption. As information technologies become increasingly more sophisticated, an accurate assessment of their respective values usually requires a more extensive range of knowledge, which makes choices difficult for most users (Bakos 1991; Duan et al. 2009). Also, information technology often has a large number of features and people may only have very limited experience with some of them when making the decision whether or not to adopt (Hiltz and Turoff 1981; Jasperson et al. 2005). What makes adoption decisions more uncertain is that it often takes time for the benefits of using a technology to unfold (Walden and Browne 2009). As a result, people are often uncertain about what the technology is truly about and what it can do for them at the time it is adopted.

Not surprisingly, people are likely to herd when they feel uncertain about a decision (e.g., Avery and Zemsky 1998; Banerjee 1992; Bikhchandani et al. 1992; Bikhchandani and Sharma 2000; Li 2004; Lieberman and Asaba 2006; Walden and Browne 2009). Uncertainty is the reason why people imitate the actions of others instead of making decisions based merely on their own information/beliefs. When uncertainty is high, an adopter is less able to analyze and understand the relationship between his/her adoption and the consequences of that adoption. This hinders making an accurate assessment of the potential utility of a particular technology. As a result, it is a legitimate strategy for one to simply follow the decision of others, doing what others have done, and discounting one's own information and beliefs, which are considered insufficient and incomplete.

H3: Uncertainty of technology adoption is positively associated with IMI.

H4: Uncertainty of technology adoption is positively associated with DOI.

Impact of Herd Behavior on Technology Adoption

Prior research on herd behavior suggests that imitation has a significant influence on one's own decision. This research posits that imitation of prior adopters of a technology has a significant and direct influence on one's intention to use this technology. First, the literature on compensation-based herding suggests that a driving force of imitation is to avoid the competitive disadvantages arising from rejecting a technology. Maug and Naik (1996) studied investors' herd behavior in situations where the compensation increased with an investor's own performance and decreased based on the performance of an established benchmark (i.e., other investors or an appropriate index). The fact that an investor's compensation may decrease if he/she underperforms with respect to the benchmark causes him/her to skew the investments toward the benchmark's portfolio (Bikhchandani and Sharma 2000). Therefore, imitation can be a legitimate way to avoid worst-case scenarios by obtaining an average compensation. The same applies to technology adoption. People may be worried about the possibility of wrongly rejecting an efficient technology and then suffering from technologically competitive disadvantages. In such situations, the adopters may demonstrate an aversion to risk by giving more weight to potential costs/risks than to predicted benefits and making decisions by *satisficing*—choosing a "good enough" option, which may or may not be the best option to enhance job performance the most (Kahneman and Tversky 1979; Thaler et al. 1997; Tversky and Kahneman 1974). Such a consideration can drive one to choose a technology adopted by many people to achieve above-average technical advantages.

Second, the literature on reputation-based herding (Bikhchandani and Sharma 2000; Graham 1999; Scharfstein and Stein 1990) also yields a similar prediction, which states that imitating others can enhance one's intention to use a technology. It has been observed that investment managers mimic the investment decisions of other managers to avoid the risk of being considered incapable (Graham 1999; Scharfstein and Stein 1990). The rationale here is that even if a manager makes an unprofitable investment by following others, such a mistake is not considered to be so bad because he/she can "share the blame" with his/her predecessors. People may "prefer the chance of being wrong with everybody else to the risk of providing a deviant forecast that turns out to be the only incorrect guess" (Anderson and Holt 1997, p. 848). As a result, herding is considered to be a legitimate strategy for both highly reputable people to protect their status (Graham 1999) and inexperienced/less reputable people to avoid damage to their reputations resulting from "bucking the consensus" (Chevalier and Ellison 1999). Similarly, in technology adoption contexts, imitation means that even if a technology adopted through herding turns out to be inefficient, it is still better than the situation where a person becomes the only one making the wrong decision of rejecting an efficient technology and then suffering damage to his/her reputation.

H5: Imitating others is positively associated with a person's intention to use a technology.

Previous studies on herd behavior have noted, explicitly or implicitly, that people may hold a different belief before than after the observation of others' actions. For example, Rao et al. (2001) suggested that financial analysts can update their assessment of a firm when observing other analysts' coverage of that firm. Therefore, this paper makes distinctions between initial beliefs and adjusted beliefs—those which are formed either before or after the observation of previous adopters. Consistent with the CCM, this study focuses on user beliefs about the usefulness of a technology. Accordingly, ***initial beliefs*** are defined as *user beliefs about the usefulness of a technology based on one's own information about that technology* ***prior to*** *the observation of others' adoption*. It is important to note that, although having the same label, the initial beliefs construct in this study is different from that in the CCM: the latter does not specify whether the beliefs are with or without the influence of observations of others' adoption. The term ***adjusted beliefs*** is defined as *user beliefs about the usefulness of a technology that are formed* ***after*** *the observation of others' adoption*. By definition, initial beliefs are formed before the observation of others' adoption and thus are more closely aligned with one's own needs and local use context. Adjusted beliefs, on the other hand, integrate the information inferred from the observation of others' adoption activities and are less relevant to one's own needs and how the technology fits into his/her own local use context.

It is important to note that individuals do not always have *ex ante* initial beliefs. For example, a person may learn about the iPhone for the first time when he/she observes that many people purchased iPhones in a local Apple store. The herd literature has clearly distinguished the situations where people have *ex ante* private information (before observing others) and where they do not: When one does not have private information or when information is limited, the decision is to simply follow the most popular decisions made by predecessors (Banerjee 1992; Bikhchandani et al. 1992). This research focuses on situations where people have private information prior to observing others' decisions to fully understand the cognitive processes people may go through when observing the actions of others.

The relationship between initial beliefs and adjusted beliefs represents a belief-updating process. The theory of belief-updating contends that people do not perceive a stimulus in its pure form; instead, the prior knowledge "is adjusted by the impact of succeeding pieces of evidence" (Hogarth and Einborn 1992, p. 8). IS researchers have applied the belief-updating process to study how prior user evaluations of a technology influence later evaluations (Kim 2009; Kim and Malhotra 2005; Venkatesh 2000). Specifically, users' prior evaluations of a technology serve as *anchors* for later evaluations. After direct experience with this technology, users may *adjust* their evaluations to reflect their direct interaction with the technology. Such new evaluations "reflect the new information but still rely on the initial anchoring criteria" (Venkatesh 2000, p. 345).

This research uses the term ***belief-adjusting*** to refer specifically to the *belief-updating process in herd behavior in technology adoption, during which people adjust their beliefs about a technology based on the observations of others' adoption of this technology*. The belief-adjusting process in herd behavior is different from the typical belief-updating process studied in prior IS research. First, belief-updating typically focuses on adjustments based on direct experience with a technology after it was adopted (Venkatesh 2000). Belief-adjusting in herd behavior, however, occurs at the adoptive stage before one makes the adoption decision. The new adjustment is based on observations of others' behavior. Second, the belief-updating process indicates that initial evaluations influence early behavior and later evaluations influence later behavior; at the same time, initial evaluations exert their influence on later behavior through later evaluations (Kim 2009; Kim and Malhotra 2005). In herd behavior, however, both initial beliefs and adjusted beliefs refer to the same adoption decision.

Nevertheless, it is expected that the basic principles of belief-updating are still applicable to the belief-adjusting process in herd behavior. Specifically, initial beliefs still serve as the "anchors" for adjusted beliefs. As mentioned earlier, people consider both their own information and their observations of others' actions, rather than just one or the other. Therefore, adjusted beliefs can be viewed as representing a synergy of initial beliefs and the information derived from observing others' actions. People subjectively determine the relative importance of these beliefs in making the adoption decision. Thus, adjusted beliefs replace initial beliefs and become the driving force for one to make the adoption decision (Kim 2009; Kim and Malhotra 2005).

H6: Adjusted beliefs mediate the impact of initial beliefs on intention to use.
- H6a: Initial beliefs are positively related to adjusted beliefs.
- H6b: Adjusted beliefs are positively related to intention to use.

In addition, discounting one's own information, by definition, means that a person relies less on his/her initial beliefs in forming the new adjusted beliefs than on the observations of others' action. The more a person discounts his/her information, the less important his/her initial beliefs are in forming adjusted beliefs, manifesting a weak anchoring effect of the initial beliefs. On the other hand, if a person does not discount his/her own beliefs, the adjusted beliefs should be essentially the same as the initial beliefs, indicating the strong anchoring effect of the initial beliefs. In short, DOI can weaken the anchoring effects of initial beliefs on the formation of adjusted beliefs during the belief-updating process. This is modeled as a negative moderating effect of DOI on the relationship between initial beliefs and adjusted beliefs.

H7: DOI will negatively moderate the relationship between initial beliefs and adjusted beliefs such that the relationship is weaker when DOI is high.

Impact of Herd Behavior on Post-Adoptive System Use

> *To the extent that adoption is based on imitation, we should expect to see overvaluation, disappointment, and abandonment.*
>
> — Rao et al. 2001, p. 503

In light of the fact that previous literature on herd behavior has focused on the low informativeness and subsequent fragility of the herd, this study proposes that herd behavior leads to negative disconfirmation at the post-adoptive stage. In CCM, disconfirmation is defined as the dissonance between the users' original expectations and subsequent observed performance; it can be either "positive or negative depending on whether the [level of] observed performance is above or below initial expectations, and is viewed as a deviation from the initial expectation" (Bhattacherjee and Premkumar 2004, p. 231). When a person experiences positive disconfirmation, his/her experience is better than what he/she originally thought. When one experiences negative disconfirmation, his/her experience turns out to be worse than he/she expected. Accordingly, this research defines ***negative disconfirmation*** as *the degree to which one believes that the observed performance of a technology is worse than early expectations*.

Prior research on herd behavior suggests that imitation leads to negative disconfirmation. When studying herd behavior in financial investment, Rao et al. (2001) argued that if an investment manager imitates others with respect to a firm, he/she is more likely to generate an unrealistic assessment of that firm and subsequently experience "post decision regrets." Abrahamson (1991) argued that organizations that imitate others may end up adopting technologically inefficient innovations. The rationale is that when people imitate others in adopting a technology, they may later find that the adopted technology does not meet their needs as anticipated or fit into their local use contexts. Parthasarathy and Bhattacherjee (1998) argued that later adopters, who are more likely to be affected by prior adopters' decisions, tend to be "vulnerable to disappointment and dissatisfaction." Hence, it is reasonable to predict that the more one imitates others, the more likely he/she is to choose a technology that does not meet his/her own needs or fit into the local use context and accordingly experiences negative disconfirmation.

H8: Imitating others at the adoptive stage is positively associated with negative disconfirmation at the post-adoptive stage.

Consistent with the CCM, this research defines modified beliefs as *the degree to which one perceives that a technology will be useful at the post-adoptive stage*. This research contends that people's post-adoptive modified beliefs are formed based on the adjusted beliefs at the adoptive stage through a belief-updating mechanism. Again, a belief-updating mechanism is the means by which one updates his/her beliefs based on both old beliefs and the new information about the technology one obtains through its actual use (Kim and Malhotra 2005). Early beliefs can be selectively stored in one's long-term memory and thus can also have distal effects on later beliefs (i.e., modified beliefs) (Kim 2009). When a new piece of information is received (e.g., from direct experience with the technology), the stored information about early beliefs is retrieved and serves as the anchor for the modified beliefs.

H9: Adjusted beliefs at the adoptive stage are positively associated with modified beliefs at the post-adoptive stage.

Herd behavior, by definition, implies a weakened anchoring effect of adjusted beliefs. User beliefs about a technology are usually stored as semantic memory, which is one type of explicit memory and is associated with memories of concepts about "what it is" (Kim 2009, p. 516). In a herding situation, people often bypass their own information to form adjusted beliefs. Thus, adjusted beliefs tend to include little information regarding what a technology is about and instead integrate a considerable amount of information regarding others' adoptions. The more one discounts his/her own information, the less information pertaining to how the technology meets his/her own needs and fits into local use contexts is stored in the long-term memory as adjusted beliefs, indicating a weaker anchoring effect of adjusted beliefs on modified beliefs.

