HERD BEHAVIOR AND INDIVIDUALS' INFORMATION SYSTEM BEHAVIORS:

USAGE, ABANDONMENT, AND EXPLORATION INTENTIONS

By

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A dissertation submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy (Management & Information Systems)
Department of Management & Information Systems
2018

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ACKNOWLEDGEMENT

This work would not have been possible without the support and help of several people. In particular, I would like to express the deepest appreciation to my committee chair Dr. Greta Polites. Without her guidance and persistent help this dissertation would not have been possible. As my teacher and mentor, she has taught me more than I could ever give her credit for here. I am also indebted to my dissertation committee members: Dr. Mary Hogue, Dr. Dong-Heon Kwak, and Dr. Christopher Groening, who have generously offered their time, helpful insights, and suggestions for improving my work along the way. I would also like to thank the College of Business Administration and the Department of Management & Information Systems for their generous financial and scholastic support.

Nobody has been more important to me in the pursuit of this journey than the members of my family. They have been a constant source of courage and inspiration. I would like to thank my mother, Mehri Heidari, and my father, Ahmad Darban, whose love and guidance are with me in whatever I pursue. I wish to thank my loving and supportive sisters, Maryam and Tala, who provided unending inspiration.

CHAPTER 1

OVERVIEW

INTRODUCTION

Information technologies (IT) have crucial impacts on our everyday lives. They are important for enhancing the efficiency of work, economic development (e.g., through creation of jobs in related industries), and individual quality of life (e.g., by using wearable health monitor technologies). However, new technology adoption for individuals and organizations can be a time consuming and capital-intensive process, and can often require complex decisions (Brown et al. 2014; Venkatesh and Morris 2000). Extant adoption theories have identified a number of factors that influence whether an individual will choose to adopt a particular technology, with these factors constantly interacting to inhibit and/or promote change (Adler and Clark 1991). This means that understanding or controlling any one factor will not guarantee success; for example, even if an individual recognizes the usefulness of a particular technology, other contextual factors (e.g., the influence of mass media) can still lead to non-adoption (Rogers, 1995). Moreover, an accurate assessment of the value of adopting a particular technology usually requires an extensive range of knowledge, especially when people are faced with considering technologies possessing features with which they have limited experience (Jasperson et al., 2005). In other words, personal factors, characteristics of the technology itself, and the influence of the individual’s context will all shape one's ultimate decision to adopt and persist in continuing to use a technology (Straub 2009).

The term "artifact" is commonly used to refer to something that has, or can be transformed into, a material existence as an artificially made object (Gregor and Hevner 2013) and information systems (IS) are among the most complex artifacts that humans have ever built (Brooks 1975; Geriner et al., 2011). For example, an aircraft has 75,000 parts flying in close formation with one pilot, a complex machine and environment. But a large IS (e.g., Enterprise Resource Planning (ERP) system) may have millions of line of code and hundreds of interfaces working in close formation with the potential of 16,000 pilots (Geriner et al., 2011). Misjudging the inherent complexity of an IS often results in poor resource allocation within organizations. The complexity and uncertainty involved in IT adoption decisions are also due to the length of time it may take for adopters to realize performance improvements from the new systems (Brynjolfsson and Hitt 1996; Walden and Browne 2009). The degree to which an individual believes using a technology will help him/her to improve job performance, both in voluntary and mandatory usage settings, has been shown to be the strongest predictor of usage intention (Venkatesh et al. 2003). Individual level usage is in turn important since the successful adoption of technology in any organization depends on it (Jasperson et al., 2005). While the final outcome of employing a *useful* technology can be tremendously beneficial to an organization, the costs of adopting an *inefficient* technology can severely outweigh its benefits. Recent failures in successfully adopting ERP systems (for example, costing AVON $125 million and the US Air Force $1 billion) show just how costly uneducated adoption decisions can be (Panorama-consulting, 2015).

An Overview of Individual-Level Technology Adoption

The dynamism and complexity of IT can make it difficult to predict whether adoption will ultimately be successful. For this reason, researchers have been investigating the factors impacting IT adoption since the mid-1980s. Individual-level adoption research has focused heavily on the technology acceptance model (TAM) (Davis 1989), the theory of planned behavior (TPB) (Ajzen 1991), and innovation diffusion theory (IDT) (Rogers 1995). Davis (1989) proposed TAM to integrate diverse theoretical perspectives and build on social psychology research to present a parsimonious model of adoption and use. TAM was presented as an adaptation of the more general theory of reasoned action (TRA; Fishbein and Ajzen 1975) from social psychology. According to TRA, a person's performance of a specific behavior is determined by her behavioral intention to perform the behavior, and behavioral intentions is jointly determined by individual's subjective norms and attitude concerning the behavior in question. TAM proposed two constructs, perceived usefulness and perceived ease of use, as the most relevant beliefs in IS usage contexts. While TAM has sparked much interest in technology adoption research and has been the dominant model over the years, several competing models -- with roots in psychology, sociology, and IS -- have been proposed.

TPB suggests that behaviors can be predicted with high accuracy based on one's attitudes toward the behavior, subjective norms, and perceived behavioral control (Azjen 1991). TPB has provided the basis for other IS adoption models such Taylor and Todd's (1995) decomposed TPB framework, that aimed to preserve the generality of TPB and TAM by tailoring the core constructs of TPB to the technology adoption context. Attitudes, subjective norms, and perceived behavioral control are related to corresponding sets of salient behavioral, normative, and control beliefs regarding behavior, but the exact nature of these relationships is still uncertain (Benbasat and Barki 2007). One reason might be that users' adoption decisions can be influenced by various individual, organizational, technological and environmental factors (Lee et al. 2001; Sun and Zhang 2006). For instance, attitudes toward performing a behavior contain instrumental (e.g., desirable – undesirable, valuable – worthless) as well as experiential (e.g., pleasant – unpleasant, interesting – boring) aspects that TPB ignores (Ajzen and Driver 1992). Similarly, subjective norms can be broken down into two main types: injunctive (i.e., perceptions of what others think one should do) and behavioral or descriptive (i.e., perceptions of what others are doing) (Cialdini 2003).

Around the same time that TPB was being employed in IS adoption studies, another model (IDT; Rogers 1995) began to be featured in explaining adoption and usage decisions. By introducing two key components of communication channels and social systems, IDT attempted to identify the contextual drivers that influence how an innovation infiltrates a population. IDT provides a comprehensive structure for understanding individual adoption by drawing on a wide range of research spanning the fields of sociology, education, psychology, and geography, among others (Rogers 1995). Over the years, IDT has influenced numerous other theories of adoption (Venkatesh et al., 2003). For example, as an alternative approach to eliciting salient beliefs in each specific case associated with an IT usage context, Moore and Benbasat (1991) proposed utilizing as a generic set of beliefs the full set of perceived characteristics of innovations identified in Rogers' influential work, *Diffusion of Innovations* (Rogers 2003). Subsequently, there have been many other applications of IDT to the study of individual technology adoption and usage decisions.

In 2003, Venkatesh et al. examined eight dominant individual adoption and use of technology frameworks, including TRA, TAM, TPB, and IDT. They brought together the more salient characteristics of the eight models to create a single unified model for understanding technology acceptance. This model, known as the Unified Theory of Acceptance and Use of Technology (UTAUT), includes four broad determinants of use as well as four key moderators of individual usage behaviors. By including subjective norms and perceived behavioral control constructs, scholars have aimed to extend the explanatory strength of adoption models to take into account key environmental elements impacting users' IS behavior (Benbasat and Barki 2007; Venkatesh et al. 2003). In the 2003 Venkatesh et al. study, UTAUT was able to account for 70 percent of the variance in usage intention – a substantial improvement over any of the previously dominant adoption models and their extensions.

Technology Adoption: Following the Crowd

Empirical research in IS has found exogenous factors (e.g., environmental uncertainty and the adoption behaviors of others) to have a significant influence on the individual adoption decision (e.g., Grover and Goslar 1993; Ravichandran and Liu 2011; Sharma and Rai 2015; Sun and Jeyaraj 2013). During the decision-making process, individuals often do not act rationally, because they lack the mental capacity to store and process all of the information related to their adoption decision (Huczynski and Buchanan 2001; Simon 1982). For this reason, their decisions are not only based on utility maximization, but may also be influenced by the adoption decisions of others. Outside the realm of technology adoption, one may observe similar decision making behaviors taking place in areas such as stock market reactions, financial forecasts, retirement investments, fashion, political voting, and organizations' strategic decisions. For instance, when two restaurants are located next to each other, people often prefer the restaurant with more occupied seats (Duan et al. 2009). Similarly, despite receiving average reviews, people may nevertheless follow the crowd in buying a New York Times bestseller, enabling it to continue as a bestseller (Bikhchandani et al. 1998). This pattern of behaviors is common in a variety of business and personal domains under conditions of uncertainty. *Uncertainty* here refers to an individual's perceived inability to accurately predict the future because of imperfect information (Milliken 1987). Following this general definition, I may view *uncertainty in the context of technology adoption* as the inability of a person to accurately predict the outcome of a technology adoption decision due to having imperfect relevant information. For example, one might be uncertain as to what a technology is to be used for. Also, a person may be uncertain as to what a technology can do for her personally, or whether or not she can deal with potential updates/changes of the technology (i.e., her future interactions with the technology). For instance, she may be uncertain as to how she will respond if a free application she is currently using is to become a license-based application in the future.

BACKGROUND

Observational Learning

Observing the behaviors of similarly situated individuals helps a decision maker in choosing whether to pursue a particular course of action under conditions of uncertainty. Individuals learn by observing the past decisions of others; for this reason, the influence of predecessors' actions on followers' decision-making processes has been studied in a number of research domains. For instance, *mimetic isomorphism* (DiMaggio and Powell 1983), the *bandwagon effect* (Abrahamson and Rosenkopf 1997; Terlaak and King 2007) and the *neighborhood effect* (Baerenklau 2005) all refer to similar phenomena which describe the tendency of individuals to imitate others' actions. A considerable body of research has investigated individual decision making from the perspective of *observational learning*, which occurs when an individual infers the usefulness and worth of a behavior based on observing others who are performing a similar behavior (Bandura 1986). Research in this subject area has shown that individuals update their own private beliefs based on their observations of others in order to make better decisions (Bandura 1978). Acquisition of information is not always free; rather, it imposes different types of costs (e.g., search or experimentation costs in the forms of time or energy). People may be inclined to observe others' actions to save costs of information searching. Hence, they end up basing their decision on incomplete and asymmetric information that they acquire observing prior users.

It is important to note that in this dissertation, I aim to clarify two slightly different conceptualizations of the broader construct of "observation" that have occasionally been used synonymously in the extant literature (Bikhchandani et al. 1992; Duan et al., Sun 2013). These two different conceptualizations must also be operationalized in different ways. In chapters 2 and 3, my focus is on one's observation of the *popularity* of a behavior (in this case, adoption of a particular technology), henceforth to be referred to as simply "observed popularity." In chapter 4, however, my focus is on observation of the *actual* behaviors of others. The former conceptualization (observed popularity), which has been commonly yet imprecisely referred to in extant literature as simply "observation," is more relevant in a herding setting in which the followers may have limited ability to observe the exact behavior of others (Bikhchandani et al. 1992). Observing the *number* of prior adopters in an IS adoption situation is more probable (Duan et al. 2009). In fact, observing that many individuals have made the same decision is a necessary condition for herd behavior to occur (Sun 2013). As the number of previous adopters grows, the adoption of one alternative becomes more likely (Rao et al. 2001). The majority of the herding research has thus conceptualized "observation" in terms of the number of prior adopters (Banerjee 1992; Bikhchandani et al. 1992; Duan et al. 2009; Zhan 2010; Sun 2013), and Sun (2013) has simply referred to the construct as "Observation of Prior Adoption." The *identity* of prior adopters is also considered important in herding settings (Bikhchandani et al. 1992). People may tend to believe that specific groups of adopters (e.g., IT experts or fashion leaders) have more accurate information about the technology and hence may opt to follow them rather than the general public (Boudreau et al. 2005). I point out that while Sun initially included a measure of the identity of prior adopters in his 2013 study of technology herding behavior, it was not found to be a significant predictor of downstream imitative behaviors. Nevertheless, I retain this aspect of observed popularity in my study to investigate its impact in a different research context. To more clearly differentiate this "new" construct from the more straightforward "observed behavior" conceptualization, I will call it "Observed Popularity" in this dissertation.

Information Cascades

Underlying many of these theoretical discussions is the concept of *information cascades* (Banerjee 1992; Bikhchandani et al. 1992; Cheung et al. 2014; Li 2004; Liu and Zhang 2014). Information cascades refer to an adoption process in which a person follows the behavior of the preceding individual, ignoring his/her own valuable information. Several recent IS studies have employed the information cascade perspective to explain individuals' convergence behaviors (i.e., uniform social behaviors of individuals, such as making similar decisions, taking similar actions, and the rapid spread of new behaviors) (Duan et al. 2009; Sun 2013; Tomasino and Fedorowicz 2014). The underlining notion of information cascades is that an individual has two main sources of information that she uses to make the best decisions: (1) her own information based on her knowledge, and (2) the information she derives from the adoption decisions of others. If these two sources of information present conflicting signals, she will follow the information source that has been given greater weight. In fact, the influence of others' behavior could be so substantial that it dominates the influence of a decision maker' own information. In this case, decision makers would imitate their predecessors without regard to their own information (Bikhchandani et al. 1992). Nevertheless, an IT adopter has a better understanding of her specific task requirements, meaning that her own information may provide valuable insights on how a technology can meet those needs. Hence, despite the availability of more relevant substitute technologies, information cascades may lead to the dominance of one technology over another, and may sometimes even result in the rejection of more efficient technologies (Abrahamson 1991). In the context of technology adoption, this means that individuals have inferred the utility of a new technology from inaccurate information obtained from prior adopters.

The fast growth of Internet technologies, and the associated ubiquity of information, provide individuals today with previously unknown opportunities to acquire and share information about new technology products. Hence, I witness numerous situations where potential adopters observe the decisions (but not the reasoning) of others, and imitate their adoption behaviors. For instance, Song and Walden (2003) found that people voiced stronger intentions to adopt a file sharing technology when they could observe that others had adopted it (via seeing the number of recent adopters), even after controlling for network size. Another study found that online users' software application choices rose and fell dramatically when the download ranking of the applications changed (Duan et al. 2009). Finally, Sun (2013) studied the role of observation of the popularity of prior adopters' decisions in an individual's adjustment of their own beliefs regarding IS adoption. He found that under conditions of uncertainty, due to the lack of accurate information on the true value of a specific technological product, observability of others' adoption behaviors was a major determinant of individuals' convergence in using a specific technology.

Herding Behavior

In fact, imitation (i.e., an individual's personal replication of an observed behavior) is one of the most characteristic learning processes found in humans (Bandura 1978). In recent years, I have witnessed several examples of individuals following others in adopting a new technology. Rapid increases in the number of individuals using certain social networking services (e.g., Facebook and MySpace), followed by en mass abandonment of these same technologies and migration to new ones (e.g. Instagram) could be considered one example of this "herd-like" phenomenon (Investopedia 2015). In the herding process, early adopters' decisions become excessively important, giving followers little opportunity to compare, and experience, other potentially better technology choices (Banerjee 1992; Bikhchandani et al. 1992). An individual user is more likely to perceive that her reputation could be damaged if she fails to quickly follow the adoption decisions of early adopters. Therefore, herding operates as a mechanism to overcome the uncertainty of decision-making by relying on others' judgment and imitating their decisions. In such situations, the decision to imitate others is made on the basis of inaccurate and poorly aggregated information, which may result in rejecting more efficient technologies and blindly accepting the popular one (Abrahamson and Rosenkopf 1997; Walden and Browne 2009).

In the case of new information becoming available, or personal evaluations being updated due to personal experience with the technology through its actual use (Kim and Malhotra 2005), these individuals may reverse their adoption decisions and en mass abandon the technology (Rao et al. 2001; Sun 2013). For instance, managers may intentionally imitate their rivals' adoption decisions due to career concerns and to avoid being considered as incapable; however, such reputation-motivated decisions usually fail to maximize expected IT investment payoffs (Ottaviani and Sørensen 2006; Scharfstein and Stein 1990), since the technology may turn out to be an inefficient choice. In this case, people may later re-examine and reverse their initial decisions. Hence, herd behaviors are sometimes fragile (Bikhchandani and Hieshleifer 1992; Walden and Browne 2009), meaning that enough newly-revealed information will lead people to stop or reverse their decisions. If some credible information is revealed to support an alternative technology, the adoption cascade can be quickly stopped or reversed.

OBJECTIVES

This dissertation investigates individuals' technology adoption and post-adoption behaviors through the lens of herding theory. Drawing on the rich extant literature on technology adoption, post-adoption usage, and technology exploration, and integrating it with other relevant research streams, I aim to shed light on understudied determinants of individual decision-making regarding technological artifacts in highly uncertain environments. I focus not only on *technology adoption* behaviors, but also on *technology abandonment* and *technology exploration*, as lines of inquiry into post-adoptive system use. I believe that applying the herding perspective can provide a more complete explanation regarding IS continuance behaviors. Specifically, I focus on investigating the determinants of en mass abandonment under herding conditions. Extending this research stream, I also study the role of herding as it relates to a particular post-adoptive behavior, i.e., explorative IT learning. To the best of my knowledge, only one published study (Sun 2013) has applied herd theory to investigate IS continuance behavior, mainly focusing on identifying the antecedents of herd behavior and its distal effect on an individual's post-adoption behavior. Employing herd theory as the core concept in each of the study's three essays, I seek to answer the following three research questions:

RQ1: How do individual and technology characteristics impact an individual's herd-like behavior in adopting a technology?

RQ2: How does herding behavior influence an individuals' task-technology fit perceptions post-adoption, and consequently their IS abandonment intentions?

RQ3: What role does herding behavior play in an individual's post-adoptive explorative IS learning intentions?

Figure 1 presents the schematic structure of this dissertation. Each of the three essays concentrates on investigating different technology related phenomena, i.e., adoption, usage, and exploration of technology by individuals through the lens of herd theory. I may view these three phenomena as the three phases of an IS life cycle which are sequentially related (Figure 2). In the first essay, which focuses on the adoption phase (i.e., when individuals develop intentions to adopt and start using an IS), I look at user and technology characteristics and their interaction with the antecedents of herd behavior, *observed popularity* and *perceived uncertainty*. In the second essay, I extend my focus to the post-adoptive context and study the impact of the herd effect on how a user's task-technology-fit (TTF) perceptions evolve over time (by measuring TTF at two phases). I also investigate factors influencing the en mass abandonment in herd-like adoption conditions. In the third essay, which focuses on a specific explorative technology behavior (here IT learning), I investigate how team level factors (i.e., team cohesion) influence herd-like adoption and consequently explorative learning behaviors in the post-adoption stage. While using herd theory as the underlying theme in all three essays, I emphasize that I are not conceptualizing herd-like behavior as a single construct. Rather, I propose the presence of several different factors to describe herd behavior in technology adoption.

Insert Figure 1 here

Insert Figure 2 here

ESSAY ONE

Attributes of the individual user (e.g., self-efficacy and experience) and focal technology (e.g., complexity and relative advantage) have been well studied in prior IS adoption research. This essay adds to the emerging IS herding literature by investigating the influence of the interaction of user and technology attributes with herding behavior in predicting IS usage intentions. More specifically, I study the moderating effects of specific user and technology characteristics on the relationships between the antecedents of herding (i.e., observed popularity and perceived uncertainty) and propensity for imitation in adopting a new technology. By doing so, I improve understanding of the determinants of en mass IS adoptions.

While the role of herding in the context of technology adoption has received some attention in recent IS research (Duan et al. 2009; Sun 2013), these studies have not recognized the potential impact that differing characteristics of individuals and technologies may have on the initiation of herding behavior. Extant research indicates that herding decisions can often be incorrect, and therefore such decisions are more likely to be later reversed (Bikhchandani et al. 1998; Sun 2013). Understanding the diverse roles of the focal user and technology characteristics will help us to explain the fragility of some adoption decisions. Consequently, I will have a clearer understanding of how some adoption behaviors lead to usage intentions of a "superior" technology, and others do not.

From a practical perspective, the essay aims to show that individual adopters who possess certain characteristics, and also technological products/services with specific characteristics, are more likely to encourage a herding effect, which can in turn boost the adoption of such products. The factors that lead to herd behavior have presented challenges to practitioners in the past, and without knowing the exact causes of such behavior, organizations have difficulty in exploiting the opportunities or addressing the challenges presented by the mass herd behavior commonly observed. Similarly, by identifying attributes of the technological artifact that impact the initiation of herding behavior, practitioners may adopt better strategies for new product introduction. For example, understanding the interplay between perceived complexity of a system (one of the technology characteristics investigated in this study) and herd-like adoption may help managers to increase implementation success by initiating a herding effect for the newly introduced system among their employees.

ESSAY TWO

The life cycle of an IS is comprised of the three main phases of *adoption*, *usage*, and *termination* (Furneaux and Wade 2011). In the adoption phase, individuals develop intentions to adopt and start using an IS (Davis 1989). In the usage phase, individuals decide whether to continue using a system (Bhattacherjee 2001). The life cycle concludes with the termination phase, in which users develop abandonment intentions (Turel 2015). Compared to phenomena related to the adoption and usage phases, the termination decision and its corresponding abandonment intentions have been largely overlooked in extant IS research. Hence, the main focus of this essay is to investigate the determinants of an individuals' abandonment intentions, which occur specially after an initial en mass adoption. More specifically, by applying a longitudinal research design, I aim to explain how en mass abandonment forms in a herding context.

To better understand the impact of the initial usage experience on perceptions in the post-adoptive stage, I apply a herding lens based on the Expectation-Confirmation Model (Bhattacherjee 2001). The ECM is grounded in Oliver's (1980) Expectation-Confirmation Theory for the purpose of explaining users' continued IT usage intentions. IS research has rarely used the herding lens to study individuals' post-adoptive usage decisions. One exception is Sun (2013), which focuses mainly on the cognitive process of individuals' herding behavior. More specifically, Sun investigated how an individual's beliefs about a technology's usefulness change in the post-adoption stage and impact her IS continuance intentions in a herding context. Similar to other research focusing on the impact of a technology's perceived utility (e.g., TAM [Davis 1989]), Sun's (2013) study employs user attitudes and beliefs to predict the utilization of a system. This approach, however, ignores the role of *fit* between the technology and the requirements of a task, which is important because using a poorly matched system (i.e., one with low fit between the user's needs and the technology's features) will not improve the user's performance (e.g., enable them to perform a task faster) (Goodhue and Thompson 1995). My study addresses this limitation of utilization focused IS models by incorporating the task related aspect of herd-like adoption to investigate the role of pre- and post-adoption perceptions of *task-technology fit* (TTF) (Goodhue and Thompson 1995). The TTF theory postulates that the degree of fit between one's necessary tasks and the focal technology will impact a user's performance. The TTF model has five key constructs: *task characteristics* (e.g., routine or non-routine tasks), *technology characteristics* (e.g., degree of stability), TTF (fit of the task and technology), *performance impact* and *utilization*. Of these five constructs, I include only TTF itself in the present research model. Hence, apart from one's adoption beliefs, I looked at their post-adoption intentions in a herd setting from a utilitarian lens, which emphasizes the instrumental value of a technology to a user.

TTF has been found to be an important determinant of individuals' usage behavior in the post adoption stage (Larsen et al., 2009). TTF recognizes that an individual's experiences with a technology define its further utilization (Goodhue et al. 1995). Specifically, after their initial interactions with a new system, they will have updated knowledge on its level of fit to their needs. The revelation of such information, when adoption has occurred in a herd setting, can then influence post adoption usage behavior. Such an influence could be *negative*, since in herd-like adoption the user has inaccurate knowledge on how the technology can address her needs and simply follows the crowd in adopting the technology. Hence, TTF is relevant in herding contexts where individuals may reverse their decisions to use a newly-adopted technology after their initial experiences with it. Prior studies on post-adoptive IS behaviors have not explicitly investigated the *fragility* of the individual's decision and its influence on their abandonment intentions. The fragility of herding behavior has, however, been recognized in the area of finance to describe how investors (e.g., in the stock market) reverse their decisions (Rao et al., 2001). While Walden et al. (2009) conducted a simulation study that found evidence for the fragility of herding decisions in the IS area, neither this study nor other extant studies have empirically investigated this characteristic of herding in the formation of abandonment decisions.

By recognizing the fragility of herding decisions, I aim to uncover the determinants of en mass technology abandonment intentions through the application of prospect theory (Kahneman and Tversky 1979), which proposes that negative evaluations of a decision have a stronger impact compared to positive evaluations of that decision. In other words, the value function is “concave for gains, convex for losses, and steeper for losses than for gains (Kahneman et al., 1979, p.263). One recent example of this phenomenon is Samsung’s Galaxy Gear (i.e., wearable smartphone), in that after a period of initial popularity it was abandoned by one-third of its previous users, with hundreds of Galaxy Gears being listed for sale on eBay barely six months after launch (Endeavour 2014).

In investigating the determinants of abandonment decisions, I also consider the central role of the observation of critical mass of abandoners in the post-adoption phase of a herd-like adoption. *Critical mass* is defined as the threshold beyond which active participants expand rapidly (Oliver et al., 1985). Lou et al. (2000) have suggested that perceptions of critical mass, as a form of social influence (Wattal et al. 2010), are important determinants of individuals' post-adoption intentions. However, I argue that in a herding context, the threshold to form a critical mass in the post adoption stage is much lower. In other words, critical mass can be reached faster in the post adoption stage (compared to the adoption stage), which can provide an explanation for en mass technology abandonment. Hence, I integrate the concept of critical mass with the arguments of prospect theory (i.e., the stronger impact of negative perceptions on individuals' decisions). This enables us to study how perceptions of the critical mass of abandoners (even if the actual number of abandoners is comparatively small) interacts with post-adoption TTF to create a cascade of abandonment intentions.

This essay also introduces the concept of *perceived niche* to the IS field. Shaefer et al. (2013) defined niche as a product's degree of specificity and uniqueness compared to the corresponding mass-market products. Niche products are used to achieve social visibility.

Hence, it is reasonable to argue that a person's effort to follow prior users, or to differentiate herself, may differ based on whether the product is a popular product consumed by everyone versus a niche item consumed by few. In the same vein, individuals may use specific social networking sites (SNSs) to try to achieve social visibility. Such differentiation behavior is relevant to herding behavior. People sometimes intentionally choose an unpopular option. This is defined as contrarian or anti herding behavior. For instance, in order to differentiate themselves from other organizations, some organizations may reject a popular innovation because too many other organizations have already adopted it (Abrahamson et al. 1993). People as well as organizations perform such contrarian behavior when they try to achieve the desired image. Therefore, I investigate abandonment intentions, which are especially prevalent among SNS users (Maier et al., 2012; 2014), by studying the interaction between individuals' perceptions of niche and post-adoption TTF.

Theoretically speaking, my adoption of a utilitarian lens for this essay enables us to explicitly recognize the dynamic nature of TTF perceptions, by introducing both pre and post TTF perceptions as critical factors impacting users' IS abandonment decisions. To the best of my knowledge, there are no published papers which have proposed such an integration. Most task-technology fit models are static, thus not reflecting reality (Goodhue 2007). Thus by recognizing the dynamic nature of TTF, I address this limitation of prior research in my study context. Moreover, by employing and developing the notions of critical mass and perceived niche, I improve understanding of patterns of technology abandonment, and contribute to the recently emerging stream of research which argues that IS discontinuance is not merely the opposite of IS continuance (e.g., Maier et al., 2015; Turel 2015).

Practically speaking, my task-focused approach will provide insights into the role of rational considerations, that is, the degree of fit between the technology and one's task (TTF) and its effect on the creation of herd-like abandonment of a previously popular IT. Understanding the dynamic nature of TTF perceptions, and their role in different phases of system introduction, is expected to benefit manufacturers/IT developers by helping them to reduce the possibility of an en mass migration of users away from their products. Further, by uncovering the role of critical mass of abandoners in forming abandonment intentions, managers may be able to influence en mass abandonment decisions. For example, it may be possible to undertake strategies designed to prevent the formation of perceptions of critical mass, for instance, by communicating the larger number of new adopters as opposed to abandoners. Moreover, organizations in some cases may want to *facilitate* the abandonment of a legacy technology to accelerate the implementation and usage of a new one. By forming a relatively small mass of abandoners and drawing other users' attention to it, organizations might be able to stimulate abandonment of the legacy system. In the same vein, IT developers might be able to prevent en mass abandonment through developing and communicating unique characteristics of a system, which might then increase niche perceptions. This way, IT developers could attempt to mitigate the negative effect of low TTF levels on individuals' continuance intentions.

ESSAY THREE

The actual benefits from an organization's IT investments accrue from behaviors that individual users perform in the post-adoption phase of system introduction (Hsieh et al., 2011). Actively revising system use and attempting to discover creative ways of applying a system (i.e., *explorative IS behavior*) extends the potential of that system, which contributes to enhancing task performance (Barki et al., 2007). However, users generally tend to employ a relatively narrow set of a given system's features (Jasperson et al., 2005). A technology's full benefits are more likely to be realized when users actively explore and take advantage of a broader range of system features (Hsieh et al., 2011; Sun 2012).

This third essay examines the determinants of a specific explorative IS behavior, i.e., *explorative IS learning*. As new systems become more complex, the role of user knowledge acquisition becomes a more salient factor in promoting an individual user’s level of proficiency (Te’eni et al., 2007). In this sense, the desired outcome of an effective IT training program is explorative learning, i.e., learning how to use more of the technology's available features. One important observation from reviewing the extant literature is that research on user exploration of technology and IT training has for the most part focused exclusively on individual-level interventions (e.g., Magni et al., 2010; Sun 2012; Senthanam et al. 2013). However, organizations today often apply team-oriented learning approaches to enhance learning outcomes (Gupta and Bostrom 2013). Despite providing a solid basis for future work, extant research provides little guidance on how to promote explorative IS learning behaviors in the case of team-based IS learning. This is significant for two reasons. *First*, in real life, organizations use teams to manage their operations and train their employees. Teams are a better source of information and creation of IT skills (Child and

Shumate 2007). Moreover, adopting a cross-level perspective in studying usage behaviors has been encouraged by prior studies (e.g., Markus and Robey 1988; Maruping and Magni 2015) in order to address the limitations of both strictly macro level studies (which ignore mental processes of the individual) and strictly micro-level studies (which ignore contextual factors). Examining IS usage behaviors in a team setting requires consideration of the team environment as well as the individual cognitions that shape post-adoptive behaviors such as exploration (Maruping and Magni 2015). *Second*, a review of the literature indicates a move toward more team-oriented learning approaches (Gupta et al. 2010). While substantial support has been found regarding the significance of team-based learning outside the IT training research context (Rohrbeck et al., 2003), its role in IT training has been unclear. Furthermore, conflicting results in extant IT training studies could be due to cross-sectional rather than longitudinal design (Gupta and Bostrom 2013).

To address these considerations, I adopt a longitudinal research design and a cross-level perspective. At the team level of analysis, I examined *team cohesion* to see how it promotes sustained IT learning in a team setting. Team cohesion is defined as the degree to which members of a team are relied upon and trusted by each other, and motivated to maintain their membership of the team (Organ and Hammer 1950). It represents an individual's assessment of her relationship with other team members (Chin et al., 1999). Overall, team cohesion is a bottom-up emergent phenomenon that results from the interpersonal interactions within teams (Kozlowski and Chao 2012). Team cohesion is conceptually related to trust and openness, which refer to the degree of emotional safety in a relationship. As Janssen and Huang (2008) indicate, people identify more intensely with a team when they have a sense of emotional involvement within the team and perceive more positive value attached to team membership. This sense of "oneness" within the team stimulates individual team members to perform in team-oriented ways to promote their collective social identity (Haslam et al. 2000).

Team-based learning provides a greater opportunity for observing others' learning behaviors and consequently imitating them (Benbunan-Fich and Hiltz 2003; Truman 2009). Observation of team members' IS usage behaviors, along with the high levels of uncertainty involved in complex IT training outcomes, may motivate individuals to imitate others (Lee et al., 2015) in exploratively learning a system -- in other words, toward herd-like explorative learning behavior. Herding behavior provides analytical support, especially by basing my argument on its theoretical underpinning, i.e., observational learning (Bandura 1977). Observational learning occurs when an individual observes the behavior of another individual and assumes the value of the behavior based upon that observation. Research has shown that people use their observations of their peers ' behaviors to update their own private beliefs before taking action (Oh and Jeon 2007). Such "herded actions" in the *small* team setting (e.g., with 3 team members in my own research context) may occur where members of the team have more opportunity (compared to a larger community/team) to observe their members' exact behaviors (Child and Shumate 2007). In such a team context in which the follower personally knows the predecessors (unlike in more traditional herding settings where the follower does *not* personally know the predecessors (Li et al. 2014), this observation of the actual behavior of the peer predecessor affects the follower's decisions, leading to herd-like decisions being made (Liu et al. 2015). In addition, due to the highly uncertain outcomes associated with an explorative IT training context (i.e., the context of my present study), compared to other forms of training (Burton-Jones and Grange 2013), observational learning is particularly influential (Gupta and Bostrom 2013). Hence, I argue that herd behavior, as a mechanism to reduce such uncertainties when individuals observe each others' actual behaviors, has the potential for explaining their *post-adoption* IS exploration behaviors.

The extant literature has largely ignored the fact that the ultimate goal of technology adoption is to improve efficiency; for that reason, prior research has tended to focus on usage (or even its proxy, usage intentions) as the ultimate dependent variable (Bagozzi 2007). Moreover, with the increasing complexity and configurability of current technologies, users' proactive exploration of system features, selective integration with legacy technology, revision of features, and subsequent adaptation to the system (by adjusting their usage processes) will ultimately determine the success of system adoption (Karahanna et al. 2006; Sun 2012; Sykes et al. 2009). By leveraging herding theory to investigate the determinants of explorative IS learning behaviors in the post-adoptive stage, I contribute to the literature on post-adoption usage, and more specifically on explorative IT usage. My study thus addresses the call for investigating behaviors other than IT use as the outcome variable in IS acceptance research (Benbasat and Barki 2007). Other recent studies (Tate et al. 2015) have also lamented these limitations of traditional technology acceptance research, and have also argued for a better conceptualization of IT use. In this study, I address this call by focusing on an individual's post-adoption exploration behavior, and more specifically on their IS learning explorations. I further contribute to Limayem et al. (2007) call for research that provides a better understanding of how to promote and sustain post-adoption behaviors. Encouraging explorative IS behavior is important since it facilitates the exploitation of system features in the long run.

In bridging the gap between the team environment and individual IT learning behaviors, I draw from recent research that incorporates *behavioral expectations* alongside *behavioral intentions* (see Maruping et al., 2015; Venkatesh et al., 2008), to understand the cognitions underlying user explorative behavior (Markus and Robey 1998). Intention and expectation represent two distinct cognitions that drive behavior (Venkatesh et al., 2006). Behavioral intention generally focuses on the internal beliefs that drive behavior (Venkatesh et al., 2006), and is defined as the degree to which a person has formulated conscious plans to perform or not perform some specific future behavior (Warshaw and Davis 1985). Behavioral expectation is a person's self-reported subjective probability of her cognitive appraisal of both volitional and non-volitional behavioral determinants (Warshaw and Davis 1984).

Behavioral intention is limited in its ability to predict behaviors that are not completely volitional since it only accounts for an individual's cognitive appraisal of the volitional factors (Warsaw et al., 1985). However, research shows that post-adoption behaviors, such as technology exploration, can also be driven by non-volitional factors (Jasperson et al., 2005). Especially in a team context in which the success of a team member in doing her assigned task is dependent on the actions of other team members, consideration of non-volitional factors is required. The limitation of using behavioral intention to evaluate external factors that affect the performance of a behavior (Venkatesh et al., 2003) despite integration of other constructs such as facilitating conditions (Ajzen 1991) and perceived behavioral control (Thompson et al., 1994), has led to the explicit inclusion of behavioral expectation into recent technology acceptance models. Hence, I include in my study one's *expectation to continue explorative learning,* which has a more external orientation and highlights the importance of contextual factors in the environment that can impede or promotes user's objective over time (Venkatesh et al., 2006). Expectation to continue explorative learning is conceptualized as the user's self-estimated probability of performing the target behavior of continuing learning a system exploratively based on her appraisal of the volitional and non-volitional behavioral determinants. I here conceptualize *intention to continue explorative learning* as a user's internal beliefs and motivation to engage in continued learning of a system in order to develop personalized and innovative ways of using it overtime. Although these two forms of cognitions are each expected to influence technology exploration, they do so based on fundamentally different orientations.

Theoretically speaking, this essay extends the herding literature by demonstrating how two complementary individual-level cognitions—intention to continue explorative learning and expectation to continue explorative learning—be triggered through initiating imitative behaviors. Moreover, the study contributes to the post-adoption literature on exploration of technology by examining the determinants of explorative IT learning. The study also addresses the call for further identifying the antecedents of exploration intentions (Magni et al., 2010) and the behavioral expectation construct in the IS domain (Venkatesh et al., 2008). Also, by empirically testing a cross-level model, the study develops a clearer picture of how the team environment (via team cohesion) influences individuals' explorative intentions.

Practically speaking, limited consideration has been given to date to the mechanisms through which organizations can foster desirable explorative learning behaviors in their members. It is possible that by encouraging imitative behaviors, organizations can positively influence further explorative learning, which in turn promotes efficiency and performance. In other words, by understanding the role of team cohesion as an antecedent of herd-like behavior in a training setting, managers can facilitate individuals' further explorative learning intentions, which may lead to more successful IS implementations (Sun 2012; Sykes et al. 2009).

REFERENCES

Abrahamson, E. 1991. "Managerial Fads and Fashions: The Diffusion and Rejection of Innovations," *Academy of management review* (16:3), pp. 586-612.

Abrahamson, E., and Rosenkopf, L. 1997. "Social Network Effects on the Extent of Innovation Diffusion: A Computer Simulation," *Organization science* (8:3), pp. 289-309.

Adler, P. S., and Clark, K. B. 1991. "Behind the learning curve: a sketch of the learning process," *Management Science* (37:3), pp. 267–281.

Ahuja, M. K., and Thatcher, J. B. 2005. "Moving Beyond Intentions and toward the Theory of Trying: Effects of Work Environment and Gender on Post-Adoption Information Technology Use," *MIS Quarterly* (29:3), pp. 427-459.

Ajzen, I. 1991. "The Theory of Planned Behavior," *Organizational behavior and human decision processes* (50:2), pp. 179-211.

Ajzen, I. and Driver, B.L., 1992. "Application of the theory of planned behavior to leisure choice," *Journal of leisure research* (24:3), p. 207-228.

Baerenklau, K. A. 2005. "Toward an Understanding of Technology Adoption: Risk, Learning, and Neighborhood Effects," *Land Economics* (81:1), pp. 1-19.

Bagozzi, R. P. 2007. "The Legacy of the Technology Acceptance Model and a Proposal for a Paradigm Shift," *Journal of the association for information systems* (8:4), p. 3.

Bandura, A. 1977. *Social learning theory*. Englewood Cliffs, NJ: Prentice-Hall.

Bandura, A. 1986. *Social Foundations of Thought and Action: A Social Cognitive Theory*. Prentice-Hall, Inc.

Banerjee, A., and Fudenberg, D. 2004. "Word-of-Mouth Learning," *Games and Economic Behavior* (46:1), pp. 1-22.