In addition, people often obtain new information about a particular technology through direct interaction with that technology as well as from other information sources such as the mass media, various experts, and other users. For instance, the trend setters may discredit a technology; this new information may cause its popularity to dissipate rapidly (Abrahamson and Rosenkopf 1993). Such new information regarding the value of the technology may be more salient in forming modified beliefs when the adoption decision was made by herding. This is because, when herding, people know that their adoption decision is based primarily on observations of others' actions and they are thus more likely to rely less on adjusted beliefs and instead give more weight to new information. This can be viewed as another discounting process: people discount the importance of their adjusted beliefs when forming modified beliefs if they discounted their own information when adopting it. This is modeled as a negative moderating effect of discount own information (DOI) on the impact of adjusted beliefs on modified beliefs.

H10: DOI will negatively moderate the anchoring effect of adjusted beliefs at the adoptive stage on modified beliefs at the post-adoptive stage such that the effect is weaker when the level of DOI is high.

Initial beliefs may also be revitalized to serve as a new information source for post-adoptive modified beliefs. When people herd, their initial beliefs, rooted strongly in their local use context, are discounted in favor of observations of previous adoptions. However, after adoption, people often actively think again about the adopted technology in the local use context when provoked by discrepancies between reality and expectation (e.g., the technology does not meet needs), by novel situations (e.g., new features are observed), and by other people (e.g., colleagues, bosses) (Jasperson et al. 2005; Louis and Sutton 1991). Such active thinking is often characterized by mindfulness and awareness of local contexts (Langer 1989; Louis and Sutton 1991). As a result, people may engage in adaptation cycles during which they revise their system use in order to achieve a better alignment between the system and the context (Ahuja and Thatcher 2005; Barki et al. 2007; Boudreau and Robey 2005; Jasperson et al. 2005; Leonard-Barton 1988; Saga and Zmud 1994). This adaptation process often leads people to reassess the adopted technology more realistically, often requiring the retrieval of early initial beliefs stored in long-term memory, which are closely related to one's own needs and local contexts (Kim and Malhotra 2005). Such a revitalization of the relationship between the technology and the local context connects the previously held initial beliefs and the modified beliefs, indicating a *belief-reviving* process.

Evidence of this belief-reviving process can also be found in the herd literature. Rao et al. (2001) argued that when financial analysts experience post adoption regret as a result of their herd behavior with respect to an investment, they are likely to adjust their early evaluations to make them closer to reality. Similarly, it has been argued that disputes between rival authority figures can undermine people's willingness to obey authority and revitalize their own ability to weigh alternatives rationally (Morck 2004). So when people observe that the evidence conflicts with their choices (such as when the technology does not fit the local use context as expected), they will think more realistically about the adopted technology, indicating the revival of initial beliefs. It is thus argued that

H11: Initial beliefs at the adoptive stage are positively associated with modified beliefs at the post-adoptive stage.

The relationships among negative disconfirmation, modified beliefs, user satisfaction, and intention to discontinue are relatively straightforward and similar relationships have been studied in prior research (Bhattacherjee and Premkumar 2004; Parthasarathy and Bhattacherjee 1998). Therefore, this paper does not discuss these relationships at length. In general, when one negatively disconfirms his/her early beliefs about a technology, such a negative disconfirmation leads to a lower level of modified beliefs and user satisfaction with respect to this technology. Modified beliefs and user satisfaction are, in turn, negatively related to the intention to discontinue: when one perceives a technology to be useful and is satisfied with it, he/she is less likely to discontinue the use of it. It is thus hypothesized that

H12: Negative disconfirmation influences intention to discontinue through modified beliefs and user satisfaction.

- H12a. Negative disconfirmation is negatively associated with modified beliefs.
- H12b. Negative disconfirmation is negatively associated with user satisfaction.
- H12c. Modified beliefs are negatively associated with intention to discontinue.
- H12d. User satisfaction is negatively associated with intention to discontinue.

This research also adds to the CCM a direct relationship between intention to use at the adoption stage and intention to discontinue use at the post-adoption stage. Recent research has support for this relationship (Kim 2009; Kim and Malhotra 2005). The rationale for including this relationship is that it captures the sequential updating mechanism. Specifically, people form their behavioral intentions in relation to their previous intentions. Previous intentions are stored in long-term memory and can be retrieved to serve as an input for the formation of subsequent behavioral intentions (Kim 2009). Therefore, there is reason to believe that intention to use at the adoption stage can have a distal influence on the post-adoption intention to discontinue.

H13: Intention to use at the adoption stage is negatively associated with post-adoption intention to discontinue.

Control Variables

As mentioned earlier, network externality and subjective norms can also influence a person's decision to adopt a technology. This research thus statistically controls for these factors by including the impact of network externality and subjective norms on initial beliefs, adjusted beliefs, and intention to use, as suggested by prior research (Li 2004; Thompson et al. 1991; Venkatesh et al. 2003). Prior research has also suggested that personal factors influence technology adoption. This research thus controls for the influence of such factors as internal self-efficacy (Compeau and Higgins

Table 2. Experimental Design

<table>
<tr><th rowspan="2">Condition</th><th colspan="3">First Survey</th><th rowspan="2">Second Survey (8 weeks after the first survey)</th></tr>
<tr><th>Pre-treatment measures</th><th>Treatment*</th><th>Post-treatment measures</th></tr>
<tr><td>0. Control Group</td><td rowspan="3">• Situating task
• Initial beliefs
• Uncertainty and control variables
• Demographic data</td><td>No</td><td rowspan="3">• Imitating others
• Discounting own information
• Intention to use
• Adjusting beliefs
• Manipulation check items</td><td rowspan="3">• Modified beliefs
• Disconfirmation
• Satisfaction
• Intention to discontinue
• Intention to continue</td></tr>
<tr><td>1. Medium-Observation Group</td><td>Treatment 1 (the *number* of prior adopters)</td></tr>
<tr><td>3. High-Observation Group</td><td>Treatment 2 (the *number* and *identity* of prior adopters)</td></tr>
</table>

*The details of the treatments can be found in Appendix C.

1995; Thatcher et al. 2008) and personal innovativeness in IT (Agarwal and Karahanna 2000; Agarwal and Prasad 1998) on initial beliefs, adjusted beliefs, and intention to use.

Methodology

Research Design and Procedure

A longitudinal online experiment was conducted to examine the research model. PBwiki (**http://pbworks.com/**)—an online wiki system that allows users to work on web pages alone or collaboratively—was used as the research technology. The use of PBwiki helped to avoid the *ex ante* branding effect.

Table 2 summarizes the experimental design. The study includes two surveys conducted at the adoptive (Time 1) and post-adoptive (Time 2) stages, with an eight-week interval in between. At the beginning of the first survey, a description of the major features of PBwiki including its function, security, and customization was presented to the subjects (Appendix B). Subjects were then requested to report an example of what PBwiki could do for them at work or in a study based on the description. By doing so, this experiment situated subjects in the context of adopting PBwiki. Subjects then answered questions about their initial beliefs about PBwiki and their perceived uncertainty regarding adoption. Control variables including network externality, subjective norms, internal self-efficacy, and personal innovativeness in IT were also measured at this time. The simulation of technology adoption means that subjects should not have any prior experience with PBwiki. Hence, an item measuring prior experience with PBwiki, adapted from Kim and Malhotra's (2005) research, was included. Only those subjects who reported having little or no prior experience with PBwiki were considered to be qualified subjects and invited to continue with the survey.

Then, the subjects received different treatments, which were designed to manipulate the level of observation of previous adopters (see Appendix C for details). Subjects were randomly assigned to three groups—one control group and two treatment groups—and received different messages regarding the ***number*** and ***identity*** of early adopters. Subjects in the **control group** did not receive any information about the others' adoption of PBwiki. The **medium-observation treatment group** received a message stating that PBwiki had been adopted by a large number of users. This message delivered the information about the *number* of previous PBwiki adopters. The **high-observation treatment group** received two pieces of information: (1) the same message the medium-observation group received, and (2) a short list of some well-known organizations that had adopted PBwiki. This treatment delivered information about both the *number* and the *identity* of previous PBwiki adopters.

After the treatment page, subjects in the medium- and high-treatment groups reported their adjusted beliefs about PBwiki. All subjects were requested to answer the questions about IMI, DOI, and intention to use. Two items for manipulation check were also included, which measured the subjects' awareness of the number and identity of previous adopters, in response to the treatments (Appendix D).

To prepare subjects for the second survey, a message appeared at the end of the first survey to encourage the subjects to use PBwiki. The message mentioned that PBwiki was free to individual and educational users and that the second survey would be based on their use of PBwiki. It was also noted that the study was in no way affiliated with PBWorks, Inc., the company hosting PBwiki. Subjects were then directed to PBwiki's website to register.

The second survey was conducted eight weeks after the first survey. At the beginning of the second survey, subjects were asked about their use of PBwiki during the previous eight weeks. Those who did not use PBwiki at all during the previous eight weeks were excluded from the analysis. Then, such variables as modified beliefs, user satisfaction, disconfirmation, and intention to discontinue were measured. Intention to continue was also measured for robustness check purposes.

Measures

Measures Adapted from Prior Research

Appendix D lists the measures utilized in this research. Wherever possible, this research utilized previously validated instruments. The items for uncertainty of technology adoption were adapted based on Sun and Fang's (2010) work. Items utilized by Kim and Malhotra (2005) were adapted to measure initial beliefs, adjusted beliefs, and modified beliefs. The original measures from CCM were utilized to measure intention to use, level of satisfaction, and intention to continue (Bhattacherjee and Premkumar 2004). Two items were adopted from prior research to measure subjective norms (Taylor and Todd 1995). Agarwal and Prasad's (1998) measures were used for measuring personal innovativeness in IT. Internal self-efficacy was measured using the items from Thatcher et al. 's (2008) research. Three items for measuring the intention to discontinue were adapted based on Parthasarathy and Bhattacherjee's (1998) research.

The operationalization of a construct should match closely with its conceptualization (Churchill 1979). To be consistent with the prior herd literature, which focused on negative disconfirmation only, this research recoded the disconfirmation construct, following Cheung and Lee's (2005) approach. Disconfirmation covers both positive and negative disconfirmation, varying from 5 to 7 for "better than expected" (positive disconfirmation, PD) and from 1 to 4 for "worse than expected" (negative disconfirmation, ND). Based on existing research on the positive–negative asymmetry (Kahneman and Tversky 1979; Mittal et al. 1998), Cheung and Lee argued that PD and ND had an asymmetric impact on user satisfaction, so they adapted Mittal et al. 's approach and recoded the disconfirmation construct into two variables representing PD and ND. If a subject gave disconfirmation a rating of 7 (much better than expected), PD was set to 7 and ND was set to zero. On the other hand, if the subject gave disconfirmation a rating of 1 (much worse than expected), ND was set to 1 whereas PD was set to zero. Consistent with Cheung and Lee's approach, this research transformed each of the four measures of disconfirmation into two variables for PD and ND, respectively. The resulting four new variables for ND served as the reflective indicators of the ND construct.

$$\text{Negative Disconfirmation (i)} = \begin{cases} 4 & \text{if Disconfirmation (i)} = 1 \\ 3 & \text{if Disconfirmation (i)} = 2 \\ 2 & \text{if Disconfirmation (i)} = 3 \\ 1 & \text{if Disconfirmation (i)} = 4 \\ 0 & \text{if Disconfirmation (i)} = 5, 6, \text{or } 7 \end{cases}$$

i = 1, 2, 3, 4

Self-Developed Measures

Since there are no previously validated instruments for measuring IMI, DOI, or NE,[8] this research developed new instruments for them. Appendix E describes in detail how the instrument was developed, following the procedure set forth by Moore and Benbasat (1991). The instrument development process resulted in three items for IMI, three items for DOI, and five items for NE (Appendix D).

Prior research on formative constructs (Diamantopoulos and Winklhofer 2001; Jarvis et al. 2003; Petter et al. 2007) and multidimensional constructs (Edwards 2001; Law et al. 1998; Wetzels et al. 2009) has suggested different ways for conceptualizing IMI and DOI: as two distinct factors, two first-order reflective factors of a second-order construct, or as two first-order formative factors of a second-order construct. This research treats them as two distinct factors for two reasons. First, DOI and IMI do not necessarily co-vary and thus should not be modeled as two first-order reflective factors of a second-order construct. People may or may not discount their own beliefs when imitating others, depending on whether or not their own beliefs are contradictory to their observations. Second, it was decided not to treat IMI and DOI as two formative factors of a second-order latent construct. There is an ongoing debate regarding the use of formative factors (e.g.,

[8]Parthasarathy and Bhattacherjee (1998) developed an instrument for measuring network externality. However, their definition of network externality was different from that used in the current study. Specifically, they conceived of network externality as being the availability and use of complementary products such as user guides, "how-to" books, and tutorials marketed by independent third-party vendors to the adopters of a technology. Accordingly, their instrument for measuring network externality focused on the availability of products (e.g., books or tutorials) that complemented the use of a technology.

Diamantopoulos et al. 2008; Edwards 2011; Kim et al. 2010; Polites et al. 2011; Shin and Kim 2011). It is still unclear under what conditions and in what forms formative factors should be specified (Kim et al. 2010). The meaning of a formative factor may vary in different contexts (i.e., interpretational confounding) (Howell et al. 2007; Kim et al. 2010; Shin and Kim 2011; Wilcox et al. 2008). Also, using distinct factors can render a better understanding of how they influence other factors in different mechanisms (Edwards 2001). This advantage is obvious in this study: as shown in the research model, treating IMI and DOI as two distinct factors helps us gain a finer-grained understanding of how they influence technology adoption and post-adoptive system use through different mechanisms.

Survey Administration

The survey was conducted at a large northeastern research university in the United States. PBwiki is free for most educational uses and has been adopted by many major universities. In fact, educational use is one of the major businesses of PBwiki.[9] As of 2010, it has over 300,000 educational workspaces.[10] Therefore, the use by students represents the typical user population of PBwiki.

The first recruitment email was forwarded by an administrative staff member at the university to a listserv of 1,600 undergraduate and graduate students of a large information school. The recruitment email included the URL of the first online survey questionnaire and recruiting information including the aim and value of the study, privacy protection policy, institutional review board approval information, and incentive information. Once a subject clicked on the URL of the online survey, he/she was randomly assigned to one of the three groups. Four days later, a reminder email was sent to the members of the same student listserv. A total of 374 (with 118 in the control group, 123 in the medium-observation group, and 133 in the high-observation group) responses were collected after the first survey, representing an overall response rate of 23.4 percent. The difference in the numbers of responses in the three groups may be the result of different questionnaires being used by the groups.

Eight weeks later, the 374 respondents to the first survey were invited to participate in the second survey. Two items were used for measuring their use of PBwiki after the first survey. Those who did not use PBwiki were excluded, resulting in a final sample of 206 valid responses. Table 3 shows the demographic characteristics of the sample. To test for nonresponse bias, a wave analysis comparing the first and last quartile of respondents was conducted (Armstrong and Overton 1977). The results indicated that early respondents and late respondents were not significantly different with respect to age, gender, and level of education, suggesting that nonresponse bias should not be a concern for this study.

Data Analysis and Results

Control and Manipulation Checks

A control check was first conducted to ensure that people performed the situating task of exploring PBwiki features. The author examined the examples provided by the subjects regarding what PBwiki could do for them. Even though providing this example was not required, most of them (261 out of 374) provided a reasonable example, indicating to a certain degree the effectiveness of the situating task. In addition, ANOVA analyses revealed that the three groups did not differ significantly in age ($p = 0.161$), gender ($p = 0.567$), or education level ($p = 0.177$). Also, none of the paired comparisons were significant. These results indicated that the random assignment of the subjects was effective.

The first survey included two items for manipulation check. Asking a subject to state to what degree he/she was aware that "a lot of people have adopted PBwiki," the first item was about the *number* of prior adopters and was meant to assess the effectiveness of the first treatment that distinguished between the control group and the two treatment groups. The second item measured the degree to which a subject was aware that "PBwiki has been adopted by a lot of well-known organizations." It measured a subject's awareness of the *identity* of prior adopters that was meant to distinguish between medium- and high-observation groups. The ANOVA results showed that both items significantly differed across the three groups ($p < 0.002$ for item 1 and $p < 0.001$ for item 2). Bonferroni paired comparisons (Table 4) showed that item 1 effectively differentiated between the control group and the two treatment groups. Item 2, however, did not effectively distinguish between the medium- and high- observation groups, although the difference was in the expected direction (mean difference = -.476). Thus, the medium- and high-observation groups were combined for the rest of the analyses (hereafter called the **treatment group**).

[9] PBwiki has focused its attention on three areas: business use, educational use, and individual use (http://pbworks.com/).

[10] According to PBwiki's own statistics (see http://pbworks.com/content/edu+ overview?utm_campaign=nav-tracking&utm_source=Home%20navigation).

Table 3. Demographic Characteristics of the Sample

Demographic		0. Control Group	1. Medium-Observation Group	2. High-Observation Group	Total
Age	18–24	25	10	14	49
	25–34	25	17	34	76
	35–44	18	11	8	37
	45–54	2	8	12	22
	55–64	8	6	8	22
	65 years or older	0	0	0	0
Gender	Male	25	19	21	65
	Female	53	33	55	141
Education Level	High school	6	0	2	8
	Associate degree	0	0	2	2
	Some college, no degree	8	4	3	15
	Four-year college degree	2	4	6	12
	Some graduate school, no degree	25	20	18	63
	Master degree	33	19	37	89
	Ph.D., M.D., J.D., or other advanced degree	4	5	8	17

Table 4. The Results of Manipulation Check (One-Way ANOVA Analysis)

		Manipulation check item 1 (number of previous adopters)	Manipulation check item 2 (identity of previous adopters)
		Mean	
0. Control group		3.32	3.32
1. Medium-observation group		4.09	3.94
2. High-observation group		4.23	4.42
		Contrast (Bonferroni tests)	
0 versus 1	Mean difference	-. 774	-.629
	Standard error	.272	.274
	Significance	.014	.067
0 versus 2	Mean difference	-.911	-1.104
	Standard error	.270	.271
	Significance	.003	.000
1 versus 2	Mean difference	-.137	-.476
	Standard error	.271	.273
	Significance	1.000	.248

Interestingly, prior research also indicated that the identity of early adopters might not be as influential as the theory may have predicted. Studying how colleges learn from each other when adapting to environmental change, Kraaz and Zajac (2001) found that colleges often tend to imitate *similar* consortium partners rather than larger and more prestigious partners. Similarly, Terlaak and King (2007) showed that smaller organizational adopters had a disproportionate influence on later adopting organizations because they allowed observers to better infer that adoption would be profitable for their own organizations. Rao et al. (2001) found that while the status-weighted number of adoptions did not give an additional effect, they concluded that high-status prior adopters were not more influential than others.

The literature on analogical reasoning may explain why the treatment for differentiating between medium- and high-observation groups was not effective. It has been suggested that people use analogies for guided thinking and problem solving (Gavetti et al. 2005; Holland et al. 1986). Specifically, people learn from others by mapping, side by side, their own parameters with those of the observed (Holland et al. 1986). The referents are used as salient data points for making intuitive relative comparisons. Such referents should be somewhat different from the observer but should still be comparable. In the present study, the individuals in the high-treatment condition group might fail to find the listed well-known organizational adopters of PBwiki comparable and thus disregard such information.

Data Preparation and Analytical Methods

It is worth noting that the control group does not have data for adjusted beliefs (AB) because it makes little sense to include user beliefs twice in one questionnaire without any intervention. Also, this design avoids the problems associated with pretesting (i.e., that subjects try to recall their early answers) (Shadish et al. 2001). This research dealt with the missing AB for the control group in two steps. First, the initial beliefs (IB) scores for the control group were used as AB scores. This is reasonable since AB should be very similar, if not identical, to IB, in light of the fact that there was no intervention for the control group. Second, multiple imputations (MI) (Rubin 1987; Schafer 1997) were utilized to generate replacement IB scores. Using MI, missing values are predicted using existing values from other variables in the data set. The predicted values (called *imputes*) are used to replace missing values. This process is done several times, resulting in multiple imputations. Only a few imputations (e.g., three to five) are needed (Rubin 1987). How they are combined can produce an overall estimation of the missing values. MI is believed to perform favorably in situations where a large number of missing values are present and data are non-normal (Enders 2006; Schafer and Graham 2002). Also, compared to other common mechanisms, such as mean replacement or listwise deletion, MI produces unbiased parameter estimates and preserves the variability in the population and the relationships with other variables (Enders 2006).

This research utilized NORM, a software program that, according to Grover and Vriens (2006), is the most popular program for performing MI.[11] Schafer's (1997) two-step (*imputation* and *posterior*) data augmentation procedure was followed. This research proposed five multiple imputations for 1,000 iterations (so that one imputation was generated after 200 iterations). Accordingly, a total of five data sets with imputed IB scores was obtained. Their combination resulted in a data set with imputed scores for the control group's IB. This new data set was then used for the subsequent analyses.

Partial least square (PLS) was utilized to accommodate the presence of a complex model and the exploratory nature of this research (Fornell and Bookstein 1982). In addition, PLS uses bootstrapping to estimate standard errors for parameter estimate, which somewhat helps avoid the restrictive distributional assumptions (Chin 1998).

Observation of prior adoptions was coded using a dummy variable to categorically capture the manipulation (0 = the control group; 1 = the treatment group). To test for the moderating effects of DOI, this research referred to the product-of-sums approaches recommended by Goodhue et al. (2007). Specifically, the latent variable scores of the moderating factor (DOI) and the independent variables (IB and AB) were multiplied to generate two interaction factors: DOI × IB and DOI × AB. They were then linked to the dependent variables (i.e., IU and MB, respectively).

Measurement Model

The measurement model was assessed in terms of its reliability, convergent validity, and discriminant validity. The reliability of the scales was assessed by examining the composite reliability, which needs to be 0.70 or higher in order to demonstrate a sufficient level of reliability (Bagozzi and Yi 1988; Bearden et al. 1993; Nunnally and Bernstein 1994). Table 5 shows that all composite reliability values meet this criterion, indicating that the scales were reliable.

For convergent validity to be sufficient, items should load highly (loading > 0.707) on their associated factors and Average Variance Explained (AVE) should be larger than 0.5 (Barclay et al. 1995; Chin 1998; Fornell and Larcker 1981). Table 5 shows that all AVEs in this study were larger than 0.5. Appendix F shows that the items loaded well on their associated factors. Therefore, an acceptable convergent validity was observed.

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[11]NORM, developed by Joe Schafer at Pennsylvania State University, is based on the routines described in his work (1997). It is available at http://sites. stat. psu. edu/~jls/misoftwa. html.