Banerjee, A. V. 1992. "A Simple Model of Herd Behavior," *The Quarterly Journal of Economics*), pp. 797-817.

Benbasat, I., and Barki, H. 2007. "Quo Vadis Tam?," *Journal of the association for information systems* (8:4), p. 7.

Benbunan-Fich, R., and Hiltz, S. R. (2003). Mediators of the effectiveness of online courses. *Professional Communication, IEEE Transactions on, 46*(4), 298-312

Bhattacherjee, A. 2001. "Understanding Information Systems Continuance: An Expectation-Confirmation Model," *MIS quarterly*), pp. 351-370.

Bikhchandani, S., Hirshleifer, D., and Welch, I. 1992. "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades," *Journal of political Economy*), pp. 992-1026.

Bikhchandani, S., Hirshleifer, D., and Welch, I. 1998. "Learning from the Behavior of Others: Conformity, Fads, and Informational Cascades," *The Journal of Economic Perspectives*), pp. 151-170.

Boudreau, M.-C., and Robey, D. 2005. "Enacting Integrated Information Technology: A Human Agency Perspective," *Organization science* (16:1), pp. 3-18.

Brooks, F. P. 1975. The Mythical Man-Month: Essays on Software Engineering. Reading, Massachusetts: Addison-Wesley Professional.

Brown, S. A., Venkatesh, V., and Hoehle, H. 2014. "Technology Adoption Decisions in the Household: A Seven - Model Comparison," *Journal of the Association for Information Science and Technology*.

Brynjolfsson, E., and Hitt, L. 1996. "Paradox Lost? Firm-Level Evidence on the Returns to Information Systems Spending," *Management science* (42:4), pp. 541-558.

Burton-Jones, A., and Grange, C. (2013). From use to effective use: a representation theory perspective. *Information Systems Research, 24*(3), 632-658.

Cameron, A. F., and Webster, J. 2005. "Unintended Consequences of Emerging Communication Technologies: Instant Messaging in the Workplace," *Computers in Human behavior* (21:1), pp. 85-103.

Chan, F. T., Chong, A. Y.-L., and Zhou, L. 2012. "An Empirical Investigation of Factors Affecting E-Collaboration Diffusion in Smes," *International Journal of Production Economics* (138:2), pp. 329-344.

Cheung, C. M., Xiao, B. S., and Liu, I. L. 2014. "Do Actions Speak Louder Than Voices? The Signaling Role of Social Information Cues in Influencing Consumer Purchase Decisions," *Decision Support Systems* (65), pp. 50-58.

Child, J. T., &andShumate, M. (2007). The impact of communal knowledge repositories and people-based knowledge management on perceptions of team effectiveness. *Management Communication Quarterly, 21*(1), 29-54.

Cialdini, R.B., 2003. "Crafting normative messages to protect the environment," *Current Directions in Psychological Science* (12:4), pp.105-109.

Davis, F. D. 1989. "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," *MIS quarterly*), pp. 319-340.

DiMaggio, P., and Powell, W. 1983. "The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields," *American Sociological Review* (48:2), pp. 147-160.

Duan, W., Gu, B., and Whinston, A. B. 2009. "Informational Cascades and Software Adoption on the Internet: An Empirical Investigation," *MIS Quarterly* (34:1), pp. 23-48.

Evans, C., Professor Raymond Hackney, D., Rauniar, R., Rawski, G., Yang, J., and Johnson, B. 2014. "Technology Acceptance Model (TAM) and Social Media Usage: An Empirical Study on Facebook," *Journal of Enterprise Information Management* (27:1), pp. 6-30.

Fishbein, M., Ajzen, I., 1975. Beliefs, Attitude, Intention and Behavior: an Introduction to Theory and Research. Addison-Wesley, Reading, MA.

Furneaux, B. and Wade, M., 2011. "An Exploration of Organizational Level Information Systems Discontinuance Intentions," *MIS Quarterly* (35:3), pp.573-598.

Geriner, P.T., Gulledge, T.R. and Hutzler, W.P. eds., 2012. *Software engineering economics and declining budgets*. Springer Science & Business Media.

Goodhue, D. L., and Thompson, R. L. 1995. "Task-Technology Fit and Individual Performance," *MIS Quarterly*, pp. 213-236.

Gregor, S. and Hevner, A.R., 2013. "Positioning and Presenting Design Science Research for Maximum Impact," *MIS Quarterly* (37:2), pp.337-355.

Grover, V., and Goslar, M. D. 1993. "The Initiation, Adoption, and Implementation of Telecommunications Technologies in Us Organizations," *Journal of Management Information Systems*, pp. 141-163.

Gu, J., Li, L., Xu, Z., and Fujita, H. 2015. "Construction of a Technology Adoption Decision-Making Model and Its Extension to Understanding Herd Behavior," *Knowledge-Based Systems*.

Gupta, S., Bostrom, R.P. and Huber, M., 2010. "End-user training methods: what we know, need to know," *ACM SIGMIS Database* (41:4), pp.9-39.

Gupta, S. and Bostrom, R., 2013. "Research Note-An Investigation of the Appropriation of Technology-Mediated Training Methods Incorporating Enactive and Collaborative Learning," *Information Systems Research* (24:2), pp. 454-469.

Haslam, S. A., Powell, C., and Turner, J. (2000). Social identity, self-categorization, and work motivation: rethinking the contribution of the group to positive and sustainable organisational outcomes. *Applied Psychology, 49*(3), 319-339.

Hirunyawipada, T., Paswan, A. K., and Blankson, C. 2015. "Toward the development of new product ideas: asymmetric effects of team cohesion on new product ideation," *Journal of Business & Industrial Marketing* (30:7), pp. 855-866.

Huczynski, A., and Buchanan, D. 2001. *Organizational Behaviour: An Introductory Text (Instructor's Manual)*. Financial Times/Prentice Hall.

Jasperson, J. S., Carter, P. E., and Zmud, R. W. 2005. "A Comprehensive Conceptualization of Post-Adoptive Behaviors Associated with Information Technology Enabled Work Systems," *MIS Quarterly* (29:3), pp. 525-557.

Janssen, O., and Huang, X. (2008). Us and me: Team identification and individual differentiation as complementary drivers of team members' citizenship and creative behaviors. *Journal of Management, 34*(1), 69-88.

Kahneman, D., and Tversky, A. 1979. "Prospect Theory: An Analysis of Decision under Risk," *Econometrica: Journal of the Econometric Society*, pp. 263-291.

Karahanna, E., Agarwal, R., and Angst, C. M. 2006. "Reconceptualizing Compatibility Beliefs in Technology Acceptance Research," *MIS Quarterly*, pp. 781-804.

Kozlowski, S.W. and Chao, G.T. 2012. "The dynamics of emergence: Cognition and cohesion in work teams," *Managerial and Decision Economics*, (33-5), pp. 335-354.

Lee, Y.J., Hosanagar, K. and Tan, Y. 2015. "Do I follow my friends or the crowd? Information cascades in online movie ratings," *Management Science* (61:9), pp. 2241-2258.

Lee, J., Runge, J., Baek, S., and Shek, S. 2001. "Adoption of Internet Technologies in Small Businesses," *PACIS 2001 Proceedings*, p. 71.

Li, X. 2004. "Informational Cascades in It Adoption," *Communications of the ACM* (47:4), pp. 93-97.

Li, X., Kauffman, R. J., Yu, F., and Zhang, Y. 2014. "Externalities, Incentives and Strategic Complementarities: Understanding Herd Behavior in It Adoption," *Information Systems and e-Business Management* (12:3), pp. 443-464.

Limayem, M., Hirt, S. G., and Cheung, C. M. 2007. "How Habit Limits the Predictive Power of Intention: The Case of Information Systems Continuance," *MIS Quarterly* (12:4), pp. 705-737.

Liu, D., Brass, D., and Chen, D. (2015). Friendships in Online Peer-to-Peer Lending: Pipes, Prisms, and Relational Herding. *MIS Quarterly, 39*(3), 729-742.

Liu, Q., and Zhang, L. 2014. "Information Cascades in Online Reading: An Empirical Investigation of Panel Data," *Library Hi Tech* (32:4), pp. 687-705.

Magni, M., Taylor, M. S., and Venkatesh, V. 2010. "'To Play or Not to Play': A Cross-Temporal Investigation Using Hedonic and Instrumental Perspectives to Explain User Intentions to Explore a Technology," *International Journal of Human– Computer Studies* (68), pp. 572-588.

Maier, C., Laumer, S., Weinert, C. and Weitzel, T., 2015. "The effects of technostress and switching stress on discontinued use of social networking services: a study of Facebook use," *Information Systems Journal (25:*3), pp. 275-308.

Markus, M. L., and Robey, D. 1998. "Information Technology and Organizational Change: Causal Structure in Theory and Research," *Management Science* (34:5), pp. 583-598.

Maruping, L. M., and Magni, M. 2015. "Motivating Employees to Explore Collaboration Technology in Team Contexts," *MIS Quarterly* (9:2), pp. 204-215.

Milliken, F. J. 1987. "Three Types of Perceived Uncertainty about the Environment: State, Effect, and Response Uncertainty," *The Academy of Management Review* (12:1), pp. 133-143.

Oh, W. and Jeon, S., 2007. Membership herding and network stability in the open source community: The Ising perspective. *Management science*, *53*(7), pp.1086-1101.

Organ, D. and Hammer, W.C., 1950. Organisational behaviour. *Plano, Tx: Business Publications*.

Ottaviani, M., and Sørensen, P. N. 2006. "Reputational Cheap Talk," *The Rand journal of economics* (37:1), pp. 155-175.

Paulus, M. 2014. "How and Why Do Infants Imitate? An Ideomotor Approach to Social and Imitative Learning in Infancy (and Beyond)," *Psychonomic bulletin & review* (21:5), pp. 1139-1156.

Rao, H., Greve, H. R., and Davis, G. F. 2001. "Fool's Gold: Social Proof in the Initiation and Abandonment of Coverage by Wall Street Analysts," *Administrative Science Quarterly* (46:3), pp. 502-526.

Ravichandran, T., and Liu, Y. 2011. "Environmental Factors, Managerial Processes, and Information Technology Investment Strategies," *Decision Sciences* (42:3), pp. 537-574.

Rogers, E. M. 1995. *Diffusion of Innovations*. New York: Free Press.

Rohrbeck, C.A., Ginsburg-Block, M. D., Fantuzzo, J.W., and Miller, T.R. 2003. "Peer-Assisted Learning Interventions With Elementary School Students: A Meta-Analytic Review," *Journal of Educational Psychology* (95:2), pp. 240-257.

Scharfstein, D. S., and Stein, J. C. 1990. "Herd Behavior and Investment," *The American Economic Review*), pp. 465-479.

Sharma, S., and Rai, A. 2015. "Adopting Is Process Innovations in Organizations: The Role of Is Leaders' Individual Factors and Technology Perceptions in Decision Making," *European Journal of Information Systems* (24:1), pp. 23-37.

Simon, H. A. 1982. *Models of Bounded Rationality: Empirically Grounded Economic Reason*. MIT press.

Song, J., and Walden, E. 2003. "Consumer Behavior in the Adoption of Peer-to-Peer Technologies: An Empirical Examination of Information Cascades and Network Externalities," *AMCIS 2003 Proceedings*, pp. 231-240.

Straub, E.T., 2009. "Understanding technology adoption: Theory and future directions for informal learning," *Review of educational research* (79:2), pp. 625-649.

Sun, H. 2012. "Understanding User Revisions When Using Information System Features: Adaptive System Use and Triggers," *MIS Quarterly* (36:2), pp. 453-478.

Sun, H. 2013. "A Longitudinal Study of Herd Behavior in the Adoption and Continued Use of Technology," *MIS Quarterly* (37:4), pp. 1013-1041.

Sun, H., and Zhang, P. 2006. "The Role of Moderating Factors in User Technology Acceptance," *International Journal of Human-Computer Studies* (64:2), pp. 53-78.

Sun, Y., and Jeyaraj, A. 2013. "Information Technology Adoption and Continuance: A Longitudinal Study of Individuals' Behavioral Intentions," *Information & Management* (50:7), pp. 457-465.

Sykes, T. A., Venkatesh, V., and Gosain, S. 2009. "Model of Acceptance with Peer Support: A Social Network Perspective to Understand Employees' System Use," *MIS Quarterly*, (6:1), pp. 371-393.

Tate, M., Evermann, J., and Gable, G. 2015. "An Integrated Framework for Theories of Individual Attitudes toward Technology," *Information & Management* (52:6), pp. 710-727.

Taylor, S. and Todd, P.A., 1995. "Understanding information technology usage: A test of competing models," *Information systems research*,(6:2), pp.144-176.

Terlaak, A., and King, A. A. 2007. "Follow the Small? Information ‐ Revealing Adoption Bandwagons When Observers Expect Larger Firms to Benefit More from Adoption," *Strategic Management Journal* (28:12), pp. 1167-1185.

Tomasino, A. P., and Fedorowicz, J. 2014. "Fad-Like Technology Adoption as a Social Action," *International Journal of Information Systems and Management* (1:1-2), pp. 37-59.

Truman, G. (2009) "Behaviour Modelling, Instruction and Exploration Training Approaches in Group and Individual Contexts," *Behaviour and Information Technology* (28:6), pp. 493-524.

Turel, O., 2015. "Quitting the use of a habituated hedonic information system: a theoretical model and empirical examination of Facebook users," *European Journal of Information Systems* (24:4), pp. 431-446.

Venkatesh, V., Brown, S. A., Maruping, L. M., and Bala, H. 2008. "Predicting Different Conceptualizations of System Use: The Competing Roles of Behavioral Intention, Facilitating Conditions, and Behavioral Expectation," *Mis Quarterly*, pp. 483-502.

Venkatesh, V., Maruping, L. M., and Brown, S. A. 2006. "Role of Time in Self-Prediction of Behavior," *Organizational Behavior and Human Decision Processes* (100:2), pp. 160-176.

Venkatesh, V., and Morris, M. G. 2000. "Why Don't Men Ever Stop to Ask for Directions? Gender, Social Influence, and Their Role in Technology Acceptance and Usage Behavior," *MIS Quarterly*, pp. 115-139.

Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. 2003. "User Acceptance of Information Technology: Toward a Unified View," *MIS Quarterly*, pp. 425-478.

Walden, E. A., and Browne, G. J. 2009. "Sequential Adoption Theory: A Theory for Understanding Herding Behavior in Early Adoption of Novel Technologies," *Journal of the Association for Information Systems* (10:1), pp. 31-62.

Warshaw, P.R. and Davis, F.D., 1984. "Self-understanding and the accuracy of behavioral expectations,"*Personality and Social Psychology Bulletin* (10:1), pp.111-118.

Warshaw, P. R., and Davis, F. D. 1985. “The Accuracy of Behavioral Intention Versus Behavioral Expectation for Predicting Behavioral Goals,” *Journal of Psychology* (119:6), pp. 599-602.

Wattal, S., Racherla, P., and Mandviwalla, M. 2010. "Network Externalities and Technology Use: A Quantitative Analysis of Intraorganizational Blogs," *Journal of Management Information Systems* (27:1), pp. 145-174.

Zhang, J., 2010. The sound of silence: Observational learning in the US kidney market. *Marketing Science*, *29*(2), pp.315-335.

APPENDICES

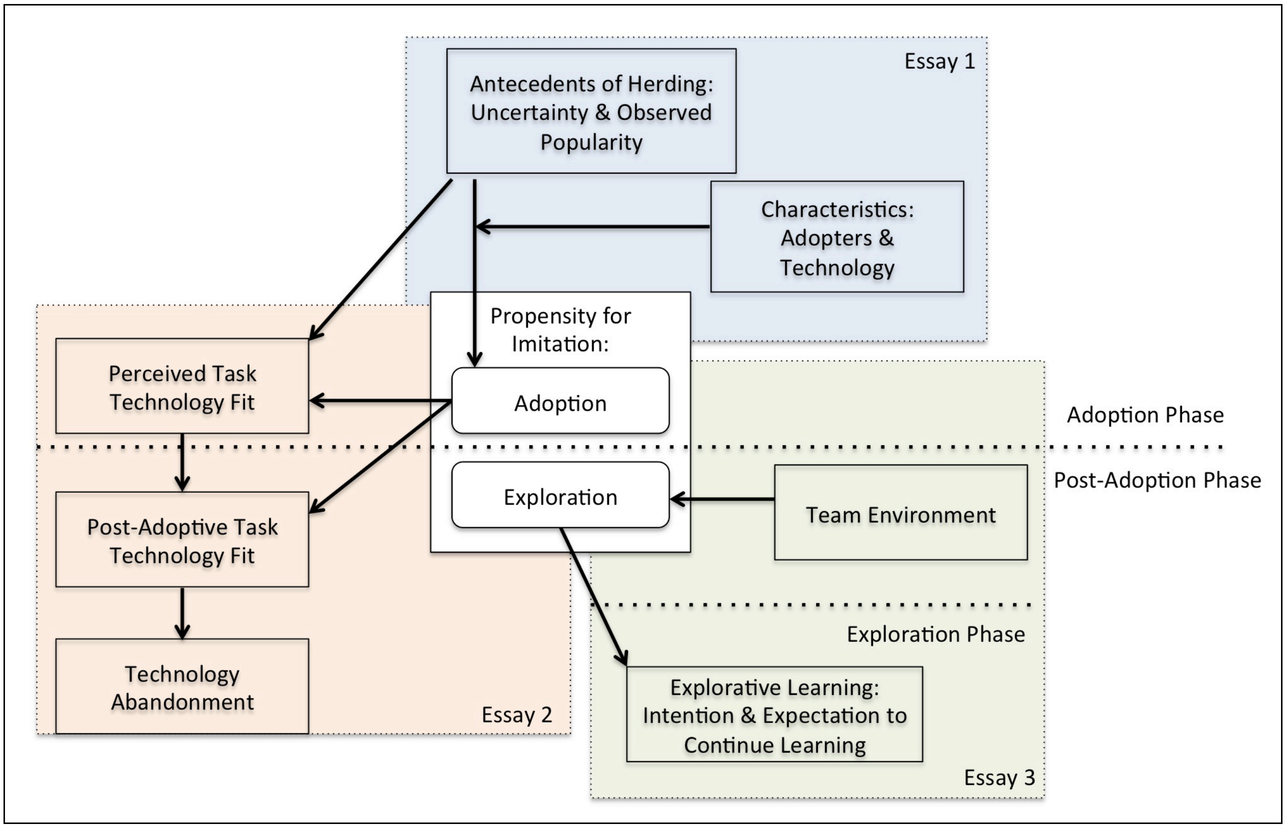


Figure 1 Schematic Structure of the Dissertation

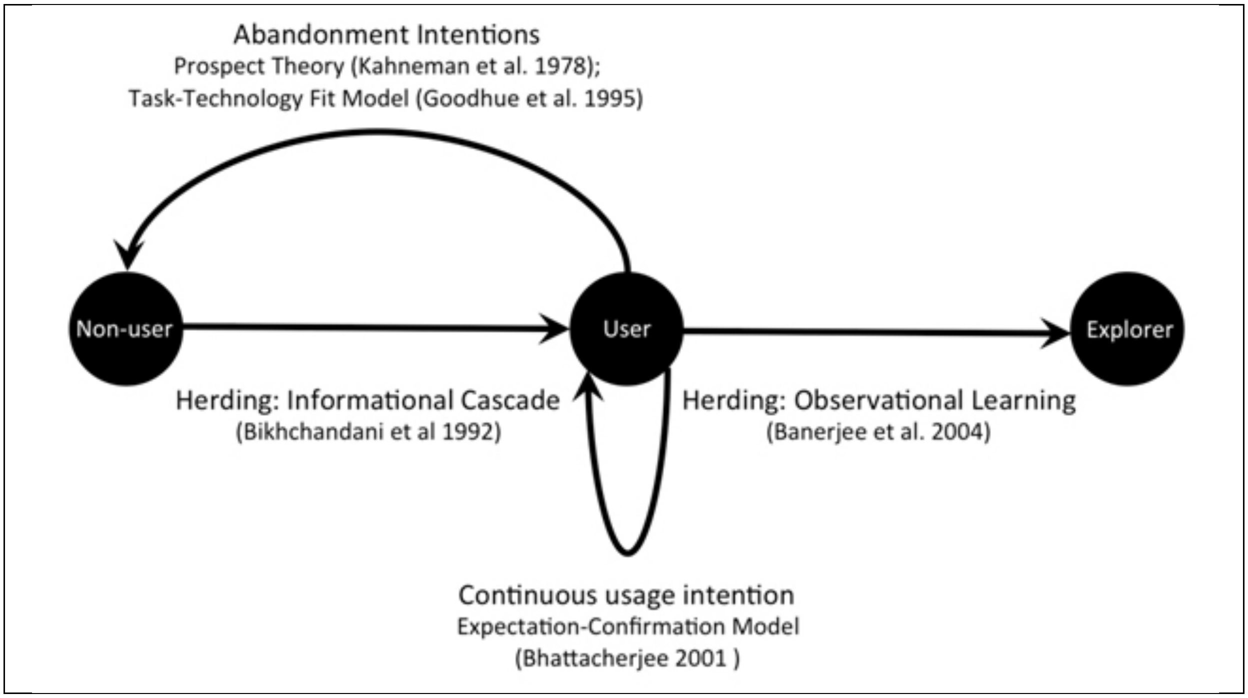


Figure 2 User Transformation

CHAPTER 2

Herd Behavior in Technology Adoption: The Role of Adopter and Technology Characteristics

INTRODUCTION

Before making decisions, people often have the opportunity to observe what others before them have decided to do, and to infer information from their actions. For example, individuals often choose the most popular product brand since they believe that its popularity is an indication of a better price/quality ratio. They also often compare the number of people currently eating at different restaurants before determining which one to choose for themselves. As Aristotle indicates "Man is very imitative and obtains his first knowledge by imitation, and then everybody takes pleasure in imitation." This leads to what is called *herd behavior*. Herding is particularly prominent in the information systems (IS) area. Technology users often adopt popular products, thus making them even more popular (Brynjolfsson et al. 1996). A number of new technologies, especially in the area of social networking systems (SNSs), have benefited from the herd-like adoption behavior of their users. For instance, Ello, a relatively new SNS, was successfully attracting 40,000 to 50,000 sign-ups per hour since its launch (Slate 2015). The same herd-like behavior occurs when people abandon a previously trendy technology (Sun 2013). An interesting example of such abandonment is FacebookThe Cambridge Analytica scandal, in which data from over 50 million Facebook profiles was secretly scraped, has led to mass abandonment of its users (Hsu 2018). Facebook is losing its young users faster than any other SNS (USA Today 2018). To preserve their discretion, teens are now opting for services such as Tumblr, Twitter, and Instagram that offer more privacy, instead of Facebook (BGR.com 2013). Obviously, this could become a problematic issue if teens continue to leave Facebook *en masse*, since they represent an entire generation of people who will grow up using various rivals of Facebook. The phenomenon of herd-like adoption is important and requires more exploration, since it is linked to the durability of popular technologies (Sun 2013). We need to take into account many factors to understand the reason for individuals` convergence in using one particular technology and then leaving it later en masse.

The observational learning literature provides another perspective for en masse convergence toward a technology. Observational learning is one of the most useful and universal tools of decision-making, and occurs when an individual observes the behavior of another person and -- based on that observation -- concludes something about the value and practicality of the behavior (Bandura 1977; Walden and Browne 2009). As Banerjee (1992) argues, herd behavior happens when "everyone does what everyone else is doing, even when their private information suggests doing something quite different" (p. 798). This implies that an individual`s decisions can become less responsive to his or her own information when faced with information on which other parties have reached a decision.

IS research can benefit from using herd theory as a lens to investigate technology adoption (Sun 2013). Computer users often adopt popular software products, thus making them even more popular, for example, when the download ranking of software products fluctuates and online users' choices of software products change dramatically (Duan et al.

2009). This shows that individuals tend to follow the previous adopters' decisions as revealed by the download ranking. Another stream of research has discussed and compared *informational cascades*, which refer to the situation in which an adopter disregards his or her own private information and follows the behavior of predecessors (Bikhchandani et al. 1992), with other parallel notions such as *network effects*, which states that the value of a technology increases as the number of its users increases (Li 2004). However, such behavior may lead to incorrect adoption decisions. Walden et al. (2009) simulated users' adoption of technology based on signals inferred from observation of the popularity of prior adoption behaviors by others, and showed that people tend to imitate others through herding, which can sometimes lead to incorrect adoption decisions, such as adopting a pedestrian (e.g., less efficient) substitute.

Characteristics of both *individuals* and the *technology* under consideration influence adoption behaviors (Foil and O'Connor 2003). Clearly, not everyone ends up joining a herd. Further, different people, based on their unique characteristics, exhibit different degrees of herd behavior (Sun 2013), since individual differences have been found to affect technology choices (Agarwal and Prasad 1999; Strong et al. 2006). Every technology has its own unique characteristics, which are perceived differently by different users (Aldhaban 2012). In the same vein, not every technology reaps the benefits of herding in the same way. The characteristics of the technology need to fit with the requirements of the task that a potential adopter wants to fulfill (Goodhue and Thompson 1995). Therefore, the interaction between the characteristics of the technology and the characteristics of individuals should be considered in order to effectively evaluate if a particular technology is meeting users' needs to perform a task. In this regard, Goodhue et al. (1995) suggested that the Task-Technology-Fit model (TTF) could be used as an effective tool in explaining system use and task performance of individuals.

This study proposes a research model to examine the impact of specific individual and technology characteristics on herd behavior. I seek to answer the following research question: *How do characteristics of the individual user, and of the focal technology, impact that individual's herd-like behavior in adopting a new technology?* By studying the significance of such characteristics in the technology adoption phase, I improve understanding of herd-like adoption decisions. One specific herd factor, namely *propensity for imitation* (defined as the degree to which an individual follows preceding adopters to adopt a specific form of technology; Rao et al. 2001), is integrated into TTF (Goodhue and Thompson 1995), which has posited specific characteristics of individuals and technology as factors leading to utilization of technology.

THEORETICAL DEVELOPMENT

Herd Behavior

In recent years, most people have both witnessed and participated in countless instances of technology adoption where the adopters were influenced strongly by the herd behavior of previous adopters (Duan et al. 2009; Walden and Browne 2009). Herd behavior has been observed in a wide variety of situations, such as the downloading of software applications (Duan et al. 2009), and in academic fields including finance and economics (Hirshleifer et al. 2003), as well as marketing (Zhan 2010). As a consequence, there is now a well-developed literature stream on herd behavior.

The network effects literature has been used in the past to provide an explanation for the occurrence of herd behavior in IS (Duan et al. 2008). As Katz and Shapiro (1994) pointed out, network effects occur when the increase of user base makes a product more valuable. However, the significant network effects anticipated by academic researchers in the IS field have often failed to materialize (Liebowitz 2002). For instance, despite the benefits of large participations (e.g., friends connected via an SNS), too many users can limit the benefits of network effects by causing a network congestion problem (Asvanund et al. 2004; Bakos 1991). Obviously in such cases, a huge network does not automatically provide more value to potential adopters. Due to the concerns about whether the network effects have positive or negative effects in the IS field, we need to shift to considering an alternative driver of herd behavior: *informational cascades* (Banerjee 1992; Bikhchandani et al. 1992; Li et al. 2004).

Informational Cascades

Informational cascades occur when potential adopters become less responsive to personal information and instead prefer to simply imitate prior adopters' decisions, presuming that the previous adopter is better informed (Bikhchandani et al. 1992). Thus, imitation and ignoring one's own information are the two main underlying characteristics of an informational cascade. This behavior usually occurs when an individual has other alternatives available, that are different from the predecessors' decisions (Bikhchandani et al. 1992; Duan et al. 2009). Rationally ignoring personal information and mimicking the prevailing decision results in losing valuable private information and poor information aggregation through blocking the flow of new information to later decision-makers (Li et al. 2014). This phenomenon creates a chain of reactions, which leads an increasing number of individuals to join a herd. In fact, as Bikhchandani et al. (2000) argue, following the first few individuals the likelihood that an informational cascade starts is very high.

As Duan et al. (2009) pointed out the underlying idea in an informational cascade is that decision makers each have some private information that can be regarded as a signal about the utility of a decision. However, the signals are noisy and imperfect, so potential adopters must make their decisions under conditions of uncertainty (Walden and Browne 2009). The signal can also be flawed since in competitive environments (which is where most IT adoptions occur), decision makers may rationally employ signal jamming to misinform others (Crawford 2003). For instance, prior users may not communicate truthful information about a newly adopted technology in order to maintain an edge over their competitors. This characteristic of the signal suggests that herd behavior is often influenced by low informativeness, which means the herd does not transfer all of the preferences and information of herd members (Lieberman and Asaba 2006). Online consumer reviews, for example, show how many people found the review as helpful so far. For example, "90 out of 100 people found this (review) helpful", this is a signal indicating other customers' evaluation of review helpfulness without knowing their decision-making process. The observable part of this course of actions is the *decisions*, rather than the signals, which are noticeable by other decision makers who then modify their beliefs about the appropriate course of action.

Observational Learning and the Uncertainty of Adoption

The pioneering studies of herding by Banerjee (1992) and Bikhchandani et al. (1992) showed that observational learning results in herd behavior. Technology adoption behavior is especially prone to learning from observation of the popularity of predecessors` decisions, since technology adoptions are fraught with uncertainties (Walden and Browne 2009). The outcomes of IT adoption decisions are often uncertain, since we are dealing with some of the most complex artifacts ever built by humans: technological components. It also takes a long time to realize the impacts of an adoption (Brynjolfsson and Hitt 1996). Due to this uncertainty and ambiguity, observational learning becomes a necessary condition for successful herd-like adoption (Walden and Browne 2009). A follower may infer that a given technology is worth adopting, because the predecessors' information must have supported their own decision to adopt that technology. Such an inference can save a great deal of cognitive effort for the follower (Cingl 2013). Ultimately, uncertain technology decisions can be made much easier by observing and utilizing the behavior of others.

Prior studies have argued that uncertainty about the adoption decision is a driver of herd-like behavior in technology adoption (Fiol and O'Connor 2003; Lieberman and Asaba 2006; Sun 2013; Walden and Browne 2009). As a result of asymmetric private or limited information, individuals may join a herd to reduce the uncertainty of their decisions about adoption (Duan et al. 2009). Moreover, observing that a particular decision is gaining *popularity* among people is essential to encouraging individuals to join the herd (Sarker and Valacich 2010). In this regard, the *number* and *identity* of the previous adopters matters (Sun 2013). Rao et al. (2001) indicated that as more people choose an alternative, it exponentially affects the herding toward this decision. Also, adopters may rely more on decisions of a particular group of predecessors, whom adopters believe has made better decisions or has more precise information, such as fashion leaders (Bikhchandani et al.

1992).

A handful of recent studies (e.g., Walden and Browne 2009; Duan et al. 2009; Sun 2013) have investigated the influence of herd behavior in IS adoption. Complementing this line of research, I empirically explore the interactive effect of herd factors (i.e., perceived uncertainty and observation of prior users) and studied characteristics (i.e., individual and technology) on herd behavior. This will provide us with a more accurate understanding of the causes of herd behavior, in order to better address its associated challenges. In accordance with the extant herd behavior literature, I define herding in the context of technology adoption as the phenomenon whereby a potential adopter follows others when making an adoption decision, even if that adopter's personal information advocates choosing an alternative. Herding aids decision makers in choosing which technology to adopt, including whether to accept or reject an available alternative. However, as I will discuss, not every user demonstrates herding behavior and herding does not occur for every technology. It is for this reason that it is important to consider specific characteristics of both the individual and the focal technology that may stimulate or accentuate herd-like adoption.

RESEARCH MODEL

The proposed research model is shown in Figure 1. While the first two hypotheses, as well as hypothesis 9, have already been theoretically posited and empirically tested in prior research (e.g., Sun 2013, who referred to the propensity for imitation construct as "imitating others"), I include them here for completeness given the relative newness of research on herding in the IS discipline.

As noted earlier, the key questions of interest in this paper are: Why do some people herd in adopting a technology, and which technology characteristics are most prone to herding? In general, people adopt only the technologies that they believe will be useful in improving the effectiveness and efficiency of performing some task (Venkatesh et al. 2003). In the same vein, individual characteristics are potentially important to the successful use of an adopted technology because different individuals have different needs (Lee et al. 2007; Zhou et al. 2010).

Insert Figure 1 here

These characteristic variations in both technologies and adopters themselves correspond directly to the core underpinnings of the Task-Technology Fit Model (TTF) (Goodhue and Thompson 1995), which recognizes these two factors as key elements that lead to ultimate system utilization. For this reason, TTF is particularly appropriate to use as the foundation for my research model of herd behavior in technology adoption.

TTF has been employed in the past to provide a conceptual basis for understanding how individuals evaluate a new information system. The TTF model has also been used to test hypotheses about the antecedents of user assessments. Goodhue and Thompson (1995) found that system characteristics and individual characteristics both influenced user evaluations of an IS. Moreover, their study revealed that individual characteristics should moderate the relationship between system characteristics and user assessments. Specifically, they found that individual characteristics moderate the strength of the link between system characteristics and users' intention to employ those systems (Goodhue

1998). I selected TTF as the theoretical lens for this study since its constructs can be easily tailored to the study of herd behavior. For instance, its explanations of the role of individual and technology characteristics and acknowledgment of their effects (which are also the focus of this study) are essential to understanding the impact of herd behavior on one's decision making. TTF is adapted and revised in the present study by incorporating two key dimensions of herd behavior, *observed popularity* and *uncertainty of adoption* (Sun 2013). The "propensity for imitation" construct is also integrated into the model as the primary outcome of the interactive relationship between herding factors and the characteristics of individuals and technologies.

Antecedents of Herd Behavior

As mentioned previously, the herd literature has suggested two key antecedents for herd behavior to occur: observation of the popularity of previous adopters` actions, and uncertainty of adoption (Banerjee 1992; Choi 1997; Sun 2013; Walden and Browne 2009; Yan-ni and Lei 2013). Observing previous adopters' performance is much easier today than in the past. Society and the media pay considerable attention to advances in information systems and publicize new developments in the latest information technologies. The Internet and other digital channels let people easily observe the decisions of others concerning technology adoption (Duan et al. 2009). For example, Apple`s App Store publishes top grossing charts to help users follow the trends. Likewise, eBay's auction feature allows for the observation of early bidders' starting bids, which leads following bidders to engage in herd behavior (Simonson et al. 2008). Also, Amazon.com lists the popular items in every category in decreasing order of purchase to facilitate observational learning (Chen et al. 2011).

Cost savings that prior adopters may have achieved are another convincing factor that encourages followers to observe the popularity of the prior adoption behaviors (Rao et al. 2001). To deal with the presence of asymmetric information, individuals employ information searching strategies (Fiol and O'Connor 2003). Information searching requires time and energy, and even financial investment. Sunk costs (e.g., wasting one's personal investment) may occur if an individual decides to maintain the status quo after having stopped to search for further information. Likewise, a potential adopter may wish to explore the features and benefits of a technology to see if it really addresses his or her needs (Goodhue 1998; McGill and Klobas 2009; Zigurs and Khazanchi 2008). All of these things require time and energy, meaning that an individual might be convinced to ignore personally held information and simply imitate the predecessors' actions, assuming that they have already done all of the necessary product research (Sun 2013). Thus I posit:

H1: Observed popularity will have a positive impact on propensity for imitation.

As previously discussed, one of the major motivations for imitation in adopting new technology is the desire to overcome uncertainty and avoid costs or blame for one's choices (Banerjee 1992; Choi 1997; Sun 2013; Walden and Browne 2009; Yan-ni and Lei 2013). In general, uncertainty occurs when a lack of accurate information reduces an individual`s prediction precision (Milliken 1978). In the context of technology adoption, therefore, uncertainty can be defined as the inability to foresee the concerns related to adoption of a technology due to inaccurate or incomplete information (Walden and Browne 2009).

Prior studies have revealed that individuals are likely to demonstrate herd-like behavior as the degree of uncertainty about a decision increases (Sun 2013; Walden and

Browne 2009; Yan-ni and Lei 2013). Uncertainty is an important driver of informational cascades, in which potential adopters, rather than making decisions based on their own private information, imitate the actions of their predecessors (Walden and Browne 2009). Higher uncertainty impedes one's ability to accurately analyze the linkage between an adoption decision and its consequences (Sun 2013). From this perspective, it makes sense for an adopter to ignore his or her incomplete privately held information and imitate the decisions of others in the presence of high uncertainty. Sun (2013) empirically tested this relationship in the context of an online wiki system (i.e., PBwiki) and could not find a significant link. He argues that the low-uncertainty nature of his study's focal technology (i.e., he found that his respondents generally found adopting PBwiki to involve little uncertainty) might be the reason. Hence, I will re-examine this link in a high-uncertainty situation, i.e., adoption of a new SNS (Maier et al. 2015). Thus I posit:

> *H2: Uncertainty associated with technology adoption will have a positive impact on propensity for imitation.*

Adopter Characteristics

It is important to include individual characteristics of the prospective adopter in my model, since there is much evidence that individual differences affect people's technology choices (Agarwal and Prasad 1999; Strong et al. 2006). For example, individuals who are highly risk-averse are less likely to adopt a technology if it involves high uncertainty (Leidner and Kayworth 2006). However, the impact of decision maker characteristics on herding behavior has not been thoroughly investigated. Prior studies in technology adoption have used a wide array of constructs to investigate the role of individual differences. For example, computer literacy (Goodhue and Thompson 1995), experience with a particular technology (Guinan et al. 1997; Strong et al. 2006), age and gender (Venkatesh et al. 2012), personal innovativeness in technology (PIIT) (Agarwal and Prasad 1998), mindfulness (Fiol and O'Connor 2003) and computer playfulness (Agarwal and Prasad 1998) have all been found to have influential individual level effects on technology adoption.

I focus here on three specific individual differences that are likely to have a noticeable effect on the herding behavior of potential technology adopters: *self-efficacy* with respect to the focal technology*, PIIT,* and *mindfulness.* Observing the extent of the usage of a technology within the reference group provides a further source of information used in forming self-efficacy (Compeau et al. 1995). IS studies have also found that the tendency to observe and adopt the IS behavior of a crowd through monitoring social network systems is higher for individuals with lower self-efficacy perceptions (Argyris and Xu 2016). Further, prior research indicates that in making online purchases, individuals with less experience in online shopping (as one of the sources of self efficacy (Bandura 1997), choose to imitate others in buying the more popular products (Chen et al. 2011). Hence, if an individual has higher levels of self-efficacy, she may weigh less heavily the importance of observing the popularity of others' adoption behaviors. It is therefore reasonable to argue that people with lower self-efficacy, in developing intentions to imitate others, will place higher importance on the observed popularity of the adoption behaviors of others.

Empirical evidence indicates that self-efficacious individuals are more active in seeking out new experiences (Tsang 2001) and more willing to explore new technologies

(Strong et al. 2006). As a result, for an efficacious person, higher perceptions of uncertainty may have less influence on the strength of her imitation intentions, since she is more likely to independently explore new technologies while believing in her abilities. Moreover, being in an uncertain situation generally motivates individuals to seek out information to make their decision (Shamsudin and Othman 2016); however, making decisions in a herding setting does not provide individuals with accurate information (Abrahamson et al. 1993). Hence, for individuals with less belief in their own abilities and skills (i.e., lower self-efficacy), higher perceived uncertainty levels will more strongly influence their decisions to imitate others behavior in order to reduce such uncertainties.

Moreover, Bandura (1977) posits that prediction of results of a behavior is one of the aspects of self-efficacy. This refers to the individual's prediction that her action could lead to a certain result (Chen et al. 2011). In this case, the high uncertainty involved in herd-like adoption decisions (Sun 2013) may be less likely lead to lead to the development of imitation intentions for an efficacious person, since she has a high level of beliefs in her abilities and skills. In addition, compared to those with low self-efficacy, individuals with high levels of self-efficacy are likely to be more comfortable in dealing with high scope tasks where they need to exercise personal judgment and make decisions independently rather than imitating others decisions (Jex et al. 2001). High scope tasks involve higher uncertainties (Johns 2010); hence, making independent rather than imitative decisions by an efficacious individual implies the existence of a buffering effect of higher perceived self-efficacy on the link between perceived uncertainty and propensity for imitation. Based on the above discussion, I argue that although in a herding setting, people may have a propensity to imitate others when they have a lower perceived ability to foresee the future (i.e., higher perceived uncertainty), when a person has higher perceptions of her own capability and skills (i.e., perceived self-efficacy), the effect of uncertainty perceptions on imitation intentions will be mitigated. Thus, I hypothesize:

H3a: Self-efficacy will moderate the relationship between observed popularity and propensity for imitation, such that the relationship is weaker for individuals with higher, rather than lower, levels of self-efficacy.

H3b: Self-efficacy will moderate the relationship between uncertainty of adoption and propensity for imitation, such that the relationship is weaker for individuals with higher, rather than lower, levels of self-efficacy.

Personal innovativeness in technology (PIIT) is a psychological trait of the potential adopter that is defined as the willingness to try out any new information technology, and is associated with more positive beliefs about IT usage in general (Agarwal and Prassad 1998). PIIT has been asserted to significantly and positively influence an individual`s adoption of new technologies (Lennon et al. 2007); however, it remains neglected in the investigation of herding behavior (Sun 2013). As each person has his or her own level of personal innovativeness, I argue that the impact of this construct should reduce one's tendency to adopt herd-like behaviors. Among the well-known individual difference factors in IS research, PIIT has received consistent support as an important determinant of cognitive beliefs and usage behavior. Outside the IS discipline, numerous researchers agree that an individual's innovativeness influences their cognitive and decision-making processes (Rogers 2003). Agarwal and Prasad (1998) have found evidence that PIIT acts as a moderator variable on the antecedents and consequences of perceptions with regard to a particular system. Therefore, consistent with the Innovation Diffusion Theory (IDT) (Rogers 2003), the tendency of individuals to innovate determines the sources of information they consider in making decisions about whether to adopt a new technology.

In the same vein, San Martin and Herrero (2012) noted that the more innovative individuals are, the less influenced they are by the opinions of other members of their social system with respect to the consequences of adopting a technology. Therefore, the higher one's personal innovativeness, the weaker the influence of others' adoption decisions should be on that individual's decision to imitate others in adopting a new behavior or technology. IS research has found high levels of PIIT can lead to explorative IS behaviors which require independent, rather than imitative, decision making (Magni et al. 2011; Wang et al. 2008). Moreover, personal innovativeness has been linked with a higher acceptance of risk by the individual (Herrero and Bosque 2008; Rogers 1995). Individual innovativeness determines one’s tendency toward novelty-seeking and risk-taking behavior while making their own independent judgments (Rogers 2003). Also, innovative individuals tend to adopt new technologies earlier than the average person, and they also tend to explore more new ways of using that technology. Therefore, perceptions regarding the importance of contextual resources are less influential in the adoption decision when individuals have a high level of personal innovativeness (San Martin and Herreo 2012). Hence, individuals with higher PIIT levels should place less importance on both the observed popularity of the prior adopters’ decisions and the high levels of uncertainty involved in adoption decisions. In other words, as innovative individuals are willing to take a higher level of risk, their ability to observe prior adoptions, as well as the level of uncertainty of the adoption decision, become less important for the development of imitation behavior. Thus I posit:

H4a: Personal innovativeness will moderate the relationship between observed popularity and propensity for imitation, such that the relationship is weaker for individuals with higher, rather than lower, PIIT.

H4b: Personal innovativeness will moderate the relationship between uncertainty of adoption and propensity for imitation, such that the relationship is weaker for individuals with higher, rather than lower, PIIT.

Langer (1989) defined mindfulness as a state of alertness that entails active information processing, and creation and refinement of distinctions, while recognizing multiple perspectives. High levels of mindfulness enable individuals to make precise interpretations and respond actively to changes in their environment, as well as help them to make better decisions that may involve unexpected outcomes (Fiol and O'Connor 2003). Mindful individuals are less anxious about the future of their decisions (Brown and Ryan 2003), even in cases where the outcome of the decision is less predictable (Weick and Sutcliffe 2001). This characteristic of mindfulness facilitates mindful individuals in being able to cope successfully with uncertainty (Langer 1989).

Mindful behavior has been characterized by openness to new information, and requires the aptitude to question existing conventions and to think in unconventional or novel ways (Langer 1997; Sternberg 2000). Mindful individuals also have higher awareness of the existence of multiple alternatives; a mindful person is more willing to seek out further information in making her IT adoption decisions (Zou et al. 2015). This means that mindful individuals have a greater ability to cognitively recognize their own needs while evaluating the existing IT adoption trends (Kreiger 2005), which in turn implies that the mindful person will place less weight on the adoption behavior of the crowd and instead make independent decisions. In the same vein, Fiol and O'Connor (2003) see mindfulness as a key to understanding whether individuals will make discriminating choices that fit their unique needs in the face of IT adoption trends, or whether they will simply follow the herd. Swanson and Ramiller (2004) found evidence for this argument, in that in an organizational context, mindfulness drives IT innovations and decreases the imitation tendencies of other firms' IT adoption behaviors. All of this means that despite recognizing the presence of the key drivers of herd behavior (i.e., perceived uncertainty and observed popularity), more mindful individuals will not be as swayed by these factors into simply imitating what others have done. Thus I hypothesize that:

H5a: Mindfulness will moderate the relationship between observed popularity and propensity for imitation, such that the relationship is weaker for individuals who are higher, rather than lower, in mindfulness.

H5b: Mindfulness will moderate the relationship between uncertainty of adoption and propensity for imitation, such that the relationship is weaker for individuals who are higher, rather than lower, in mindfulness.

Technology Characteristics

A large body of research has revealed that various characteristics of a technology itself, as experienced by decision makers, can potentially influence their adoption decisions (Venkatesh 2000; Rogers 2003; Tornatzky and Klein 1982). Innovation Diffusion Theory

(IDT) is a leading theory for analyzing technology characteristics in relation to their impact on technology adoption. According to IDT, the rate and pattern of the adoption and diffusion of ideas, practices, or objects through populations of potential adopters is affected by the characteristics of both the technology and the adopter (Rogers 1983). According to IDT, the core constructs affecting technology adoption include relative advantage, compatibility, complexity, observability and trialability (Table 1).

Insert Table 1 here

Tornatzky and Klein's (1982) and Arts, Frambach, and Bijmolt's (2011) meta-analyses of research on innovation characteristics both found that not all technology characteristics, as proposed by Rogers' (2003) framework, were equally important in explaining innovation adoption, and that relative advantage, complexity, and compatibility were the only innovation characteristics that were consistently related to adoption. In the same vein, the literature suggests that among the five technology characteristics, relative advantage is not only one of the most frequently tested characteristics, but also one of the most reliable predictors of adoption behavior (Plouffe et al. 2001). Moore and Benbasat (1991) found that relative advantage of a technological device is positively associated with the rate of adoption. For example, when a potential adopter perceives clear advantages offered by mobile banking compared to traditional face-to-face banking, they are more likely to have a positive attitude toward adopting mobile banking (Al-Jabri and Sohail 2012). Evidence further suggests that when users perceive a new technology to have a relative advantage over the incumbent one, they are more prone to adopt it (Bhattacherjee, Limayem and Cheung 2012; Tsai, Lee and Wu 2010).

Higher perceptions of relative advantage have also been found to negatively correlate with uncertainty beliefs (Coursaris and Osch 2015). For instance, Montoya-Weisse et al. (2003) found that the quality of a web site's information content can influence its perceived relative advantage by reducing the uncertainty associated with its use. This implies that higher perceived relative advantage of a technology decreases the uncertainty perceptions of adopters. Viewing a technology as highly advantageous can mitigate the low-informativeness (i.e., the characteristic of inaccurate information that stimulates herd-like adoption) of the herding setting. For example, higher perceptions of relative advantage lead to a technology being viewed as more useful (Riquelme and Rios 2010); as a result, an individual will have a reduced tendency to imitate others solely as a consequence of observing others' adoptions and/or the uncertainty involved. Instead, she can make an independent decision if she perceives a clear distinction between the new and legacy technologies. The IT fashion literature also provides support for my argument (Abrahamson 1996). Studies have found that when individuals decide to adopt a fashioned IT, they tend to discount the importance of popularity of an IT (e.g., Big Data & Cloud Computing) and unquantifiability of their values (which implies high uncertainty) if they perceive a high relative advantage to the technology (Chen et al. 2015; Polyviou et al. 2014). Similarly, Lia et al. (2010) found that in an organizational context, observing the adoption behavior of rivals can impose a pressure to imitate their adoption; however, having low perceptions of the technology's relative advantage may mitigate such pressure. Thus I posit:

H6a: Relative advantage will moderate the relationship between observed popularity and propensity for imitation, such that the relationship is weaker in the presence of higher, rather than lower, perceived relative advantage.

H6b: Relative advantage will moderate the relationship between uncertainty of adoption and propensity for imitation, such that the relationship is weaker in the presence of higher, rather than lower, perceived relative advantage.

Compatibility refers to the degree to which an innovation is perceived as being consistent with the existing values, past experiences, and needs of potential adopters (Moore and Benbasat 1991; Rogers 2003). Perceived compatibility is often used in the IS adoption literature as a determinant of intentions (Art et al. 2011; Karahanna et al. 1999; Venkatesh et al. 2003) and perceived usefulness (Sun et al. 2009). Lack of perceived compatibility with one's values and experiences leads to lower intrinsic motivation (Varllerand 1997), which increases inconsistency with an internal belief system and overt actions, hence leading to increased cognitive dissonance (Festinger 1957). Karahanna et al. (1999) found that users reduce high levels of cognitive dissonance through looking for positive assessments and signals about a new technology. In a herding context, observing that a large number of people are adopting a technology can be viewed by a user as an example of such positive signals; hence, they place more weight on their observation of the popularity of previous adopters' behavior in a herding context if they perceive a technology to be incompatible. In an organizational setting, Lai et al. (2010) found that for adopters who perceive a technology to be highly incompatible, observing that a large number of companies are adopting the technology can mitigate their concerns over incompatibility in following others and adopting the new technology.

Greater compatibility between an innovation and the individual is preferable, because it presents the potential adopter with less uncertainty (Rogers 2003); this is because higher perceived compatibility implies that one has the cognitive schemas in place to utilize the technology, which in turn results in less effort to utilize the technology (Karahanna et al. 2006). In contrast, if the new technology is significantly different from experiences the user has had in the past (i.e., it is highly incompatible), the prior experiences of the individual will interfere with her ability to learn the new technology (McGeoch and Irion 1952); this constraining of the learning process will consequently influence her perceived uncertainty. In the same vein, several studies have found that higher perceived compatibility positively influences perceptions of the usefulness and ease of use of a technology (Hardgrave et al. 2003; Karahanna et al. 206;Moqbel et al. 2014). It is unlikely that a person who believes a technology offers instrumental value (usefulness) and lower cognitive burden (ease of use) will make her adoption decision based on others' behavior. Hence, individuals with higher perceptions of compatibility can be expected to be less likely to follow the crowd in making adoption decisions merely due to the uncertainty involved in making such decisions. This is because they have a more positive perception of how the new technology will fit with their existing values and experiences. Therefore, despite the existence of some degree of perceived uncertainties (common to any technology adoption), such perceptions of uncertainties will have less influence on their propensity for imitation.

Moreover, perceived compatibility refers to the degree of perceived consistency between the technology and the past experiences of the user (Rogers 1983; Karahanna et al. 2006). Hence, it is reasonable to argue that a person with higher perceptions of the compatibility of a technology can make her adoption decision independently from the crowd. Empirical studies have found support for the argument that higher perceptions of incompatibility also lead individuals to place a higher importance on the behavior of prior adopters and may lead to the formation of imitative adoption behaviors (Lai et al. 2010). Another stream of research also indicates that individuals with higher perceived compatibility have a greater tendency to directly communicate with prior users to seek out knowledge and information about a new technology, since they believe that they have the capability to learn it (Chen et al. 2015; Wang et al. 2010). This tendency can reduce the effect of the low informativeness of the herd-based adoption, and consequently mitigate the roles of herding drivers in forming imitation intentions. Thus I posit that:

H7a: Compatibility will moderate the relationship between observed popularity and propensity for imitation, such that the relationship is weaker in the presence of higher, rather than lower, perceptions of technology compatibility.

H7b: Compatibility will moderate the relationship between uncertainty of adoption and propensity for imitation, such that the relationship is weaker in the presence of higher, rather than lower, perceptions of technology compatibility.

The complexity of an innovation refers to the degree to which it is perceived as relatively difficult to understand and use (Rogers 1995). The perceived complexity of a technology plays a key role in technology adoption, and prior research has revealed that it is a critical determinant of the adoption of new technologies (Sarkar and Valacich 2010). As an IS becomes increasingly complex, an exact evaluation of its benefits usually requires a more profound and detailed knowledge, yet most potential adopters lack such knowledge

(Bakos 1991; Duan et al. 2009). To reap the benefits of a new IS, most individuals need to invest substantial time and energy, which causes the outcome of their adoption decisions to become more uncertain (Walden and Browne 2009). Therefore, potential adopters with higher perceptions of system complexity will experience more uncertainty related to the execution and outcome of the new technology (Bala and Venkatesh 2013).

The technology adoption literature has considered complexity to be the reverse of the notion of ease of use (Agarwal and Prasad 1997). Various studies have found that higher perceived ease of use (PEOU) leads to higher perceived usefulness levels (e.g., Cheng et al. 2006), which in turn lead to diminishing perceived uncertainty rates. By definition, higher perceived uncertainty reflects an individual's reduced ability to predict the outcome of her adoption decision (Walden and Browne 2009). Based on the above discussion, I argue that for a person with higher perceived uncertainty, perceiving the technology to be easy to understand and use (i.e., lower complexity) can mitigate the role of uncertainty in her decision to join the crowd in adopting a new technology. Moreover, complex technologies require greater skills and resources while discouraging the individual from independently seeking out the required knowledge and information, which implies higher intentions to follow others (Sia et al. 2004). Especially in a herding situation, where the behavior of others is observable and the uncertainty is high (i.e., due to the low informativeness of the herding setting), if an individual perceives a technology to be highly complex, imitating others may seem like a rational decision to them. This argument is in line with the finding of a recent study, which argues that firms tend to follow decision of high status organizations in adoption a technology, and this tendency is higher when the focal technology is a more complex system (i.e., ERP systems [Lai et al. 2010]).

Individuals may also feel that because of the complexity of the system, they will also need to learn several new features of the technology. In voluntary technology adoption settings, higher perceived complexity of a technology has been found to increase an individual's motivation to learn its functions (Nicholson et al. 2008). Observing that so *many* people have already adopted such complex technologies plays an influential role in boosting the individual's motivation to follow the prior adopters (Banerjee 1992; Bikhchandani et al. 1992). This is because when a person has high perceptions of the complexity of a new technology, she will be likely to have more positive anticipations about the learning/adoption outcomes of that technology if she observes similar behavior by others (Pieschl 2009). Similarly, Bolt et al. (2002) found that the individuals with higher perceptions of complexity of an IT will follow their peers' when they have access to the peers' decisions. In line with models of observational learning, the behavioral modeling literature also supports this argument by highlighting the role of the observation of others as a mechanism that facilitates the transfer of information to the followers (Taylor et al. 2005). All of the above-mentioned arguments imply that in developing a propensity for imitation in a herding setting, people with higher perceptions of system complexity will give more weight to both observed popularity and perceived uncertainty. Thus I hypothesize that:

H8a: Complexity will moderate the relationship between observed popularity and propensity for imitation, such that the relationship is stronger in the presence of higher, rather than lower, perceived complexity.

H8b: Complexity will moderate the relationship between uncertainty of adoption and propensity for imitation, such that the relationship is stronger in the presence of higher, rather than lower, perceived complexity.

The herd literature suggests that informational cascades have a significant influence on an individual's own adoption decisions. Scharfstein and Stein (1990) found that individuals tend to discount their private information and imitate other's assessments in order to avoid reputational damage, such as being regarded as incompetent if making a decision that is different from others. As a defensive strategy, individuals usually opt for sharing the blame by imitating others' decisions in order to avoid their own performance lagging behind that of their peers. Such reputation-motivated strategies rarely help exploit projected IT investment payoffs (Ottaviani and Sørensen 2006). In the same spirit, Trueman (1994) investigated the reputation-based herd behavior of stock market analysts, and found that analysts have incentives to make predictions biased toward the market's previous expectation. Zwiebel (1995) has argued that most individuals tend to imitate their predecessors in order to avoid competitive disadvantages resulting from refusing a particular technology. In the IS discipline, Sun (2013) found a positive relationship between propensity for imitation (which he referred to as the construct of "imitating others") and intention to use. He argues that adoption of the technology through herding is a better decision than rejecting it since the individual may suffer damages to her reputation, even if the technology turns out to be inefficient one. Therefore, propensity for imitation can increase one's intention to use a technology, since it is one way to evade the worst-case scenario of lagging behind one's peers. Thus I posit:

H9: Propensity for imitation will have a positive impact on one's intention to use a new technology.

METHODOLOGY

Research Design and Procedure

I conducted an online experiment to test the research model. Ello, a social networking website, was used as the focal technology. I chose Ello because at the time of the study, it was a relatively new social networking tool that successfully attracted a large number of individuals in its early days of launch. The voluntary usage characteristic of an SNS like Ello (Maier et al. 2015) was expected to further help us to observe herding behavior more clearly. AT the time of data collection, Ello was becoming popular, and there were other alternatives available to using it, both of which were conditions required for an investigation of herding.

Table 2 summarizes the experimental design. Data collection consisted of one survey administered at the pre-adoption stage. At the beginning of the survey, a description of the major features of Ello including its function, features, and customization were presented to the participants (see Appendix A). They were invited to visit the Ello website by clicking on an embedded link, and then asked to report an example of what Ello could do for them based on the provided description. By doing so, this experiment situated subjects within the context of adopting Ello. Subjects then answered questions about their perception of Ello’s technology characteristics, individual difference constructs, their perceived uncertainty regarding adoption of Ello, and several control variables (i.e., facilitating conditions, subjective norms, and network effects). Only those individuals who had no prior experience with Ello were allowed to participate in the experiment. I enforced this condition by asking respondents to answer a question at the beginning of the survey regarding their prior experience with Ello. Those individuals who responded that they had prior Ello experience were excluded from the study.

The subjects were randomly divided into two groups: a control group and a treatment group. The treatment group (i.e. high observation) received information about the number and identity of prior adopters of Ello, while the control group (i.e. non-observation) was not exposed to such information (see Appendix B). After reading the treatment messages, subjects were asked to answer questions regarding their propensity for imitation, intention to use Ello, and two manipulation check items to measure their awareness of the number and identity of prior adopters. Also, three bogus items with a clear correct answer (e.g., "I have been to every country in the world") were used as a data screening technique that allowed us to control for the engagement of the respondents. If the respondent chooses the incorrect response, it is assumed that she was not attending to the content of the other items of the survey either (Meade and Craig 2012). Using bogus items helps with identifying those participants that may tend to provide "straight-line" responses (Herzog and Bachman 1981) that may be more likely to occur without an interviewer such as an online survey. Responses that include an incorrect selection on this engagement question were dropped from further analysis (Appendix C).

Insert Table 2 here

Measures

I used previously validated seven-point Likert scales for all constructs, with the exception of self-efficacy, which was measured using a ten-point Likert scale. Respondents were asked to indicate the extent to which they agreed with a given statement, ranging from ''strongly disagree'' (1) to ''strongly agree'' (7). Using validated scales has been commonly practiced in the IS research (Marakas et al. 2007). This approach can lead to creation of solid research practices (Keen 1980) and also it improves content validy of the studies (McLaren et al. 2011). I preserved the exact wording of the items and only replaced the name of the focal research technology with my own. Where applicable, references to ''the system'' in the items derived from the literature were replaced with "Ello" as the study's focal technology.

The three items used to measure observation were based on Sun (2012). These items were developed to measure observation of others' usage behavior in an IS setting, in which individuals are engaging with a new system. I used three items from Sun and Fang (2010) to measure uncertainty. Milikan, in his seminal 1978 paper, conceptualized uncertainty in three dimensions (i.e., state, effect, and response). Based on this conceptualization, Sun and Fang developed a three-item scale to measure an individual's uncertainty in the IS environment, with each item representing one dimension of the original reflectively measured uncertainty construct. I used Sun's (2013) measures of "imitating others" to assess propensity for imitation, as these items have been developed and validated in an IS herding setting. I used the exact wording of the original items, except to replace the focal research technology with my own. Intention to use was measured using previously validated scales adapted from prior technology acceptance studies (e.g., g., Bhattacherjee and Premkumar 2004; Davis et al. 1989; Karahanna et al. 1999; Taylor and Todd 1995b; Venkatesh and Davis 2000). These items have also been used and validated in a herding setting (Sun 2013), and were only slightly modified to fit this research context.

Moderators

Self-efficacy (Bandura 1986) has been adapted for study in the IS field by Compeau and Higgins (1995) to represent computer self-efficacy. In this study, I adopt their conceptualization of self-efficacy that refers to judgment of one's ability to apply skills in the future, and employ their scale, which was specifically developed for use in an IT context. Thatcher et al. (2008), in a multi-study article, found that a six-item scale of self-efficacy (dropping four items of the original set developed by Compeau et al.) yielded a better measurement fit. Hence, I used the reduced six-item scale to measure individual self-efficacy, changing the wording of the focal research technology (i.e., Ello) to fit my context. Given my definition of personal innovativeness matches that of Agarwal and Prasad (1999), I used their previously developed PIIT scale. This scale has previously been used in the study of both SNS and herd-like technology adoption contexts (Sun 2013; Zhong et al. 2011). Four items were adapted from Sun and Fang (2010) to measure mindfulness. These items have also been previously validated in herd-like IT adoption studies (e.g., Zou et al. 2015).

Items to measure perceived technology characteristics (relative advantage, compatibility, and complexity) were adapted from Moore and Benbasat (1991). These scales were originally developed for use in an IS setting, based on IDT's conceptualizations of technology characteristics (Rogers 1983), and have been used and validated not only in

IS adoption studies (e.g., Karahanna et al. 1999; Tan and Teo 2000), but have also been applied to the study of SNS adoption (e.g., Coursaris et al. 2013; Lin et al. 2011; Slyke et al. 2007). I slightly reworded the scales to reflect my research context.

Controls

Apart from the herding phenomenon, an individual's technology adoption decisions can be influenced by other factors such as subjective norms and facilitating conditions (Li 2004; Venkatesh et al. 2003). Examining the impact of herding is difficult without controlling for the aforementioned constructs (Duan et al. 2009). Thus, I controlled for the impact of both subjective norms and facilitating conditions on the propensity for imitation as suggested in prior research (Li 2004).

Despite essential distinctions from the herding concept, subjective norms (representing how a person believes those important to her will view her as a result of conducting the referent behavior; see Thompson et al. 1991, Venkatesh et al. 2003), can also influence a person's decisions. Subjective norms have been commonly decomposed into the two aspects of injunctive and descriptive norms. Injunctive norms refer to normative influences in which a behavior is approved by others, whereas descriptive norms refer to normative influences in which a behavior is typically performed by others (Cialdini, Reno and Kallgren 1990). To control for the influence of both types of norms, four items for injunctive norms and four items for descriptive norms were derived from Rhodes and Coureneya (2003) and Hagger and Chatzisarantis (2005), which have been used and validated in several prior IS studies. The original survey items were modified by replacing the name of the focal technology (Ello).

Facilitating conditions, which reflects the availability of the resources required to engage in a behavior (Triandis 1979), is an important predictor of individual IS behaviors (Venkatesh et al. 2003), and is proposed as a construct that partially addresses the role of external factors (Venkatesh et al. 2008). I used a three-item scale for facilitating conditions that was originally developed and validated by Thompson et al. (1991) specifically for the IS setting, and which has been further used and validated in a number of prominent IS studies (e.g., Venkatesh et al. 2003).

Network effects refer to the phenomenon that "the value of a technology increases as the number of its users increases" (Li 2004, p. 94). Although research indicates that this concept differs from herding in several key ways (e.g., the way information is inferred from others, its motivations, and its long-term impacts), network effects have been controlled for in prior herding studies (e.g., Sun 2013). Therefore, in this study I also controlled for its effect on propensity for imitation, adopting items that have previously been developed and validated specifically for the herd-like IT adoption context by Sun (2013). Also, in order to detect careless respondents I added three bogus questions. An example of those questions is: I have been to every country in the world (Meade and Craig 2012).

Survey Administration

I recruited participants using Amazon's Mechanical Turk (MT), an online crowd-sourcing platform in which participants receive money for completing tasks. The use of MT has several benefits compared to the student subjects which are commonly used in IS research. Its population is more diverse and reliable, thus increasing the external validity of the behavioral research study (Berinsky et al. 2012; Mason and Suri 2012). Further, MT precludes potential effects of researchers coming in contact with the subjects as all studies are completed online and MT acts as an intermediary (Mason and Suri 2012).

MT is organized around micro-tasks called human intelligence units (HITs). Amazon provides a way for tasks to be completed on an external online survey tool. In my case, I designed an external website HIT which was hosted by Qualtrics. Then I created a HIT that included the URL of the survey questionnaire. Once the HIT was posted to MT, it became available for respondents to complete. Restrictions were set to limit HIT completions to participants from the United States to reduce the possible confounding effect of surveying different cultures (Holden et al. 2013). Individuals that qualified for the HIT viewed a short task description along with the pay rate, and chose whether or not to accept the task. The survey automatically assigned participants to one of the treatment conditions. The treatment group read a situating task, with manipulation checks included to ensure that they carefully read and understood the corresponding vignette.

I recruited 320 participants for the experiment. Thirty-four respondents failed to answer the bogus questions correctly, eight respondents marked almost the same scale responses throughout, thirteen respondents did not complete the entire survey, and five respondents had extremely short response time. These individuals' responses were thus eliminated from further statistical analysis. In total, 260 surveys were judged appropriate for hypothesis testing. The demographic profile of the respondents is shown in Table 3.

Insert Table 3 here

Analysis

I conducted a confirmatory factor analysis (CFA) using AMOS 24 to assess the psychometric properties of the scales (Fornell and Larcker 1981). I assessed discriminant, convergent validities and internal consistency of constructs. To evaluate the results of the CFA, several commonly used goodness-of-fit indices were examined (commonly accepted thresholds are shown in parentheses): root mean square error of approximation (RMSEA: between .05 and .08), comparative fit index (CFI: ≥ .95), Tucker-Lewis index (TLI: ≥ .95), Probability of Close Fit (PClose: ≥ 0.05), and standardized root mean squared residual (SRMR: ≤ .08) (Gefen et al. 2011; Hair et al. 2009). The structural model was tested in a similar manner, again using AMOS 24.

RESULTS

The results are presented into several parts. First, I discuss results of testing the manipulation checks. Next, I discuss results of testing the measurement model to confirm the reliability and validity of the constructs, as well as the presence of common method bias. Finally, I discuss testing the structural model and its hypothesized relationships among constructs. Both the measurement and structural models were tested using AMOS 24, with maximum likelihood estimation. The reliability and validity of the scales were examined via confirmatory factor analysis (CFA), while the strength and direction of the hypothesized causal paths among the constructs were analyzed via structural equation modeling (SEM). Tests for skewness and kurtosis indicated acceptable univariate normality, and no significant outliers were detected (Hair et al. 2009).

Manipulation Checks

ANOVA analyses revealed that the two groups (control and treatment) did not differ significantly in age (F [1, 258] = 0.641, p = 0.424), gender (X^2 = 0.115), or education level (F [1, 258] = 0.009, p = 0.924). These results indicate that the random assignment of the subjects was effective. The survey included two items as a manipulation check. The first item asked the subject to state to what degree (s)he was aware that "a lot of people have adopted Ello," and thus focused on the *number* of prior adopters. The second item asked the subject to what degree (s)he was aware that "Ello has been adopted by a lot of well-known people and organizations," and thus measured a subject's awareness of the *identity* of prior adopters. These items assess the effectiveness of the treatment that distinguished between the control and treatment groups. The ANOVA results indicate that both items significantly differed across the two groups ($p < 0.002$ for item 1 and $p < 0.001$ for item 2).

Measurement Model Evaluation

Internal Consistency

Before analyzing the structural model, I performed a CFA to test the psychometric properties of the scales. As shown in Table D1 in Appendix D, all items had loadings on their respective constructs of greater than the suggested threshold of 0.707 (Chin 1998). Estimates of CR greater than .70 and AVE greater than .50 support internal consistency (Bagozzi and Yi 1988), and as I show in Table 1, composite reliability (CR) values range from .71 to .96, while average variance extracted (AVE) ranges from .55 to .89, indicating acceptable convergent validity.

Discriminant validity was established based on the square root of AVE for each construct exceeding its correlations with other constructs in the model (Fornell and Larcker 1981). This condition is satisfied, as shown in Appendix D, Table D2. To evaluate overall fit of the CFA model, I examined several commonly used fit indexes (Gefen et al. 2011; Hu and Bentler 1999). All values fall within acceptable ranges, indicating good model fit (Table 4).

Insert Table 4 here

Common Method Bias

I employed both procedural and statistical remedies for common method bias (CMB) following Podsakoff et al. (2003), and did not find any significant threats of such biases in the data. In terms of procedural remedies, the participants were informed that their responses would be anonymous, assured that there were no right or wrong answers, and requested that they answer questions as honestly as possible. This way I was able to protect respondent anonymity and reduce evaluation apprehension. Second, by randomizing the scale items within each questionnaire block, and also randomizing the blocks themselves, I counterbalanced them (Straub et al. 2004). For example, items related to perceptions of technology characteristics were randomized, and the blocks for technology characteristics and individual characteristics were also randomized.

In terms of statistical remedies, I first conducted a Harman's single-factor test in SPSS, to see whether a single factor explained a majority of the variance in the data set (Podsakoff et al. 2003). The emergent factor explained only 23.7 percent of the variance.

However, authors generally believe that Harman's test is not sensitive enough to detect common method bias. Hence, I also added an unmeasured latent method factor to the CFA model, and allowed all self-reported items to load on both their theoretical constructs and the method factor (Bagozzi 2011). The analysis indicates that the common variance is less than 22 percent. The item loadings on the method factor were not statistically significant, and also much lower than the loadings on their respective constructs. The model fit remains essentially similar after the inclusion of a method factor (model without common latent factor: $\chi 2$ /d.f. = 2.183, model with common latent factor: $\chi 2$ /d.f. = 2.122.

I further investigated the impact of CMB by comparing the standardized item loadings of the latent constructs in the two measurement models (i.e., a model with a common latent factor and a model without the common latent factor). CMB typically decreases the item loadings, such that path estimates in the measurement model which excludes the common latent factor are higher. CMB could be an issue if there are differences in the standardized estimates between the two models that exceed a value of 0.20 (Gaskin 2012). The differences were found to be marginal (<0.20), and thus the impact of CMB is not considered substantial in this study.

Nevertheless, in order to partial out any potential effect of CMB, I added a common latent factor to the full structural model and allowed all of the indicators for the theoretical constructs to load on it. Also, I created the interaction terms for the structural model based on imputed factor scores from the CFA that included a common latent factor. Hence, I was able to partial out the effect of common method bias on the structural model. After adding the method factor to the structural model, estimates for the hypothesized effects remained almost unchanged, which suggests that CMB did not noticeably affect the results. In sum, the results of the various analyses described here provide confidence that common method bias is not a major concern in my study.

Structural Model

In Table 5, I present results from testing the structural model; the overall fit statistics confirm that the hypothesized model provides a good representation of the structures that underlie the observed data (CMIN/DF = 1.53, CFI = .95, SRMR = .040, RMSEA = .045, Pclose = .91).

Insert Table 5 here

Regarding the hypothesized direct paths, in line with previous research (i.e., Sun 2013) I also found significant links between observed popularity and propensity for imitation (H1: β = 0.66, p < 0 .001) and also between propensity for imitation and intention to use (H9: β = 0.43, p < 0.001). For the relationship between uncertainty and propensity for imitation, I did not find uncertainty to be a significant predictor of the sampled individuals' propensity for imitation (H2: β = -0.18, p = 0.40).

Overall, seven out of twelve interaction effects were significant. However, four of these significant effects were in the opposite direction of what I had hypothesized. Therefore, I assessed the level of multicollinearity between the independent variables and calculated variance inflation factor (VIF) for each variable. The largest VIF value was 3.7 (self-efficacy), which is slightly larger than the threshold of 3.3 suggested by

Diamantopoulos et al. (2006) and smaller than the threshhold of 5 sugessted by Hair et al. (2011). All other VIF values were are smaller than 3.3.

PIIT buffers the effects of both observed popularity (β = -0.54, p = 0.03) and uncertainty (β = -0.38, p = 0.02) on propensity for imitation, as I hypothesized, supporting hypotheses 4a and 4b. Employing the procedure suggested by Aiken and West (1991), I computed the simple slopes of the moderation effects one standard deviation below and above the mean to investigate the significant interactions. Simple slope tests indicated that the simple slopes were significant for individuals with low PIIT levels (b = 1. 86, $p < .001$), and also for individuals with high PIIT levels (b = 0.51, $p < 0.05$), verifying the study's hypothesis that higher PIIT values dampen the positive relationship between observed popularity and propensity for imitation. In words, as PIIT levels decrease, the relationship between observed popularity and propensity for imitation becomes more positive. In support of H4b, simple slope tests show that the simple slopes were significant for individuals with low (b = .74, $p < .001$), and also with high (b = -.57, $p < .01$) PIIT levels. Similarly, relative advantage was found to have a significant buffering effect (β = -0.30, p = 0.02) on the relationship between uncertainty and propensity for imitation, supporting hypothesis H6b. Conducting simple slope tests also indicates that for adopters with low RA perceptions (b = .68, $p < .001$) and high RA perception (b = -.26, $p < .001$) the simple slopes were significant. Figures 2a, 2b, and 2c graphically illustrate the nature of these moderating relationships, which are consistent with my predictions.

The proposed model explains a significant amount of variance in the focal dependent variable, propensity for imitation (R^2 = 0.78). The variance explained in the terminal dependent variable, intention to use, is relatively small (0.19). Small R-squared values such as this are not uncommon in behavioral science research and do not present a threat to the model's overall validity (Cyr et al. 2009). In addition, intention to use is modeled here as influenced by only a single construct (i.e., IMI), and such an association tends to result in low *R* square values compared to multi-relationship models (Cyr et al. 2009).

Insert Figure 5 here

Mediation Effects

I used the bootstrapping technique in AMOS 24 (see Preacher and Hayes 2004) to further examine the mediating effect of propensity for imitation on the relationship between observed popularity and intention to use. 2,000 bootstrapping samples were generated from the original data set (N = 260) by random sampling in order to estimate the indirect effect of the predictor variable on the outcome variable via a proposed mediator. This method possesses several advantages relative to the Baron and Kenny (1986) approach: (1) it tests all paths of a model simultaneously, (2) it does not assume a normal distribution of the indirect effect, and (3) it decreases the likelihood of making a Type I error (Preacher and Hayes 2004). The results of the mediation analysis indicate that observed popularity does not have a significant direct impact on intention to use ($\beta = 0.14$, $p = 0.21$). At the same time, the indirect effect of observed popularity on intention to use through propensity for imitation is significant ($\beta = 0.21$, $p = 0.01$). In summary, these results support a full mediating effect of propensity for imitation on the relationship between observed popularity and intention to use.

DISCUSSION

Decision makers often face challenges related to technology adoption due to the lack of relevant information. The information can be noisy and inaccurate which encourages the adopters observe the actions of previous decision makers to update their beliefs in order to make reasonable decisions. Technology users often adopt popular products, thus making them even more popular (Brynjolfsson et al. 1996), which may lead to *herd*-like adoptions (Walden and Brown 2009). The study contributes to research exploring individual herd-like adoption behaviors by explicitly incorporating both the adopter and technology characteristics.

This study helps to integrate the substantial body of research on technology adoption (e.g., Venkatesh and Davis 2000, Venkatesh et al. 2003) and the impact of user and technology attributes (e.g., Foil and O'Connor 2003;Rogers 2003; Strong et al. 2006) with the growing body of IS herd research (e.g., Duan et al. 2009; Lee et al. 2015; Sun 2013). Specifically, my research helps to explain the interplay between the herding factors and the characteristics of the adopter as well as the technology itself in influencing an individual's propensity for imitating others' IS adoption behaviors.

Major Findings

The results show both the existence, and the significant influence, of herd behavior in the context of technology adoption, more specifically SNS adoption. Drawing on prior herd behavior research, I developed a framework (Figure 1) and conducted an empirical test to advance our understanding of the determinants of IS herding and, importantly, depict how characteristics of the individual adopter and specific technology in a herding context facilitate usage intentions. The study answers Sun's (2013) call for future research to identify and examine individual and technology differences that explain *herd*-like IS behaviors.

The study identifies the influence of others' behaviors in an SNS context. The context is more relevant to the modern era of technology use in which the Internet has fundamentally accelerated the capacity for like-minded people from around the world to join herds (e.g., following hash tags). The findings indicate that observed popularity of a behavior leads a decision maker to imitate. Choosing an SNS as the research context helped to further identify and differentiate the effect of herding despite the existence of Network effects (which is typically an important determinant of SNSs growth). Hence, I extend the findings of prior research on IS herding (i.e., Sun 2013; Walden and Brown 2009), which investigated herding in other contexts (i.e., PBwiki and a simulation model). This provides further support for the argument that preceding adopters' actions influence individuals' decision-making (Hey and Morone 2004). Propensity for imitation also has a significant positive effect on one's intention to use a technology at the adoption stage.

The results further indicate that an individual's level of PIIT has significant dampening effects on the relationships between both observed popularity and uncertainty, and propensity for imitation. This suggests that observed popularity plays an important role in initiating herd-like adoption; however, it is less important when the adopter has high levels of personal innovativeness. This aligns my work with prior research on PIIT that suggests that decision makers with higher PIIT perceptions have fewer tendencies to be influenced by the decisions of others (Magni et al. 2011; San Martin and Herrero 2012).

Similarly, the results show an interesting interaction effect between perceived uncertainty associated with technology adoption and perceived relative advantage of the focal technology in shaping an adopter's propensity for imitation. Although, like Sun's (2003) study of IS herding behavior, I could not detect a *direct* effect of uncertainty on propensity for imitation, the interaction effects between uncertainty and PIIT, and between uncertainty and RA, were significant. This finding supports the argument that perceptions regarding the importance of contextual resources are less influential in adoption decisions when individuals have a high level of RA (Chen et al. 2015; Polyviou et al. 2014). PIIT and RA have been previously found to have a significant influence on individuals' behavioral intentions in adopting new technologies (Lennon et al. 2007; Rogers 2003; San Martin et al. 2012). However, this study is the first, to my knowledge, that shows their moderating effects on the relationship between the three key factors in herding: observed popularity and uncertainty, and propensity for imitation.