Table 5. Descriptive Statistics					
Construct	No. of Items	Mean	Std. Dev.	AVE	Composite Reliability
1. UNC	4	2.96	1.53	0.64	0.88
2. DOI	3	3.52	1.12	0.56	0.79
3. IMI	3	4.10	1.42	0.82	0.93
4. IB	4	4.97	1.10	0.82	0.95
5. AB	4	3.67	0.96	0.87	0.96
6. IU	3	4.31	1.48	0.89	0.96
7. NE	5	4.42	1.21	0.71	0.93
8. SN	2	3.60	1.48	0.93	0.96
9. PIIT	3	5.10	1.47	0.81	0.93
10. SE	3	7.43	2.13	0.84	0.94
11. ND	4	0.78	0.67	0.89	0.97
12. MB	4	4.17	1.28	0.93	0.98
13. SAT	4	4.43	1.24	0.90	0.97
14. DIC	4	3.43	1.42	0.72	0.91

UNC: Uncertainty of Adoption
IB: Initial Beliefs
NE: Network Externality
SE: Self Efficacy
SAT: Satisfaction
IMI: Imitation
AB: Adjusted Beliefs
SN: Subjective Norms
ND Negative Disconfirmation
DIC: Intention to Discontinue
DOI: Discount of Own Information
IU: Intention to Use
PIIT: Personal Innovativeness in IT
MB: Modified Beliefs

Table 6. Square Roots of AVEs and Correlations†														
Construct	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. UNC	**.80**													
2. DOI	.24	**.75**												
3. IMI	-.12	.03	**.90**											
4. IB	-.19	-.08	.09	**.90**										
5. AB	-.31	-.10	.28	.55	**.93**									
6. IU	.44	-.18	.56	.36	.67	**.94**								
7. NE	-.08	-.13	.50	.25	.51	.52	**.85**							
8. SN	-.23	.02	.32	.31	.35	.43	.22	**.96**						
9. PIIT	-.15	-.13	.12	.05	.18	.12	.21	.02	**.90**					
10. SE	-.48	-.08	-.08	.13	.21	.16	.03	.18	.24	**.92**				
11. ND	.38	.15	-.28	-.10	-.10	-.38	-.17	-.23	-.07	-.20	**.94**			
12. MB	-.35	.18	.38	.24	.25	.49	.23	.27	.02	.26	-.55	**.96**		
13. SAT	-.42	-.14	.28	.07	.31	.25	.21	.20	-.01	.17	-.72	.51	**.95**	
14. DIC	.44	.18	-.22	-.16	-.25	-.59	-.18	-.21	.18	-.10	.61	-.46	-.76	**.85**

†The diagonal elements (in bold) are the square roots of the variance shared between the constructs and their measurement (AVE). Off diagonal elements are the correlations among constructs. Diagonal elements should be larger than off-diagonal elements in order to exhibit discriminant validity.

Two criteria were examined to assess the discriminant validity. First, the square root of the AVE should be greater than the variance shared among the construct and other constructs (i.e., correlations) (Chin 1998; Compeau et al.1999). This condition was satisfied, as shown in Table 6. Second, items should load more highly on their associated factors than on other factors. Appendix F showed that this criterion was met. Therefore, it is concluded that the desired discriminant validity was also achieved.

The longitudinal nature of this study helped to overcome the common method bias to some degree. In addition, a Harman's single-factor test was employed. This test loads all variables into an exploratory factor analysis and examines the unrotated factor solution to determine the number of factors that are necessary to account for the variance in the variables. According to Podsakoff et al. (2003, p. 889), common method bias may exist if a single factor emerges from the unrotated factor solution or if one general factor accounts for the majority of the covariance in the variables. Neither situation occurred in this study: no single factor accounted for a majority of the covariance. In addition, the longitudinal nature of the survey helped to overcome the common method bias. Therefore, the common method bias should not be a concern for this study.

Structural Model

As can be seen in Figure 2 and Table 7, most of the hypotheses were confirmed. Hypotheses 1 through 4 are about the antecedents of IMI and DOI. OBV was shown to be a significant antecedent of IMI (b = 0.204, t = 3.288, $p < 0.01$); UNC was shown to be a significant antecedent of DOI (b = 0.237, t = 3.998, $p < 0.01$). Hypotheses 1 and 4 were thus supported. However, the relationships between OBV and DOI (b = -0.018, t = 0.182) and between UNC and IMI (b = -0.110, t = 1.576) were not significant. Hypotheses 2 and 3 were not supported. A supplementary ANOVA analysis showed that the control group had a significantly lower level of IMI than the treatment group (contrast = -1.78, standard error = 0.59) (Appendix G, Analysis 1).

Hypotheses 5 through 7 are about the impact of herd factors at the adoptive stage. The results show that IMI had a significant effect on intention to use (b = 0.292, t = 6.114, $p < 0.01$), thus supporting hypothesis 5. Hypothesis 6 describes the mediating effects of adjusted beliefs on the relationship between initial beliefs and intention to use. The results show that IB had a significant impact on AB (b = 0.435, t = 7.559, $p < 0.01$); AB in turn significantly influenced IU (b = 0.437, t = 8.461, $p < 0.01$). Thus, hypotheses 6a and 6b were supported. A supplementary analysis showed that AB fully mediated the relationship between IB and IU (Appendix G, Analysis 2). Hypothesis 7, which was about the negative moderating effect of DOI on the impact of IB on IU, was also supported (b = -0.224, t = 2.016).

The results also show that herding is different from network externality and subjective norms and that they influence technology adoption at different magnitudes. Specifically, the image-driven SN had a significant impact on IB (b = 0.249, t = 4.166, $p < 0.01$), AB (b = 0.112, t = 2.107, $p < 0.05$), and IU (b = 0.148, t = 3.582, $p < 0.01$). The benefits-driven NE, on the other hand, significantly influenced IB (b = 0.192, t = 2.771, $p < 0.01$), AB (b = 0.292, t = 5.028, $p < 0.01$), and IU (b = 0.116, t = 2.212, $p < 0.05$). As for the herd factors, IMI had a significant direct impact on IU, which was beyond the influence of beliefs.

Hypotheses 8 through 13 are about the distal influence of herd behavior on post-adoptive system use. Hypothesis 8, concerning the positive relationship between imitation and negative disconfirmation was, although significant, in the opposite direction (b = -0.231, t = 3.383, $p < 0.01$). Thus, hypothesis 8 was not supported. AB had a significant impact on MB (b = 0.296, t = 3.864, $p < 0.01$). Also, DOI was found to have a significantly negative moderating effect (b = -0.171, t = 3.222, $p < 0.01$) on the relationship between AB and MB. So hypotheses 9 and 10 were supported. IB also had a significant effect on MB (b = 0.186, t = 2.032, $p < 0.05$), showing the belief-revival process (H11).

Hypothesis 12 concerns the relationships among negative disconfirmation, modified beliefs, satisfaction, and intention to discontinue. The results show that ND had significant negative effects on MB (b = -0.463, t = 9.899, $p < 0.01$) and SAT (b = -0.724, t = 28.982, $p < 0.01$), supporting hypotheses 12a and 12b. SAT significantly influenced DIC (b = -0.660, t = 14.950, $p < 0.01$), supporting hypothesis 12d. The relationship between MB and DIC was not significant (b = -0.051, t = 1.009). Thus, hypothesis 12c was not supported. In addition, a supplementary analysis was conducted to test the mediating effects of SAT and MB on the relationship between ND and DIC (Appendix G, Analysis 3). The results showed that SAT fully mediates the relationship between ND and DIC.

Hypothesis 13, concerning the direct relationship between intention to use at the adoption stage and intention to discontinue at the post-adoption stage, was supported (b = -0.159, t = 3.515, $p < 0.01$).

The model explains a significant amount of variance in the dependent variables including the intention to discontinue (R^2 = 0.61), modified beliefs (0.42), satisfaction (0.52), intention

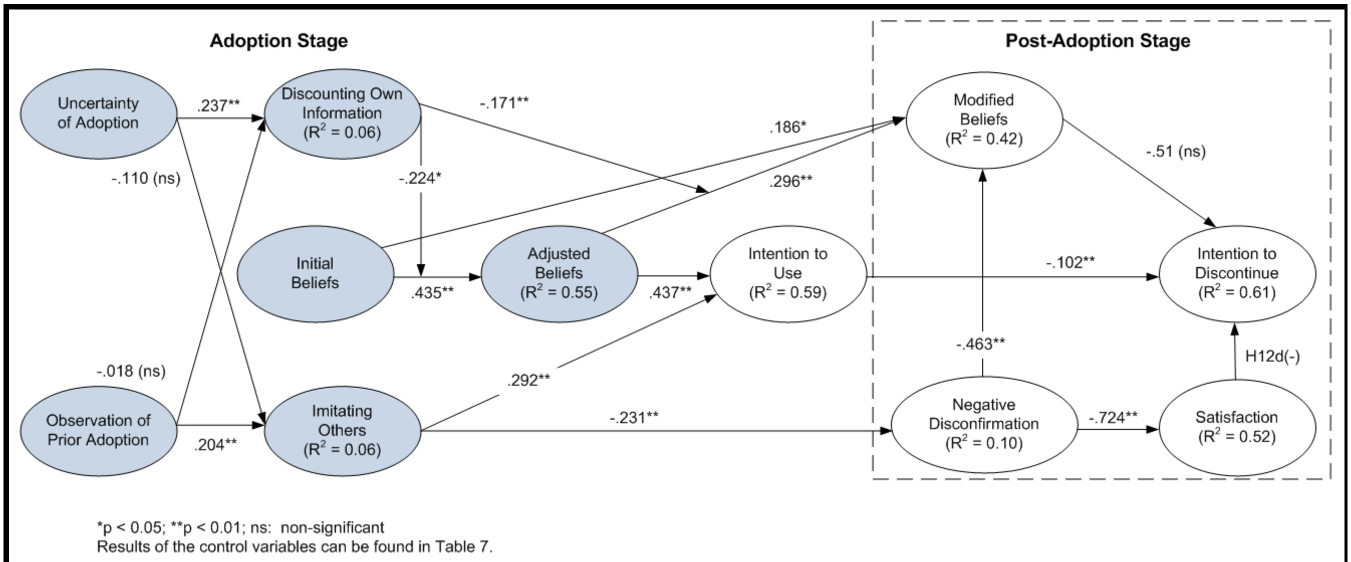

Figure 2. PLS Results of the Proposed Research Model

to use (0.59), and adjusted beliefs (0.55). A supplementary analysis showed that herd factors have a large effect on intention to use and a medium impact on modified beliefs (Appendix G, Analysis 4). The R-square for negative disconfirmation is relatively small (0.10). Small R-squares at this level are not uncommon in behavioral science research and do not present a threat to the model's validity (Cyr et al. 2009). The amount of actual association between constructs is often greater than the R square depicts (Cohen 1988; Cyr et al. 2009). In addition, negative disconfirmation is influenced by a single construct (i.e., IMI) and such an association tends to result in low R square values compared to multirelationship models (Cyr et al. 2009; Nunnally and Bernstein 1994).

Post Hoc Analyses

A model with extreme negative disconfirmation (eND) was tested because it has been argued that social salience (e.g., others' behavior) often results in extreme rather than moderate evaluations (Fiske and Taylor 1991). An eND was defined as *one's disconfirmation of his/her prior beliefs being extremely negative*. When the original disconfirmation was 1 or 2, eND was coded as 1, indicating an extremely negative disconfirmation, and was otherwise set to 0. This is consistent with Cohen and Cohen's (1983) guideline that one standard deviation above or below the mean can be considered as the cutoff for determining extreme values, given that disconfirmation has a mean of 4.39 and a standard deviation of 0.93. Dichotomizing eND is also consistent with Rao et al. 's (2001) method. The results (Table 7, Model 2) show that imitation has a significant impact on eND (b = -0.254, t = 4.576, $p < 0.01$).

The unexpected negative relationship between imitation and negative disconfirmation indicates that imitation can actually reduce post-adoptive negative disconfirmation. Subsequently, it might be possible that imitation can not only reduce post-adoptive negative disconfirmation, but also it even could enhance a positive disconfirmation and thus drive one to continue to use the technology. Thus, a model was tested that replaced the negative disconfirmation with positive disconfirmation and intention to discontinue with the intention to continue. Positive disconfirmation (PD) was conceived of as *the degree to which one believes that the observed performance of a technology is better than his/her early expectations*. Again, this research focused only on the extreme positive confirmation (ePD). An ePD was coded as 1 when the disconfirmation was 6 or 7 (4 is neutral), and was otherwise set to 0. As shown in Table 7 (Model 3), IMI did not influence ePD significantly (b = 0.057, t = 0.789).