As mentioned previously, I did not find a significant direct link between perceived uncertainty and propensity for imitation. This suggests that higher degrees of uncertainty do not necessarily lead one to imitate others in adopting a new technology, and confirms the findings of prior studies that argue decision makers may still imitate others even when they are certain about the decision (e.g., Prechter 1999; Sun 2013). The results indicate that the sampled respondents, on average, found the level of uncertainty to be only moderately high (mean = 4.16). The nonsignificant *negative* link between uncertainty and propensity for imitation may also imply that a high degree of uncertainty may actually *discourage* the adopter from following the herd in adopting that technology, no matter what the previous adopters have done. This finding is in line with the argument of

Bikhchandani et al. (1998) that in conditions of moderately high uncertainty, decision makers tend to show less convergence behavior. However, this argument needs to be further examined and validated in future studies.

Theoretical Contributions and Implications for Research

The study contributes to the stream of IT adoption research that focuses on understanding the role of contextual factors that define IT adopters' decision making processes (e.g., Strong et al. 2006; Lennon et al. 2007; Leidner et al. 2006). I extend extant theory on herding (e.g., Banerjee 1992; Bikhchandani et al. 1992) by identifying the attributes that influence formation of herd-like behaviors and show that despite the presence of herding factors (i.e., observed popularity of a behavior and perceived uncertainty related to adoption), people may still choose not to form convergence behavior and reject imitating others. Thus, the study addresses the question of why specific factors commonly associated with herding do not always lead to actual creation of herd behaviors (Walden et al. 2009), as well as how personal and technological characteristics influence herd behaviors (Sun 2013).

The study also contributes to the emerging literature on herding in the IS field (e.g., Greenwood et al. 2017, Li et al. 2015, Shim et al. 2018; Sun 2013; Zhan et al. 2017). Prior research has identified herd behavior, along with social norms and network effects, as three different types of the general "influence of others." My research seeks to define boundary conditions for IS herd behavior by finding the moderating roles of PIIT and RA on the relationships between the antecedents of herding and the Propensity for Imitation. These two attributes of the decision-makers and the technology further explain IS herding behavior of the individuals. I thus address the limitation of prior IT herding studies that have attributed herding in technology adoption to a single underlying mechanism (i.e., the direct effects of the factors of herding) without considering other drivers, thereby potentially overstating the impact of the observed driver (Duan et al. 2009). By simultaneously examining multiple drivers of IT adoption, the study sheds light on the dominant drivers of herding in different situations.

Personal Innovativeness

This study is an initial effort to confirm the predicted psychological influence of personal innovativeness in an IT-herd study. The finding that higher levels of PIIT weaken the probability of herding in the presence of the key factors of herding (i.e., observed popularity and uncertainty) is consistent with the notion that high PIIT levels provide individuals with a psychological safety perception that is needed for them to engage in more experimental rather than imitative behaviors (Magni et al. 2011). Innovation Diffusion Theory (IDT) argues that PIIT is an indicator of a person's adoption behavior (Rogers 2003). Research on innovation diffusion reports that Personal Innovativeness is an important variable in determining outcomes of technology adoption (Bhattacherjee et al. 2012; Tsai et al. 2010). I contribute to this stream of research by extending herd theory to this widely studied area of IDT.

The findings confirm the crucial role of PIIT in determining adopters' herd-like behavior in IT adoption contexts, extending understanding of its role by showing that an individual's natural tendency to try out a new technology reduces the possibility of herd behaviors in high observation and uncertainty situations. This supports the view that omission of personality variables results in a more simplistic picture of an adopter's decisions making processes than what really exists (Aldas-Manzano et al. 2009). I thus contribute to the stream of IT adoption studies that focus on understanding psychological factors in people's adoption decision making. Interestingly, different levels of Uncertainty*PIIT lead to higher changes of Propensity for Imitation than different levels of Observed Popularity*PIIT on Propensity for Imitation (see Figure 2). This also highlights the crucial roles of person's perceptions (i.e., Uncertainty) and her personal attributes (i.e., PIIT) on adopter's decision making. I also conducted moderation effect size analyses. The change in the R^2 value when a specific predictor variable (here the interaction variable) is omitted from the model can be evaluated to determine whether the omitted construct has a substantive impact on the dependent variable (Hair et al., 2009). The results of applying Cohen's f^2 (1988) formula[*] indicate that Observed Popularity*PIIT have larger effect (i.e., .03) on the dependent variable than Uncertainty*PIIT (i.e., .01). This reinforces the fact that although uncertainty has not been found to be a *direct* antecedent of imitation, it nevertheless plays an important role in initiation of herding behavior. Realizing the patterns of interplay between factors of herding and PIIT will help to advance our understanding of the cognitive underpinnings of IS adoption decisions.

Relative Advantage

Relative advantage, as the key technology- related characteristic introduced by IDT, was a significant factor in moderating the relationship between uncertainty and propensity for imitation. This finding has theoretical implications, in that it shows the value of combining notions from the IT herding and IDT literatures to offer a more comprehensive

[*] Effect size (f^2) is calculated by the formula (R^2included – R^2 excluded)/(1 - R^2 included).

model for explaining and testing technology adoption. Furthermore, it shows that the initiation of herd-like behavior can be better explained not only by considering user-related characteristics such as PIIT, but also by considering technology characteristics such as RA. In other words, this may imply that herd behavior is largely based on both individual's psychological perceptions about herself (i.e., PIIT) and her utilitarian needs.

The unexpected significant positive moderation effect of RA on the relationship between observed popularity and propensity for imitation may imply that observed popularity can still be an important factor of herding for the individuals who have higher RA perceptions. This might be because of the presence of high levels of uncertainty that encourage them to take into account the popularity of a technology alongside its level of relative advantage over other technologies in developing imitative behaviors. This finding is consistent with prior research that has emphasized that higher RA perceptions are correlated with higher levels of trust in the accuracy of information (Choudhury at al. 2008) as well as in the signals (here, the popularity of a product) that the decision maker gets from the environment (Benbasat et al. 2005). Also, higher RA levels suggest that an adopter can make an adoption decision more rapidly when the focal technology is perceived to be better than similar products (Rogers 2003). Hence, to increase the pace of decision-making even more and skip time-consuming information gathering steps, such an adopter may put more weight on the observation of the popularity of an IT and, consequently, herding can be sensible strategy in such a situation.

Uncovering the roles of RA and PIIT in the formation of herd-like behaviors has implications for studying and understanding the *fragility* characteristic of herd behavior (Banerjee 1992; Bikhchandani et al. 1992; Li et al. 2014; Liu et al. 2015; Zhan et al. 2017).

The findings extend this notion by identifying personal and technological characteristics that influence the role of environmental factors (i.e., popularity and uncertainty) and may lead to potentially correct herd decisions (i.e., herd-like decisions that are not fragile and the adopter will not reverse her decision after the update of her information). Prior research has only discussed the low informativeness of a herd as a factor accounting for incorrect and fragile herding decisions. However, people may also form correct herds even in less informative contexts (Walden and Browne 2009). This research might imply that alongside initial low informativeness of a herd, levels of PIIT and RA could be the factors that explain the fragility of the herd decisions. As innovative individuals are willing to take on a higher level of risk, their ability to observe prior adoptions, as well as the level of uncertainty of the adoption decision, becomes less important for the development of imitation behavior (see Figure 2). Hence, it is sensible to argue that more innovative individuals will be less influenced by new contrary information in a herding setting and will have fewer tendencies to reverse their decision (since there is a significant positive association between propensity for imitation and intention to use). Similarly, I could argue that higher perceptions of RA may lead to herding decisions, which are less fragile. This may also explain why Walden and Brown (2009) found that contrary information can easily reverse a herd decision in some cases and not always.

Mindfulness

In my analysis, mindfulness had an unexpectedly positive moderating effect on both relationships between the factors of herding (i.e., observed popularity and uncertainty) and propensity for imitation. This contradicts the argument that mindful people may have fewer tendencies to imitate predecessors' behaviors (Swanson et al.

2004). This finding may potentially be explained by a careful review of relevant research on mindfulness characteristics. In the mindful state, individuals will be sensitive to the environment and will search *externally* (what others have said and done in a similar situation, i.e., similar concepts to Observed Popularity) (Fiol and O'Connor 2003). Also, mindfulness helps an individual to develop strategies to cope with uncertainties, such as being more flexible and developing an action repertoire to match to the changing environments (Levinthal and Rerup 2006). Moreover, mindfulness can also promote the perceived usefulness of a particular technology to adopters (Sun and Fang 2016). Hence, by considering this prior research, the results suggest that mindful people may add herd behavior to their action repertoire that helps them to reduce environmental uncertainty in making adoption decisions. However, this argument needs to be further tested and validated in future studies.

Self-efficacy

In contrast to my hypothesis, the results indicate that there is a positive moderating effect of self-efficacy on the relationship between Uncertainty and Propensity for Imitation. This might be due to the fact that self-efficacious people tend to be more optimistic (Bandura 1977) and more accurate in predicting the outcome of a behavior (Chen et al. 2011). Such a person is more likely to develop favorable perceptions of a new technology (Agarwal et al. 2000), thus she has less motivation to learn about the new technology (Bakke and Henry 2015). In other words, such as person has positive beliefs about the outcome of her abilities (in learning and using the new technology) and also about the outcome of the decision (here, imitating others in adoption a new technology). In addition, efficacious people tend to have higher perceptions of control over the situations that they face (Bakke and Henry 2015). Hence, instead of independently seeking further information, a self-efficacious person may form herd-like behavior believing that she has the control over the outcome of her decision.

Practical Implications

These findings have practical implications for producers of new technology and organizations looking to implement technological innovations. The paper showed that individual adopters who possess certain attributes, and also technological products/services with specific characteristics, are more likely to encourage a herding effect, which can in turn boost the adoption of such products. The distinction between different types of adopters suggests that different mechanisms could be successful in encouraging different individuals to use new technologies. For example, based on the results managers can initiate herd-like adoptions for the newly introduced systems among their employees with lower PIIT levels by stimulating the observed popularity of that technology among other users. Hence, understanding the interplay between PIIT levels and herd-like adoption elements may help managers increase implementation success of new systems.

Moreover, the factors that lead to herd behavior have presented challenges to practitioners in the past, and without knowing the exact causes of such behavior, organizations have difficulty in exploiting the opportunities or addressing the challenges presented by the mass herd behavior commonly observed. By identifying attributes of the technological artifact that impact the initiation of herding behavior, practitioners may adopt better strategies for new product introduction. For instance, organizations can encourage adoption by designing IT implementation initiatives that focuses on communicating the advantages of the new IT (compare to the legacy system) while providing effective training that reduces uncertainty.

The focal research technology in this study was an SNS. Hence, the findings have implications for SNS practitioners. I believe that social networking firms should invest in approaches to identify the characteristics of their prospective users (i.e., PIIT) to enhance the formation of *en mass* herd-like adoptions. One potential step would be to alleviate uncertainty for their more innovative adopters by providing information about the popularity of the introduced system. The results suggest that the extent of herding is moderated considerably by perceptions of relative advantage. Increasing the visibility of the offered advantages of the new IT and effectively communicating those advantage with the potential adopters (via trainings and marketing practices, for example) may encourage *en mass* herd-like usage of the SNS.

While my study focuses primarily on individual's adoption of consumer-oriented products, it has implications for corporate IT adoption as well. Prior studies have indicated that herd theory could be applied to the corporate IT adoption environment (Kauffman and Li 2003; Li 2004; Terlaak and King 2006). These studies consistently found that IT managers are more likely to adopt popular information systems, and one of the drivers of the phenomenon is herd behavior. Given the high stakes involved and the earlier findings that IT managers are impacted by herd-like decisions, my results suggest that a corporation can mitigate the situation by providing more information to IT decision makers, and also by creating environments that encourage experimentation and innovative practices. This could involve providing better training, providing access to professional product research reports, and/or hiring the IT managers who have higher rates of personal innovativeness.

Limitations and Directions for Future Research

As with any study, mine has several limitations that must be acknowledged. I collected all data at a single point in time, and used survey methods to measure the constructs in the model. Naturally, this raises concerns about common method variance. I employed a number of procedural and statistical remedies for common method biases to attempt to alleviate these concerns. As adding the method factor to the both measurement and structural model almost did not change, respectively, the factor loadings and estimates for the hypothesized effects, which suggests that common method bias did not noticeably affect the results. Also, I focused on the voluntary use of the technology, so findings may differ if mandatory technology usage is investigated (Venkatesh et al. 2003). Future research might repeat my study in organizational settings where IT usage is mandatory, for example, during an enterprise system implementation.

Future longitudinal multi-case studies could provide us with a better understanding of the role of technological and personal attributes in forming herd behaviors, specifically, how post-adoptive IS behaviors are shaped over time via the interactive effects of the herd factors and both personal and technological elements. In words, it would be interesting to explore why, and in what conditions, people engage in *continued* herd-like IS usage behaviors. In addition, examination of the roles of personal and technological attributes in the formation of other herd-like IS behaviors (e.g., IT training, online rating and reviewing, online crowd founding, loan markets, etc.) would be a fruitful direction for future research.

Finally, the unexpected moderating relationships that I found may have no immediately clear theoretical explanation. It would be interesting to examine similar relationships in future studies and in other contexts. Such unexpected findings can spawn more directed theoretical development in the future (Grover and Lyytinen 2015; Hambrick 2007).

Conclusion

How people choose a technology that fits their task requirements and meets their needs is a topic of great value since making incorrect adoption decisions may lead to wasted money, time, and increased opportunity costs (Abrahamson 1991). It has been argued that we do not yet have a systematic understanding of the soundness of technology adoption decisions (Sun 2011). Herd theory can be used as one indicator of the soundness of such decisions. This paper extends the existing body of research on IS herding by identifying the effects of personal and technological attributes, and provides many opportunities for further research in this area.

REFERENCES

Abrahamson, E. (1991). Managerial fads and fashions: the diffusion and rejection of innovations. *Academy of Management Review, 16*(3), 586-612.

Agarwal, R. and Karahanna, E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage. *MIS Quarterly*, pp.665-694.

Agarwal, R., and Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. *Information Systems Research*, 9(2), 204-215.

Agarwal, R., and Prasad, J. (1999). Are individual differences germane to the acceptance of new information technologies?. *Decision Sciences*, 30(2), 361-391.

Aguinis, H., Beaty, J.C., Boik, R.J. and Pierce, C.A. (2005). Effect size and power in assessing moderating effects of categorical variables using multiple regression: a 30-year review. *Journal of Applied Psychology*, *90*(1), 94-111.

Aldás-Manzano, J., Lassala-Navarré, C., Ruiz-Mafé, C. and Sanz-Blas, S. (2009). The role of consumer innovativeness and perceived risk in online banking usage. *International Journal of Bank Marketing*, *27*(1), 53-75.

Aldhaban, F. (2012). Exploring the adoption of smartphone technology: literature review". In Technology Management for Emerging Technologies (PICMET), *Proceedings of PICMET*, 2758-2770.

Al-Jabri, I. M., and Sohail, M. S. (2012). Mobile Banking Adoption: Application of Diffusion of Innovation Theory. *Journal of Electronic Commerce Research*, 13(4),379-391.

Argyris, Y.E.A. and Xu, J.D. (2016). Enhancing self-efficacy for career development in Facebook. *Computers in Human Behavior*, *55*, 921-931.

Arts, J. W., Frambach, R. T., and Bijmolt, T. H. (2011). Generalizations on consumer innovation adoption: A meta-analysis on drivers of intention and behavior. *International Journal of Research in Marketing*, 28(2), 134-144.

Bagozzi, R.P. (2011). Measurement and meaning in information systems and organizational research: Methodological and philosophical foundations. *MIS Quarterly*, *7*(1),261-292.

Bagozzi, R. P., and Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the academy of marketing science*, 16(1), 74-94.

Bakke, S. and Henry, R. (2015). Unraveling the Mystery of New Technology Use: An Investigation into the Interplay of Desire for Control, Computer Self-efficacy, and Personal Innovativeness. *AIS Transactions on Human-Computer Interaction*, *7*(4), 270-293.

Bakos, J. Y. (1991). A strategic analysis of electronic marketplaces. *MIS Quarterly*, *9*(3), 295-310.

Bandura, A. (1977). Self-efficacy: toward a unifying theory of behavioral change. *Psychological Review*, *84*(2), 191-215.

Bandura, A. (1986). Fearful expectations and avoidant actions as coeffects of perceived self-inefficacy. *American Psychologist, 4,* 1389-1391.

Banerjee, A. V. (1992). A simple model of herd behavior. *The Quarterly Journal of Economics*, *107*(3), 797-817.

Baron, R. M., and Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of personality and social psychology*, *51*(6), 1173-1201.

Benbasat, I. and Wang, W. (2005). Trust in and adoption of online recommendation agents. *Journal of the Association for Information Systems*, *6*(3),45-61.

Berinsky, A. J., Huber, G. A., and Lenz, G. S. (2012). Evaluating online labor markets for experimental research: Amazon. com's Mechanical Turk. *Political Analysis*, *20*(3), 351-368.

Bhattacherjee, A., Limayem, M. and Cheung, C.M. (2012). User switching of information technology: A theoretical synthesis and empirical test. *Information & Management*, *49*(7), 327-333.

Bikhchandani, S., Hirshleifer, D., and Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy*, pp. 992-1026.

Bikhchandani, S., and Sharma, S. (2000). Herd behavior in financial markets: A review, IMF Working Paper, 1-32.

Bluestein, A. (2015). This Social Network Once Challenged Facebook. Now It's Trying to Make a Comeback on Mobile. Retrieved from http://www.slate.com/blogs/moneybox/2015/06/19/ello_social_network_can_a_new_mobile_app_revive_a_network_that_once_challenged.html.

Bolt, M.A., Killough, L.N. and Koh, H.C. (2001). Testing the interaction effects of task complexity in computer training using the social cognitive model. *Decision Sciences*, *32*(1), 1-20.

Brynjolfsson, E., and Hitt, L. (1996). Paradox lost? Firm-level evidence on the returns to information systems spending. *Management Science*, *42*(4), 541-558.

Chen, K., Chen, J. V., and Yen, D. C. (2011). Dimensions of self-efficacy in the study of smart phone acceptance. Computer Standards & Interfaces, 33(4), pp. 422-431.

Chen, Y., Wang, Q., and Xie, J. (2011). Online social interactions: a natural experiment on word of mouth versus observational learning. *Journal of Marketing Research*, *48*(2), 238–254.

Cheng, J.M.S., Sheen, G.J. and Lou, G.C. (2006). Consumer acceptance of the Internet as a channel of distribution in Taiwan—a channel function perspective. *Technovation*, *26*(7), 856-864.

Chin, W. W. (1998). The Partial Lease Squares Approach for Structural Equation Modeling,. in *Modern Methods for Business Research*., G. A. Marcoulides (ed.), Mahwah, NJ: Lawrence Erlbaum, 295-336.

Choi, J. P. (1997). Herd behavior, the" penguin effect," and the suppression of informational diffusion: an analysis of informational externalities and payoff interdependency. *The Rand Journal of Economics*, 407-425.

Choudhury, V. and Karahanna, E. (2008). The relative advantage of electronic channels: a multidimensional view. *MIS Quarterly*, *13*(1),179-200.

Cingl, L. (2013). Does Herd Behaviour Arise Easier Under Time Pressure? Experimental Approach. *Prague Economic Papers*, 4, 558-582.

Cohen, J. (1988). Statistical power analysis for the behavioral sciences Lawrence Earlbaum Associates. Hillsdale, NJ.

Coursaris, C.K. and Van Osch, W. (2015). Lifestyle-technology fit: Theorizing the role of self-identity in IS research. *Computers in Human Behavior*, *49*, 460-476.

Coursaris, C.K., Van Osch, W., Sung, J. and Yun, Y. (2013). Disentangling Twitter's adoption and use (dis) continuance: A theoretical and empirical amalgamation of uses and gratifications and diffusion of innovations. *AIS Transactions on Human-Computer Interaction*, *5*(1), 57-83.

Crawford, V. P. (2003). Lying for strategic advantage: Rational and boundedly rational misrepresentation of intentions. *American Economic Review*, 133-149.

Chen, Y. and Hew, K.F. (2015). Knowledge sharing in virtual distributed environments: Main motivators, discrepancies of findings and suggestions for future research. *International Journal of Information and Education Technology*, *5*(6), 466-483.

Chen, Hong-Mei, Rick Kazman, and Florian Matthes. (2015). Demystifying Big Data Adoption: Beyond IT Fashion and Relative Advantage. In *Proceedings of Pre-ICIS (International Conference on Information System) DIGIT workshop*.

Chen, Yubo, Qi Wang, and Jinhong Xie (2011). Online social interactions: A natural experiment on word of mouth versus observational learning. *Journal of Marketing Research, 48*(2), 238-254.

Cyr, D., Head, M., Larios, H., and Pan, B. (2009). Exploring human images in website design: a multi-method approach. *MIS Quarterly*, *11*(4), 539-566.

Davis Jr, F. D. (1986). A technology acceptance model for empirically testing new end-user information systems: Theory and results. Doctoral dissertation, Massachusetts Institute of Technology".

Diamantopoulos, A., and Siguaw, J. A. (2006). Formative versus reflective indicators in organizational measure development: A comparison and empirical illustration. *British Journal of Management*, *17*(4), 263-282.

Duan, W., Gu, B., and Whinston, A. (2009). Informational cascades and software adoption on the internet: an empirical investigation. *MIS Quarterly*, *33*(1), 23-48.

Festinger, L. (1957). *Theory of Cognitive Dissonance*, Row, Peterson, Evanston, IL.

Fiol, C. M., and O'Connor, E. J. (2003). Waking up! Mindfulness in the face of bandwagons. *Academy of Management Review*, *28*(1), 54-70.

Fornell, C., and Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 39-50.

Gaskin, J., (Year video uploaded). *Common method bias using common latent factor,* Gaskination's Statistics. http://youtube.com/Gaskin

Gefen, D., Rigdon, E. E., and Straub, D. (2011). Editor's comments: an update and extension to SEM guidelines for administrative and social science research. *MIS Quarterly*, *35*(2), III–XIV

Goodhue, D. L., and Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly*, 213-236.

Goodhue, D. L. (1998). Development and Measurement Validity of a Task-Technology Fit Instrument for User Evaluations of Information System. *Decision Sciences*, *29*(1), 105-138.

Greenwood, B.N. and Gopal, A. (2017). Ending the Mending Wall: Herding, Media Coverage, And Colocation in IT Entrepreneurship. *MIS Quarterly*, *41*(3), 301-342.

Grover, V. and Lyytinen, K. (2015). New State of Play in Information Systems Research: The Push to the Edges. *MIS Quarterly*, *39*(2), 271-296.

Guinan, P.J., Cooprider, J.G., and Sawyer, S. (1997). The Effective Use of Automated Application Development Tools. *IBM Systems Journal*, 36(1),124-139.

Hambrick, D. C. (2007). The Field of Management's Devotion to Theory: Too Much of a Good Thing. *Academy of Management Journal*, *50*(6), 1346-1352.

Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E. and Tatham, R.L. (2009). *Multivariate Data Analysis* (Vol. 5, No. 3, pp. 207-219). Upper Saddle River, NJ: Prentice Hall.

Hair, J. F., Ringle, C. M., and Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing theory and Practice*, *19*(2), 139-152.

Hardgrave, B.C., Davis, F.D. and Riemenschneider, C.K. (2003). Investigating determinants of software developers' intentions to follow methodologies. *Journal of Management Information Systems*, *20*(1),123-151.

Herrero, A., and Bosque, R. (2008). The effect of innovativeness on the adoption of B2C e-commerce: a model based on the theory of planned behavior. *Computers in Human Behavior*, 24, 2830-28.

Herzog, A.R. and Bachman, J.G. (1981). Effects of questionnaire length on response quality. *Public Opinion Quarterly*, *45*(4), 549-559.

Hey, J.D. and Morone, A. (2004). Do markets drive out lemmings—or vice versa?. *Economica*, *71*(284), 637-659.

Hirshleifer, D., and Hong Teoh, S. (2003). Herd behaviour and cascading in capital markets: A review and synthesis. *European Financial Management*, *9*(1), 25-66.

Holden, C.J., Dennie, T. and Hicks, A.D. (2013). Assessing the reliability of the M5-120 on Amazon's mechanical Turk. *Computers in Human Behavior*,*29*(4), 1749-1754.

Hoeffler, S. (2003). Measuring preferences for really new products. *Journal of Marketing Research*, *40*(4), 406-420.

Hsieh, J.P.A., Rai, A. and Keil, M. (2008). Understanding digital inequality: Comparing continued use behavioral models of the socio-economically advantaged and disadvantaged. *MIS Quarterly*, *13*(1), 97-126.

Hu, L. T., and Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1-55.

Hue, T. (2018). For Many Facebook Users, a 'Last Straw' That Led Them to Quit. Retreived from https://www.nytimes.com/2018/03/21/technology/users-abandon-facebook.html.

Jex, S.M., Bliese, P.D., Buzzell, S. and Primeau, J. (2001). The impact of self-efficacy on stressor–strain relations: Coping style as an explanatory mechanism. *Journal of Applied Psychology*, *86*(3), 401-421.

Johns, G. (2010). Some unintended consequences of job design. *Journal of Organizational Behavior*, *31*(2-3), .361-369.

Kauffman, R.J. and Li, X. (2003). Payoff externalities, informational cascades and managerial incentives: a theoretical framework for IT adoption herding. In *Proceedings of the 2003 INFORMS Conference on IS and Technology, Atlanta, GA, October 2003*.

Karahanna, E., Straub, D.W. and Chervany, N.L. (1999). Information technology adoption across time: a cross-sectional comparison of pre-adoption and post-adoption beliefs. *MIS Quarterly*, *13*(3), 183-213.

Katz, M., and Shapiro, C. (1994). Systems competition and network effects. *Journal of Economic Perspectives*, *8*(2), 3-93.

Koivisto, M., and Urbaczewski, A. (2004). The relationship between quality of service perceived and delivered in mobile Internet communications. *Information Systems and e-Business Management, 2*(4), 309-323.

Langer, E. J. (1989). Mindfulness. New York, NY: Perseus Books.

Lai, V.S., Liu, C.K., Lai, F. and Wang, J. (2010). What influences ERP beliefs—Logical evaluation or imitation?. *Decision Support Systems*, *50*(1), 203-212.

Lee, C. C., Cheng, H. K., and Cheng, H. H. (2007). "An empirical study of mobile commerce in insurance industry: Task–technology fit and individual differences", *Decision Support Systems*, *43*(1), 95-110.

Lee, Y.J., Hosanagar, K. and Tan, Y., 2015. Do I follow my friends or the crowd? Information cascades in online movie ratings. *Management Science*, *61*(9), 2241-2258.

Leidner, D., E., and Kayworth, T., (2006). Review: a review of culture in information systems research: toward a theory of information technology culture conflict. *MIS Quarterly*, *30*(2), 357-399.

Lennon, S. J., Kim, M., Johnson, Jolly, L., Damhorst, M., and Jasper, C. (2007). A longitudinal look at rural consumer adoption of online shopping. *Psychology & Marketing 24*(4), 375-401.

Levinthal, D. and Rerup, C. (2006). Crossing an apparent chasm: Bridging mindful and less-mindful perspectives on organizational learning. *Organization Science*, *17*(4), 502-513.

Li, X. (2004). Informational cascades in IT adoption. *Communications of the ACM*, 4, 93-97.

Li, X., Kauffman, R.J., Yu, F. and Zhang, Y. (2014). Externalities, incentives and strategic complementarities: understanding herd behavior in IT adoption. *Information Systems and e-Business Management*, *12*(3), 443-464.

Lieberman, B., and Asaba, S. (2006). Why do firms imitate each other?. *Academy of Management Review*, *31*(2), 366-385.

Liebowitz, S. (2002). Rethinking the networked economy: The true forces driving the digital marketplace. AMACOM Div. American Mgmt Assn, Dallas.

Lin, T.T., Chiu, V.C. and Lim, W. (2011). Factors affecting the adoption of social network sites: examining four adopter categories of Singapore's working adults. *Asian Journal of Communication*, *21*(3),221-242.

Liu, D., Brass, D.J., Lu, Y. and Chen, D. (2015). Friendships in Online Peer-to-Peer Lending: Pipes, Prisms, and Relational Herding. *MIS Quarterly*, *39*(3),729-742.

Lu, J., Yu, C., Liu, C., and Yao, J. (2003). Technology acceptance model for wireless internet. *Internet Research, 13*(3), 206-222.

Magni, M., Maruping, L., Caporarello, L. and Basaglia, S. (2011). Innovating with technology in team contexts: a trait activation theory perspective. In Proceedings of *International Conference on Information Systems*,1286-1305.

Marakas, G. M., Yi, M. Y., and Johnson, R. D. (1998). The multilevel and multifaceted character of computer self-efficacy: Toward clarification of the construct and an integrative framework for research. *Information Systems Research*, *9*(2),126-163.

Mason, W., and Suri, S. (2012). Conducting behavioral research on Amazon's Mechanical Turk. *Behavior Research Methods*, 44(1), 1-23.

McGeoch, J. A., and Irion, A. L. (1952). *The Psychology of Human Learning*, Longmans, New York,.

McGill, T., J., and Klobas, J. (2009). A task–technology fit view of learning management system impact. *Computers & Education, 52*(2), 496-508.

Meade, A.W. and Craig, S.B. (2012). Identifying careless responses in survey data. *Psychological Methods*, *17*(3), 437-457.

Milliken, F. J. (1978). Three types of perceived uncertainty about the environment: State, effect, and response uncertainty. *Academy of Management Review*, *12*(1),133-143.

Montoya-Weiss, M.M., Voss, G.B. and Grewal, D. (2003). Determinants of online channel use and overall satisfaction with a relational, multichannel service provider. *Journal of the Academy of Marketing Science*, *31*(4),.448-458.

Moore, G. C., and Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research*, *2*(3),192-222.

Moqbel, M., Bartelt, V., and Al-Suqri, M. 2014. A Study of Personal Cloud Computing: Compatibility, Social Influence, and Moderating Role of Perceived Familiarity. In proceedings of Twentieth *Americas Conference on Information Systems*, Savannah, 2014.

Nicholson, J., Nicholson, D. and Valacich, J.S. (2008). Examining the effects of technology attributes on learning: A contingency perspective. *Journal of Information Technology Education*, *7*(11),185-204.

Ong, C. S., Lai, J. Y., and Wang, Y. S. (2004). Factors affecting engineers' acceptance of asynchronous e-learning systems in high-tech companies. *Information & Management*, *41*(6), 795-804.

Ottaviani, M., and Sørensen, P. N. (2006). Reputational cheap talk. *The Rand Journal of Economics*, 37(1), 155-175.

Podsakoff, P., MacKenzie, S., Lee, J. and Podsakoff, N. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879-903.

Polyviou, Ariana, Nancy Pouloudi, and Katerina Pramatari. (2014). "Cloud Adoption: Relative Advantage or IT Fashion?". In Proceedings of the *European Conference on Information Systems*, Tel Aviv, Israel, 2014.

Pieschl, S. (2009). Metacognitive calibration—an extended conceptualization and potential applications. *Metacognition and Learning*, *4*(1), 3-31.

Plouffe, R., Hulland, J., and Vandenbosch, M. (2001). Research report: richness versus parsimony in modeling technology adoption decisions-understanding merchant adoption of a smart card-based payment system. *Information Systems Research*, *12*(2), 208-222.

Preacher, K. J., and Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods*, *36*(4), 717-731.

Prechter, R. R. (1999). *The Wave Principle of Human Social Behavior and the New Science of Socionomics*, Gainesville, GA: New Classics Library.

Riquelme, H.E. and Rios, R.E. (2010). The moderating effect of gender in the adoption of mobile banking. *International Journal of Bank Marketing*, *28*(5), 328-341.

Rogers, E. M. (2003). Diffusion of innovations (5th ed.). New York: Free Press.

Rao, H., Greve, H. R., and Davis, G. F. (2001). "Fool's gold: Social proof in the initiation and abandonment of coverage by Wall Street analysts, *Administrative Science Quarterly*, *46*(3), 502-526.

San Martín, H., and Herrero, Á. (2012). Influence of the user's psychological factors on the online purchase intention in rural tourism: Integrating innovativeness to the UTAUT framework. *Tourism Management*, *33*(2), 341-350.

Sarker, S., and Valacich, J. S. (2010). An alternative to methodological individualism: a non-reductionist approach to studying technology adoption by groups. *MIS Quarterly*, *34*(4), 779-808.

Scharfstein, D., and Stein, J. (1990). Herd Behavior and Investment. *American Economic Review*, *80*(3), 465-9.

Schepers, J., and Wetzels, M. (2007). A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects. *Information & Management*, *44*(1), 90-103.

Shah, R. and Goldstein, S.M. (2006). Use of structural equation modeling in operations management research: looking back and forward. *Journal of Operations Management*, *24*(2), 148-169.

Shamsudin, S. and Othman, R., (2016). Consequences of Causal Ambiguity on Motivation in Lean Production System Adoption: The Role of Moderating Variables. *Journal of Advanced Management Science Vol*, *4*(1), 321-349.

Shim, S., Lee, B. and Kim, S.L. (2018). Rival precedence and open platform adoption: An empirical analysis. *International Journal of Information Management*, *38*(1), 217-231.

Sia, C.L., Teo, H.H., Tan, B.C. and Wei, K.K. (2004). Effects of environmental uncertainty on organizational intention to adopt distributed work arrangements. *Engineering Management, IEEE Transactions on*, *51*(3), 253-267.

Spector, P. (2006). Method variance in organizational research truth or urban legend? *Organizational Research Methods*, *9*(2), 221-232.

Straub, D., Boudreau, M.C. and Gefen, D., 2004. Validation guidelines for IS positivist research. *The Communications of the Association for Information Systems*, *13*(1), 380-427.

Strong, D. M., Dishaw, M. T., and Bandy, D. B. (2006). Extending task technology fit with computer self-efficacy. *ACM SIGMIS Database*, 37(2-3), 96-107.

Sun, H. (2013). A Longitudinal Study Of Herd Behavior In The Adoption And Continued Use Of Technology. *MIS Quarterly*, *37*(4),1013-1041.

Sun, H. (2011). Making Sound Adoption Decisions: A Longitudinal Study of Mindfulness in Technology Adoption and Continued Use. In Proceedings of the 32nd *International Conference on Information Systems* (ICIS), Shanghai, China.

Sun, Y., Bhattacherjee, A. and Ma, Q. (2009). Extending technology usage to work settings: The role of perceived work compatibility in ERP implementation. *Information & Management*, *46*(6), 351-356.

Sun, H. and Fang, Y. (2016). Choosing a fit technology: Understanding mindfulness in technology adoption and continuance. *Journal of the Association for Information Systems*, *17*(6),377.

Sun, H. and Fang, Y., 2015. Understanding Post-Adoption Regret from the Perspectives of Herding and Mindfulness. In proceeding of *International Conference for Infromation Systems*, Fort Worth, USA.

Swanson, E.B. and Ramiller, N.C. (2004). Innovating Mindfully with Information Technology. *MIS Quarterly*, *28*(4), 553-583.

Tan, M., and Teo, T. S. H. Factors Influencing the Adoption of Internet Banking. *Journal of the AIS*, *1*(5), 1-42.

Taylor, P. J., Russ-eft, D. F., and Chan, D. W. (2005). A meta-analytic review of behavior modeling training. *Journal of Applied Psychology*, *90*(2), 692–709.

Teens turn to Tumblr to escape parents on Facebook. Retrieved 22, January 2014 from http://bgr.com/2013/05/22/tumblr-facebook-teens-usage/

Terlaak, A. and King, A.A. (2006). The effect of certification with the ISO 9000 Quality Management Standard: A signaling approach. *Journal of Economic Behavior & Organization*, *60*(4), 579-602.

Tsai, M.C., Lee, W. and Wu, H.C. (2010). Determinants of RFID adoption intention: Evidence from Taiwanese retail chains. *Information & Management*, *47*(5), pp.255-261.

Tsang, E. W. K. (2001). Adjustment of mainland Chinese academics and students to Singapore. *International Journal of Intercultural Relations*, *25*(4), 347–372.

Timeline. Retrieved January 25, 2014 from http://newsroom.fb.com/ content/default. aspx?NewsAreaId=20.

Tornatzky, G., and Klein, K. (1982). "Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings", *IEEE Transactions on Engineering Management*, 1, 28-45.

Trueman, B. (1994). "Analyst forecasts and herding behavior", *Review of Financial Studies*, *7*(1), 97-124.

Vijayasarathy, L. R. (2004). "Predicting consumer intentions to use on-line shopping: the case for an augmented technology acceptance model", *Information & Management*, *41*(6),7-762.

Venkatesh, V. (2000). "Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model", *Information Systems Research*, *11*(4), 342-365.

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

Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. (2003). "User acceptance of information technology: Toward a unified view", *MIS Quarterly*, *27*(3), 425-478.

Venkatesh, V., Thong, J.Y. and Xu, X. (2012). "Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology", *MIS Quarterly*, *36*(1),157-178.

Walden, E. A., and Browne, G. J. (2009). "Sequential Adoption Theory: A Theory for Understanding Herding Behavior in Early Adoption of Novel Technologies", *Journal of the Association for Information Systems*, *10*(1), 31-62.

Wang, Wei-Tsong, and Zu-Hao Wei. (2011). "Knowledge sharing in wiki communities: an empirical study." *Online Information Review, 35*(5),799-820.

Yan-ni, M., and Lei, Z. (2013). "Herd Behavior Analysis Based on Evolutionary Game Theory in the Decision-Making of Innovation Adoption", In Social Media Retrieval and Mining, *13*(5), 106-115.

Yi, M. Y., and Hwang, Y. (2003). "Predicting the use of web-based information systems: self-efficacy, enjoyment, learning goal orientation, and the technology acceptance model", *International Journal of Human-Computer Studies*, *59*(4), 431-449.

Zhang, K. and Chen, X. (2017). Herding in a P2P lending market: Rational inference OR irrational trust?. *Electronic Commerce Research and Applications*, *23*(1),45-53.

Zhao, J. and de Pablos, P.O. (2011). Regional knowledge management: the perspective of management theory. *Behaviour & Information Technology*, *30*(1), 39-49.

Zolkepli, I. A., and Kamarulzaman, Y. (2011). "Understanding Social Media Adoption: The Role Of Perceived Media Needs And Technology Characteristics", *Journal of Social Sciences*, *1*(1), 188-199.

Zhou, T., Lu, Y., and Wang, B. (2010). "Integrating TTF and UTAUT to explain mobile banking user adoption", *Computers in Human Behavior*, *26*(4), 760-767.

Zhong, B., Hardin, M. and Sun, T. (2011). Less effortful thinking leads to more social networking? The associations between the use of social network sites and personality traits. *Computers in Human Behavior*, *27*(3),1265-1271.

Zigurs, I., and Khazanchi, D., "From profiles to patterns: A new view of task-technology fit", *Information Systems Management*, *25*(1), 8-13.

Zwiebel, J.,"Corporate conservatism and relative compensation", *Journal of Political Economy*, *34* (3), 1-25.

APPENDICES

Table 1. Technology Characteristics Influencing Adoption (Rogers 2003)

Relative advantage	The degree to which a technology is perceived as being better than its predecessor.
Compatibility	The degree to which a technology is perceived as being consistent with adopters' needs.
Complexity	The degree to which a technology is perceived as being difficult to use.
Observability	The degree to which the results of a technology's use are observable to others.
Trialability	The degree to which a technology may be experimented with before adoption.

Table 2. Experimental Design

<table>
<tr><th>Condition</th><th>Pre-Treatment Measures</th><th>Treatment</th><th>Post-Treatment Measures</th></tr>
<tr><td>0. Control Group</td><td rowspan="2">• Situating task
• Uncertainty
• Adopter and technology characteristics
• Control variables
• Demographic data</td><td>No</td><td rowspan="2">• Propensity for Imitation
• Intention to use
• Manipulation check items</td></tr>
<tr><td>1. Treatment Group</td><td>The number and identity of prior adopters</td></tr>
</table>

Table 3. Demographic profile of the sample

Variable	Category	Frequency
Gender	Female	112(43.1%)
	Male	148(56.9%)
Age	≤18	7(2.7%)
	19-24	50(19.2%)
	25-34	108(41.5%)
	35-44	56(21.5%)
	45-54	26(10.0%)
	55 – 64	9(3.5%)
	65+	4(1.5%)
Education	<High school	2(.8%)
	High School	27(10.4%)
	College	111(42.7%)
	Bachelor’s	78(30%)
	Master’s	40(15.4%)
	Ph.D.	2(.8%)

Table 4. Goodness-of-Fit indicators of proposed model

Measure	MIN/DF	CFI	SRMR	RMSEA	PClose	TLI
Threshold	Between 1 and 3	>0.95	<0.08	<0.06	>0.05	>0.95
Estimate	1.37	0.97	0.04	0.03	0.99	0.97

Table 5. Summary of Hypotheses

Hypotheses	Findings	Path coefficients
(H1) OBS→IMI	Supported	0.66***
(H2) UNC→IMI	Direct relationship not supported	-0.18
(H3a) OBS/SEF→IMI	Not supported	0.21
(H3b) UNC/SEF→IMI	Significant in opposite direction	0.42***
(H4a) OBS/PIIT→IMI	Supported	-0.54**
(H4b) UNC/PIIT→IMI	Supported	-0.38**
(H5a) OBS/MND→IMI	Significant in opposite direction	0.22*
(H5b) UNC/MND→IMI	Significant in opposite direction	0.18*
(H6a) OBS/RA→IMI	Significant in opposite direction	0.59***
(H6b) UNC/RA→IMI	Supported	-0.30**
(H7a) OBS/CPA→IMI	Not supported	-0.20
(H7b) UNC/CPA→IMI	Not supported	-0.06
(H8a) OBS/CMX→IMI	Not supported	0.17
(H8b) UNC/CMX→IMI	Not supported	0.09
(H9) IMI→INT	Supported	0.43***
Control Variables		
NT→IMI	Significant	0.33**
SN→IMI	Not significant	0.01
FC→IMI	Not significant	0.03

***p<0.01; **p<0.05; *p<0.10

Notes: UNC: Uncertainty; IMI: Propensity for imitation; SEF: Self-Efficacy; RA: Relative Advantage; CPA: Compatibility; CMX: Complexity; FC: Facilitating Conditions; SEF: Self-efficacy; PIIT: Personal Innovativeness; SN: Subjective Norms; NT: Network effect; IU: Intention to use; MND: Mindfulness.

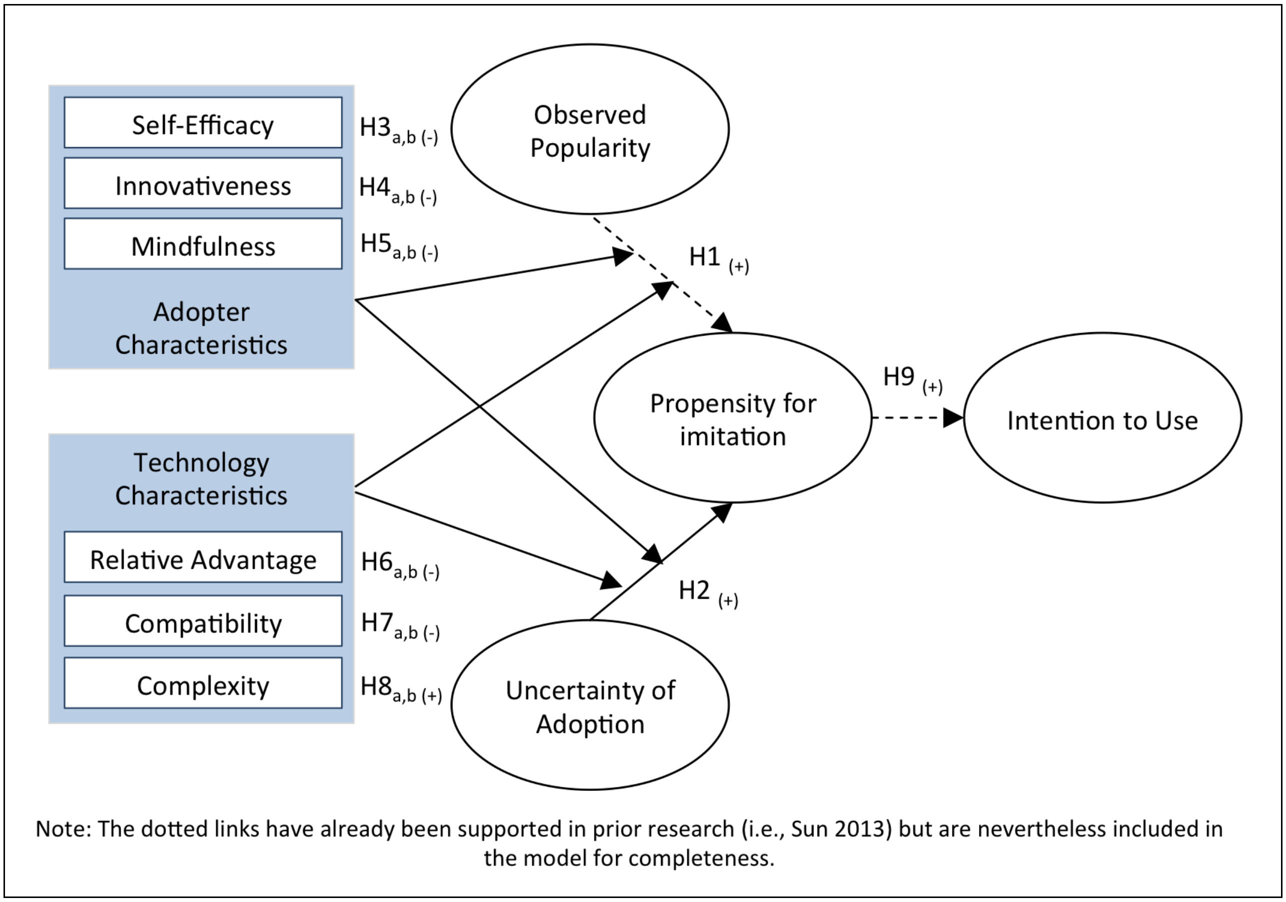


Figure 1. Research Model

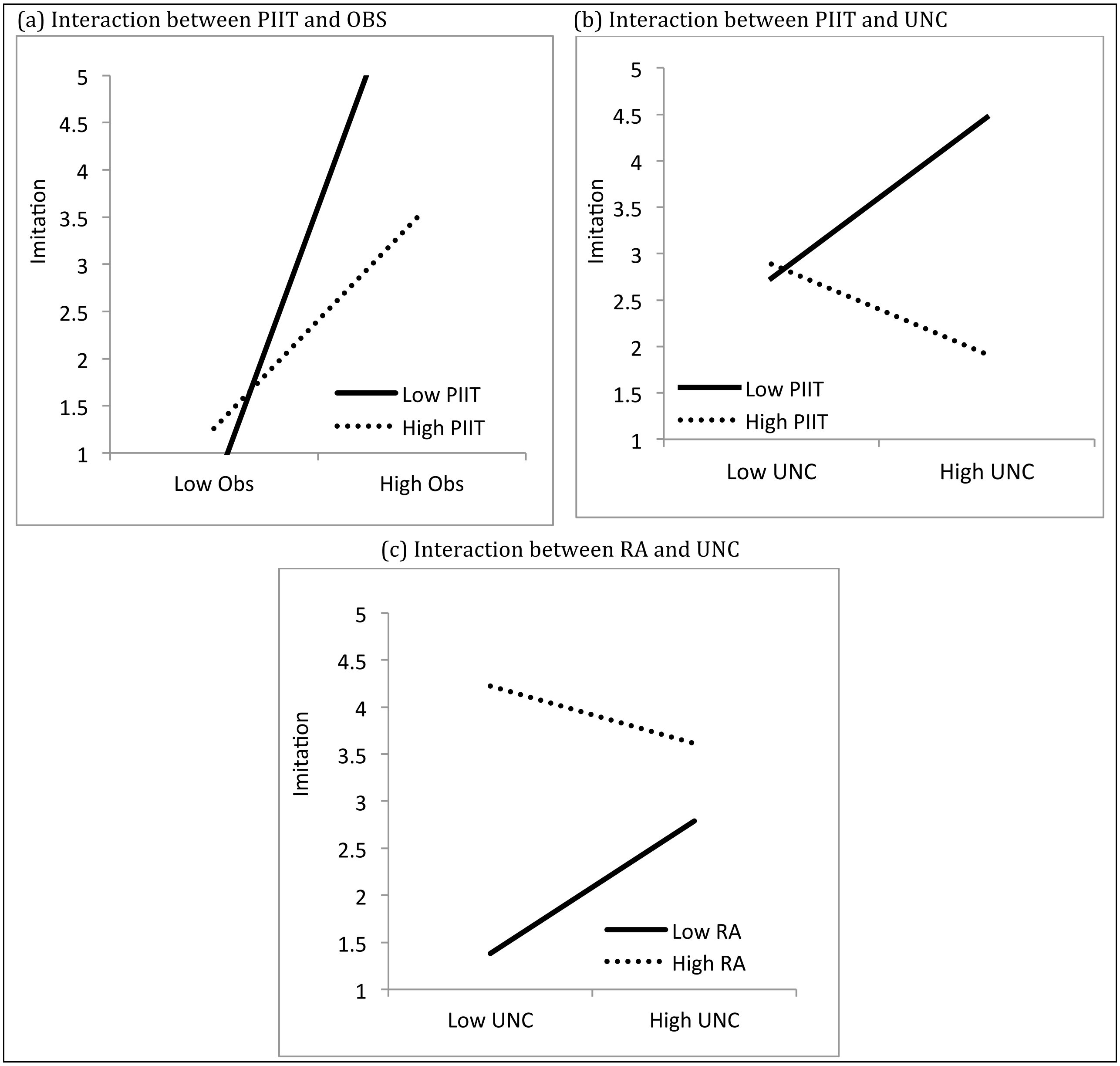


Figure 2. The Moderation Effects

APPENDIX A
Situating Task

Ello is a free social network created by a small group of artists and designers. Ello is free, but to join it you need to get an invitation.

Like every other social network, you can post status updates and photos. You can also comment on posts and reply directly to your friends, as well as see how many people have viewed a post and edit a post if you overlooked a typo before pushing it live.

There is also a Noise section that showcases posts by people you might not know arranged in a loose grid. It is like an online art show at the neighborhood gallery. All posts are viewable to the public, and there are no "Like" or "Share" features. Ello says that it will be offering further features in the future that users can pay for.

Ello is still in beta version right now. It has a long list of new features that it is working on, but no timetable for these updates has been published. These features include:

- Support for online video and audio posts from YouTube, Vimeo, Vine, Instagram and Soundcloud.
- Ello does not have a user-blocking system yet.
- Ello does not enforce a real-name policy and hasn't built a Verified tool yet, so you can’t be sure that an account is not fake.
- Ello is also working on getting inappropriate content flagging, private accounts, reposts with author attribution, a notification center, iOS and Android apps, and private messaging.

APPENDIX B

Treatments

Both the *number* and *identity* of previous adopters matter (Sun, 2013). To create a suitable environment 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 contends that the probability of herding rises when the aggregate public information is strongly held by a lot of people and reinforced by the actions of the market leader.

The treatment group will receive a message that not only states that Ello has been used by a lot of people, but also specifies some famous adopters. The treatment messages were composed based on information from Ello's website and Mashable (a technology and social media blog).

Treatment Group: The following message will appear:

(a) Number

- Ello is getting 40,000 sign-ups per hour. The beginning of a mass migration from Facebook to another Ello (Forbes).

(b) Identity

a. Some major companies in such as Apple, AUDI, Acura, McDonald, Domino's, Taco Bell, Dr. Pepper, Harley-Davidson.

b. Here are some celebrity Ello users: Rihanna, Harry Styles, Ariana Grande, Joseph Gordon-Levitt, Ashley Greene, Blake Lively, Jared Leto.

APPENDIX C
Questionnaire Items

Prior Experience (adapted from Kim & Malhotra 2005)

How long have you been using Ello? (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)

Uncertainty (UNC) (adapted from Sun & Faiung, 2010)

UNC1. I am NOT sure what Ello 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 Ello.

UNC3. I feel uncertain whether I would be able to respond appropriately to any changes/upgrades of Ello.

UNC4. I feel that collaborating using Ello involves a high degree of uncertainty.

Propensity for Imitation (adapted from Sun, 2013)

IMI1. I will follow others in accepting Ello.

IMI2. It is a good idea to follow others in using Ello.

IMI3. I like the idea of using Ello, since many other people are already using it.

IMI4. It seems that Ello is the dominant social networking system; therefore, I would like to use it as well.

Technology Characteristics

Relative Advantage (RA) (adapted from Moore & Benbasat, 1991)

RA1. Using Ello would help me to accomplish tasks (i.e., social networking) more quickly.

RA2. Using Ello would improve the quality of my work (i.e., social networking).

RA3. Using Ello would make it easier to do my work (i.e., social networking).

RA4. Using Ello would enhance my effectiveness on the task (i.e., social networking).

RA5. Using Ello would give me greater control over my work (i.e., social networking).

Compatibility (CPA) (adapted from Moore & Benbasat, 1991)

CPA1. Using Ello would be compatible with all aspects of my activity (i.e., social networking).

CPA2. I think that using Ello would fit well with the way I like to work (i.e., social networking).

CPA3. Using Ello would fit into my work (i.e., social networking) style.

Complexity (CMX) (adapted from Moore & Benbasat, 1991)

CMX1. Using Ello would require a lot of mental effort.

CMX2. Using Ello can be frustrating.

CMX3. I believe that Ello would be cumbersome to use.

Intention to Use (IU) (adapted from Bhattacherjee and Premkumar, 2004)

IU1. I plan to use Ello for photo massaging.

IU2. I intend to use Ello as my future social networking app.

IU3. It is very likely that I will use Ello in the near future.

Adopter Characteristics

Self-efficacy (SEF) (adapted from Compeau et al,1995; Venkatesh et al, 2003; 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.")

SEF1. I could use Ello if there was no one around to tell me what to do.

SEF2. I could use Ello if I had never used a software program like it before.

SEF3. I could use Ello if I had only the online help for reference.

SEF4. I could use Ello if I had seen someone else using it before trying it myself.

SEF5. I could use Ello if I had someone else helped me get started.

SEF6. I could use Ello if I could call someone for help if I got stuck.

SEF7. I could use Ello if I had just the built-in help facility for assistance.

Personal innovativeness (PIN) (adapted from **Agarwal and Prasad 1998)**

PIIT1. If I heard about a new information technology, I would look for ways to experiment with it.

PIIT2. Among my peers, I am usually the first to try out new information technologies.

PIIT3. In general, I am hesitant to try out new information technologies.[reverse-scored item]

PIIT4. I like to experiment with new information technologies.

Mindfulness (adapted from Sun and Fang 2010)

MND1. I am aware that Ello seems to be different from any social network websites that I have used before.

MND2. I will look for additional information about Ello from sources other than its own website.

MND3. I am aware that there are alternatives to Ello.

MND4. I have thought about how Ello could match my specific needs.

Control Variables

Subjective Norm: Two aspects

Aspect one: Descriptive Norm (DN) (adapted from Hagger and Chatzisarantis 2005)

DN1. Most of my co-workers are using Ello

DN2. . Most of my friends are using Ello.

DN3. Most people I know are using Ello.

DN4. Most people who are important to me use Ello.

Aspect two: Injunctive Norm (IN) (adapted from Rhodes and Coureneya 2003)

IN1. Most people in my social circle want me to use Ello.

IN2. Most people in my social circle approve of my using Ello.

IN3. Most people who are important to me want me to use Ello.

IN4. Most people I know think I should use Ello.

Facilitating Conditions (Thompson et al. 1991)

FC1. A specific person is available for assistance with Ello's difficulties.

FC2. Guidance is available to me when I need to use Ello.

FC3. Specialized instruction is available to help me with Ello's difficulties

Network Effects (Sun 2013)

NT1. The more people use Ello, the more valuable it is to users.

NT2. By adopting Ello, I would help increase its value to other users.

NT3. My adoption of Ello would make it more useful for people I know who already use it.

NT4. I hope that more people will adopt PBwiki because that will increase the value of Ello to me.

NT5. Ello will be more useful if more people adopt it.

Manipulation Check Items (MCH) (Sun, 2013)

MCH1. I am aware that a lot of people have adopted Ello.

MCH2. I am aware that Ello has been adopted by a lot of well-known people and organizations.

Bogus Items

1. I have been to every country in the world.
2. I have never brushed my teeth.
3. All my friends are aliens.

APPENDIX D
Item Loadings and Correlations

Table D1. Items and Factor Loadings

Construct	Item		Loading
Uncertainty	UNC2.	I feel uncertain whether my needs when engaging in collaborative work could be met by using Ello.	.814
	UNC3.	I feel uncertain whether I would be able to respond appropriately to any changes/upgrades of Ello.	.933
	UNC4.	I feel that collaborating using Ello involves a high degree of uncertainty.	.837
Imitation	IMI2.	It is a good idea to follow others in using Ello.	.796
	IMI3.	I like the idea of using Ello, since many other people are already using it.	.831
	IMI4.	It seems that Ello is the dominant social networking system; therefore, I would like to use it as well.	.759
Compatibility	CPA1.	Using Ello would be compatible with all aspects of my activity (i.e., social networking).	.742
	CPA2.	I think that using Ello would fit well with the way I like to work (i.e., social networking).	.787
	CPA3.	Using Ello would fit into my work (i.e., social networking) style.	.783
Self-Efficacy	SEF1.	I could use Ello if there was no one around to tell me what to do.	.890
	SEF2.	I could use Ello if I had never used a software program like it before.	.905
	SEF3.	I could use Ello if I had only the online help for reference.	.890
Innovativeness	PIIT1.	If I heard about a new information technology, I would look for ways to experiment with it.	.765
	PIIT3.	In general, I am hesitant to try out new information technologies.[reverse-scored item]	.841
	PIIT4.	I like to experiment with new information technologies.	.848
Facilitating Condition	FC1.	A specific person is available for assistance with Ello's difficulties.	.836
	FC2.	Guidance is available to me when I need to use Ello.	.940
	FC3.	Specialized instruction is available to help me with Ello's difficulties	.792
Relative Advantage	RA1.	Using Ello would help me to accomplish tasks (i.e., social networking) more quickly.	.948
	RA3.	Using Ello would make it easier to do my work (i.e., social networking).	.987
	RA4.	Using Ello would enhance my effectiveness on the task (i.e., social networking).	.894
Complexity	CMX2.	Using Ello can be frustrating.	.797
	CMX3.	I believe that Ello would be cumbersome to use.	.876
Subjective Norm	SNin2.	Most people in my social circle approve of my using Ello.	.763

	SNin3.	Most people who are important to me want me to use Ello.	.745
	SNdn2.	Most of my friends are using Ello.	.812
Network Effects	NT3.	My adoption of Ello would make it more useful for people I know who already use it.	.728
	NT4.	I hope that more people will adopt PBwiki because that will increase the value of Ello to me.	.790
	NT5.	Ello will be more useful if more people adopt it.	.814
Mindfulness	MND2.	I will look for additional information about Ello from sources other than its own website.	.740
	MND4.	I have thought about how Ello could match my specific needs.	.753

Table D2. Descriptive statistics and inter construct correlations

	Mean	SD	CR	AVE	UNC	IMI	SEF	PIIT	RA	CPA	CMX	FC	SN	NT	IU	MND
UNC	4.16	1.42	0.904	0.758	**0.871**											
IMI	3.08	1.32	0.906	0.763	0.565	**0.873**										
SEF	4.37	2.24	0.942	0.801	0.002	0.623	**0.895**									
PIIT	3.65	1.55	0.869	0.689	0.133	0.619	0.096	**0.830**								
RA	2.74	1.99	0.961	0.892	0.106	0.574	0.108	0.025	**0.944**							
CPA	2.34	1.13	0.821	0.605	-0.106	-0.435	0.088	0.027	0.138	**0.778**						
CMX	2.72	1.28	0.834	0.716	-0.138	0.506	0.066	0.155	-0.082	0.134	**0.846**					
FC	2.30	.94	0.910	0.836	-0.284	0.505	0.037	0.042	0.020	-0.013	-0.168	**0.914**				
SN	3.77	1.15	0.820	0.603	-0.084	-0.478	0.045	-0.072	-0.024	0.390	0.004	-0.146	**0.777**			
NT	2.78	.94	0.825	0.612	-0.156	0.381	0.013	0.004	-0.072	-0.073	-0.063	0.082	0.051	**0.782**		
IU	2.82	1.07	0.806	0.679	-0.389	-0.436	-0.056	-0.056	0.029	-0.226	0.034	0.053	0.068	0.033	**0.824**	
MND	2.84	.98	0.712	0.553	0.110	-0.487	0.075	0.154	0.236	0.044	-0.152	-0.076	0.156	0.130	-0.116	**0.743**

Notes: Values on the diagonal in the table of inter-construct correlations represent the square root of AVE. Off diagonal elements are the correlations among constructs.

UNC: Uncertainty; IMI: Propensity for imitation; SEF: Self-Efficacy; RA: Relative Advantage; CPA: Compatibility; CMX: Complexity; FC: Facilitating Conditions; SEF: Self-efficacy; PIIT: Personal Innovativeness; SN: Subjective Norms; NT: Network effect; IU: Intention to use; MND: Mindfulness.

CHAPTER 3

Herd Behavior and Continued Use of Technology: The Case of Technology Abandonment Intentions

INTRODUCTION

The individual is the fundamental unit of analysis according to cognitive psychology (Goldstone & Janssen, 2005). However, a complex system of social structures that ground and organize much of our behavior surrounds all of us. Here, I consider one of the many bridges that link individuals and the social structures in which they are embedded: a form of convergent social behavior termed *herding*. Specifically, herd behavior represents a situation where "everyone does what everyone else is doing" (Banerjee 1992, p. 798). Extant research has attempted to interpret these observations of convergent behavior among decision makers by suggesting a variety of underlying mechanisms. Informational cascades (i.e., the situation "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" (Bikhchandani et al. 1992, p. 994), network effects (i.e., the perception that a product becomes more valuable as its user base expands (Katz and Shapiro 1994), and social learning (i.e., learning from the behavior of others [Bandura 1977]) have all been proposed as the primary mechanisms for herd behavior (Bikhchandani et al. 1998; Hirshleifer et al. 2003).

Herd behavior is particularly prominent in the information technology (IT) industry. Several new technologies have benefited from herd-like adoption behavior by users. Some better-known examples include the social networking sites (SNSs) Ello and Instagram, which both attracted a large number of users within a short period of time after their launch. Duan et al. (2009) have also documented herd-like behavior in the online software market (e.g., software products listed at CNET Download.com). The convergent behavior of users of these technologies, coupled with factors such as the fast growth of the Internet, have provided potential users with the previously-unavailable opportunity to observe the behavior of others and make their own adoption decisions accordingly (Sun 2013). However, such *en mass* convergent behavior can be *fragile* (Banerjee 1992; Walden and Browne 2009). In other words, a group of adopters who has rapidly achieved conformity can likewise easily change their decisions and *abandon* system use when even small amounts of contradictory information are presented (Li 2004; Walden et al. 2009).

The fragility of herd-like behaviors has also been recognized within an organizational context. For instance, Abrahamson (1991) suggests that many managers abandon their initial adoption decisions too quickly, by starting to follow the next trend in imitation of what other organizations are doing, before having even had the chance to truly reap the benefits of the prior trend. This phenomenon of herd-like abandonment, at both individual and organizational levels, is significant and requires more investigation, since it is connected to the durability of particular products and technologies in the marketplace. Facebook is an example of such a phenomenon, taking place at the individual level of analysis, as it is losing its younger users *en masse* to other SNSs (Deutsch 2015).

Technology abandonment intentions are developed in the third and final phase of the information systems (IS) life cycle, known as the *termination* phase (Furneaux and Wade 2011; Turel 2015). As Maier et al. (2015, p. 276) mentioned "In the first phase, *adoption*, individuals develop intentions to adopt and start using an IS (Davis 1989), and in the second phase, *usage*, individuals develop intentions to continue using an already-adopted IS (Bhattacherjee 2001)." Compared to phenomena related to the adoption and usage phases, phenomena associated with the termination phase have been largely overlooked in extant IS research (Maier et al. 2015). The formation of abandonment intentions, which users develop when they want to quit usage of a particular system and not go back to it, are particularly relevant to the herding situation. This is because of the fragility characteristic of herd-like adoption decisions. Hence, applying herd theory to this rarely studied stream of research has the potential to provide us with a better understanding of how *en mass* IS abandonment occurs.

As Sun (2013) has previously pointed out, only a limited number of studies have been conducted to apply herd theory to technology adoption and usage contexts (e.g., Duan et al. 2009; Kauffman & Li 2003; Li 2004; Simonshon and Ariely 2008; Sun 2013; Walden et al. 2009). These papers, despite their significant contributions to IS adoption, have two limitations that hinder our understanding of herd behavior in technology abandonment. First, post-adoptive research has rarely used the herding lens to study individuals' ongoing usage decisions. The only study to date that has investigated the role of herding in a post-adoption IS context (Sun 2013) has focused mainly on the cognitive process associated with individuals' herding behavior. Specifically, Sun investigated how an individual's beliefs about a technology's usefulness change in the post-adoption stage and impact her IS continuance intentions in a herding context. Similar to other research focused on the impact of a technology's perceived utility (e.g., the technology acceptance model [TAM; Davis 1989]), Sun employed user attitudes and beliefs to predict system utilization. This approach, however, ignores the role of *fit* between the focal technology and the user's task requirements, which is important because using a poorly matched system (i.e., one with low fit between the user's needs and the system's features) will not improve the user's performance (e.g., enable them to perform a task faster [Goodhue and Thompson 1995). This study addresses this limitation by incorporating task-related aspects of herd-like adoption to investigate the role of pre- and post-adoption perceptions of *task-technology fit* (TTF) (Goodhue and Thompson 1995). Hence, I investigate this phenomenon from a utilitarian lens, which emphasizes the instrumental value of a technology to a user. Second, IS studies have only recently started investigating the technology abandonment phenomenon (e.g., Maier et al. 2015; Turel 2015). To address these limitations and thereby to improve our understanding of the impact of herding behavior on technology (dis)continuance, I develop the following research question:

> *How does herding behavior influence an individuals' post-adoptive task-technology fit perceptions, and consequently their IS abandonment intentions?*

To approach this research question, I integrate prospect theory (Kahneman and Tversky 1979), which proposes that negative evaluations of a decision have a stronger impact compared to positive evaluations of that decision, with the concept of *critical mass* in the post-adoption phase of a herd-like adoption. Critical mass is defined as the threshold beyond which the number of active participants expands rapidly (Oliver et al. 1985). In other words, I investigate how observation of the critical mass of abandoners (even if the actual number of abandoners is comparatively small) interacts with post-adoption TTF to create a cascade of abandonment intentions. Moreover, by testing the proposed model in an SNS environment, I introduce the concept of perceived *niche* systems to the IS literature, which reflects how different and specific the user perceives a system (here an SNS) to be, compared to other systems. Specifically, I investigate abandonment intentions, which are especially prevalent among SNS users (Maier et al. 2012; 2014) by studying the interaction between individuals' perceptions of niche and their post-adoption TTF in predicting abandonment intentions.

THEORETICAL BACKGROUND

The technology acceptance model (TAM) (Davis 1989) and the task-technology fit model (TTF) (Goodhue and Thompson 1995) are two of the most commonly used theories for understanding individual level technology adoption decisions. While TAM has been highly cited for over two decades, many scholars nevertheless regard it with reservations. One of its limitations, according to Bagozzi (2007), is its focus on over-simplified constructs (i.e., perceived usefulness, perceived ease of use), which leads to poor practical guidance for managers, designers, and trainers on how to actually enhance adoption and use (Venkatesh et al. 2007). The second major limitation of TAM is that the intention-behavior link is uncritically assumed that the focal behavior (system use) is treated as a terminal goal, failing to recognize the intervening practical elements (Bagozzi 2007). For instance, it is possible that although users may perceive a particular technology as being advanced, they will not adopt if they view that technology as unfit with their task. Therefore, even though the TAM model is useful for identifying factors that influence people's technology acceptance, it cannot fully explain why people use a particular technology.

Extant TAM-based research tends to extend the TAM framework by incorporating additional constructs and adjusting its original associations in order to overcome its restrictions. The most recent major iteration in the TAM evolutionary stream is the unified theory of acceptance and usage of technology (UTAUT [Venkatesh et al. 2003]). The UTAUT model is deceptively parsimonious (Straub and Burton-Jones 2007), consolidating a very large number of related constructs that are said to summarize the research stream, but in fact they have little coherent integration (Bagozzi 2007). UTAUT is the result of a synthesis of TAM studies that has brought us back full circle to TAM's origins (i.e., the Theory of Reasoned Action [TRA; Fishbein and Ajzen 1975] and the Theory of Planned Behavior [TPB; Ajzen 1991]). After years of investigation, UTAUT adds the *facilitating conditions* and *social influences* constructs to the two core constructs of TAM, resulting in a model that is not very different from the original TPB (given the considerable conceptual overlap of these two constructs with TPB's constructs of perceived behavioral control and subjective norms).

Benbasat et al. (2007) argue that the above-mentioned problems associated with overemphasizing TAM-based models to predict usage behavior can be resolved if we shift to more practical aspects of system utilization, such as through employing the TTF concept (Goodhue and Thompson 1995). TTF models explicitly include task characteristics and the fit between the technology and the task requirements, which is a weakness of TAM-based models (Dishaw and Strong 1999; Zou et al. 2010). TTF has been widely used for explaining and predicting how fit between one's task requirements and a focal technology's features can improve both task performance and technology utilization. Unlike TAM, the TTF model explicitly recognizes the fact that more utilization of a technology will not automatically result in higher performance (Goodhue and Thompson 1995). Even in situations in which new technology adoption is voluntary, a poor system may come to be widely utilized, but that system will not improve the individual's performance. Adoption of a less efficient alternative technology is also possible when people rely heavily on predecessors' decisions (Bikhchandani and Sharma 2000; Simonsohn et al. 2008). However, as new information is revealed (i.e., as the user becomes more familiar with the technology for herself), she may revise her initial adoption decision and abandon it (Li 2004). Integrating TTF with the herd literature will provide a more task-oriented lens from which to look at such convergent behaviors, and has the potential to improve our ability to explain and predict IS abandonment.

Herd Theory

Herding among individuals has been studied across a number of different research domains. Bikhchandani et al. (1992) modeled herding behavior in the market of initial public stock offerings, and demonstrated that investors could imitate other investors' decisions even if private information suggested doing otherwise. One may observe this behavior when people, drawing on information they have about the choices of others, fall into jointly irrational conformity and "informational cascades" based on having imperfect information, which does not properly reflect their preferences. Beyond the realm of financial investment (e.g., Hirshleifer et al. 2003), empirical evidence of herding has also been documented in the context of political elections (Battaglini 2005), the emotional state of individuals (Fowler and Christakis 2008), donation trends (Frot and Santiso 2011) emerging technology adoption (Sun 2013), online reading behaviors (Liu and Zhang 2014), and product and movie rating behaviors (Lee et al. 2015).

Banerjee (1992) and Bikhchandani et al. (1992) developed informational cascade theory to explain how the decisions of early adopters can affect both (1) which followers converge, and (2) why they converge so quickly on some behaviors. Cascading is a process by which individuals influence each other's decisions. Specifically, they ignore their own private knowledge and instead follow the publicly identified decisions of others (Raafat et al. 2009). The underlying notion of informational cascade theory, in the context of technology adoption decisions, is that individuals must make inferences about the value of a technology based on incomplete and asymmetric information. Although they can observe their predecessors' adoption actions, they are not aware of how those individuals reached their decisions to adopt. In an information cascade, signals and actions are passed throughout the herd from the predecessors to followers, often in an imperfect way. This suggests that a herd does not carry all of the information/preferences of herd members (Banerjee 1992; Lieberman and Asaba 2006). The informational cascade perspective argues that the influence of others' actions can be so substantial that they dominate the influence of an individual's own information (Bikhchandani et al. 1992). Consequently, followers will rely on the judgments of their predecessors and imitate their actions as a strategy to reduce their own cognitive effort and uncertainty about the outcome of adopting a particular technology.

A few recent IS studies have considered the influence of informational cascades on individual IS behaviors. Duan et al. (2009) discovered that informational cascades significantly impact online software downloads. In an exploratory study, Li (2004) investigated herd behavior and argued that informational cascades can be applied to the corporate IT adoption environment, and that they influence IT managers' technology adoption decisions. Walden et al. (2009) adopted a simulation approach, finding that herding in IT adoption can be a useful strategy in situations of high uncertainty. Similarly, Sun (2013) referred to the informational cascade concept in testing the post-adoptive behavior of technology imitators. In this study, I ground my arguments in informational cascade theory to examine the consequences of herd-like adoption at later stages of IS usage.

Herd Behavior vs. Network Effects

Although prior studies (e.g., Shapiro and Varian 1999) have related IT users' imitative behaviors to the similar concept of network effects, more recent empirical studies have found that the network effect is not the only determinant of imitative IS behavior, and in some cases it plays a more prominent role in IT adoption (Duan et al. 2009; Lee et al. 2015). Similar to herd theory, network effect theory explains the influence of other people on one's own adoption of a technology. Hence, it is important to distinguish between these two concepts. A key difference in these two phenomena is that they have different value-adding mechanisms (Sun 2013). Network effects represent the growing significance of a technology associated with the resultant enlarged user base. As Sun (2013) has pointed out herding is strategy for followers to mitigate high levels of uncertainty and escape the potential costs of searching information. In addition, network effects can serve to reinforce the value of a technology and make the user base less fragile (Li 2004). In contrast, herd-like adoptions are fairly volatile and prone to reversal (Walden et al. 2009).

Antecedents of Herding

The herd literature has proposed two antecedents for herd behavior to occur: (1) *observation* of previous adopters' actions, which refers here to the observed *popularity* of their actions, and (2) *uncertainty* of the adoption decision (Abrahamson 1991; Banerjee 1992; Sun 2013). As Sun (2013) has pointed out, observing early adopters' performance is now easier than ever before. It is easy to identify a vast amount of information about others' purchase decisions and product evaluations on the Internet. For instance, in online review communities, herd behavior often occurs given that consumers can easily identify popular products based on the number of reviews (Shen et al. 2016). The media pays considerable attention to new IT advances, and broadcasts new technological developments. The Internet allows people to easily observe the decisions of others concerning technology adoption (Duan et al. 2009), including both the number of adopters and their identities. For example, Apple`s App Store publishes top grossing charts to help users follow the trends. Likewise, eBay's auction feature in which observing early bidders' starting bids lead following bidders to engage in herd behavior (Simonson et al. 2008).

The second antecedent of herding behavior arises from one's desire to reduce uncertainty in adopting a new technology. DiMaggio and Powell (1983, p.149) refer to a "poor understanding of technologies" or "ambiguous goals" when they claim that uncertainty is a trigger for imitation. In general, uncertainty occurs when a lack of accurate information reduces an individual's prediction precision (Berger et al. 1975; Milliken 1987). In the context of financial markets, people may herd when they want to reduce uncertainty and avoid information asymmetry (Devenow and Welch, 1996). In the field of technology adoption, uncertainty has be defined as the inability to foresee problems related to the adoption of a new technology due to having inaccurate and incomplete information (Walden et al. 2009).

RESEARCH MODEL AND HYPOTHESES

Figure 1 shows the proposed research model. The focus of my study is on the post-adoption stage (the shaded part of the model), in which I integrate constructs from TTF theory (Goodhue and Thompson 1995) and the expectation-confirmation model (Bhattacherjee 2001). Specifically, I expect propensity for imitation, as the focal outcome of herding theory in the adoption stage, to impact both one's perceptions of task-technology fit at the adoption stage, and confirmation (i.e., the extent to which the individual's initial expectations of the technology are confirmed) at the post adoption stage. Perceptions of TTF and confirmation will in turn impact one's post-adoptive TTF perceptions. The relationship between post-adoptive TTF and abandonment intentions, as the ultimate outcome variable, is moderated by one's perceptions of both niche and critical mass. The relationships between the antecedents of herding (observed popularity of prior adoption and uncertainty of adoption) have already been theoretically justified and (with the exception of the uncertainty-propensity for imitation link) empirically supported (see Duan et al. 2009; Sun 2013). Hence, I include them here for completeness but do not formally investigate them, as they are not the focus of my study.

Propensity for Imitation[2]

Information serves to reduce uncertainty and increase predictability (Berger and Calabrese 1975). In the context of technology adoption, possession of incomplete and/or

[2] It is important to note that "propensity for imitation" is not conceptualized as a personality trait in this study. Rather, it refers to an individual's intention to imitate others.

asymmetric information encourages adopters to herd (Bikhchandani et al. 2000; Fiol and O'Connor 2003; Lieberman and Asaba 2006; Sun 2013). Otherwise, it would take a substantial amount of time and energy for them to search for information about, and experiment with using, new technologies on their own. Actually realizing the benefits of a new technology requires further time. Therefore, potential adopters who have the greatest reservations about a new technology will tend to observe the outcome of other people's adoption decisions, in order to gather additional information and learn more about the potential consequences of making that same decision (Kraatz and Zajac 2001).

Insert Figure 1 here

An individual who decides to follow others may simply assume that a technology "must be worth adopting because the prior adopters' information must have supported their decision." Such an extrapolation can save a great deal of cognitive effort for the follower (Cingl 2013). One way that decisions makers save potential costs of searching for additional information and experimenting new technology is through observation of others' behavior (Rao et al. 2001). Such observations reduce the need for further investigation, and convince the follower of the low risk of his/her adoption decision. The influence of observation is also due to reputational factors (Sun 2013; Trueman 1994). According to informational cascade theory, an individual is more likely to recognize that her reputation could be damaged if she opposes the opinions of the majority of earlier adopters (Lee et al. 2015). It is reasonable to argue that this fear of dissenting from mainstream beliefs may become more noticeable as more and more people express their opinion. However, if only a small number of opinions are being revealed or expressed, the individual may feel less need to conform to the majority opinion (Berger and Heath 2008). Similarly, Barasch and Berger (2014) found that people are likely to discount the possibility of negative experiences they may have with a new technology when they are faced with a large cluster of existing users.