Finally, a robustness check was conducted to address the observed high correlation (r = -0.76) between satisfaction and intention to discontinue. One strategy for dealing with such high correlations is to delete one or more of the highly redundant variables (Tucker and Chase 1980). Therefore, a new model without user satisfaction was examined. This model

Table 7. Results of the Structural Models

	Main Model		Alternative Models	
	Path coefficient and significance	**Hypothesis confirmed?**	**Model 2 (with extreme negative disconfirmation)**	**Model 3 (with extreme positive disconfirmation and intention to continue)**
Antecedents of herd factors				
OBV → IMI (H1)	0.204**	Y	0.203**	0.204**
OBV → DOI (H2)	-0.018$^{(ns)}$	N	-0.018$^{(ns)}$	-0.018$^{(ns)}$
UNC → IMI (H3)	-0.110$^{(ns)}$	N	-0.109$^{(ns)}$	-0.110$^{(ns)}$
UNC → DOI (H4)	0.237**	Y	0.237**	0.237**
Influence of herd factors at the adoptive stage				
IMI → IU (H5)	0.292**	Y	0.289**	0.292**
IB → AB (H6a)	0.435**	Y	0.435**	0.435**
AB → IU (H6b)	0.437**	Y	0.438**	0.437**
DOI → IB/AB (H7)	-0.224*	Y	-0.225*	-0.224*
Influence of herd factors at the post-adoptive stage				
IMI → ND (H8)	-0.231**	N (in opposite direction)	(IMI → eND) -0.254**	(IMI → ePD) 0.057(ns)
AB → MB (H9)	0.296**	Y	0.376*	0.330*
DOI → AB/MB (H10)	-0.171**	Y	-0.205*	-0.184**
IB → MB (H11)	0.186*	Y	0.223*	.186*
ND → MB (H12a)	-0.463**	Y	(eND → MB) -0.244**	(ePD → MB) 0.280**
ND → SAT (H12b)	-0.724**	Y	(eND → SAT) -0.377**	(ePD → SAT) 0.691**
MB → DIC(H12c)	-0.051$^{(ns)}$	N	-0.051(ns)	(MB → IC) 0.135**
SAT → DIC (H12d)	-0.660**	Y	-0.660**	(SAT → IC) 0.445**
IU → DIC (H13)	-0.159**	Y	-0.159**	(IU → IC) 0.347**
Control variables				
NE → IB	0.192**		0.192**	0.192**
NE → AB	0.292**		0.293**	0.292**
NE → IU	0.116*		0.116*	0.114*
SN → IB	0.249**		0.250**	0.250**
SN → AB	0.112*		0.112*	0.112*
SN → IU	0.148**		0.149**	0.148**
PIIT → IB	-0.019$^{(ns)}$		-0.019$^{(ns)}$	-0.019$^{(ns)}$
PIIT → AB	0.058$^{(ns)}$		0.058$^{(ns)}$	0.058 $^{(ns)}$
SE → IB	0.079$^{(ns)}$		0.079	0.079
SE → AB	0.160**		0.159**	0.160**
SE → IU	0.063$^{(ns)}$		0.062$^{(ns)}$	0.063$^{(ns)}$

	Main Model		Model 2		Model 3	
No. of cases	ND>0	148	eND > 0	23	ePD > 0	44
	ND=0	57	eND = 0	175	ePD = 0	154

$^{*}p < 0.05$ $^{**}p < 0.01$ $^{(ns)}$Nonsignificant

IMI: Imitation
UNC: Uncertainty
ND: Negative Disconfirmation
OBV: Observation
AB: Adjust Beliefs
IB: Initial Beliefs
DOI: Discounting Own Information
IU: Intention to Use
MB: Modified Beliefs
SAT: Satisfaction
SE: Self Efficacy
IC: Intention to Continue
NE: Network Externality
SN: Social Norm
ePD: Extreme Positive Disconfirmation
DIC: Intention to Discontinue
PIIT: Personal Innovativeness in IT
eND: Extreme Negative Disconfirmation

had a new direct relationship between negative disconfirmation and intention to discontinue. The results were very similar to the original model, suggesting that the high correlation between satisfaction and intention to discontinue did not influence the findings significantly.

Discussion

In adopting a new technology, people often imitate others and discount their own information about the technology. This research developed a model to investigate how people herd when adopting a technology and how such herd behavior has distal influences on post-adoptive system use. This model was examined using a sample of 206 undergraduate and graduate students who used a wiki system.

Major Findings

The results show the existence and the significant influence of herd behavior in the context of technology adoption. Observation of a large number of previous adopters can cause one to imitate others. Uncertainty with respect to adoption leads one to believe that his/her own information is insufficient, and thus he/she is likely to discount it. Imitation has a large effect on one's intention to use a technology at the adoptive stage. People adjust their initial beliefs to integrate the observation of prior adopters and form new adjusted beliefs; such adjusted beliefs subsequently become the major determinant of their intention to use. The significant negative moderating effect of discount own information on the transformation of initial beliefs into adjusted beliefs indicates that people give less weight to their initial beliefs when discounting own information. When juxtaposed against the finding that initial beliefs still influence adjusted beliefs significantly, this finding shows how people adjust their beliefs. Specifically, initial beliefs based on one's own information still play an important role in anchoring adjusted beliefs; however, they are less important when the adopter discounts his/her own information. This supports prior arguments that people consider both their own information and others' actions in their decision making (Avery and Zemsky 1998; Hey and Morone 2004).

This research did not confirm the impact of observation of prior adoption on discounting own information, implying that observing prior adopters does not necessarily lead one to discount his/her own information. This may happen when a person's observation is consistent with that person's previously held beliefs (Banerjee 1992). Similarly, the results show that uncertainty of adopting a technology does not directly drive one to imitate others. This supports the prior findings that people may still imitate others when they are certain about the decision (e.g., Prechter 1999). Also, a very high level of uncertainty may actually prevent one from imitating others to adopt a technology, no matter what other people do with it.

The results also show the distal effects of herd behavior on post-adoptive system use. When herding, people rely on adjusted beliefs, which are less relevant to one's own needs and local use contexts. As a result, adjusted beliefs have relatively weak anchoring effects on modified beliefs about a technology, which people form after adoption. The more a person discounts his/her initial beliefs to form adjusted beliefs, the weaker are the anchoring effects of adjusting beliefs in forming modified beliefs. On the other hand, although not influencing the intention to use directly at the adoptive stage, initial beliefs are revitalized to influence modified beliefs, indicating that people return to their own needs and local use contexts at the post-adoptive stage.

Imitation had a significant negative effect on post-adoptive negative disconfirmation, suggesting that this research observed a well-informed correct herd (i.e., accepting a technically sound technology). Although unexpected, this result is not surprising. After all, correct herds are, in general, more likely to appear than incorrect ones (Bikhchandani et al. 1998; Walden and Browne 2009). The use of PBwiki may somewhat account for the formation of a correct herd in this study. PBwiki is a relatively simple technology with a straightforward purpose and design. Therefore, potential adopters are less uncertain about adopting it, as reflected by the low uncertainty of adoption in this study (mean = 2.96). In such low-uncertainty situations, people are more likely to converge on the correct herd (Bikhchandani et al. 1998).

Apparently, the relationship between imitation and post-adoptive negative disconfirmation needs to be studied separately in correct herds and incorrect herds. This study shows that in a correct herd imitation is a legitimate strategy to reduce post-adoptive negative disconfirmation. This somewhat explains Walden and Browne's (2009) finding that correct herds are robust in the face of contrary information. Moreover, imitation does not help to choose a technology that best fits people's needs and brings beyond-expectation experiences, as suggested by the nonsignificant relationship between imitation and positive disconfirmation. Therefore, one may still consider leaving a correct herd and moving toward a superior technology when the signal in favor of that technology is strong enough. In incorrect herds, on the other hand, it is reasonable to believe that people may form unrealistic beliefs based on observation of others' adoption and are more sensitive to contrary information and more likely to experience negative disconfirmation (Rao et al. 2001; Walden and Browne 2009).

Research Implications

This research enriches the understanding of the widely studied relationship between user beliefs and intention to use. IS researchers have long been interested in initial user adoption of technology (i.e., Davis et al. 1989; Igbaria et al. 1997; Straub et al. 1997). Existing research on user technology acceptance, for example the technology acceptance model (Davis 1989; Davis et al. 1989), has emphasized the impact of users' *own* beliefs on their adoption, and, as a result, are not very effective when attempting to explain herding behaviors, which are characterized by the discounting of these personal beliefs. This study shows the importance of considering the direct influence of imitation on the formation of intention to use, beyond that of user beliefs.

This research distinguishes between three types of user beliefs: initial beliefs, adjusted beliefs, and modified beliefs. People may form distinct types of beliefs at the adoption stage, before and after the observation of others' adoption. After adoption, people also form modified beliefs. Initial beliefs and modified beliefs are more closely aligned with one's own needs and local use contexts; adjusted beliefs are the result of herding and less related to one's needs and local contexts.

This research to some degree addresses the "efficient-choice" assumption held in prior IS research. This assumption suggests that one always takes into account all of the information he/she has and always make the best possible choice; this assumption inhibits the understanding of the question of why technically inefficient information systems are sometimes accepted or efficient ones are rejected (Abrahamson 1991). This research suggests that herd behavior may account for why people do not always choose the most efficient technology: people may bypass their own beliefs and instead base their adoption decisions on observations of others' adoption. Imitation becomes a strategy of satisficing: people do not always choose the most efficient technology but instead choose an acceptable one. Although this strategy may not lead to the selection of the most efficient technology, it helps to avoid the worst-case scenario by reducing negative disconfirmation.

The results suggest that the general "influence of others" can be decomposed into three different types. First, a person considers how the people important to him/her would view him/her as a result of adopting a technology (subjective norm) in forming his/her initial beliefs about this technology. Second, he/she may consider the benefits resulting from the fact that he/she and others will use the technology together (network externality). Both subjective norm and network externality can not only enhance his/her beliefs about the usefulness of the technology but also directly drive his/her intention to use it. Finally, people may adopt a technology by simply observing previous adopters (herd behavior).

This research also has implications for studying post-adoptive system use. More attention has been given to studying post-adoptive behavior in recent years (e.g., Bhattacherjee 2001; Burton-Jones and Straub 2006; Jasperson et al. 2005; Limayem et al. 2008). IS researchers have investigated the bridge between initial adoption and post-adoptive behavior from various perspectives such as belief updating (Kim and Malhotra 2005), memory theory (Kim 2009), habit (Kim et al. 2005; Limayem et al. 2008), and expectation–confirmation (Bhattacherjee 2001), to name a few. This study adds to the existing research by presenting a new mechanism by which initial adoption and post-adoptive behavior are connected: imitation can reduce post-adoptive negative disconfirmation. In addition, this research enriches the understanding of the belief-updating process. First, the anchoring effects of adjusted beliefs on post-adoptive modified beliefs can be weakened if one discounts his/her own beliefs when adopting the technology. Second, people may revitalize their initial beliefs as a new information source to form new beliefs at the post-adoptive stage.

This research suggests that prior research on herding may have overemphasized the fragility of herd resulting from low informativeness: the assertion that low informativeness leads to this fragility may be too simplistic. First, low informativeness does not necessarily mean incorrect herds. People are more likely to form correct herds, which, although they may still be less informative, are more stable than incorrect herds (Walden and Browne 2009). This research shows that in a correct herd, imitation can actually fortify the position of the herd by reducing post-adoptive negative disconfirmation. Second, the initial low informativeness of a herd is only one factor accounting for the fragility of the herd. Existing studies have shown that post-adoption factors—such as the newly recognized value of the technology and the industry standard (David and Strang 2006), switching costs and sunk costs (Farrell and Klemperer 2004), and network externality (Li 2004)—may reinforce a herd's position. Third, the influence of new contrary information may not be sufficient to reverse the position of a herd. Walden and Browne (2009) found that contrary information was very harmful to incorrect herds, but not very damaging to correct herds. In summary, rather than focusing on the low level of informativeness, and the resulting fragility of the herd, it may be more essential to distinguish between incorrect and correct herds, to consider post adoption factors that may offset the influence of low informativeness, and to investigate how contrary signals may have reversed the position of a herd.

One implication of this study is that negative disconfirmation and positive disconfirmation are influenced asymmetrically by imitation. This observation supplements prior arguments about the asymmetric effects that negative and positive disconfirmations have an asymmetric influence on user satisfaction (Cheung and Lee 2005; Mittal et al. 1998).

Contributions

Conceptually, this research has defined two new factors—imitating others and discounting own information—to describe herd behavior in technology adoption. Both factors enrich the understanding of user technology adoption and its continued use. The research also developed new instruments for measuring IMI, DOI, and NE. Theoretically, this research developed a research model of herd behavior in technology adoption and its continued use, which describes herd behavior in technology adoption, a phenomenon that, to date, has received little attention from IS research. This paper highlights the *belief-adjusting* and the *belief-reviving processes* that are essential for herd behavior in technology adoption. This research also contributes to the existing body of herd literature. First, as mentioned earlier, this research suggests that prior herd research may have overemphasized the fragility of the herd. Second, the delineation of the micro-level cognitive process underlying herd behavior complements the existing herd literature and can be used to distinguish between true herding and spurious herding.

Limitations and Future Research

The sample size, albeit acceptable in the general view, is still small. Although PLS was used since it is believed to be sufficiently robust in the case of small sample sizes (e.g., Fornell and Bookstein 1982; Lohmöller 1989), a larger sample size would have been desirable to increase the statistical power of the study. The use of PBwiki in this research may also have posed some limitations. People were generally less uncertain about what it is and how it is used. The low level of uncertainty may have interfered with our gaining an understanding of herd behavior, especially, as mentioned earlier, the influence of herd behavior on post-adoptive negative disconfirmation. Future research can address this limitation by choosing a technology about which potential adopters are generally more uncertain.

Not measuring adjusted beliefs in the control group is another limitation of this study. Indeed, it represents a methodological dilemma. On the one hand, initial beliefs and adjusted beliefs use the same measures and it makes little sense to measure the same item twice in one questionnaire. Also, measuring the same items twice can create pretesting bias which threatens internal validity (Shadish et al. 2001). On the other hand, not measuring AP directly is admittedly a methodological shortcoming. To somewhat overcome this shortcoming, this research utilized multiple imputations to deal with missing values. Nevertheless, an alternative, and probably preferable, way to do this is to measure AP directly, keeping in mind the potential threat to internal validity of pretesting bias.

One promising topic would be to investigate which group of previous adopters is usually followed. This question regarding who to follow may be more complex than previously thought. Prior research has often assumed people follow the most prestigious adopters (e.g., fashion leaders). However, in the present study, the identity of previous adopters did not appear to make much difference for people in making their decisions to herd. Prior research on analogical reasoning may be a good starting point to pursue this topic (Gavetti et al. 2005; Holland et al. 1986).

Another interesting topic concerns contrarian behaviors: people may sometimes explicitly seek to avoid joining a herd. For example, financial analysts may intentionally avoid making forecasts that are too close to the publicly available forecasts to avoid being considered mediocre (Bernhardt et al. 2009; Cipriani and Guarino 2005; Drehmann et al. 2005). Similarly, in studying organizations' adoption of innovation, Abrahamson and Rosenkoft (1993) argued that "certain organizations are intent on looking different than other organizations and reject an innovation because too many other organizations have adopted it" (p. 505). The same may apply to technology adoption: people may intentionally avoid joining a herd when adopting a technology. People may feel that adopting a popular or fashionable technology may make them look mediocre. Also, a technology may be so popular that people start questioning prior adopters' rationality and reject joining the herd. Future research may investigate why and in what conditions people engage in contrarian behavior with respect to technology adoption.

Also, it is appealing to investigate the relationship between system design features—for example, system restrictiveness

(Silver 1990) and complexity (Walden and Browne 2009)—and herd behavior. For example, system complexity may contribute to uncertainty of adoption and thus induce herd behavior. More thinking along this line may produce fruitful findings for system design and implementation.

Finally, a promising topic would be to study the influence of individual factors on herd behavior. After all, not everyone ends up joining a herd, and different people exhibit different degrees of herd behavior. Studying who is more likely to join a herd is, therefore, worth further examination. For example, Fiol and O'Conner's (2003) research implies that mindfulness may influence one's decision about whether or not to join a herd.

Practical Implications

For IT practitioners, this paper shows that herd behavior exerts a strong influence on users' adoption of a technology. A herd is idiosyncratic in that early adopters determine the choice upon which followers converge. This explains to some degree why people have converged so quickly on some technologies such as the iPhone and iPad. Hence, creating herding effects can dramatically boost the adoption of a technology. It is important to note that the results of this study showed that the presentation of highly prestigious organizational adopters is ineffective to create a herd phenomenon. Individual users may not find that the advertised organizational adopters are compatible with their decisions. Therefore, to create herd effects, IT practitioners should consider the similarities between the advertised prior adopters and potential users.

IT practitioners are often under pressure to show the staying power of their user groups. Twitter. com, for example, is "facing pressure to prove it has staying power, as a good number of users lose interest in the service after trying it for a while."[12] The good news is that people can stay with a technology after adopting it by imitating others. However, IT practitioners should keep in mind that people who adopt a technology by herding may leave this herd *en masse*, which risks collapsing the current user base. Users eventually will revitalize their own needs and local use contexts. Therefore, creating network externalities, actively thinking of the value of their technology, and effectively presenting these values to their users is crucial to increase the staying power of the herd.

[12]Jessica E. Vascellaro, "Twitter Trips on Its Rapid Growth," *Wall Street Journal*, May 26, 2009 (http://online.wsj.com/article/SB124329188281552341. html).

For IT users, this research suggests that imitation may be a legitimate strategy for choosing an acceptable technology. Imitation can help reduce post-adoptive negative disconfirmation, but, at the same time, it does not promote positive disconfirmation or lead to beyond-expectation experience. So if the purpose is to choose an acceptable technology, imitation is a legitimate strategy, especially when collecting all the relevant information is considered to be unrealistic or not worth the effort. However, if the purpose is to find the most efficient technology, the user should avoid imitation. The most popular technology could be technically inferior and the fad may soon dwindle. To choose the most efficient technology that meets one's own needs and use contexts, a user should try to avoid unwittingly following a herd but should be mindful of the technology being adopted and of his/her own needs.

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RESEARCH ARTICLE

A LONGITUDINAL STUDY OF HERD BEHAVIOR IN THE ADOPTION AND CONTINUED USE OF TECHNOLOGY

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Appendix A

Summary of Relevant Literature on Herd Behavior

Study	Area	Definition of Herd Behavior or Similar Concepts	Major Findings
Abrahamson 1991	The diffusion of innovations across organizations	Organizations imitate others when adopting innovations.	Organizations may imitate each other when adopting innovations as fads or fashions. As a result, technologically inefficient innovations may diffuse among organizations and technologically efficient ones may be rejected.
Abrahamson and Rosenkopf 1993	The diffusion of innovations across organizations	Conceptualized as a bandwagon effect and defined as "diffusion processes whereby organizations adopt an innovation, not because of their individual assessments of the innovation's efficiency or returns, but because of a bandwagon pressure caused by the sheer number of organizations that have already adopted this innovation" (p. 488).	Bandwagon pressure, prompting other organizations to adopt this innovation. People join a bandwagon to avoid appearing different from the many other adopters.
Anderson and Holt 1997	General prediction decision making	Information cascades occur when people follow the established patterns, regardless of their private information.	When initial decisions coincide, it is rational for subsequent decision makers to follow the established patterns, regardless of their private information. Reverse cascade may also occur: "the initial decision makers are unfortunate to observe private signals that indicate the incorrect state, and a large number of followers may join the resulting pattern of "mistakes," despite the fact that their private signals are more likely to indicate the correct state" (p. 847).

Study	Area	Definition of Herd Behavior or Similar Concepts	Major Findings
Avery and Zemsky 1998	Financial investment	Herding happens when a trader who is pessimistic about the value of an assess buys it given the positive history of trading and his/her own information.	The price mechanism of the financial markets prevents information cascade from happening. Herding may occur in the presence of multi-dimensional uncertainty. As the number of dimensions of uncertainty increase, herding becomes possible. When traders are uncertain about the quality of the information they have, they are likely to follow the trend of past trades and can mis-price the asset values.
Banerjee 1992	General decision-making	Herd behavior means "everyone doing what everyone else is doing, even when their private information suggests doing something quite different" (p. 798).	People follow others in making decisions. People may join a herd, ignoring their own information. This inflicts a negative herd externality on the followers. Herd behavior may lead to undesirable outcomes. The equilibrium of a herd resulting from herd externality is quite volatile.
Bernhardt et al. 2009	Financial forecasting	Herding is a choice that biases a forecast away from an analyst's best estimate of earnings (i.e., the mean or median of his posterior), toward the consensus forecast of earlier analysts. Anti-herding is a choice to announce a forecast of earnings that is further from the consensus than the analyst's information suggests, so that the analyst's forecast overshoots his prior estimate of earnings away from the consensus in the direction of his private information.	Financial analysts anti-herd: they try to avoid herd behavior by issuing biased forecasts that fall in between his/her own forecasts and the public-available consensus forecasts. They do so in order to distinguish their forecasts from others.
Bernheim 1995	General decision making	Conformity: People conform to a single, homogeneous standard of behavior (social norm)despite heterogeneous underlying preferences.	People conform to social norms to avoid their social status being seriously impaired. The society censures nonconformists.
Bikhchandani et al. 1992	General decision making	Information cascade: An information cascade occurs when it is optimal for an individual, having observed the actions of those ahead of him, to follow the behavior of the preceding individual without regard to his own information.	People follow others in making decision when uncertainty is present. They observe the actions of others and make decisions, based on their own information and observations. Information cascades occur when people disregard their private information and follow whatever others did. Mass behavior resulting from information cascades is often fragile; small shocks can lead to large shifts in behavior.

Study	Area	Definition of Herd Behavior or Similar Concepts	Major Findings
Çelen and Kariv 2004	General decision making	Cascade behavior: acting irrespective of their private signal. Herd: individuals choose the same action.	Both meaning that people do the same thing, an information cascade and herd behavior are inherently different. The former implies that when making a decision, people ignore their private information; the latter occurs when people make an identical decision, not necessarily ignoring their private information. Therefore, an information cascade implies a herd but a herd is not necessarily the result of an information cascade. Informational cascades are usually reflected in unobservable beliefs; herds are observable actions.
Cipriani and Guarino 2005	Financial investing	Informational cascade is a situation in which it is optimal for a rational agent to ignore his own private information and conform to the established pattern of trade.	The price mechanisms of financial markets effectively prevent herding from happening. Traders do not herd. Furthermore, they show contrarian behavior: they ignore their private information to trade against the market.
David and Strang 2006	Management fashion	Management fashion: attention rapidly coalesces around a management practice as a powerful and robust means of achieving competitive success (p. 215).	This paper investigates the phenomenon of a fashion boom turning into a fashion bust, using the fashion of total quality management (TQM). The authors observed the fragility of fashion booms. The fashionable practice seems to have considerable staying power. The fashion may help practitioners find the value of the innovation.
Drehmann et al. 2005	Financial investing	An informational cascade is said to occur when it becomes rational to ignore one's own private information and instead follow the predecessors' decisions (p. 1404).	Consistent with Avery and Zemsky (1998), this study does not find herd behavior in financial markets. The price mechanism effectively incorporates public information and subsequently prevents herding from happening. This study supports the existence of contrarian behavior. People may doubt the rationality of others and consequently mistrust others' decisions. This can lead to contrarian behaviors: One trades again his/her own information and again the market.
Fiol and O'Connor 2003)	Managers' decision making	Bandwagons are diffusion processes whereby individuals or organizations adopt an idea, technique, technology, or product because of pressures caused by the number of organizations that have already adopted it.	This paper studies "micro-level processes" of managers' decision making. Managers' mindfulness influences how they scan and integrate information and consequently influences their decisions to join a bandwagon.
Graham 1999	Financial investment	Herd behavior is often said to occur when many people take the same action, perhaps because some mimic the actions of others (p. 237).	If an analyst has high reputation or low ability, or if there is strong public information that is inconsistent with the analyst's private information, he/she is likely to herd. Herding is also common when informative private signals are positively correlated across analysts (p. 237).