Task–Technology Fit

Goodhue and Thompson (1995) developed the "technology-to-performance chain" (TPC) model, in which technology utilization depends on the fit between a technology and the tasks it supports. Their model, more commonly known today as the TTF model, has been used to explain the adoption of Internet services (Shang et al. 2007), location-based systems (Junglas et al. 2008), computer applications (Sarker & Valacich 2010), and mobile device use (Negahban and Chung 2014). As previously stated, my primary argument for extending a model of post-adoption herding behavior to include core concepts from TTF is due to the lack of attention given in current herding models to the potential impact of task-related issues. I adopt Goodhue's (1995) definition of TTF as one's initial perception of the fit between the focal technology and the requirements of their task in the decision-making stage of a herding influenced adoption. Since users have incomplete information about the new technology's capabilities and whether it will actually satisfy their needs prior to adoption (Banerjee 1992; Bikhchandani et al. 1992, 1998; Lieberman et al. 2006), they develop a preliminary perception of technology fit. In the post-adoption stage, i.e., after a period of time actually using the system, the individual's perceptions of TTF will further develop and influence their post-adoption behavior. In the section below, I argue that the degree of propensity for imitation in a herding setting can affect the formation of one's initial (pre-adoption) perceived TTF, and such initial perceptions of fit may in turn impact post-adoption behaviors through influencing later perceptions of actual (experienced) TTF.

Pre-Adoptive TTF

Pre-adoptive TTF depends on the level of agreement between the perceived capabilities of the technology, the needs of the task, and the competence of the users (Strong et al. 2006). However, in a herding situation, individuals have limited information about the capabilities of the technology they are considering adopting. Incomplete or asymmetric private information creates uncertainty about the adoption decision, and observing others' adoption behaviors leads potential adopters to ignore the possibility of low fit between their needs and the actual capabilities of the technology. A potential adopter receives signals from prior adopters, often without much new information being added (Sun 2013). This process of information aggregation refers to the low informativeness characteristic of herd behavior, and implies that the information gets noisy and less accurate as it transfers from the head of the herd to the later followers (Banerjee 1992; Bikhchandani et al. 1992, 1998; Lieberman et al. 2006). As a result, I argue that in such "low informativeness" environments, where individuals are simply following others in their adoption behavior and deferring to the herd, these individuals will tend to overestimate the level of fit between the technology's capabilities and their own task requirements, as a consequence of having now joined the herd and already discounted their private information.

Support for this argument can be found in the behavioral finance literature, which reveals that such information-based herding occurs when a financial analyst lacks confidence about her private information (Hirshleifer and Teoh 2003). As a consequence, the analyst abandons her private information and follows the herd in making financial forecasts. Research shows that analysts who have made herd-influenced investment decisions exhibit more confidence in the accuracy of their forecasts (Hong et al. 2000; Maug and Naik 1996). Prior research further shows that imitation can be a legitimate way for organizations to avoid worst-case scenarios by obtaining an average compensation (Bikhchandani et al. 2000).

The same phenomenon may apply in individual IT adoption settings. That is, by imitating others, a person may overlook his or her actual needs and thus mistakenly adopt a technology that is not actually suitable for those needs (Abrahamson 1991). I would expect these imitators to base their perceptions of a technology's fit on prior adopters' behavior, and discount the need to search for accurate information on actual fit. As with organizational adoption, they exhibit risk averse behavior through imitation, meaning that they do not want to take the chance of rejecting a potentially useful technology that others have already adopted. This risk aversion will prevent them from seeking out a better fitting technology, which may or may not lead to better performance (Kahneman and Tversky 1979; Thaler et al. 1997). An adopter influenced by such considerations will be more likely to have a favorable perception of TTF prior to adoption, and any potential misfit between his/her needs and the technology’s features will be ignored. The low informativeness in the environment, by its very nature, requires adopters to be able to actually explore and learn about the newly adopted technology for themselves (over time and through post adoptive use) in order to form accurate TTF perceptions. For instance, Ello, a relatively new social networking website, was receiving 40,000 to 50,000 new requests each hour from potential new users after its initial release (Inc 2015). These individuals could not be expected to form accurate perceptions about the features or even the interface of the site, since without having an invitation code they could not actually access the Ello application. This situation creates a high propensity for imitation, and consequently (as with the financial analysts' overconfidence in their herd-based decisions), an overestimation of fit between their needs and features of the technology. Thus I posit:

> ***H1:*** *Propensity for imitation will have a positive impact on a person's pre-adoptive task-technology fit at the adoption stage.*

Pre-Adoptive TTF and Post- Adoptive TTF

The belief update literature provides an appropriate lens for understanding the process by which individuals' TTF perceptions change from the adoption to post-adoption stages. Prior technology acceptance studies have relied on expectation confirmation models to explain changes in user perceptions, highlighting the belief change process as the core theme and proposing that a better understanding of how user beliefs evolve from the pre-usage to the post-adoption stage is critical (Kim and Oh 2011; Kim and Malhotra 2005). According to Bhattacherjee and Premkumar (2004), pre-adoption assessments may lead to false expectations for a technology because such perceptions have been based on second-hand information. After users are able to actually interact with the technology for themselves, their initial perceptions may change, which results in a revision of their initial unrealistic perceptions and the formation of new post-adoption beliefs. This belief change process can be explained by the sequential updating mechanism, which posits that one's subsequent evaluations are updated in the context of one's prior perceptions (Kim et al.

2005). It also suggests that current perceptions can serve as a reference point (anchor) for future evaluations, which will be updated based on new experiences. Put differently, people do not perceive an external stimulus in its pure form as it is presented. Rather, as Hogarth and Einhorn put it, their prior knowledge “is adjusted by the impact of succeeding pieces of evidence” (1992, p. 8). In other words, individuals make judgments and possible changes to their attitudes by comparing the new piece of information with their prior knowledge (Lankton and McKnight 2012).

Drawing on belief update theory (Kim et al. 2005), I argue that one's perceptions of TTF prior to adoption will impact their TTF perceptions at the post adoption stage. Perceptions of the ability of a technology to address specific task requirements can modify the user's behavior in such a way that his/her actual fit will be influenced favorably. This argument is also in line with the process of *imbrication*, that is, the change of a user's behavior to integrate a technology into their routines (Leonardi 2011). As Leonardi (2011) has pointed out the notion of imbrication is based on the view that humans and technology are distinct phenomena and by themselves neither are empirically important, but when they become imbricated- interlocked in particular sequences- they together may change routines. In other words, since routines (representing the specific ways in which individuals interact with a technology) are increasingly flexible, when an individual perceives that the capability of a technology matches the requirement of a task (i.e., imbrication) she may be likely to change her routines. Leonardi (2011) argues that individuals construct a perception of a technology that either constrains or affords[3] their

[3] Affordance of technology is the perception that a technology offers possibilities for action. In most cases, affordances are defined and understood as the perception of what the technology offers to that particular user (Jenkins 2008).

ability to complete their routines and achieve their goals. When individuals perceive a higher degree of affordance in a technology that helps them to complete their routines, they may even change their behavior in order to imbricate the technology into their routines (Leonardi 2011).

Originally proposed by Festinger (1962), cognitive dissonance theory has become one of the most influential and widely documented theories in social psychology (Cooper, 2007). Its central proposition is that people experience an uncomfortable tension when they simultaneously hold two inconsistent cognitions (which may include any combination of inconsistent ideas, beliefs, values, attitudes, emotions, or behaviors). This tension motivates individuals to either adjust or justify their beliefs, attitudes, and behaviors to eliminate the source of dissonance (Festinger 1962). Technology adoption research that is grounded in cognitive dissonance theory has found that in cases of deviation between one's expected and experienced system quality, the individual will adjust her perceptions and behaviors to assimilate toward expectations (Szajna and Scamell 1993). Similarly, Karahanna et al. (1999) found that in order to reduce cognitive dissonance, users try to adjust their usage behavior by looking for positive information to reinforce their past adoption decision. Thus, I argue that individuals in a herding situation will tend to adjust their needs in order to justify adoption of the new technology, which results in higher degrees of perceived TTF levels in the post adoption stage. Therefore, I posit:

> ***H2:*** *Higher pre-adoptive task-technology-fit will lead to higher post-adoptive perceptions of task-technology fit.*

Task-Technology Fit and the Expectation-Confirmation Model

The TTF model has considerable potential to explain users' abandonment intentions in a herding context. The fit between technology features and task requirements becomes more important once an adopter has started using a technology (Leonard-Barton and Sinha 1993). A meta-analysis by Petter et al. (2013) confirms that TTF has a strong influence on the post-adoption phase of user behavior, specifically on system usage.

Many IS studies have validated the links between IS continuance intention (representing a user's intention to further use an already-adopted technology) and task-technology fit (Larsen et al. 2009; Lin 2012; Zhou et al. 2010). However, research has not empirically tested a two-stage model combining the post-adoption model of IS continuance (Bhattacherjee 2001) and TTF. In words, no research has recognized the dynamic nature of the TTF construct (i.e., pre and post–adoptive TTF perceptions) and its relation to IS continuance intention (Goodhue 2007). Li (2004) related perceived task-technology fit to satisfaction and found that perceived fit and satisfaction are important antecedents of intention to continue using a learning system. Likewise, Larsen et al. (2009) proposed a post adoption model that revealed that the TTF model has a determinant role in explaining users' continuance intention.

Once an individual adopts a technology, what is the motivation underlying their intention to continue to use it at a later date? The durability of a new system relies on individuals' sustained usage of the system (Bhattacherjee 2001; Karahanna et al. 1999). If initial excitement over adoption of a technology weakens after an individual gains actual experience using it, then the technology will be faced with a diminishing user base, and may even be subsequently abandoned altogether.

Many studies of continuance intention are grounded in the expectation–confirmation model (ECM; Bhattacherjee 2001) (Figure 2). The ECM posits that confirmation of expectations from prior use and post-adoption perceptions of the usefulness of a system lead to user satisfaction. Confirmation also influences perceived usefulness directly. Perceived usefulness and satisfaction together impact intentions to continue using the system. The ECM has been applied to the study of IS continuance in a variety of settings, including online shopping (Chiu et al. 2012), e-government (Lin et al. 2011), e-learning (Limayem and Cheung 2008), and social network services (Kang, et al. 2009). Bhattacherjee (2001) likened an IS user's continuance decision to that of a consumer's repurchase decision because both follow the sequences of (1) making an initial acceptance or purchase decision, (2) experiencing initial use of the product or service, (3) making an *ex-post* decision of continued use or reversal of the initial decision.

Insert Figure 2 here

In this study, my focus is on the degree of fit between task and technology in the post-adoption stage and its impact on users' post-adoptive herding behavior, rather than simply user perceptions of characteristics of the technology itself. In the expectation-confirmation paradigm, expectation is usually defined as individual beliefs, or as the sum of different beliefs, about specific characteristics possessed by a product or service (Oliver 1980). Perceived usefulness (PU) is often used as the surrogate for post-adoption expectation, since among the various beliefs studied in technology acceptance research, it has been shown to be the most consistent predictor of an individual's usage intentions (Venkatesh et al. 2003). I use post-adoptive TTF as the surrogate for expectation in the proposed model since it reflects adopters' beliefs about a technology's level of task fit at the post-adoption stage. In doing so, I also address the limitations of TAM-based adoption models which have used PU as the salient belief in predicting individual behavior while ignoring instrumental value and utilitarian characteristics of the new system (Benbasat et al. 2007). In other words, by using TTF instead of expectation as a proxy to measure individuals' perceptions about a technology, I can capture the influence of task-related beliefs in continuing or reversing adoption behaviors.

Propensity for Imitation and Confirmation

In an informational cascade, significant private information is lost due to uninformative imitations, which reduces overall decision precision and quality. Adopters may end up selecting an inferior technology simply because valuable information is lost, since they only observe their predecessors' final decisions and not their adoption decision-making processes. Due to the low informativeness (Banerjee 1992; Bikhchandani et al. 1992, 1998; Lieberman et al. 2006) and subsequent fragility of such adoption decisions (Brown et al. 2009), I argue that herd behavior results in negative confirmation at the post-adoptive stage.

Following their initial adoption of a technology, individuals will assess its subsequent performance and compare it with their original expectations; they will then determine the extent to which their expectation has been confirmed (Bhattacherjee 2001).

In ECM, confirmation is defined as the degree of coherence between the adopter's original expectations and the observed performance of the technology. Any deviation of observed performance from the initial expectations will result in either positive or negative confirmation. If actual performance exceeds the adopter’s original expectations, he/she will conclude positive confirmation, and if it is inferior to what was anticipated, he/she will experience negative confirmation (sometimes referred to as disconfirmation).

Prior research on herd behavior and informational cascades has found that imitation leads to overly optimistic expectations of performance and subsequently negative confirmation. For example, financial analysts who imitated others following an informational cascade were more likely to conclude overly optimistic evaluations about the prospective earnings of a firm, and developed post-decision regret and disappointment (Rao et al. 2001). Likewise, Greve (1996) contends that observation of the successful actions of prior adopters may raise aspiration levels beyond what can realistically be accomplished. In the same vein, Persons and Warther (1997) suggest that the adoption of financial innovations based upon imitation will end in disappointment. Similarly in the IS area, Abrahamson (1991) argued that managers that imitate others may end up adopting technologically inferior innovations, since when people imitate others in adopting a technology, they may later realize that the adopted technology does not perform in a way that addresses their needs.

Later adopters are more affected by prior adopters’ behaviors if they over rely on them. This leads to a deviation between original expectations and experienced performance; consequently, the later adopters become disappointed and dissatisfied (Parthasarathy and Bhattacherjee 1998). However, in cases where there is low uncertainty about adopting a technology, Sun (2013) found that mimicking others' adoption decisions leads to *positive* confirmation at the post-adoptive stage, suggesting a "correct" form of herding (i.e., properly adopting a superior technology). This implies that uncertainty has a regulating effect on this association. Thus, I would expect that under high uncertainty conditions, imitation of prior adopters will lead to choosing a technology that does not live up to one's expectations and consequently results in negative confirmation:

H3: *Propensity for imitation at the adoptive stage will have a negative impact on confirmation, at the post-adoptive stage.*

Confirmation and Post-adoptive TTF

Individuals may have inaccurate pre-adoption TTF perceptions for a new technology since they are unsure what to expect from its use. Nonetheless, they may join the herd and want to adopt the technology with the intention of developing more accurate perceptions later based on their actual usage experiences (Bhattacherjee 2001). The individual's post-adoptive TTF perceptions may be adjusted as a result of the confirmation experience when users realize that their initial perceptions were unrealistically low. To support this association, I refer to cognitive dissonance theory (Festinger 1962), which suggests that users may experience psychological tension (cognitive dissonance) if their pre-adoption perceptions (which resulted in adoption) are disconfirmed based on actual use. Therefore, users may try to minimize this unwelcomed state by distorting or adjusting their beliefs and perceptions about the attributes of the technology and its fit level with their task requirements. Specifically, they modify their perceptions to be more consistent with reality. Thus, I argue that positive confirmation (e.g., the technology performed better than their expectations) will tend to elevate users' TTF perceptions at the post adoptive stage, whereas negative confirmation (e.g., the technology performed worse than their expectations) will reduce it:

H4: *Positive confirmation will lead to higher post-adoptive TTF.*

Abandonment

According to Furneaux and Wade (2011), the IS life cycle is comprised of the three main phases of *adoption*, *usage*, and *termination* (Figure 3). In the adoption phase, individuals develop intentions to adopt and start using an IS (Davis 1989). In the usage phase, individuals develop intentions to continue using the previously adopted IS (Bhattacherjee 2001). The life cycle concludes with the termination phase, in which users develop abandonment intentions (Turel 2015). There has been extensive research conducted to date on both IS adoption and continuance (Lankton and McKnight 2012; Bhattacherjee and Lin 2014). However, IS research has largely neglected the concept of technology abandonment despite its importance. Most research has assumed that IS continuance and abandonment are opposite extremes along the same continuum (Turel et al. 2013). Recently, however, scholars (Appendix A) have begun focusing more on IS discontinuance as a distinct phenomenon, concluding that it is not in fact merely the opposite of IS continuance (Turel 2014).

Insert Figure 3 here

Research has shown that continuous usage (more commonly referred to as "IS continuance") and abandonment decisions are driven by different factors (Turel 2014).

However, in most studies on IS continuance it has been assumed that continuance and abandonment share the same predictors. While in some cases this may be correct, one should also consider the possibility that some predictors of continuance may have a different, very weak, or no effect on abandonment decisions, and vice versa. Indeed, past research provides some support for this view, for example, group support system continuance has been shown to be driven by different factors than those driving abandonment (Pollard 2003), and technology characteristics had different effects on teachers' IS continuance and abandonment intentions (Aldunate and Nussbaum 2013). Similarly, prior studies have found that seemingly opposite concepts such trust and distrust (Dimoka 2010) and knowledge sharing and hiding (Connelly et al. 2012) can co-exist and have possibly different antecedents and outcomes. In a website usage context, Turel (2015) empirically demonstrated that abandonment intention is not just the opposite extreme of continuance intentions on a continuum, but rather it is a different intended behavior that can independently exist.

To justify this finding, Turel (2015) argues that abandonment is a post-adoption intention that likely develops after continuance intentions have been in place (i.e., the person already uses the system) and each of these intentions is driven by an affiliated behavioral attitude. When a new attitude that counterbalances an existing one forms, the new attitude does not always replace the existing one and a dual-attitude structure is developed, which can translate into opposing intentions. In addition, the two-factor approach for negative and positive phenomena (abandonment and continuance intentions, in my case) is more accurate than treating them as the opposite poles of the concept because the brain can process them separately and simultaneously (Cacioppo and Berntson 1994; Cacioppo et al. 1999).

Table A1 in Appendix A summarizes extant research on perceptions influencing abandonment intentions. For instance, Maier et al. (2015) found that in an SNS usage context, higher perceptions of switching-exhaustion (i.e., an individual's psychological reaction to switching-stressors [Maier et al. 2015]), and SNS-exhaustion (i.e., an individual's psychological reaction to stress-creating conditions caused by using SNSs [Maier et al. 2014]) are significant predictors of SNS abandonment intentions. However, prior research in this stream has not established a similar direct link between the construct of exhaustion and continuance intentions (e.g., Ayyagari et al. 2011; Maier et al. 2014). None of the perceptual constructs that I investigate in this study (TTF, critical mass, and niche) have been considered in the past as determinants of abandonment intentions. To better illustrate how my study incorporates these three perceptions in a herd-like setting, I again highlight the fragility of herding behavior (Bikhchandani and Hieshleifer 1992; Walden and Browne 2009). Fragility in herding means that adopters tend to reverse their usage behavior of a newly adopted technology when new information is revealed (Bikhchandani and Sharma 2000). If credible information is revealed to support the rejection of a technology, the adoption cascade can be quickly reversed. One recent example of this phenomenon is Samsung's Galaxy Gear (a wearable smartphone), in that after a period of initial popularity it was abandoned by one-third of its previous users, with hundreds of Galaxy Gears being listed for sale on eBay barely six months after launch (Endeavour 2014).

Post-Adoptive TTF and Abandonment

In a herding situation, decisions are made in the presence of low and inaccurate information (Bikhchandani et al. 1992). Hence, direct interaction and experience with a technology are important sources of more accurate information and can create more salient evaluations about the technology's value in the post-adoption stage. Evaluating how a technology fits the user's needs after a short period of usage (i.e., post-adoption TTF perceptions) should be a determining factor in predicting the individual’s further usage or abandonment decisions. Previous IS research suggests the importance of TTF perceptions in IS-related behaviors (e.g., Dishaw et al. 1999; Lin and Huang 2008; and Shang et al. 2007). Larsen et al. (2009) tested an IS utilization model and found a direct effect of TTF on individuals' post adoption behaviors. Lin (2012) developed a hybrid model by integrating IS continuance theory with TTF to explore the antecedents of the continuance intentions of a virtual learning system within a university, and demonstrated that TTF significantly and positively impacted both IS satisfaction and continuance intentions. Similarly, Furneaux and Wade (2010) suggest that declining perceptions about a system's suitability (a similar concept to TTF) will be an important indication that a system is nearing the end of its life and users will stop using it.

How can post-adoptive TTF drive abandonment intentions? First, in order to provide a rationale to justify the relationship between post-adoptive TTF and abandonment intentions, I draw upon the concept of “unfaithful appropriation” of a technology (Dennis et al. 2001). This concept represents a user’s intention to employ the technology in a manner inconsistent with its spirit and core functionality. The "spirit" of the technology refers to the general intent regarding the technology’s values and goals as prescribed by its designers, and is associated with a set of features (DeSanctis et al. 2008). In words, unfaithfulness is a behavioral intention that veers away from the spirit of the technology. Research has found that when TTF perceptions are low, due to a higher tendency for unfaithful appropriation behavior, the use of a new technology leads to less desirable outcomes for users, and consequently dissatisfaction and abandonment of the that technology (Fuller and Dennis 2009).

Second, negative post-adoption perceptions leave strong affective traces known as "markers" in individuals' episodic memories, that is, easy to access and retrieve memories (Westbrook and Oliver 1991). Undesirable post-adoption perceptions signal to people that something is wrong, make them more aware of their problems, and motivate them to do something about them (Salovey et al. 2000). Experiencing such negative perceptions is particularly relevant to the SNS context due to the stress associated with using an SNS (Maier et al. 2015) and has been found to have a significant influence on developing SNS abandonment intentions (Turel 2015). It is therefore reasonable to expect that people who have weaker perceptions of post-adoptive TTF will have an increased accessibility to relevant episodic memory markers; they develop strong awareness of their problems, and can be more motivated to act to alleviate them. Prior studies have identified abandoning a technology as an adaptation strategy that mitigates the undesirable effect of negative perceptions (Beaurdy and Pinsonneault 2005). Hence, users who perceive lower fit between their needs and the offerings of the adopted technology may engage in an adaptation strategy and ultimately stop using the technology. Thus, I posit:

H5: *Post-adoptive TTF will have a negative impact on abandonment intentions.*

The Moderating Effect of Critical Mass

Following other people's decisions, and relying on different heuristic cues such as social proof (i.e., inferring the value of a behavior based on its popularity [Cialdini 2003]), may lead to overvaluation of one's choice and regret about the adoption decision. Prior research has argued that people who make decisions by herding may experience post-decision regret and consequently abandonment (Rao et al. 2001). Likewise, Bikhchandani et al. (1992) point out that herding behavior is inherently fragile and subject to reversal. Through adopting technologies, it is expected that individuals can perform their tasks more efficiently; however there are many occasions in which the adopted technologies fail to live up to their promise (Abrahamson and Fairchild 1999), resulting in waves of adoption and abandonment (Barley and Kunda 1992). To uncover the determinants of abandonment intentions in fragile herd-like decision-making, I apply the concept of critical mass.

Critical mass is defined broadly as the threshold beyond which the number of active participants expands rapidly (Oliver et al. 1985). Just as a critical mass of positive adoptive actions is required to trigger initial herding, the emergence of a sufficient number of negative information (e.g., observing others abandonments) will reverse the adoption process (Rao et al. 2001). Formation of critical mass may describe the collapse of the Internet bubble in the mid-2000s. As negative evaluations of the expanding Internet bubble began to appear and grew rapidly, people started to abandon it swiftly causing the collapse of the Internet market (Lieberman et al. 2006; Sun 2013). Lou et al. (2000) have suggested that perceptions of critical mass, as a form of social influence (Wattal et al. 2010), are important determinants of individuals' post-adoption intentions. In an IS context, the concept of critical mass suggests the point at which a certain minimum number of users are demonstrating similar behavior (in this case, technology abandonment) such that the rate of abandonment of the technology suddenly takes off (Slyke et al. 2007).

Prospect theory (Kahneman et al. 1979) can help us to understand the interaction between post-adoptive TTF and observation of critical mass, and illustrate its effect on abandonment intentions. Prospect theory argues that losses are weighted more heavily than gains (Tversky and Kahneman 1991). More specifically, it proposes that the value function is "concave for gains, convex for losses, and steeper for losses than for gains (Kahneman et al. 1979, p. 263). Hence, realizing the stronger impact of negative (as opposed to positive) perceptions of an adoption decision on one's continuance or abandonment decision, I would expect that abandonment intentions are more likely to develop when an individual observes even a small number of abandonments (as compared to the number of adopters in the adoption stage) and over-evaluates its weight (i.e., a negative perception). In other words, the threshold for the critical mass of abandoners is lower compared to the threshold of the critical mass of adopters in the adoption stage for a person when herding.

People obtain new information about a particular technology through both direct interactions with that technology, as well as through other information sources such as the mass media, various types of experts, and other users. As an example, I might highlight the role of "trend setters" who may discredit a technology; this new information may then cause the popularity of the technology to dissipate rapidly (Abrahamson and Rosenkopf 1993). As I discussed earlier, due to the fragility of herding decisions (Bikhchandani and Sharma 2000), the disclosure of new information about a technology may be more salient in forming post-adoption intentions. This is because when herding, people know that their adoption decision is based primarily on inaccurate information and signals they received from the herd leaders (i.e., prior adopters) (Duan et al. 2009), and they are thus more likely to give more weight to new information that materializes later. In this research context, this new information comes in at least two forms: (1) updated perceptions of TTF, and (2) observation of a critical mass of abandoners.

I have previously argued that individuals with low adjusted (post-adoptive) perceptions of TTF would be expected to have higher abandonment intentions; I expect that this effect will thus be magnified in the presence of critical mass. However, even for individuals whose adjusted TTF perceptions are still at acceptable levels, meaning that they would normally not consider abandoning the technology for this reason, the negative link between post-adoptive TTF and abandonment intentions will be weakened (or suppressed) in the presence of a critical mass of abandoners. In other words, the relationship between post-adoptive TTF and abandonment intentions depends on the observation of critical mass. This argument is in line with cognitive dissonance theory (Festinger 1962), which argues that expectations create inertia in which adoption outcomes are consistent with expectations (here, post-adoptive TTF). However, observation of a new piece of information (e.g., the existence of a critical mass of abandoners) can weaken this inertia. Therefore, obtaining two conflicting pieces of information in the post-adoption stage (positive TTF perceptions combined with observation of the critical mass of abandoners) will increase the likelihood of developing abandonment intentions.

In sum, the adopter in a herding situation may weight negative evaluations and behaviors of prior adopters, i.e. abandonment, more heavily than other probable positive evaluations. When this biased evaluation of loss couples with the creation of critical mass, I expect that the negative association between post-adoptive perceptions of TTF and abandonment intentions will be weakened, making abandonment more likely. Thus, I hypothesize that:

> ***H6:*** *Critical mass will moderate the negative relationship between post-adoptive TTF and abandonment intentions, such that it is weaker (less negative) for individuals who observe a critical mass of abandoners.*

The Moderating Effect of Perceived Niche

The tendency of an individual to purchase and exhibit expensive goods is known as conspicuous consumption (Veblen 1899). As Schaefers (2014) indicates Veblen's (1899) early understanding of conspicuous consumption was limited to the process of using publicly visible and luxurious products to signal social status. More recent researches have extended the conspicuous consumption notion to integrate multiple dimensions of social needs (Chaudhuri and Majumdar 2006; Chen et al. 2008; Gierl and Huettl 2010). Similarly, Shaefer et al. (2013) argued that using *niche* products, defined as products possessing a higher degree of specificity and uniqueness than corresponding mass market products, is a means to satisfy one's desire for an improved social standing. People are more likely to seek to differentiate themselves with niche products that contribute to self-expression than mainstream products that are universally adopted and unlikely to impact a person's ability to express their identity (Berger and Heath 2008). In fact the use of niche product helps the user achieve high social visibility since those products are easily recognizable from mainstream products. Hence, it is reasonable to argue that an individual's effort to follow prior users, or to differentiate herself from them, may differ based on whether the product is a popular one consumed by everyone versus a niche product consumed by few. For instance, Dellarocas et al. (2010) found that very obscure movies attract more on-line reviews than mainstream movies. Moreover, studies have found that compared to mass product consumers, niche product users are more likely to behave in disagreement with preceding users (Hu and Li 2011; Lee et al. 2015).

Prior research (e.g., Mason 1981; Brewer 2003; Patsiaouras and Fitchett 2012; Schaefers 2014) argued that people may have desires for conspicuous consumptions in order to influence other's perceptions about themselves, and acquiring and using niche products can serve such a desire. SNS users would thus decide to use niche SNSs to achieve their intended level of differentiation from others. As niche SNSs might be seen as a unique and differentiated product than similar mainstream SNSs (e.g., Facebook), their use may seem as a mechanism for satisfying one's yearning for distinctiveness (Schaefers 2014). This would imply that niche products are not only used because they address the users' functional needs better than corresponding mainstream alternatives but also because of their symbolic meaning (Gierl and Huettl 2010; Shavitt 1990). Additionally, using niche products can provide consumers with the feeling that they are pioneers (since few other people have used such products), and could signal their possession of inside information (Phang et al. 2013). Thus, the need to differentiate oneself and better express one's identity may be more prominent for niche SNSs.

Differentiation needs are relevant to the study of herding behavior. People sometimes intentionally choose an unpopular option. This is defined as contrarian or anti herding behavior. People perform contrarian behavior when they try to achieve a desired image.

For example, to differentiate themselves from other organizations, some organizations reject a popular innovation because too many other organizations have already adopted it (Abrahamson et al. 1993). Similarly, in the forecasting of financial variables (e.g., commodity prices and exchange rates), studies have found anti-herding behaviors, in which forecasters differentiate themselves through extreme forecasts when they expect a high pay off from such behavior in the forms of reputation and image (Bernhardt et al. 2006; Laster et al. 1999).

In the technology adoption context, contrarian behavior can be viewed as an individual's adoption of a niche technology, instead of a more popular mainstream technology. Understanding the fact that individuals can enjoy more effective self-representation and self-expression through using a niche SNS, despite the fact that such an SNS is not accurately addressing their task needs, can explain why individuals may continue using a technology and refuse to abandon it. In fact, high perceptions of niche can mitigate the influence of potentially low post-TTF levels on abandonment intentions. This is in line with the main argument of cognitive dissonance theory (Festinger 1962), which suggests that the user's experience of dissonance due to the gap between her pre- and post-usage perceptions can act as a motivational factor in adjusting her perceptions, as long as the revealed value (here, post-adoption TTF) does not differ significantly. The abandonment decision will be based on the magnitude of the gap, which due to the fragility characteristics of herding behaviors can be expected to be an influential factor. However, in the case of high perceptions of niche, users might find an element that reduces the unwelcomed dissonance gap, and thus refuse to abandon the technology. Hence, I hypothesize that in a herding setting, a user's judgment of whether the newly adopted SNS qualifies as a "niche" product will influence the relationship between their actual, post-adoptive TTF evaluations and their intentions to abandon the SNS:

***H7**: Perceived niche will moderate the negative relationship between post-adoptive TTF and abandonment intentions, such that the relationship is stronger (more negative) in the presence of higher, rather than lower, niche perceptions.*

METHOD

Research Design and Procedure

A longitudinal online experiment was conducted to test the research model. Ello, a social networking website, was the focal technology. I selected Ello as it is a relatively new social networking tool (launched in 2014) that successfully attracted a large number of individuals in its early days of launch. Further, its voluntary and uncertainty-creating nature (Maier et al. 2015) was expected to help us to observe herding behavior more clearly. Like most SNSs, use of Ello is voluntary and individuals can sign up for an account for free, to use on different platforms such as laptops and smartphones. Voluntary usage of an IT is a primary condition in which I can detect a possible herding effect. In addition, adoption of a SNS may involve substantial uncertainty among its users (Maier et al. 2015; Tarafdar et al. 2007). If the SNS has recently launched, the levels of uncertainty will rise because it may get several updates and interface changes periodically to fix potential bugs. Moreover, Ello requires that potential adopters first create an account before letting them enter the website to view its interface and features.

At the time of data collection, Ello was becoming more popular (The Guardian 2016), and yet there were many alternatives to it (e.g., Path, Slack, Bebo, Facebook); both of these things were required conditions for studying herd behavior. Ello also qualifies as a niche SNS. It has a manifesto that indicates it is ads-free, does not perform any data mining, and does not use any algorithms designed to make decisions about what its users should see. In other words, in sharp contrast to other mainstream SNSs (e.g., Facebook), Ello does not turn its users into products (Ello 2014). Additionally, Ello aims to attract a very specific segment of SNS users (i.e., people who are interested in digital art, fashion, design, music, and web culture). As the creator of Ello, Paul Budnitz, expresses: “We don’t want everyone on Ello. That’s not what we’re building” (Forbes 2014). Ello is the only online community designed and built for creators, by creators. It consists of robust and growing community of artists, designers, musicians, writers, illustrators, photographers, architects, and GIF makers, without the commercialized aspects that discourage them from other social networks. Thanks to a very specific community, Ello has found its niche. Ello also offers some additional features for purchase, such as the ability to have multiple profiles. The posted art-works and ideas are mostly original. As one of the posts on Ello reads: “There is very little re-posting and there is little on Ello that is trivial or superficial.” Similarly, another Ello user mentions: “Ello is remarkably different what one is likely to find elsewhere” (Hopkinson 2016). For all of these reasons, I believe that Ello meets all of the criteria for this study, as a niche technology with potential for the development of herd-like behaviors by its users.

Table 1 summarizes the experimental design. The study included two surveys conducted at the adoptive (Time 1) and post-adoptive (Time 2) stages of the IS life cycle, with an eight-week interval in between. The announced number of abandoners was manipulated at the post-adoption stage. At the beginning of the first survey, a description of

Ello's major features (including its functionality, security, and customization options) was presented to the participants (Appendix B). In this study, it is important that I have respondents without any prior experience with Ello in order to simulate a technology adoption situation. Therefore, by asking a question about their level of Ello experience, I was able to exclude individuals who have used the technology previously. In order to simulate herd-like adoption, the participants received information about both the number and the identity of some of well-known prior adopters of Ello (Sun 2013). After reading these messages, the participants were asked to answer questions regarding their basic demographic characteristics, pre-adoptive TTF, and propensity for imitation (Appendix C). Participants were encouraged to create an Ello account by highlighting the fact that using Ello is free, and that the second survey was based on their actual use of Ello. They were then directed to Ello's website to register.

Insert Table 1 here

The second survey was administered eight weeks after the first survey. At the beginning of the second survey, subjects were asked about their use of Ello within the last eight weeks. They were asked if they had posted any material on Ello and had followed / were being followed by others. Those who had not used Ello at all during the previous eight weeks were excluded from the analysis. After answering questions about Ello's perceived niche, they were randomly assigned to two groups (control or treatment). The treatment group (i.e. high abandoners) received information about the number of prior adopters who abandoned their use of Ello, while the control group (i.e. non-abandoners) did not receive this information. They were then asked to answer questions corresponding to the following constructs: post-adoptive TTF, confirmation, intention to abandon, as well as manipulation check items.

Measures

Most of the items in the survey instrument (Appendix D) are based on previously validated seven-point Likert-type agreement scales, which is an accepted practice in the IS field (Marakas et al. 2007). In this way, research studies can maintain high levels of content validity (McLaren et al. 2011). Also, using previously validated scales is considered a crucial step toward creating an established research tradition (Keen 1980). The study stayed loyal to the wording of the original items and only modified the focal research technology of my study (Ello).

I used three items from Sun and Fang (2010) to measure uncertainty. Milikan's seminal (1978) paper conceptualized uncertainty in three dimensions (i.e., state, effect, and response). Basing on this conceptualization, Sun and Fang developed a three-item scale to measure an individual’s uncertainty in the IS environment, with each item representing one dimension of the reflectively measured uncertainty construct. Four items were adapted to measure the “propensity for imitation” construct (Sun 2013), which was developed for, and previously validated in, an IS herding setting. I used the exact wording of the items while replacing the focal research technology with my own. Items for abandonment intentions were adapted from the behavioral intention items of Venkatesh et al. (2008), which have been validated in a number of IS adoption studies. In a recent study in the SNS abandonment area, Turel (2015) adopted and slightly modified their scale to fit a research context very similar to mine. Hence, my study used Turel's version of the scale, replacing the focal research technology with my own. I also added three bogus items to identify inattentive respondents. Bogus items are items, which have only one correct response for all participants, for example, “All my friends are aliens.” (Meade et al. 2012).

Perceived TTF

Goodhue (1998) originally developed items for measuring perceptions of TTF. His instrument was designed in the context of an organizational setting that involved the use of several technologies. Drawing ideas from the initial definition and operationalization of TTF from Goodhue (1998) and Goodhue and Thomson (1995), Jarupathirun and Zahedi (2007) developed scales for perceived TTF in the context of on-line technology adoption at the individual level of analysis. This scale has been applied and validated in several IS studies (e.g., Lin and Huang 2008). I adopted their scale, replacing only the wording for the focal research technology. Perceived TTF was measured at both the adoption and post-adoption stages using similar items.

Self-Developed Measure: Perceived Niche

Since there was no previously validated instrument available for measuring one's niche perceptions, I developed a new instrument to capture it. The scale was developed following the procedure set forth by Moore and Benbasat (1991). First, items for measuring perceived niche were created based on its definition and extant literature. Based on Porter’s (1980) generic strategic approach and other relevant studies (e.g., Dalgic and Leeuw 1994; Echols and Tsai 2005; Parrish et al. 2006; Tisdell and Seidl 2004) on niche marketing strategies, I can determine that niche products represent distinctiveness and differentiation. These two aspects refer to the main defining criterion for a niche product, that is, *specificity.* Hence, perceived niche is defined as a user's belief about the degree of specificity and uniqueness of the attributes of a product (Shaefer et al. 2013). Seven-point Likert scales were used, with 1 representing "strongly disagree," 4 "neutral," and 7 "strongly agree."

A two-step Q-sort (Moore and Benbasat 1991) was conducted, with four judges (PhD students) in each round. The Q-sort was designed on Qualtrics and asked the four judges in the first round to sort items into groups. They could create as many groups as they want, but were required to name the resulting groups. In the second round, four different judges were given the name and description of the focal category (Perceived Niche) and a second "too ambiguous/does not fit" category. Then, they assigned the cards to those two categories.

To assess construct validity, I examined the item placement ratios, as described by Moore and Benbasat (1991). 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). The method required analysis of how many items were placed by the panel of judges for each round within the "target" construct. If an item is consistently placed into its intended construct, the researcher may reasonably be confident that the item has high construct validity. Scales based on categories, which have a high degree of "correct" placement of items within them, can be considered to have a high degree of construct validity, with a high potential for good reliability scores. It must be emphasized that this procedure is more of a qualitative analysis than a rigorous quantitative procedure. There are no established guidelines for determining "good" levels of placement, but the matrix can be used to highlight any potential problem areas (Moore and Benbasat 1991). To further assess the reliability of the sorting by the judges for each pair of judges in each sorting step, their level of agreement in categorizing items was measured using Cohen's Kappa (Cohen 1960). Kappa scores greater than .65 are considered acceptable.

Q-sort Results

Four judges were involved in each of the first two sorting rounds, which included items developed for the perceived niche construct (see Appendix F). In the first round, two judges created one category, while the other two had two. In this study, the first round yielded an overall item placement ratio of 64% (= 18 [total hits] / 28 [total item placement]). An average Kappa score of 0.73 was also obtained. In this round, two items were dropped from the item pool because items were found to ambiguous (fitting in an unintended category) by two (out of four) judges (Moore and Benbasat 1999). The four new judges in the second round were asked to sort the remaining five items based on construct definition, which was provided. The overall item placement ratio within target construct for the second round was 75% (= 15 [total hits] / 20 [total item placement]) and Kappa averaged 0.87. One item was identified as being too ambiguous by two judges; hence, it was dropped. The improved values of the item placement rate and also the value of Kappa (which is well above the threshold of 0.65) indicated that items were generally being placed as they were intended. Thus, it was concluded that the development process had resulted in scales, which demonstrated construct validity, with a high potential for very good reliability coefficients.