Study	Area	Definition of Herd Behavior or Similar Concepts	Major Findings
Grinblatt et al. 1995	Financial investment	Herding: The extent to which the group of mutual funds either pre-dominantly buys or predominantly sells the same stock at the same time (p. 1089).	Herding may occur when people rely on the same information. The study did find a significant, though small, herding effect in investment.
Hey and Morone 2004	Financial investment	The same as (Banerjee 1992) and (Bikhchandani et al. 1992).	Although some prior research shows that the price mechanisms in markets can aggregate private information effectively, which can prevent herd behavior from happening, the authors challenged this assertion. Their findings show that socially undesired results are present. This indicates that herd behavior may exist in markets.
Kraatz and Zajac 2001	Organizations' imitations	Imitation.	This study proposed hypotheses from different perspectives such as bandwagon imitation, status-driven imitation, and social learning perspectives. The findings show that private colleges, in turbulent years, tended to imitate similar consortium partners that were performing well in adaptation to changes.
Li 2004	IT adoption	Herd behavior may arise because of informational cascades, which occur when rational individuals ignore their private information and instead mimic the actions of previous decision makers (p. 93).	IT managers often make adoption decisions in uncertainty environment and with imperfect information. Information cascades may explain why people herd in technology adoption. Network externality may reinforce information cascades and reduce the possibility of cascade reversals.
Rao et al. 2001	Securities analysts' coverage of firms listed on the NASDAQ market.	Herd behavior is reflected by investors' coverage of a firm, following previous coverage by others.	Social proof, inferred from observing the actions of others especially the most recent ones, is easy to use, but at the same time, leads to errors and subsequent decision reversal. People do not use external cues for making choices about abandon of a course of action. They argued that uncertainty may be needed for herd of abandonment to occur at the post-adoptive stage.
Walden and Browne 2009	IT adoption		Using simulation, they found herd behavior in adoption of technology. Correct herds are more likely to appear than incorrect herds. Incorrect herd is more likely than correct herds to be reversed by contrary signals. Theoretically, all herds will eventually be corrected.

Appendix B

Situating Task[1]

(Message eliciting initial beliefs) A wiki system allows collaborators to work on the same web pages and share files. PBwiki is a wiki system that is free for most individual use. PBwiki has the following features:

1. **Function:**
    - **Collaborative Editing:** Encourage group projects by allowing people to edit pages and contribute to your workspace.
    - **Complete History and Audit Trail:** PBwiki keeps a complete audit trail of every change made to your workspace. See who changed what. Reverse any change with a couple clicks. Your PBwiki workspace allows you to maintain full accountability of your users.
    - **Easily invite others:** Get users on the workspace by inviting them with email. No more complicated user provisioning and no more waiting for IT. Inviting users is easy.
2. **Security:**
    - **Access Controls:** Control the access level of your users for the entire workspace. PBwiki includes robust access levels (Reader, Writer, Editor, and Administrator) for differentiating access to your workspace.
    - **Page- and Folder-level Access:** In addition to controlling workspace-wide access levels, control which specific pages users can access. You can set access controls on specific pages, or groups of pages. Only the people you choose can see pages with special security settings.
    - **Hideable and Lockable Pages:** Hide pages so only administrators can view or edit, or lock a page so only administrators can edit.
3. **Customization**
    - **Multimedia Plugins:** Use PBwiki Plugins to add multimedia content with a few clicks, including images, videos, photo slide shows, and more! Almost any online tool with an embed code can be used in PBwiki.
    - **Color Choice:** Chose from nine custom colors. Users have unlimited color choices, and can upload a logo to brand their workspace as a personal site. Upload a logo and PBwiki will automatically match the look and feel of your workspace to the logo.
    - **Customizable Templates:** Add templates to your workspace and stop recreating your work.

Task: *Based on the above descriptions, please report an example of what PBwiki could do for you at work or study:*

[1]The description of PBwiki is primarily from PBworks's website.

Appendix C

Treatments

Both the number and identity of previous adopters matter. To generate the situation for herding, the information should depict "how many adopters there are and who specifically has adopted the innovation" (Fiol and O'Connor 2003, p. 56). Graham (1999) also argued that the likelihood of herding increases when the aggregate public information is strongly held by a lot of people and reinforced by the actions of the market leader.

The simulation experiment manipulated both the *number* and *identity* of previous adopters. Specifically, the experiment included three groups: control group, medium-observation group, and high-observation group. The control group did not receive any information about previous adopters. The medium-observation group received a message stating that PBwiki has been accepted by a large number of people. The high-observation group received a message that not only states that PBwiki has been accepted by a lot of people, but also specifies some large organizational adopters. The treatment messages were composed based on information from PBwiki's website and ComScore. com (a website that can report the number of visitors of a website).

Control Group: Subjects do not receive any information about previous adopters (It is also ensured that the URL of PBwiki did not appear anywhere in the survey to prevent subjects in the control groups from obtaining information regarding previous adoptions by themselves.)

Medium-Observation Treatment Group: The following message appears:
PBwiki is the largest business and educational wiki host in the world. Millions of people have accepted and are using it for online collaborations, knowledge management, project management, and a host of other business processes and workflows. Currently, PBwiki manages 50,000 wiki groups, with 10 million pages and 3 million users per month, according to the company. ComScore shows healthy growth and 2. 1 million unique visitors worldwide of PBwiki as of 2009.

High-Observation Treatment Group: The following message appears:

(a) *PBwiki is the largest business and educational wiki host in the world. Millions of people have accepted and are using it for online collaborations, knowledge management, project management, and a host of other business processes and workflows. Currently, PBwiki manages 50,000 wiki groups, with 10 million pages and 3 million users per month, according to the company. ComScore shows healthy growth and 2. 1 million unique visitors worldwide of PBwiki as of 2009.*

(b) *PBwiki is serving teams at around half of the Fortune 500, being home to three presidential campaigns, the United Nations, The Financial Times, FedEx, and Harvard University.*

Appendix D

Measures

The scales for measuring internal self-efficacy, disconfirmation, and satisfaction are specified below. All other factors use a seven-point Likert scale, where 1 indicates "strongly disagree," 4 indicates "neutral," and 7 indicates "strongly agree."

Measures at Time 1

Prior Experience (adapted from Kim and Malhotra 2005)
How long have you been using a wiki system? (Never used it before, less than 3 months, 3 to less than 6 months, 6 to less than 12 months, 1 to less than 2 years, 2 years or more)

Uncertainty (UNC) (adapted from Sun and Fang 2010)
UNC1. I am NOT sure what PBwiki is about and what it could do for me.
UNC2. I feel uncertain whether my needs when engaging in collaborative work could be met by using PBwiki.
UNC3. I feel uncertain whether I would be able to respond appropriately to any changes/upgrades of PBwiki.
UNC4. I feel that collaborating using PBwiki involves a high degree of uncertainty.

Imitating Others (IMI) (self-developed)
IMI1. It seems that PBwiki is the dominant wiki system; therefore, I would like to use it as well.
IMI2. I follow others in accepting PBwiki.
IMI3. I would choose to accept PBwiki because many other people are already using it.

Discounting Own Information (DOI) (self-developed)
DOI1. My acceptance of PBwiki would not reflect my own preferences for collaboration tools.
DOI2. If I were to use PBwiki for collaborative work I wouldn't be making the decision based on my own research and information.
DOI3: If I did not know that a lot of people have already accepted PBwiki, I might choose another wiki system for my work.

Initial Beliefs (IB) (adapted from Kim and Malhotra 2005)
IB1. I think PBwiki would allow me to accomplish tasks more quickly.
IB2. Using PBwiki could help improve the quality of my work.
IB3. PBwiki would give me greater control over my work.
IB4. Using PBwiki would enhance my effectiveness in my work.

Adjusted Beliefs (AB) (using the same items as IB, but measured after the treatment)

Intention to Use (IU) (adapted from Bhattacherjee and Premkumar 2004)
IU1. I plan to use PBwiki for collaboration.
IU2. I intend to use PBwiki for my future work.
IU3. It is very likely that I will use PBwiki in the near future.

Network Externality (NE) (self-developed)
NE1. The more people use PBwiki, the more valuable it is to users.
NE2. By adopting PBwiki, I would help increase its value to other users.
NE3. My adoption of PBwiki would make it more useful for people I know who already use it.
NE4. I hope that more people will adopt PBwiki because that will increase the value of PBwiki to me.
NE5. PBwiki will be more useful if more people adopt it.

Subjective Norm (SN) (adapted from Taylor and Todd 1995; Venkatesh and Davis 2000)
SN1. People who influence my behavior think that I should use a wiki system like PBwiki.
SN2. People who are important to me think that I should use a wiki system like PBwiki.

Personal Innovativeness in IT (PIIT) (adapted from Agarwal and Prasad 1998)
PIIT1. When I hear about a new piece of information technology, I generally think about ways I could use and experiment with it.
PIIT2. Among my peers, I am usually the first to try out new information technologies.
PIIT3. I like to experiment with new information technologies.

Internal Self-Efficacy (SE) (adapted from Thatcher et al. 2008) (measured on a 10-point Likert scale, where 1 indicates "Not At All Confident," 5 indicates "Moderately Confident," and 10 indicates "Totally Confident.")

SE1. I could use PBwiki to collaborate with other people if there was no one around to tell me what to do.
SE2. I could use PBwiki to collaborate with other people if I had never used a wiki system like it before.
SE3. I could use PBwiki to collaborate with other people if I had only the online help for reference.

Manipulation Check Items (self-developed)

MC1. I am aware that a lot of people have adopted PBwiki.
MC2. I am aware that PBwiki has been adopted by a lot of well-known organizations.

Measures at Time 2

Modified Beliefs (MB) (adapted from Kim and Malhotra 2005)

MB1. Using PBwiki helps me to accomplish tasks more quickly.
MB2. Using PBwiki improves the quality of the work I do.
MB3. Using PBwiki gives me greater control over my work.
MB4. Using PBwiki enhances my effectiveness in my work.

Disconfirmation(DC) (adapted from Bhattacherjee and Premkumar 2004) (measured on a 7-point Likert scale, where 1 indicates "much worse than expected," 4 indicates "neutral," and 7 indicates "much better than expected.")

Compared to my initial expectations, the ability of PBwiki _____

DC1. to improve my performance was______
DC2. to increase my productivity was______
DC3. to enhance my effectiveness was______
DC4. to be useful for my work or study was______

Satisfaction (SAT) (adapted from Bhattacherjee and Premkumar 2004)

All things considered, I am _________ with my use of PBwiki

SAT1: 1 "Extremely displeased" ——— 4 "Neutral" ——— 7 "Extremely pleased"
SAT2: 1 "Extremely frustrated" ——— 4 "Neutral" ——— 7 "Extremely content"
SAT3: 1 "Extremely terrible" ——— 4 "Neutral" ——— 7 "Extremely delighted"
SAT4: 1"Extremely dissatisfied" ——— 4 "Neutral" ——— 7 "Extremely satisfied"

Intention to Discontinue (DIC) (adapted from Parthasarathy and Bhattacherjee 1998)

DIC1. I intend to discontinue my use of PBwiki,even though I am not particularly dissatisfied with it, because I found another technology that is superior to PBwiki for my needs.
DIC2. I plan to stop using PBwiki, using something else superior instead.
DIC3. I predict that I will not use PBwiki any longer, even if I cannot find something else to replace it, because it does not fit my needs.
DIC4. I plan to stop using PBwiki and to find something else because I am dissatisfied with it.

Intention to Continue(IC) (adapted from Bhattacherjee and Premkumar 2004)

IC1. I intend to use PBwiki in the next two months.
IC2. I plan to use PBwiki in the next two months.
IC3. I predict that I will use PBwiki in the next two months.

Appendix E

The Instrument Development Process

The new measures for initating others (IMI), discounting own information (DOI), and network externality (NE) were developed following the procedure set forth by Moore and Benbasat (1991). First, items for measuring IMI, DOI, and NE were created based on their definitions and existing literature. The wording for the items measuring IMI and DOI were drawn primarily from prior herd literature. The items for IMI focus on the consistency between one's own adoption decision and that of others (i.e., one makes the same decisions they observe others making). The items for DOI focus on measuring the extent to which a person chooses to not refer to his/her own information when making an adoption decision (or in other words, how one's decision does not reflect his/her own preferences). Items for measuring NE were created, which are consistent with the definition of NE (i.e., the value of a technology increases when more people use it). Seven-point Likert scales were used, with 1 representing "strongly disagree," 4 "neutral," and 7 "strongly agree." The initial items for measuring IMI, DOI, and NE were examined by an external researcher to help ensure face and content validities based on which necessary revisions of the wording were made.

A two-step Q-sort (Moore and Benbasat 1991) was then conducted. The Q-sort has two steps with four judges in each round. The eight judges were four university faculty and staff members in the first round and four graduate students in the second round. The four judges in the first round took small cards upon which the items for IMI, DOI, and NE were printed and sorted them into groups. They were allowed to create as many groups as they wanted, but were required to name the resulting groups. In the second round, four different judges were given the names and descriptions of the three categories (IMI, DOI, and NE). They then assigned the cards to those three categories. A fourth "too ambiguous/ doesn't fit" category was also included to ensure that judges did not attempt to force-fit any item into a particular category.

To assess construct validity, item placement ratios, as described by Moore and Benbasat, were examined. The item placement ratio is an assessment of the overall frequency with which judges place items within their intended theoretical constructs (or in other words, place them in the intended groups). If an item is consistently placed into its intended construct, the researcher may reasonably be confident that the item has high construct validity. In this study, the first round yielded an overall item placement ratio of 0. 75 (= 39 (total hits) / 52 (total item placement)). The ratio was 0.81 for IMI, 0.67 for DOI, and 0.71 for NE respectively. The overall item placement ratio for the second round was 0.81 (0.75 for IMI, 0.88 for DOI, and 0.79 for NE). An average Kappa of 0.77 and 0.85 were obtained for the first round and second round card-sorting respectively. The misplaced items were examined and revised accordingly. No items were dropped because, in both rounds, no item was misplaced by more than two (out of four) judges.

An initial pilot test of the overall instrument was conducted using 73 graduate students at the researcher's school. An exploratory principle component analysis (PCA) was conducted using Varimax rotation in SPSS 16. 0. The loadings and cross-loadings were examined to assess the discriminant and convergent validities of the instruments. Loadings greater than 0. 707 are considered adequate (Chin 1998). For item purification, Cronbach's Alpha was utilized to assess the reliability of the items. A Cronbach's Alpha higher than .70 indicates that an item has good reliability(Cronbach 1970). Items with low inter-item and item-total correlations, high "Cronbach's Alpha if item deleted" statistics, or small standard deviation scores (and thus low explanatory power) were candidates for deletion (Moore and Benbasat 1991). The results of the pilot test suggested that all items should be retained. The final version of the instruments includes three items for IMI, three items for DOI, and five items for NE. Those items were included in the final questionnaire for the longitudinal study (Appendix D).

Appendix F

Loadings and Cross-Loadings[2]

	UNC	DOI	IMI	IB	AB	IU	DC	MB	SAT	DIC	NE	SN	PIIT	SE
UNC1	**0. 72**								-0. 35	0. 34				-0. 43
UNC2	**0. 89**					-0. 42	0. 39	-0. 30	-0. 44	0. 45				-0. 40
UNC3	**0. 82**													-0. 47
UNC4	**0. 77**				-0. 38	-0. 36		-0. 33		0. 32				-0. 35
DOI1		**0. 75**												
DOI2		**0. 70**												
DOI3		**0. 79**												
IMI1			**0. 90**		0. 41	0. 61	-0. 33		0. 32		0. 45			
IMI2			**0. 91**		0. 33	0. 46					0. 45	0. 31		
IMI3			**0. 90**			0. 39					0. 45			
IB1				**0. 89**	0. 47	0. 32								
IB2				**0. 90**	0. 47	0. 33						0. 32		
IB3				**0. 88**	0. 54	0. 32								
IB4				**0. 95**	0. 50	0. 32						0. 31		
AB1	-0. 31		0. 36	0. 56	**0. 99**	0. 66		0. 41			0. 51	0. 34		
AB2				0. 50	**0. 93**	0. 62		0. 38			0. 51	0. 31		
AB3			0. 32	0. 45	**0. 86**	0. 55		0. 31			0. 35			
AB4			0. 43	0. 53	**0. 94**	0. 66		0. 43	0. 35		0. 52	0. 36		
IU1	-0. 39		0. 49	0. 38	0. 65	**0. 94**	-0. 38	0. 42	0. 47	-0. 46	0. 51	0. 39		
IU2	-0. 39		0. 60	0. 31	0. 65	**0. 95**	-0. 38	0. 42	0. 44	-0. 47	0. 53	0. 42		
IU3	-0. 45		0. 49	0. 33	0. 60	**0. 94**	-0. 31	0. 41	0. 47	-0. 50	0. 42	0. 40		
ND1	0. 33					-0. 37	**0. 94**	-0. 50	-0. 72	0. 58				
ND2	0. 35					-0. 38	**0. 95**	-0. 50	-0. 66	0. 58				
ND3	0. 38					-0. 34	**0. 96**	-0. 54	-0. 67	0. 59				
ND4	0. 39					-0. 34	**0. 93**	-0. 52	-0. 68	0. 56				
MB1	-0. 36				0. 39	0. 43	-0. 54	**0. 96**	0. 47	-0. 45		0. 31		
MB2	-0. 36				0. 39	0. 44	-0. 51	**0. 97**	0. 47	-0. 46				
MB3	-0. 30				0. 41	0. 40	-0. 52	**0. 96**	0. 53	-0. 43				
MB4	-0. 34				0. 40	0. 42	-0. 53	**0. 97**	0. 51	-0. 44				
SAT1	-0. 41					0. 51	-0. 71	0. 51	**0. 95**	-0. 74				
SAT2	-0. 37					0. 43	-0. 64	0. 45	**0. 94**	-0. 70				
SAT3	-0. 40				0. 33	0. 44	-0. 68	0. 50	**0. 95**	-0. 72				
SAT4	-0. 42				0. 31	0. 47	-0. 71	0. 50	**0. 96**	-0. 74				
DIC1						-0. 43	0. 48	-0. 32	-0. 56	**0. 86**				
DIC2						-0. 44	0. 47	-0. 35	-0. 60	**0. 91**				
DIC3	0. 48		-0. 33		-0. 33	-0. 48	0. 59	-0. 49	-0. 74	**0. 81**				
DIC4	0. 42					-0. 34	0. 52	-0. 36	-0. 64	**0. 80**				

[2]Loadings with absolute values less than 0.3 are suppressed.

	UNC	DOI	IMI	IB	AB	IU	DC	MB	SAT	DIC	NE	SN	PIIT	SE
NE1			0. 45		0. 35	0. 40					**0. 82**			
NE2			0. 47		0. 39	0. 44					**0. 86**			
NE3				0. 31	0. 46	0. 35					**0. 76**			
NE4			0. 54		0. 51	0. 56					**0. 86**			
NE5			0. 43		0. 42	0. 42					**0. 91**			
SN1			0. 32		0. 36	0. 44						**0. 97**		
SN2				0. 31	0. 30	0. 38						**0. 96**		
PIIT1													**0. 93**	
PIIT2													**0. 80**	
PIIT3													**0. 96**	
SE1														**0. 91**
SE2	-0. 51													**0. 95**
SE3	-0. 35							0. 31						**0. 89**

UNC: Uncertainty of Adoption
IB: Initial Beliefs
NE: Network Externality
SE: Self Efficacy
SAT: Satisfaction
IMI: Imitation
AB: Adjusted Beliefs
SN: Subjective Norm
ND Negative Disconfirmation
DIC: Intention to Discontinue
DOI: Discount of Own Information
IU: Intention to Use
PIITP Personal Innovativeness in IT
MB: Modified Beliefs

Appendix G

Supplementary Analyses

Analysis 1: Difference of IMI Between the Control Group and the Treatment Group

An ANOVA analysis was conducted to examine the difference between group means for the dependent variable of OBV (i.e., IMI) that was shown to be significant in the above PLS analysis. As shown in Table G1, the F-statistics is significant, indicating that the control group is significantly different from the treatment group in IMI. The contrast showed that the difference is -1. 78, meaning that the control group has lower levels of IMI than the treatment group. With a standard error of 0. 59, this difference is significant ($p < .003$).

Table G1. A Summary of the Results of the ANOVA Analysis*

	Sum of Squares	d.f.	Mean Square	F	Sig.
Control Group versus Treatment Group	152.912	1	152.912	9.115	.003
Contrast†			**Dependent variable: IMI**		
Control Group versus Treatment Group	Contrast estimate		-1.78		
	Standard error		0.59		
	Significance mean		.003		

*Dependent Variable: IMI; Independent Variable: OBV
†The contrast is based on the average of the three items of IMI.

Analysis 2: AB Mediating the Relationship Between IB and IU

This research utilized the Preacher and Hayes (2008) method to further examine the mediating effect of AB on the relationship between IB and IU.[3] The results show that before AB was introduced as a mediator, IB had a significant total effect on IU (coefficient = 0.492, t = 8.07, p < 0.001). When AB was introduced as the mediator, IB did not have a significant direct impact on IU (coefficient =0. 089, t=1. 31). At the same time, the indirect effect of IB on IU through AB was 0. 403 with a 95 percent bootstrap confidence interval (CI) of 0.264 and 0.562. Since this CI did not contain zero, the indirect effect was significantly different from zero. In summary, these results support a full mediating effect of AB on the relationship between IB and IU.

Analysis 3: SAT and MB Mediating the Relationship Between ND and DIC

The Preacher and Hayes method was utilized to analyze the mediating effects of SAT and MB on the relationship between ND and DIC. The results show that before SAT and MB were introduced as mediators, ND has a significant total effect on DIC (coefficient = 0.614, t = 11.10, p < 0.001). When SAT and MB were introduced as mediators, the direct effect of ND on DIC became nonsignificant (coefficient = 0.103, t = 1.51). The total indirect effects, via SAT and MB, were significant (coefficient = .511, CI = (0.398; 0.665)). Specifically, the indirect effect through SAT was 0.474, which is significant (CI = (0.375; 0.613)). The indirect effect through MB was, on the other hand, not significant (coefficient = 0.037, CI = (-0.025; 0.108)). In conclusion, SAT, but not MB, fully mediates the relationship between ND and DIC.

Analysis 4: Effect Sizes for Herd Factors

To assess the effect sizes for herd factors, a model without herd factors (i.e., UNC, OBV, IMI, DOI, and AB) was examined, resulting in a model with only the initial beliefs, intention to use, and control variables at the adoptive stage. This model was then compared with the full model to assess the effect sizes, based on Cohen's f^2 formula. As shown in Table G2, the size of the effect of herd factors on intention to use is large (0.44), while the effect size on modified beliefs is medium (0.16).

Table G2. Effect Sizes of Herd Factors

Dependent Variable	R-Square with Herd Factors	R-Square Without Herd Factors	Effect Size†
Intention to use	0. 59	0. 41	0. 44 (large)
Modified beliefs	0. 42	0. 33	0. 16 (medium)

†Effect size (f^2) is calculated by the formula ($R^2_{full} - R^2_{partial}$) /)1 – R^2_{full}). Cohen (1988) suggested 0.02, 0.15, and 0.35 as operational definitions of small, medium and large effect sizes respectively.

[3] An SPSS script, developed by Preacher and Hayes, was used to calculate the bootstrap statistics. The script can be found at http://www.comm.ohio-state.edu/ahayes/SPSS.programs/indirect.htm.

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