Pilot Test

I recruited 40 participants from Amazon's Mechanical Turk (MT), which is an online crowd-sourcing platform, to conduct a pilot test of the overall instrument. An exploratory (principle components) factor analysis using Varimax rotation in SPSS was conducted on the collected data to assess the reliability of the scale (Moore and Benbasat 1999). Varimax is the most popular factor rotation methods focusing on simplifying the columns in a factor matrix. This method is generally considered superior to other factor rotation methods in achieving a simplified factor structure and gives a clearer separation of the factors compared to other rotation methods such as QUARTIMAX (Hair et al. 2009). Loadings greater than 0.70 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). Nine items with low loadings and high "Cronbach's Alpha if item deleted" statistics were deleted with the content validity in mind. The final version of the instruments includes four items for the perceived niche construct.

Controls

The study controlled for the effect of several other constructs. Specifically, previous studies have shown that subjective norm, facilitating conditions, and network effects can all have an impact on individuals' IS behaviors (Goldenberg et al. 2009; Li 2004; Venkatesh et al. 2003). Specifically in the herding context, both Duan et al. (2009) and Sun (2013) controlled for the effects of these constructs. Although they found only nonsignificant or weak relationships between each of these constructs and behavioral intentions, I nevertheless statistically controlled for any possible effects.

Subjective norms, which represent how an individual believes those important to her will view her as a result of performing the referent behavior (Thampson et al. 1991; Venkatesh et al. 2003), can potentially influence a person's technology adoption decisions. In the area of technology abandonment, Echkhardt et al. (2009) and Maier et al. (2015) controlled for the influence of subjective norms on users' abandonment intentions, although the latter study reported a non-significant link. Subjective norms are commonly decomposed into the two aspects of injunctive and descriptive norms. Injunctive norms refer to normative influences in which a behavior is approved by others whereas descriptive norm refers to normative influences in which a behavior is typically performed by others (Cialdini et al. 1990). Put differently, injunctive norms reflect perceptions of others' approval or disapproval of certain behaviors, while descriptive norms refer to one's perceptions of the actual behavior of most others. In any given situation, injunctive and descriptive norms can align, but they can also be in conflict and interact to guide behavior (Smith and Louis 2008). To statistically control for the influence of both types of norms, four items for injunctive norms and four items for descriptive norms were derived from Rhodes and Courneya (2003) and Hagger and Chatzisarantis (2005); these items have been used in several previous IS studies (e.g., Ortbach et al. 2013; Ramayah et al. 2009). The wordings of the original scale items were modified to focus on the focal technology in this study (Ello).

The construct of *facilitating conditions*, which reflects the availability of resources required to engage in a behavior (Triandis 1979), is another important predictor of individual IS behaviors (Venkatesh et al. 2003), and is proposed as a control variable that partially addresses the role of external factors (for example, the availability of resources such as manuals and instructions for using a technology) (Venkatesh et al. 2008). The study used a three-item scale developed by Thompson et al. (1991) specifically for the IS setting. These items have been used and further validated in a number of more recent IS studies (e.g., Nagai et al. 2007; Teo 2009).

Network effects refer to the phenomenon that "the value of a technology increases as the number of its users increases" (Li 2004, p. 94). Although prior research indicates that this concept differs from herding in several ways (e.g., the way information is inferred from others, the motivations, and the long-term impacts), network effects have been found to have a statistically significant influence on individual's IS behaviors in a herding setting (Sun 2013). Therefore, in this study I also controlled for its effect on the propensity for imitation, using items developed and validated specifically in a herd-like IT adoption context by Sun (2013).

Survey Administration

I used Amazon's Mechanical Turk (MT) to collect the data for testing the research model. MT is an online crowd-sourcing platform in which members complete tasks and receive money for it. MT is organized around micro-tasks called human intelligence tasks (HITs). The use of MT has several benefits over using student subjects in research. Its population is more diverse and reliable, thus increasing the external validity of the behavioral research study (Berinsky et al. 2012; Mason and Suri 2012).

MT is organized around micro-tasks called human intelligence units (HITs). Amazon provides a way for tasks to be completed on an external online survey tool. In my case, I designed an external website HIT which is hosted by Qualtrics. Then I created a HIT that includes the URL of the survey questionnaire. Once the HIT was posted to the service, it became available for respondents to complete. Restrictions were set to limit HIT completions to participants from the USA to reduce the possible confounding effect of cultures (Holden et al., 2013). Individuals that qualified for the HIT viewed a short task description along with the pay rate, and chose whether or not to accept the task.

The participants were provided with the URL of the first survey questionnaire. Eight weeks later, the respondents to the first survey were invited to participate in the second survey. Three items were first used to make sure that the participant was actually using Ello. Those who did not use Ello during the previous eight weeks were excluded from further participation. The respondents who passed this initial screening process were then provided with a URL to complete the second survey, after being randomly assigned to one of the two treatment groups.

I recruited 350 participants for this experiment. Out of these individuals, thirty-eight declined to participate in the second survey and were thus eliminated from further statistical analysis. Out of the individuals who answered both surveys, thirteen failed to answer the bogus questions correctly, seven marked almost the same answers throughout the entire survey, five did not finish the survey, and twenty-eight did not use Ello since taking the first survey. In total, 259 surveys were judged appropriate for hypothesis testing. The demographic profile of the respondents is shown in Table 2.

Insert Table2 here

ANALYSIS AND RESULTS

The results are presented into several parts. First, I discuss the result of the manipulation checks, and then I discuss my tests of the measurement model to confirm the convergent and discriminant validity, as well as the reliability, of the constructs. Finally, I discuss my tests of the structural model and its hypothesized relationships among the constructs. I tested both the measurement model and structural model using AMOS 24 statistical software, with maximum likelihood estimation. The reliability and validity of the scales were examined via confirmatory factor analysis (CFA), while the strength and direction of the hypothesized causal paths among the constructs were analyzed via structural equation modeling (SEM). Tests for skewness and kurtosis indicated acceptable univariate normality, and no significant outliers were detected (Hair et al. 2009).

Control and Manipulation Checks

ANOVA analyses revealed that the two groups (control and treatment groups) did not differ significantly in age (F[1, 257] = 1.907, p = 0.1680), gender (X^2 = 0.906), or education level (F[1, 257]= 0.048, p = 0.827). These results indicated that the random assignment of the subjects was effective. The survey included two items as a manipulation check. The first item asked the subject to state to what degree (s)he was aware that "a lot of people have abandoned Ello." This item thus focuses on knowledge of the *number* of prior adopters. The second item measured the degree to which a subject was aware that "Ello has been abandoned by a lot of well-known prior users." Thus, it measured a subject's awareness of the *identity* of prior adopters. These items were meant to assess the effectiveness of the treatment that distinguished between the control and the treatment group. The ANOVA results indicate that both items significantly differed across the two groups ($p < 0.000$ for both items 1 and 2).

Measurement Model

Internal Consistency

Before analyzing the structural model, I performed a CFA to test the psychometric properties of the scale. As shown in Table E1 in Appendix E, all items had loadings on their respective constructs of greater than the suggested threshold of 0.707 (Chin 1998). Estimates of CR greater than .70 and AVE greater than .50 support internal consistency (Bagozzi and Yi 1988), and as I show in Appendix E Table E2, the CRs for my study range from .79 to .93, while the AVEs range from .61 to .86, indicating acceptable convergent validity.

Two criteria were examined to assess discriminant validity. First, discriminant validity was established based on the values for the square root of AVE for each construct exceeding its correlations with other constructs in the model (Chin 1998; Fornell et al. 1981). This condition was satisfied, as shown in Appendix E, Table E2. Second, items should load more highly on their associated factors than on other factors without cross loading (Hair et al. 2009). Appendix E, Table E2 indicates that this criterion was met. To evaluate the overall fit of the CFA model, I examined several commonly used fit indexes (Hu and Bentler 1999). All model fit indexes were within accepted thresholds (Table 3).

Insert Table 3 here

Testing for Method Bias

I employed both procedural and statistical remedies for common method bias following Podsakoff et al. (2003), and did not find any significant threats of such biases in this study. In terms of procedural remedies, the data was collected at two different points in time. The longitudinal nature of the study thus helps to overcome concerns regarding common method bias (CMB) to some degree. Sharma et al. (2009) note that a longitudinal design is less susceptible to CMB, compared to cross-sectional designs. In addition, the participants were ensured that their responses would be anonymous. Also, they were informed that there were no right or wrong answers, and requested that they answer questions as honestly as possible. This way, I was able to protect respondent anonymity and reducing evaluation apprehension. Second, I counterbalanced the items by randomizing them within each survey block (i.e., items that measure each construct). I also randomized the survey blocks (Straub et al. 2004). For example, items measuring confirmation were randomized, and the constructs (i.e., blocks) were randomly ordered for each participant.

In terms of statistical remedies, I first conducted a Harman's single-factor test in SPSS, to see whether a single factor explains a majority of the variance in the data set (Podsakoff et al. 2003). This test assesses the threat of common method bias by indicating whether a single latent factor offers a viable alternative explanation of the analysis. According to Podsakoff et al. (2003), CMB may exist if a single factor emerges from the unrotated factor solution or if one general factor accounts for the majority of the variance in the variables. The emergent factor explained 22.1 percent of the variance in the data set, indicating no serious problems with method bias. However, Harman's test is not an accurate enough test to identify the strength of CMB. Therefore, I also added an unmeasured latent method factor to the CFA and allowed all self-reported items to load on both their respective theoretical constructs and the method factor (Bagozzi 2011). The analysis indicates that the common variance is less than 11 percent; further, the item loadings on the common method factor were not statistically significant and were much lower than the loadings on their respective constructs. Comparing the model fit of these two different models (the model with and the model without common method factor also revealed that the inclusion of common method facto did not changed the value of the model fit (CMIN/DF values were 1.29 and 1.28, respectively).

Finally, a CFA model, which had a common latent factor, was used to impute the factor scores for creation of the interaction terms in the model. I added a common latent factor to the full structural model and associated it to the indicators of the constructs. This enabled us to partial out any possible effect of common method bias on the structural model. The results indicate that after including a common latent factor in the full structural model, the estimates for the hypothesized effects remained virtually the same, which also suggests that common method bias did not affect the results. In sum, the results of the above analyses provide confidence that common method bias is not a concern in this study.

Structural Model

In Table 5, I present the structural model results; the overall fit statistics confirm that the hypothesized model provides a good representation of the structures that underlie the observed data (CMIN/DF = 1.63, CFI = .93, SRMR = .07, RMSEA = .04, Pclose = .54).

Insert Figure 4 here

In H1, I predicted that propensity for imitation would have a positive relationship with pre-adoptive TTF. Consistent with this hypothesis, the coefficient for propensity for imitation is positive and significant in predicting pre-adoptive TTF (H1: $\beta = 0.69$, $p < 0$ .001). The study found a positive and significant association between the pre-adoptive and post-adoptive TTF constructs (H2: $\beta = 0.64$, $p < 0$ .001), providing support for H2. H3 stated that propensity for imitation would negatively influence confirmation. As the results in Figure 4 indicate, propensity for imitation has a negative and significant relationship with confirmation (H3: $\beta = -0.26$, $p < 0$ .001). For the relationship between confirmation and post-adoptive TTF, the study found that uncertainty is a significant predictor of the sampled individuals' post-adoptive TTF (H4: $\beta = 0.24$, $p < 0.01$). H5 posited a negative relationship between post-adoptive TTF and abandonment intentions. As the results show, the coefficient for post-adoptive TTF is negative and significant (H5: $\beta = -0.59$, $p < 0$ .001). In H6 and H7 I predicted moderating influences of perceived niche and critical mass on the relationship between post-adoptive TTF and abandonment intentions. Both of these moderating effects were found significant and consistent with my hypotheses. The results did not find any significant direct effect of perceived niche and critical mass on the dependent variable. Table 4 indicates the R-squared values of each endogenous construct. Small R-squared values (i.e., the R^2 value of confirmation) are not uncommon in behavioral science research and do not present a threat to the model's overall validity (Cyr et al. 2009). In addition, confirmation is modeled here as influenced by only a single construct (i.e., IMI), and such an association tends to result in low R^2 values compared to multi-relationship models (Cyr et al. 2009).

Insert Table 4 here

Critical mass has a significantly positive moderating effect (H6: β = 0.37, p < 0 .001) on the association between post-adoptive TTF and abandonment intentions. Figure 5a the nature of this interaction. Following the methods of Aiken and West (1991), I calculated the simple slopes of the moderation effects one standard deviation below and above the mean to investigate the significant interactions. Simple slope tests indicated that the simple slope was significant for individuals with a low critical mass observation (b = -.51, p < .001), while the slope for individuals with high critical mass observation was not (b = -0.04, p = 0.48), confirming the study's hypothesis that observing critical mass of abandoners dampens the negative relationship between post-adoptive TTF and abandonment intentions. Perceived niche has a significant negative moderating effect (H7: β = -0.14, p < 0 .05) on the relationship between post-adoptive TTF and abandonment intentions (Figure 5b). Simple slope tests reveal that the simple slopes for persons with low (b = -.23, p <0.001) and for persons with high (b = - 0.52, p < 0.001) levels of perceived niche were both significant. Simple slope tests, confirming my hypothesis, indicate that as perceived niche values increase, the relationship between post-adoptive TTF and abandonment intentions becomes more negative (with the highest perceived niche value [5.55], b= -0.66, p < 0.001).

Insert Figure 5 here

Mediation Analyses

I used the bootstrapping technique in AMOS 24 (see Preacher and Hayes 2004) to further examine the mediating effects in the research model (see Table 5). 2,000 bootstrapping samples were generated from the original data set (N = 259) by random sampling in order to estimate the indirect effect of the predictor variable on the outcome variable via a proposed mediator. This method possesses several advantages relative to the Baron and Kenny (1986) approach: (1) it tests all paths of a model simultaneously, (2) it does not assume a normal distribution of the indirect effect, and (3) and it decreases the likelihood of Type I error (Preacher and Hayes 2004). The results of the mediation analysis show propensity for imitation had a significant indirect effect on post adoptive-TTF but the study could not detect any significant direct impact of it on post-adoptive TTF. At the same time, the direct effects of confirmation and pre-adoptive TTF on post-adoptive TTF were significant. In summary, these results indicate that the effect of propensity for imitation on post-adoptive TTF is fully mediated by confirmation and pre-adoptive TTF.

I also analyzed the mediation of post-adoptive TTF. Results indicate that confirmation has a significant *indirect* effect on abandonment intentions, but the study could not detect any significant *direct* impact of it on abandonment intentions. At the same time, the direct effect of confirmation on post-adoptive TTF and also the direct effect of post-adoptive TTF on ABD were significant. In summary, these results indicate that the effect of confirmation on abandonment intentions is fully mediated by post-adoptive TTF. As can be seen in Table 5, the mediation analysis found that the effect of pre-adoptive TTF on abandonment intentions is fully mediated by post-adoptive TTF.

Insert Table 5 here

DISCUSSION

As emphasized by Maier et al. (2015), the life cycle of an information system is comprised of the three main phases of *adoption*, *usage*, and *termination* (Furneaux and Wade 2011). Potential adopters develop tendencies to adopt and use a new technology in the adoption phase (Davis 1989). Decisions are being made by the user in regard to continuing to use an IS in the usage phase (Bhattacherjee 2001). Abandonment intentions emerge during the concluding phase of the life cycle, i.e., the termination phase (Turel 2015). Compared to phenomena related to the adoption and usage phases, the termination decision and its corresponding abandonment intentions have been largely overlooked in extant IS research (Maier et al. 2015). However, the main source of benefit for organizations comes from the IS behavior of individuals at the later phases of IS life cycle, here, abandonment of IS (Hsieh et al. 2011).

My inquiry provides the basis for the development of a theoretical model of IS abandonment in a herding context. My model hypotheses were tested via a longitudinal research design, which surveyed adopters at two different points of time. The study examined the determinants of adopters' abandonment intentions, which occur specially after an initial *en mass* adoption (i.e., a herding setting). Results suggest that post-adoptive TTF levels, perceptions of niche, and observation of a critical mass of abandoners are all salient factors impacting IS abandonment intentions. These results can thus be regarded as an important step in the development of literature related to IS abandonment.

Major Findings

The findings indicate that herd behavior has an important role in the IS abandonment context. More specifically, individuals' propensities for imitation directly impact their confirmation and pre-adoptive TTF perceptions. By measuring TTF at the post-adoption stage, I also found that both confirmation and pre-adoptive TTF perceptions have a significant effect on post-TTF creation. The findings reveal the powerful significant negative impact of post-TTF on abandonment intentions, and also highlight the interactive effects of perceived niche and observation of critical mass on this association. In confirming all of the hypothesized relationships, the research model explained substantial variance in both post-TTF (R^2= 0.41) and abandonment intentions (R^2= 0.52)

In addition to evaluating the R^2 of the dependent variables, the change in the R^2 value when a specific independent variable is omitted from the model can be evaluated to determine whether the omitted construct has a substantive impact on the dependent variable (Hair et al., 2009). Table 6 shows the calculated effect sizes of various model constructs using Cohen's f^2 formula. The interaction between critical mass and post-TTF has a large effect on the dependent variable, abandonment intentions (0.49). Perceived niche has a small effect on abandonment intentions (0.07). Similarly, pre-TTF has a large effect on post-TTF (0.64), while confirmation has a medium effect (0.24).

Insert Table 6 here

Theoretical Contributions

The findings have significant implications for research on IS herding and its impacts on individuals' IS behaviors at the later phase of the IS lifecycle, i.e., the termination phase. This study builds its argument on the findings of recent studies (e.g., Turel 2015; Maier et al. 2015) that have argued that abandonment intentions should be studied as a standalone phenomenon that merits its own line of theorizing and research. However, most IS post-adoption studies has been incorrectly assumed that continuance and abandonment share the same predictors (Turel 2015). My study thus enriches the understanding of the recent argument that continuance and abandonment are two distinct theoretical issues, leading to the conclusion that considering abandonment as the "flip side" of continuance may be a somewhat naïve stance (Pollard 2003; Turel 2015). The study also addresses the calls by recent inquiries (e.g., Shen et al. 2018; Maier et al. 2015) pointing to the need for studies that provide a better understanding of the largely neglected concept of technology abandonment to enhance the success rate of newly introduced information systems. Consequently, the paper argues that although IS researchers should keep on focusing on continued use as a key phenomenon, but also pay attention to the theory development of abandonment intentions, especially in contexts in which users may be motivated to do so, and have the ability to quit the use of an IS.

Contribution to the Herd Literature

This study extends extant theory and research on herding (Banerjee 1992; Bikhchandani et al. 1992) by identifying the role of herding in the creation of mass abandonment intentions. Specifically, I have highlighted the importance of considering the impact of herding behavior on the development of IS abandonment intentions in the later post-adoptive (i.e. termination) phase. Few prior studies have analyzed users' post-adoptive IS behaviors through such a herding lens. Prior studies of IS herding have also primarily focused on the cognitive process of herding, while I extend this approach by including a task-focused perspective (i.e., TTF). Also, via integrating pre and post TTF constructs in my herd model, I adopted a utilitarian lens in investigating herding decisions. Hence, my study enriched the understanding of herd-like post-adoption behaviors from a task-oriented perspective. In doing so, I employed the expectation confirmation model (Bhattacherjee and Premkumar 2004) and belief update theory (Kim et al. 2005) to explain the changes in adopter's TTF levels through the IS adoption stages.

Specifically, the study provides a clearer picture of the *fragility* of the herd decisions (Banerjee 1992; Bikhchandani et al. 1992; Li et al. 2014; Liu et al. 2015; Zhan et al. 2017). Prior studies on post-adoptive IS behaviors have not explicitly investigated the *fragility* of the individual's decision and its influence on their abandonment intentions. The fragility of herding behavior has, however, been recognized in the area of finance to describe how investors (e.g., in the stock market) reverse their decisions (Rao et al., 2001). While Walden et al. (2009) conducted a simulation study that found evidence for the fragility of herding decisions in the IS area, neither this study nor other extant studies have empirically investigated this characteristic of herding in the formation of abandonment decisions. The finding extends this notion of fragility by identifying the significant role of TTF as a determinant of reversal decision-making (i.e., abandonment). Thus, I can argue that although adopters may overestimate the level of fit between the technology's capabilities and their needs in a herding context (i.e., there is a positive significant relationship between propensity for imitation and Pre-TTF), as new information becomes available they will adjust their perceived TTF rates (i.e., Post-TTF) and may then form abandonment intentions.

Contribution to the TTF Literature

The significant negative impact of post-TTF on IS abandonment intentions indicates that adopters tend to focus primarily on what systems lack rather than what they provide when contemplating this form of abandonment. The tendency to emphasize a system's shortcomings is in general accord with expectation disconfirmation theory (EDT; Oliver 1980). EDT suggests that the likelihood that a user will discontinue the use of a system depends on the magnitude of the discrepancy between what the system delivers in practice and what it is expected to deliver. Abandonment intentions would thus be predicted to fall when the perceptions of a system's fit exceed the adopter's expectations, and to rise when its capabilities fall below these expectations. The formation of post adoptive TTF after a period of usage can create significant discrepancies between the capabilities that the system offers and those capabilities that are expected, thereby contributing to increased abandonment intentions. Prior studies have identified technology abandonment as an adaptation strategy that mitigates the undesirable effect of negative perceptions (Beaurdy and Pinsonneault 2005). Hence, users who perceive lower fit between their needs and the offerings of the adopted technology may engage in an adaptation strategy and ultimately stop using the technology. Thus, an important message of this study is that, while a herding setting may help form adopter's initial TTF perceptions and resulting IS adoption, it is the low post-TTF levels that serve as the key driver of abandonment.

Contribution to the IS Continuance Literature

The study has implications for organizational IS continuance research as well. The finding that TTF levels directly impact the formation of abandonment intentions extends research that focuses on identifying change drivers in organizations. Similar to my findings, this literature argues that shortcomings in system performance lead to abandonment decisions (Furneaux and Wade 2011). By incorporating TTF (which taps explicitly on *fit* between the user's task and the technology's features) I added a potentially new pressure source for change.

By finding a moderating effect related to observing a smaller (compared to a larger) mass of adopters in an IS termination phase, my study adds to the stream of research that argues that continuance and abandonment are two distinct phenomena (Pollard 2003;Turel 2015; Maier et al. 2015). The study's results indicate that the observation of a smaller mass of abandoners (as compared to a larger mass of adopters in the adoption phase) is a powerful factor in IS abandonment. As Figure 5 shows, observation of critical mass significantly dampens the negative effect of high post-TTF in a fragil

e herd-like decision-making context. Hence, I have presented and examined the role of negative information (i.e., observing others' abandonment) that can lead to creation of a *herd* of abandoners. This finding is in line with the main argument of prospect theory, which proposes that the value function is "concave for gains, convex for losses, and steeper for losses than for gains (Kahneman et al. 1979, p. 263). Put differently, negative (as opposed to positive) events and information have a stronger impact on one's abandonment decision and the threshold for the critical mass of abandoners is lower compared to the threshold of the critical mass of adopters in the adoption stage for a person when herding.

Perceived Niche

The study also extends current research on conspicuous consumption (Veblen 1899) and introduces the concept of *niche* to IS adoption research (Chaudhuri and Majumdar 2006; Chen et al. 2008; Gierl and Huettl 2010; Shaefer et al. 2013). More specifically, I contribute to theory by identifying and investigating the role of perceptions of niche in an SNS adoption setting. The current study has developed and validated a scale to measure the perceived niche construct. To the best of my knowledge, niche technology adoptions of individuals have not been studied in prior IS research. Due to the advent and popularity of recent niche SNSs (e.g., Ello, Dribbble, Diaspora), it would be interesting to examine the dynamics of individuals' adoption of those technologies. Hence, the study can be considered as one of the first to look at niche technology adoption behavior. In so doing, I have extended the herd literature by identifying *anti*-herding behavior in a niche technology adoption context. Although anti-herding has been identified in other disciplines (e.g., finance and economics) it has not been recognized in the IS literature (Babalos and Stavroyiannis 2015; Bohl et al. 2017).

The finding that higher perceptions of niche counterbalance the influence of potentially low post-TTF levels on abandonment intentions is in line with the main argument of the Coping Model of User Adaptation (CMUA; Beaudry and Pinsonneault, 2005). Hence, it is interesting to consider potential similarities and relationships between the findings and the CMUA (Beaudry and Pinsonneault, 2005). In other words, the implications of the study that higher perceptions of niche diminish the impact of low post-TTF on development of abandonment intentions can be discussed in relation to CMUA. According to the CMUA, when users perceive an unwelcomed situation stemming from an IT event, they engage in adaptation strategies, which in turn can result in attempts to minimize the negative consequences of the IT event and to restore personal emotional stability. Hence, adjustment of the levels of niche perceptions (as cognitive dissonance theory argues) is an adaptation strategy for people who make adoption decisions in a herding setting where decisions can be fragile.

Practical Implications

Aside from the theoretical implications, several potential practical implications also emerge from this study. First, system designers, including SNS designers, are often interested in discouraging abandonment. User abandonment is a strategic issue for SNS providers, who have a vested interest in reducing such intentions on the part of their users (Xu et al., 2014). This can be achieved, as per Figure 2, via acknowledging and employing drivers and inhibitors of abandonment intentions. One way of preventing the formation of abandonment involves increasing one's perceptions of post-adoptive TTF. Extant studies have rarely looked at the determinants of TTF perceptions. The findings suggest that effective initiation of herd-like decision-making practices can lead to higher pre-adoption TTF beliefs, which in turn improves adopters later TTF levels and consequently reduces her abandonment tendencies. TTF perceptions can be augmented by emphasizing ease of use and enjoyment characteristics of a system (Negahban and Chung, 2014). Also, Hansen et al. (2018) found that higher levels of trust can lead to higher ease of use perception among SNS users. Hence, practitioners and application designers should implement activities to increase perceived trust. For instance, as pointed out by Hansen et al. (2018) awareness initiatives and programs by SNS vendors could lead to establishment of more trustful and secure environment for the SNS users. Since, such programs reduce the potential risks of loss of information and cyber victimization. All these could lead to improvement of users' perceptions of the degree to which the system addresses their needs.

Second, the findings indicate that reducing the significance of others' similar behaviors might discourage the formation of abandonment intentions. For instance, managers can communicate the number of new adopters to mitigate the negative effect of observation of quitters. More specifically, my results suggest that managers can alleviate the negative effect of observation of abandoners by improving the niche perceptions among the users. In words, to increase the influence of post-TTF and develop continuance behaviors, system designers should implement measures to differentiate their systems as much as possible from similar ones in order to create higher niche perceptions among their users. Thus, companies need to effectively show and convey their uniqueness to its consumers. It might be also reasonable to refer to the abandonment behavior of others as a sign of distinctiveness of the system. It means that practitioners can convey this message to their users that their system is not for everyone since it is not a mainstream product. Moreover, organizations in some cases may want to facilitate the abandonment of a legacy technology to accelerate the implementation and usage of a new one. By forming a relatively small mass of abandoners and drawing other users' attention to it, organizations might be able to stimulate abandonment of the legacy system.

Limitations and Directions for Future Research

The study has several limitations. As has pointed out by Maier et al. (2015), research on voluntary vs. mandatory IS use may lead to different findings (Venkatesh et al., 2003). My focus was on voluntary system usage; future studies could replicate this study in mandatory usage settings. For example, it might be interesting to investigate organizational networking systems (e.g., Yammer an organizational SNS developed by Microsoft). Second, the generalizability of this study is limited. It focused on a mostly young-adult segment of users of an SNS, which is utilized mostly for personal purposes. It is possible that the abandonment of other applications, for example, other IS such as videogames, or work applications, such as ERP systems is driven by other factors than the ones examined in this study. More research involving other user segments and applications should be conducted for examining the boundaries of the research model and its generalizability.

A logical continuation of this work could consider the formation of the actual abandonment behavior and consequences of abandonment intentions over time, from the point of the formation of intentions to abandonment (this paper's focus) to actual abandonment decisions as well as post-abandonment behaviors. For example, an interesting avenue to explore is the question of how an individual looks back and reflects upon a past IS after a period of abandonment and change to a new system. Future research could examine what triggers the initiation and growth of actual abandonment behaviors, and under what circumstances they become dominant and lead to actual abandonment attempts.

To further distinguish between the two concepts of continuance and abandonment, future research should explicitly conceptualize and empirically investigate the differences between continuance and abandonment behaviors. For instance, future studies can examine and measure both constructs in a single model to identify their distinct determinants in a more accurate way. IS abandonment is an important, yet mostly overlooked phenomenon. IS abandonment represents the missing piece of the full life cycle of IS – from inception to termination (Furneaux and Wade, 2011; Maier et al. 2015), and deserves research attention at least in certain contexts in which users have the ability and motivation to quit using an IS.

Conclusion

This paper adds to the existing body of research on IS continuance intentions by focusing on IS abandonment intentions in the context of IS herding. It advances our understanding of abandonment intentions that may form after an initial en mass IS adoption. Hence, it explicitly investigates the fragility of the individual's decision and its influence on their abandonment intentions. This study identifies the significant effect of perceived *fit* between the technology and user needs on development of abandonment intentions. Also, it demonstrates how this effect is moderated by the user's perceived niche levels and also her observation of the abandonment behaviors of others. These relationships were evaluated in a longitudinal experimental research approach that introduced individuals to a new SNS (i.e., Ello). Ultimately, this study serves as a platform for further research on IS abandonment that represents an increasingly important yet missing piece in the technology use life cycle.

REFERENCES

Abrahamson, E. (1991). Managerial fads and fashions: the diffusion and rejection of innovations. *Academy of Management Review, 16*(3), 586-612.

Abrahamson, E., & Fairchild, G. (1999). Management fashion: Lifecycles, triggers, and collective learning processes. *Administrative Science Quarterly, 44*(4), 708-740.

Ajzen, I. (1985). *From intentions to actions: A theory of planned behavior*: Springer.

Ajzen, I., & Fishbein, M. (1977). Attitude-behavior relations: A theoretical analysis and review of empirical research. *Psychological bulletin, 84*(5), 888-918.

Aiken, L. S., & West, S. G. (1991). Multiple regression: Testing and interpreting interactions. London, England: Sage.

Bagozzi, R. P. (2007). The Legacy of the Technology Acceptance Model and a Proposal for a Paradigm Shift. *Journal of the Association for Information Systems, 8*(4), 244-254.

Babalos, V. & Stavroyiannis, S. (2015). Herding, anti-herding behaviour in metal commodities futures: a novel portfolio-based approach. *Applied Economics*, *47*(46), 4952-4966.

Bagozzi, R.P.(2011). Measurement and meaning in information systems and organizational research: Methodological and philosophical foundations. *Mis Quarterly*, *35*(2), 261-292.

Banerjee, A. V. (1992). A simple model of herd behavior. *The Quarterly Journal of Economics*, *107*(3), 797-817.

Barasch, A., & Berger, J. (2014). Broadcasting and narrowcasting: How audience size affects what people share. *Journal of Marketing Research, 51*(3), 286-299.

Barley, S. R., & Kunda, G. (1992). Design and devotion: Surges of rational and normative ideologies of control in managerial discourse. *Administrative Science Quarterly*, 363-399.

Baron, R.M. & Kenny, D.A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of personality and social psychology*, *51*(6), 1173-1182.

Battaglini, M. (2005). Sequential voting with abstention. *Games and Economic Behavior, 51*(2), 445-463.

Beaudry, A. & Pinsonneault, A. (2005). Understanding user responses to information technology: A coping model of user adaptation. *MIS Quarterly*, *29*(3), 493-524.

Beaudry, A. and Pinsonneault, A., 2010. The other side of acceptance: studying the direct and indirect effects of emotions on information technology use. *MIS Quarterly*, *34*(4), 689-710.

Benbasat, I., & Barki, H. (2007). Quo vadis TAM? *Journal of the Association for Information Systems, 8*(4), 211-218.

Banerjee, A. V. (1992). A simple model of herd behavior. *The Quarterly Journal of Economics*, *107*(3), 797-817.

Berger, C. R., & Calabrese, R. J. (1975). Some explorations in initial interaction and beyond: Toward a developmental theory of interpersonal communication. *Human Communication Research, 1*(2), 99-112.

Berger, J., & Heath, C. (2008). Who drives divergence? Identity signaling, outgroup dissimilarity, and the abandonment of cultural tastes. *Journal of Personality and Social Psychology, 95*(3), 593-607.

Berinsky, A. J., Huber, G. A., & Lenz, G. S. (2012). Evaluating online labor markets for experimental research: Amazon. com's Mechanical Turk. *Political Analysis, 20*(3), 351-368.

Bernhardt, D., Campello, M. & Kutsoati, E. (2006). Who herds?. *Journal of Financial Economics*, *80*(3), 657-675.

Bhattacherjee, A. (2001). Understanding information systems continuance: an expectation-confirmation model. *Mis Quarterly*, *25*(3), 351-370.

Bhattacherjee, A., & Premkumar, G. (2004). Understanding changes in belief and attitude toward information technology usage: a theoretical model and longitudinal test. *Mis Quarterly*, *28*(2), 229-254.

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of political Economy*, *100*(5), 992-1026.

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1998). Learning from the behavior of others: Conformity, fads, and informational cascades. *The Journal of Economic Perspectives*, *12*(3), 151-170.

Bikhchandani, S., & Sharma, S. (2000). Herd behavior in financial markets. *IMF Staff Papers*, *47*(3), 279-310.

Bagozzi, R.P. & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science*, *16*(1), 74-94.

Bohl, M.T., Branger, N. & Trede, M. (2017). The case for herding is stronger than you think. *Journal of Banking & Finance*, *85*(1), 30-40.

Brewer, G.A. (2003). Building social capital: Civic attitudes and behavior of public servants. *Journal of Public Administration Research and Theory*, *13*(1), 5-26.

Brown, S. A., Venkatesh, V., & Goyal, S. (2012). Expectation confirmation in technology use. *Information Systems Research, 23*(2), 474-487.

Cacioppo, J.T. & Berntson, G.G. (1994). Relationship between attitudes and evaluative space: A critical review, with emphasis on the separability of positive and negative substrates. *Psychological Bulletin*, *115*(3), 401-423.

Cacioppo, J.T., Gardner, W.L. & Berntson, G.G. (1999). The affect system has parallel and integrative processing components: Form follows function. *Journal of Personality and Social Psychology*, *76*(5), 839-855,

Chaudhuri, H.R. & Majumdar, S. (2006). Of diamonds and desires: understanding conspicuous consumption from a contemporary marketing perspective. *Academy of Marketing Science Review*, *2006*(11), 1-18.

Cheung, C. M., & Lee, M. K. (2006). Understanding consumer trust in Internet shopping: A multidisciplinary approach. *Journal of the American Society for Information Science and Technology, 57*(4), 479-492.

Chin, W.W. (1998). The partial least squares approach to structural equation modeling. In: Marcoulides, G.A. (Ed.), Modern Methods for Business Research. Lawrence Erlbaum Associates, Mahwah, NJ, 295–336.

Chiu, C.-M., Hsu, M.-H., Lai, H., & Chang, C.-M. (2012). Re-examining the influence of trust on online repeat purchase intention: The moderating role of habit and its antecedents. *Decision Support Systems, 53*(4), 835-845.

Cialdini, R. B. (2003). Influence: Science and practice (3rd ed.). New York, NY: Harper Collins

Cingl, L. (2013). Does Herd Behaviour Arise Easier Under Time Pressure? Experimental Approach. *Prague Economic Papers, 2013*(4), 558-582.

Cohen, J. (1960) A coefficient of agreement for nominal scales. *Educational and Psychological Measurement*, *20*(1), 37–46.

Compeau, D., Higgins, C.A. & Huff, S. (1999). Social cognitive theory and individual reactions to computing technology: A longitudinal study. *MIS Quarterly*, *23*(2),145-158.

Cronbach, L.J. & Furby, L. (1970). How we should measure" change": Or should we?. *Psychological Bulletin*, *74*(1), 68-80.

Dalgic, T. & Leeuw, M. (1994). Niche marketing revisited: Concept, applications and some European cases. *European Journal of Marketing*, *28*(4), pp.39-55.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *Mis Quarterly*, *13*(3), 319-340.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: a comparison of two theoretical models. *Management Science, 35*(8), 982-1003.

Devenow, A. & Welch, I. (1996). Rational herding in financial economics.*European Economic Review*, *40*(3), 603-615.

De Wulf, K., Schillewaert, N., Muylle, S., & Rangarajan, D. (2006). The role of pleasure in web site success. *Information & Management, 43*(4), 434-446.

DiMaggio, P. J., & Powell, W. W. (1983). The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields. *American Sociological Review*, 147-160.

Duan, W., Gu, B., & Whinston, A. B. (2009). Informational cascades and software adoption on the internet: an empirical investigation. *Management Information Systems Quarterly, 33*(1), 23-48.

Ello Manifesto (2014, July 3). Retrieved from https://ello.co/wtf/about/ello-manifesto/

Eckhardt, A., Laumer, S. and Weitzel, T., 2009. Who influences whom? Analyzing workplace referents' social influence on IT adoption and non-adoption. *Journal of Information Technology*, *24*(1), pp.11-24.

Echols, A. & Tsai, W. (2005). Niche and performance: The moderating role of network embeddedness. *Strategic Management Journal*, *26*(3), 219-238.

Festinger, L. (1962). *A theory of cognitive dissonance* (Vol. 2): Stanford university press.

Fiol, C. M., & O'Connor, E. J. (2003). Waking up! Mindfulness in the face of bandwagons. *Academy of Management Review, 28*(1), 54-70.

Fowler, J. H., & Christakis, N. A. (2008). Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the Framingham Heart Study. *Bmj, 337*, a2338.

Frot, E., & Santiso, J. (2011). Herding in aid allocation. *Kyklos, 64*(1), 54-74.

Furneaux, B. and Wade, M.R., 2011. An exploration of organizational level information systems discontinuance intentions. *MIS Quarterly*, *35*(3), 573-598.

Gefen, D. (2000). E-commerce: the role of familiarity and trust. *Omega, 28*(6), 725-737.

Gierl, H. & Huettl, V. (2010). Are scarce products always more attractive? The interaction of different types of scarcity signals with products' suitability for conspicuous consumption. *International Journal of Research in Marketing*, *27*(3), 225-235.

Goldenberg, J., Han, S., Lehmann, D.R. & Hong, J.W. (2009). The role of hubs in the adoption process. *Journal of Marketing*, *73*(2), 1-13.

Goldstone, R. L., & Janssen, M. A. (2005). Computational models of collective behavior. *Trends in cognitive sciences, 9*(9), 424-430.

Goodhue, D. L. (1998). Development and measurement validity of a task-technology fit instrument for user evaluations of information system. *Decision Sciences, 29*(1), 105-138.

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *Mis Quarterly*, *19*(2), 213-236.

Greve, H. R. (1996). *Performance, Aspirations and Risky Organizational Change.* Paper presented at the Academy of Management Proceedings.

Hagger, M.S. & Chatzisarantis, N.L. (2005). First-and higher-order models of attitudes, normative influence, and perceived behavioural control in the theory of planned behaviour. *British Journal of Social Psychology*, *44*(4), 513-535.

Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E. & Tatham, R.L. (2009). *Multivariate data analysis* (Vol. 5, No. 3, pp. 207-219). Upper Saddle River, NJ: Prentice hall.

Hansen, J. M., Saridakis, G., & Benson, V. (2018). Risk, trust, and the interaction of perceived ease of use and behavioral control in predicting consumers' use of social media for transactions. *Computers in Human Behavior*, *80*, 197-206.

Hirshleifer, D., & Hong Teoh, S. (2003). Herd behaviour and cascading in capital markets: A review and synthesis. *European Financial Management, 9*(1), 25-66.

Holden, C.J., Dennie, T. & Hicks, A.D. (2013). Assessing the reliability of the M5-120 on Amazon's Mechanical Turk. *Computers in Human Behavior*, *29*(4), pp.1749-1754.

Hopkinson, D. (8 July, 2016). Retrived from: https://ello.co/dave63/post/lly4g-lnkyjwojf2bk4w5q

Hsieh, J. P.-A., Rai, A., & Xu, S. X. (2011). Extracting business value from IT: A sensemaking perspective of post-adoptive use. *Management Science, 57*(11), 2018-2039.

Huang, T. C.-K., Wu, I.-L., & Chou, C.-C. (2013). Investigating use continuance of data mining tools. *International Journal of Information Management, 33*(5), 791-801.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: a multidisciplinary journal*, *6*(1), 1-55.

Hunt, E. (2016). *Alternative Social Networks.* Retrieved from https://www.theguardian.com/media/2016/jan/16/ello-is-anybody-there-alternative-social-networks-abound-for-the-peachy-keen

Jarupathirun, S., & Zahedi, F. (2007). Exploring the influence of perceptual factors in the success of web-based spatial DSS. *Decision Support Systems, 43*(3), 933-951.

Junglas, I., Abraham, C., & Watson, R. T. (2008). Task-technology fit for mobile locatable information systems. *Decision Support Systems, 45*(4), 1046-1057.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the Econometric Society*, 263-291.

Kang, Y. S., Hong, S., & Lee, H. (2009). Exploring continued online service usage behavior: The roles of self-image congruity and regret. *Computers in Human Behavior, 25*(1), 111-122.

Karahanna, E., Straub, D. W., & Chervany, N. L. (1999). Information technology adoption across time: a cross-sectional comparison of pre-adoption and post-adoption beliefs. *Mis Quarterly*, 183-213.

Kauffman, R. J., Lai, H., & Lin, H.-C. (2010). Consumer adoption of group-buying auctions: an experimental study. *Information Technology and Management, 11*(4), 191-211.

Kauffman, R. J., & Li, X. (2003). *Payoff externalities, informational cascades and managerial incentives: a theoretical framework for IT adoption herding.* Paper presented at the Proceedings of the 2003 INFORMS Conference on IS and Technology, Atlanta, GA, October 2003.

Keen, P. (1980). Reference disciplines and a cumulative tradition, in: Proceedings of the International Conference on Information Systems, pp. 9–18.

Kim, B., & Han, I. (2009). The role of trust belief and its antecedents in a community-driven knowledge environment. *Journal of the American Society for Information Science and Technology, 60*(5), 1012-1026.

Kim, B., & Oh, J. (2011). The difference of determinants of acceptance and continuance of mobile data services: A value perspective. *Expert Systems with Applications, 38*(3), 1798-1804.

Kim, S. S., & Malhotra, N. K. (2005). A longitudinal model of continued IS use: An integrative view of four mechanisms underlying postadoption phenomena. *Management Science, 51*(5), 741-755.

Kraatz, M. S., & Zajac, E. J. (2001). How organizational resources affect strategic change and performance in turbulent environments: Theory and evidence. *Organization Science, 12*(5), 632-657.

Lankton, N. K., & McKnight, H. D. (2012). Examining two expectation disconfirmation theory models: assimilation and asymmetry effects. *Journal of the Association for Information Systems, 13*(2), 88-115.

Larsen, T. J., Sørebø, A. M., & Sørebø, Ø. (2009). The role of task-technology fit as users' motivation to continue information system use. *Computers in Human Behavior, 25*(3), 778-784.

Laster, D., Bennett, P. & Geoum, I.S. (1999). Rational bias in macroeconomic forecasts. *The Quarterly Journal of Economics*, *114*(1), 293-318.

Lee, Y.-J., Hosanagar, K., & Tan, Y. (2015). Do I Follow My Friends or the Crowd? Information Cascades in Online Movie Ratings. *Management Science*.

Leonard-Barton, D., & Sinha, D. K. (1993). Developer-user interaction and user satisfaction in internal technology transfer. *Academy of Management Journal, 36*(5), 1125-1139.

Leonardi, P. M. (2011). When flexible routines meet flexible technologies: Affordance, constraint, and the imbrication of human and material agencies. *Mis Quarterly, 35*(1), 147-167.

Li, X. (2004). Informational cascades in IT adoption. *Communications of the ACM, 47*(4), 93-97.

Lieberman, M. B., & Asaba, S. (2006). Why do firms imitate each other? *Academy of Management Review, 31*(2), 366-385.

Liljander, V., & Strandvik, T. (1993). Estimating zones of tolerance in perceived service quality and perceived service value. *International Journal of Service Industry Management, 4*(2), 6-28.

Limayem, M., & Cheung, C. M. (2008). Understanding information systems continuance: The case of Internet-based learning technologies. *Information & Management, 45*(4), 227-232.

Lin, F., Fofanah, S. S., & Liang, D. (2011). Assessing citizen adoption of e-Government initiatives in Gambia: A validation of the technology acceptance model in information systems success. *Government Information Quarterly, 28*(2), 271-279.

Lin, K.-Y., & Lu, H.-P. (2011). Why people use social networking sites: An empirical study integrating network externalities and motivation theory. *Computers in Human Behavior, 27*(3), 1152-1161.

Lin, T.C. & Huang, C.C. (2008). Understanding knowledge management system usage antecedents: An integration of social cognitive theory and task technology fit. *Information & Management*, *45*(6), 410-417.

Lin, W.-S. (2012). Perceived fit and satisfaction on web learning performance: IS continuance intention and task-technology fit perspectives. *International Journal of Human-Computer Studies, 70*(7), 498-507.

Liu, D., Brass, D., & Chen, D. (2014). Friendships in Online Peer-to-Peer Lending: Pipes, Prisms, and Relational Herding. *Prisms, and Relational Herding (June 1, 2014)*.

Liu, Q., & Zhang, L. (2014). Information cascades in online reading: an empirical investigation of panel data. *Library Hi Tech, 32*(4), 687-705.

Liu, Y., & Sutanto, J. (2012). Buyers' purchasing time and herd behavior on deal-of-the-day group-buying websites. *Electronic Markets, 22*(2), 83-93.

Locke, C. (2016, May 17). *Remember Ello? You Abandoned It, But Artists Don't.* Retrieved from http://www.wired.com/2016/05/ello-artists/

Marakas, G.M., Johnson, R.D. and Clay, P.F. (2007). The evolving nature of the computer self-efficacy construct: An empirical investigation of measurement construction, validity, reliability and stability over time. *Journal of the Association for Information Systems*, *8*(1), p.15-28.

Maier, C., Laumer, S., Weinert, C. & Weitzel, T. (2015). The effects of technostress and switching stress on discontinued use of social networking services: a study of Facebook use. *Information Systems Journal*, *25*(3), 275-308.

Mason, W., & Suri, S. (2012). Conducting behavioral research on Amazon's Mechanical Turk. *Behavior research methods, 44*(1), 1-23.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management review, 20*(3), 709-734.

McKnight, D. H., Cummings, L. L., & Chervany, N. L. (1998). Initial trust formation in new organizational relationships. *Academy of Management Review, 23*(3), 473-490.

McLaren, T.S., Head, M.M., Yuan, Y. & Chan, Y.E. (2011). A multilevel model for measuring fit between a firm's competitive strategies and information systems capabilities. *MIS Quarterly*, *35*(4), 909-929.

Meade, A. W., & Craig, S. B. (2012). Identifying careless responses in survey data. *Psychological Methods*, 17, 437–455

Milliken, F. J. (1987). Three types of perceived uncertainty about the environment: State, effect, and response uncertainty. *Academy of Management review, 12*(1), 133-143.

Moore, G.C. & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research*, *2*(3),192-222.

Negahban, A., & Chung, C.-H. (2014). Discovering determinants of users perception of mobile device functionality fit. *Computers in Human Behavior, 35*, 75-84.

Ngai, E. W. T., Poon, J. K. L., & Chan, Y. H. C. (2007). Empirical examination of the adoption of WebCT using TAM. Computers and Education, *48*(2), 250–267

Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of Marketing Research*, 460-469.

Ortbach, K., Köffer, S., Bode, M., & Niehaves, B. (2013). Individualization of Information Systems-Analyzing Antecedents of IT Consumerization Behavior.

Ottaviani, M., & Sørensen, P. N. (2006). Reputational cheap talk. *The Rand journal of economics, 37*(1), 155-175.

Preacher, K.J. and Hayes, A.F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior research methods, instruments, & computers*, *36*(4), 717-731.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y. and Podsakoff, N.P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879-891.

Pollard, C. (2003). Exploring continued and discontinued use of IT: a case study of OptionFinder, a group support system. *Group Decision and Negotiation*, *12*(3),171-193.

Parasuraman, A., Berry, L. L., & Zeithaml, V. A. (1991). Refinement and reassessment of the SERVQUAL scale. *Journal of retailing, 67*(4), 420-441.

Parrish, E.D., Cassill, N.L. & Oxenham, W. (2006). Niche market strategy for a mature marketplace. *Marketing Intelligence & Planning*, *24*(7), 694-707.

Parthasarathy, M., & Bhattacherjee, A. (1998). Understanding post-adoption behavior in the context of online services. *Information Systems Research, 9*(4), 362-379.

Patsiaouras, G. and Fitchett, J.A., 2012. The evolution of conspicuous consumption. *Journal of Historical Research in Marketing*, *4*(1),154-176.

Persons, J. C., & Warther, V. A. (1997). Boom and bust patterns in the adoption of financial innovations. *Review of Financial Studies, 10*(4), 939-967.

Petter, S., DeLone, W., & McLean, E. R. (2013). Information systems success: The quest for the independent variables. *Journal of Management Information Systems, 29*(4), 7-62.

Porter, M.E. (1980), Competitive Strategy: Techniques for Analyzing Industries and Competitors, Free Press, New York, NY.

Raafat, R. M., Chater, N., & Frith, C. (2009). Herding in humans. *Trends in Cognitive Sciences, 13*(10), 420-428.

Ramayah, T., Rouibah, K., Gopi, M., & Rangel, G. J. (2009). A decomposed theory of reasoned action to explain intention to use Internet stock trading among Malaysian investors. *Computers in Human Behavior*, *25*(6), 1222-1230.

Rao, H., Greve, H. R., & Davis, G. F. (2001). Fool's gold: Social proof in the initiation and abandonment of coverage by Wall Street analysts. *Administrative Science Quarterly, 46*(3), 502-526.

Rhodes, R.E. & Courneya, K.S. (2003). Investigating multiple components of attitude, subjective norm, and perceived control: An examination of the theory of planned behaviour in the exercise domain. *British Journal of Social Psychology*, *42*(1),129-146.

Rogers, E. (2003). Diffusion of Innovations, 5th edn Free Press. *New York*.

Sarker, S., & Valacich, J. S. (2010). An alternative to methodological individualism: a non-reductionist approach to studying technology adoption by groups. *Mis Quarterly, 34*(4), 779-808.

Scharfstein, D. S., & Stein, J. C. (1990). Herd behavior and investment. *The American Economic Review*, 465-479.

Shang, R.-A., Chen, Y.-C., & Chen, C.-M. (2007). Why people blog? An empirical investigations of the task technology fit model. *PACIS 2007 Proceedings*, 5.

Shapiro, C., & Varian, H. R. (1999). *Information rules: a strategic guide to the network economy*: Harvard Business Press.

Sharma, R., Yetton, P. & Crawford, J. (2009). Estimating the effect of common method variance: The method—Method pair technique with an Illustration from TAM Research. *Mis Quarterly*, *33*(3), 473-490.

Shen, X.L., Li, Y.J. & Sun, Y. (2018). Wearable Health Information Systems Intermittent Discontinuance: A Revised Expectation-Disconfirmation Model. *Industrial Management & Data Systems*, *118*(3), 506-523.

Shen, X.L., Zhang, K.Z. & Zhao, S.J. (2016). Herd behavior in consumers' adoption of online reviews. *Journal of the Association for Information Science and Technology*, *67*(11), 2754-2765.

Simonsohn, U., & Ariely, D. (2008). When rational sellers face nonrational buyers: evidence from herding on eBay. *Management Science, 54*(9), 1624-1637.

Smith, J.R., & Louis, W.R. (2008). Do as we say and as we do: The interplay of descriptive and injunctive group norms in the attitude–behaviour relationship. *British Journal of Social Psychology*, *47*(3), 647–666.

Strong, D. M., Dishaw, M. T., & Bandy, D. B. (2006). Extending task technology fit with computer self-efficacy. *ACM SigMIS Database, 37*(2-3), 96-107.

Straub, D. W., 1989. Validating instruments in MIS research. MIS Quarterly, 13(2), 147.

Sun, H. (2013). A longitudinal study of herd behavior in the adoption and continued use of technology. *Mis Quarterly, 37*(4), 1013-1041.

Sun, H., & Fang, Y. (2010). *Toward a Model of Mindfulness in Technology Acceptance.* Paper presented at the ICIS.

Tarafdar, M., Tu, Q., Ragu-Nathan, B.S. & Ragu-Nathan, T.S. (2007). The impact of technostress on role stress and productivity. *Journal of Management Information Systems*, *24*(1), 301-328.

Teo, T. (2009). Modelling technology acceptance in education: A study of pre-service teachers. *Computers & Education*, *52*(2), 302-312.

Thaler, R. H., Tversky, A., Kahneman, D., & Schwartz, A. (1997). The effect of myopia and loss aversion on risk taking: An experimental test. *The Quarterly Journal of Economics*, 647-661.

Thompson, R.L., Higgins, C.A. & Howell, J.M. (1991). Personal computing: toward a conceptual model of utilization. *MIS Quarterly*, *3*(1), 125-143.

Tisdell, C. & Seidl, I. (2004). Niches economic competition: implications for economic efficiency, growth and diversity. *Structural Change and Economic Dynamics*, *15*(2), 119-135.

Triandis, H.C., (1979). Values, attitudes, and interpersonal behavior. In *Nebraska symposium on motivation*. University of Nebraska Press.

Trueman, B. (1994). Analyst forecasts and herding behavior. *Review of Financial Studies, 7*(1), 97-124.

Turel, O. (2015). Quitting the use of a habituated hedonic information system: a theoretical model and empirical examination of Facebook users. *European Journal of Information Systems*, *24*(4), 431-446.

Tversky, A., & Kahneman, D. (1991). Loss aversion in riskless choice: A reference-dependent model. *The Quarterly Journal of Economics*, 1039-1061.

Van Slyke, C., Ilie, V., Lou, H., & Stafford, T. (2007). Perceived critical mass and the adoption of a communication technology. *European Journal of Information Systems, 16*(3), 270-283.

Veblen, T. (1899). *The theory of the leisure class: An economic study in the evolution of institutions*. Macmillan.

Venkatesh, V., Brown, S.A., Maruping, L.M. & Bala, H. (2008). Predicting different conceptualizations of system use: the competing roles of behavioral intention, facilitating conditions, and behavioral expectation. *MIS Quarterly*, *23*(3), 483-502.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425-478.

Walden, E. A., & Browne, G. J. (2009). Sequential adoption theory: a theory for understanding herding behavior in early adoption of novel technologies. *Journal of the Association for Information Systems, 10*(1), 31-62.

Wattal, S., Racherla, P., & Mandviwalla, M. (2010). Network externalities and technology use: a quantitative analysis of intraorganizational blogs. *Journal of Management Information Systems, 27*(1), 145-174.

Xu, Y.C., Yang, Y., Cheng, Z. & Lim, J. (2014). Retaining and attracting users in social networking services: An empirical investigation of cyber migration. *The Journal of Strategic Information Systems*, *23*(3), 239-253.

Zahedi, F. M., & Song, J. (2008). Dynamics of trust revision: using health infomediaries. *Journal of Management Information Systems, 24*(4), 225-248.

Zhang, K. & Chen, X. (2017). Herding in a P2P lending market: Rational inference OR irrational trust?. *Electronic Commerce Research and Applications*, *23*(2), 45-53.

Zhang, H., Lu, Y., Gupta, S., & Gao, P. (2015). Understanding group-buying websites continuance: an extension of expectation confirmation model. *Internet Research, 25*(5), 767-793.

Zhou, T., Lu, Y., & Wang, B. (2010). Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in Human Behavior, 26*(4), 760-767.

Zwiebel, J. (1995). Corporate conservatism and relative compensation. *Journal of Political Economy*, 1-25.

APPENDICES

Table 1. Experimental Design

<table>
<tr><th rowspan="2">Condition</th><th rowspan="2">First Survey</th><th colspan="3">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="2">• Demographic data
• Pre-adoptive TTF
• Propensity for imitation
• Control variables</td><td rowspan="2">• Ello account ID
• Perceived Niche</td><td>NO</td><td rowspan="2">• Post-Adoptive TTF
• Confirmation
• Abandonment intentions
• Manipulation check</td></tr>
<tr><td>1. Treatment Group</td><td>The number of prior adopters who stopped using Ello.</td></tr>
</table>

Table 2. Demographic profile of the sample

Variable	**Category**	**Frequency**
Gender	Female	120(46.3%)
	Male	139(53.7%)
Age	≤18	4(1.5%)
	19-24	39(15.1%)
	25-34	106(40.9%)
	35-44	61(23.6%)
	45-54	34(13.1%)
	55 – 64	12(4.6%)
	65+	3(1.2%)
Education	<High school	1(.4%)
	High School	25(9.7%)
	College	100(38.6%)
	Bachelor’s	88(34.0%)
	Master’s	44(17.0%)
	Ph.D.	1(.4%)

Table 3. Goodness-of-Fit indicators for the CFA model

Measure	**MIN/DF**	**CFI**	**SRMR**	**RMSEA**	**PClose**	**TLI**
Threshold	Between 1 and 3	>0.95	<0.08	<0.06	>0.05	>0.95
Estimate	1.28	0.98	0.04	0.03	1.00	0.97

Table 4. R-squared values

Construct	Pre-adoptive TTF	Confirmation	Post-adoptive TTF	Abandonment intentions
R-Square Value	0.48	0.07	0.41	0.52

Table 5. Mediation analyses

Relationship	Direct effect	Indirect effect	Result
IMI→CNF&Pre-TTF→Post-TTF	0.086 (ns)	0.277**	Full Mediation
CNF→Post-TTF→ABD	0.028 (ns)	-0.173***	Full Mediation
Pre-TTF→Post-TTF→ABD	0.077(ns)	-0.442***	Full Mediation

*** = p < 0.001; ** = p < 0.01; ns = "not significant"

Table 6. Effect Sizes

Dependent Variable	R^2 without Moderators		R^2 with Moderators	Effect Size[a]
Abandonment Intentions	Without Critical Mass*Post-TTF	0.28	0.52	0.49 (Large)
	Without Perceived Niche*Post-TTF	0.49		0.07 (Small)
Dependent Variable	**R^2 without Antecedents**		**R^2 with Antecedents**	**Effect Size[a]**
Post-TTF	Without Pre-TTF	0.03	0.41	0.64 (Large)
	Without Confirmation	0.27		0.24 (Medium)

[a] Effect size (f^2) is calculated by the formula *(R^2 included - R^2 excluded)/(1 - R^2 included)*. Cohen (1988) suggested 0.02, 0.15, and 0.35 as operational definitions of small, medium and large effect sizes respectively.

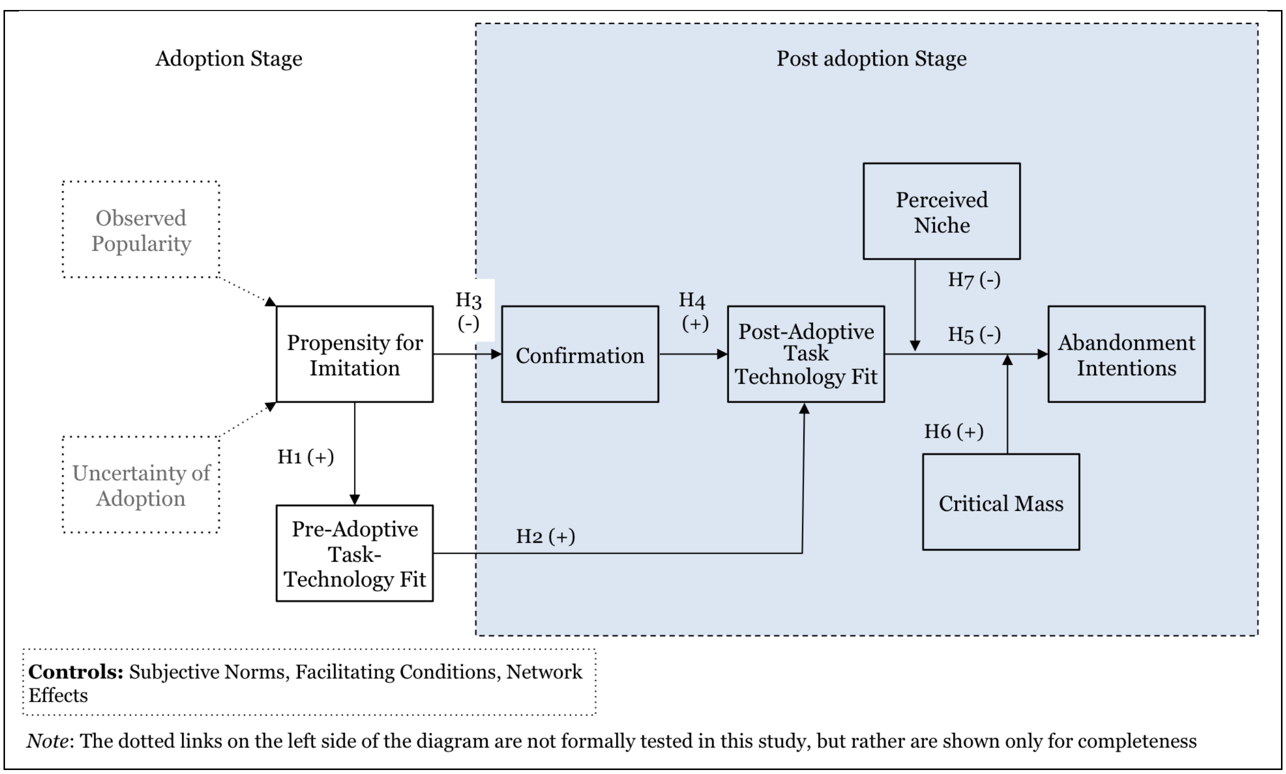


Figure 1. Research Model

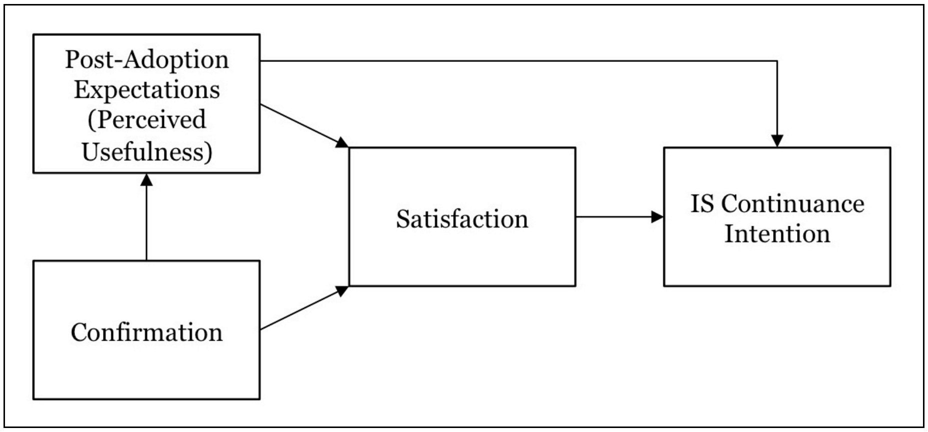


Figure 2. Expectation-Confirmation Model

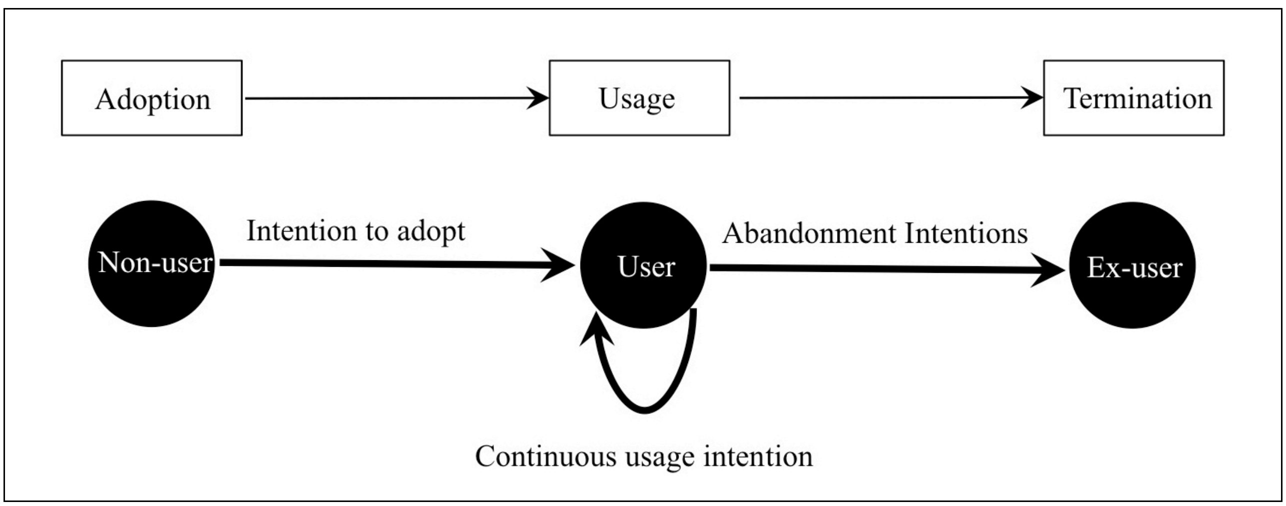


Figure 3. User Transformation Model (Maier et al. 2015)

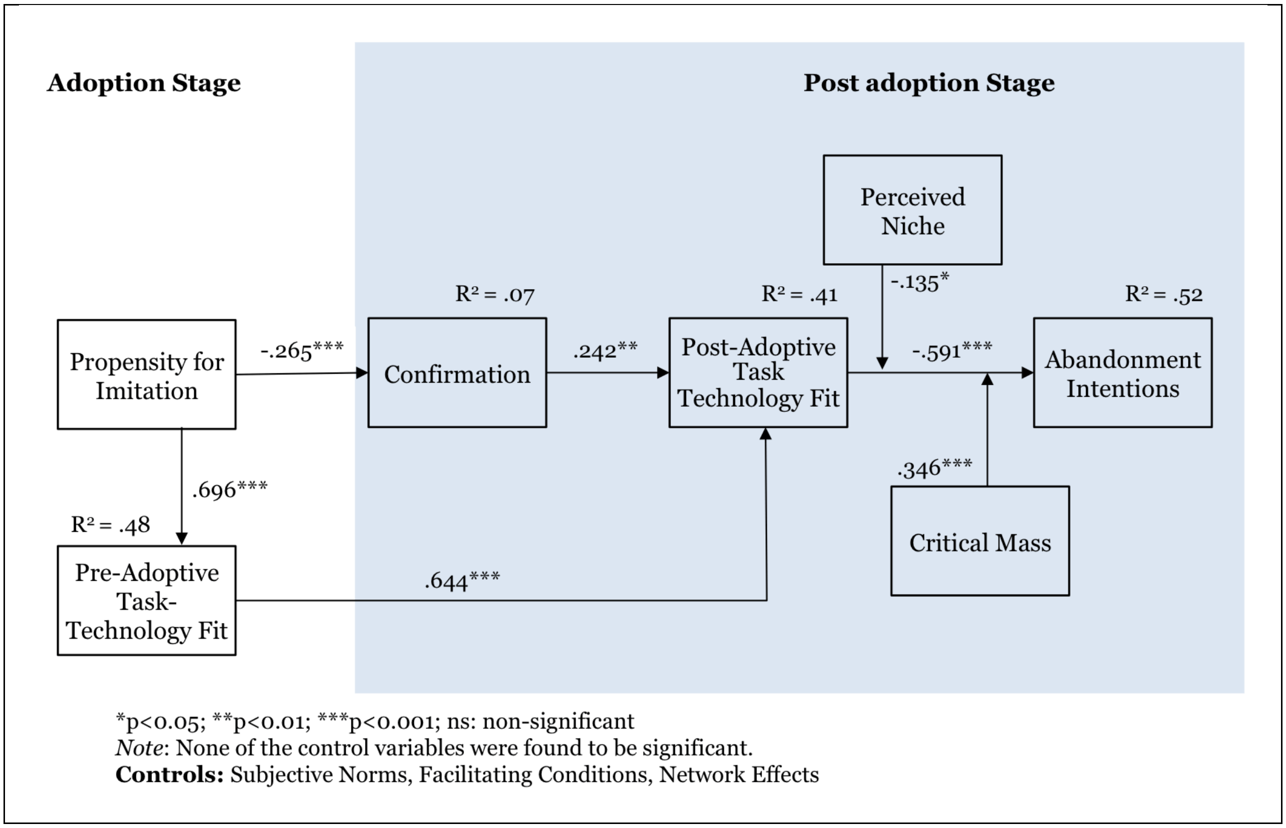


Figure 4. Structural Model Results

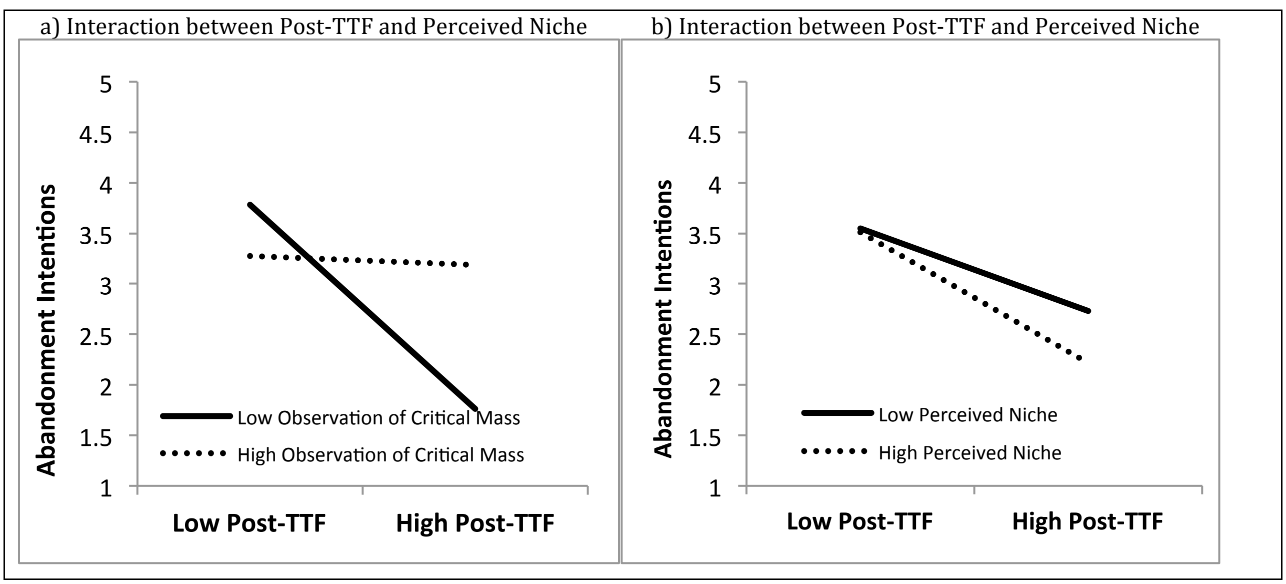


Figure 5. The Moderation Effects

PPENDIX A
Summary of Relevant Literature On Abandonment

Table A1. Research on post-adoption discontinuance (abandonment) intentions

Category	Antecedents
Technology Characteristics	Compatibility (Parthasarathy and Bhattacherjee 1998; Pollard 2003) Complexity (Pollard 2003) Reliability (Pollard 2003) System capabilities shortcomings (Furneaux and Wade 2011) System performance (Furneaux and Wade 2010) Technical integration (Furneaux and Wade 2011) Usefulness (Parthasarathy and Bhattacherjee 1998) System suitability (Furneaux and Wade 2010)
Environment Characteristics	Group size (Pollard 2003) Infrastructure (Pollard 2003) Social Influence (Parthasarathy and Bhattacherjee 1998) Support (Pollard, 2003, Furneaux and Wade, 2010 2011) Social overload (Maier et al. 2014)
Affective	Attitude (Pollard 2003) Satisfaction (Sun 2013, Turel 2014) Techno-stress (Maiaer et al. 2015)
Behavioral	Habit (Turel 2014) Intention to use (Pollard 2003, Sun 2013) Utilization (Parthasarathy and Bhattacherjee 1998)
Individual Characteristics	Self-efficacy (Turel 2014) Guilt feelings (Turel 2014)

APPENDIX B
Situating Task

Ello is a free social network created by a small group of artists and designers. Ello is free to join. Like every other social network you can post status updates and photos. You can also comment on posts and reply directly to your friends and you can also see how many people have viewed a post and edit a post if you missed a typo before pushing it live. There's also a Noise section that showcases posts by people you might not know arranged in a loose grid. It's like an online art show at the neighborhood gallery. Ello offers features that users can pay for. Ello has app versions for iOS and Android devices.

APPENDIX C
Herd Simulation

Time 1 (Adoption Stage)

To create 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 contended that the probability of herding rises when the aggregate public information is strongly held by a lot of people and reinforced by the actions of the market leader.

The participants receive a message that not only states that Ello has been used by a lot of people, but also specifies some famous adopters. The treatment messages were composed based on information from Ello's website and Mashable (a technology and social media blog).

The following message appears:

a) Number

- Ello is getting 40,000 sign-ups per hour. The beginning of a mass migration from Facebook to another Ello (Forbes).

(b) Identity

c. Some major companies in such as Apple, AUDI, Acura, McDonald, Domino's, Taco Bell, Dr. Pepper, Harley-Davidson.

d. Here are some celebrity ello users: Rihanna, Harry Styles, Ariana Grande, Joseph Gordon-Levitt, Ashley Greene, Blake Lively, Jared Leto.

Treatment

Time 2 (Post-Adoption Stage)

In order to study the effect of mass of abandoners on post adoption decision of individuals, we manipulate the magnitude of prior abandonments. A message was sent to the treatment group about the number of prior adopters of Ello who chose to stop using it and uses other alternatives. The treatment message provided *smaller* number of abandoners, compared to the number of adopters in the simulation message (i.e., Time 1).

APPENDIX D
Questionnaire Items

Please complete the following:

- Age: _____ Years
- Gender: M F
- Education level:

Prior Experience (adapted from Kim and Malhotra 2005)
How long have you been using Ello? (Never heard about it, Heard but never used it before, less than 1 months, 1 to less than 3 months, 3 to less than 6 months, 6 months or more)

Propensity for imitation (IMI): (adapted from Sun 2013):
IMI1. I will follow others in accepting Ello.
IMI2. It is a good idea to follow others in using Ello.
IMI3. I like the idea of adopting Ello, since others are also using it.
IMI4. It seems that Ello is the dominant social networking website; therefore, I would like to use it as well.

Per-Adoptive and Post Task-technology fit (TTF): will be measured at both t_1 and t_2 (adapted from Goodhue and Thompson 1995; Jarupathirun and Zahedi 2007)
TTF1. Ello's functions are very adequate.
TTF2. Ello's functions are very appropriate for social networking.
TTF3. Ello's functions are very useful for social networking.
TTF4. Ello's functions are very compatible with social networking.
TTF5. Ello's functions are very helpful.
TTF6. Ello's functions are very sufficient.
TTF7. Ello's functions make social networking very easy.
TTF8. In general, Ello's functions fit social networking.

Time-2 Survey Items
Ello Usage (Screening) Items
Ell1. How many followers do you have on Ello?
Ell2. How many Ello accounts do you follow?
Ell3. How many times you have posted on Ello?

Confirmation (CNF) (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 Ello _____

CNF1. to improve my performance was______
CNF2. to increase my productivity was______
CNF3. to enhance my effectiveness was______
CNF4. to be useful for my work or study was______

Perceived Niche (NCH) (Self-developed)
NCH1. Ello is designed for a specific cluster of SNS users.
NCH2. Ello is distinct from other SNSs.
NCH3. Other more popular SNSs are not similar to Ello.
NCH4. There are characteristics that are specific to Ello.

Intention to Abandonment (ABD) (adapted from Turel 2015; Venkatesh et al., 2008)
ABD1. I intend to abandon my use of Ello.
ABD2. I plan to stop using Ello.
ABD3. I predict that I would stop using Ello in the future.

Control Variables

Facilitating Conditions (Thompson et al. 1991)
FC1. A specific person is available for assistance with Ello's difficulties.
FC2. Guidance is available to me when I need to use Ello.
FC3. Specialized instruction is available to help me with Ello's difficulties

Subjective Norm: Two aspects
Aspect one: Descriptive Norm (DN) (adapted from Hagger and Chatzisarantis 2005)
DN1. Most of my friends are using Ello.
DN2. Most of my co-workers are using Ello.
DN3. Most people I know are using Ello.
DN4. Most people who are important to me use Ello.

Aspect two: Injunctive Norm (IN) (adapted from Rhodes and Coureneya 2003)
IN1. Most people in my social circle want me to use Ello.
IN2. Most people in my social circle approve of my using Ello.
IN3. Most people who are important to me want me to use Ello.
IN4. Most people I know think I should use Ello.

Network Effects (Sun 2013)
NE1. The more people use Ello, the more valuable it is to users.
NE2. By adopting Ello, I would help increase its value to other users.
NE3. My adoption of Ello 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 Ello to me.
NE5. Ello will be more useful if more people adopt it.

Time 2-Manipulation Check Items (MCH)
MCH2-1. I am aware that a lot of people have stopped using Ello.
MACH2-1. I am aware that Ello has been abandoned by a lot of well-known prior users.

Bogus Items

4. I have been to every country in the world.
5. I have never brushed my teeth.
6. All my friends are aliens.

APPENDIX E
Item Loadings and Correlations

Table E1. Items and Factor Loadings

	IMI	Pre-TTF	CNF	NCH	ABD	Post-TTF	FC	SN	NE
IMI1	.764	.176	-.128	-.080	-.003	.186	.085	.008	.061
IMI2	.824	.251	-.086	-.107	-.043	.074	.089	.006	.007
IMI3	.813	.204	-.138	-.003	.006	.162	-.066	.043	.015
IMI4	.847	.125	-.003	.012	-.031	.079	-.018	-.017	-.018
Pre-TTF4	.299	.765	.026	-.090	-.059	.247	.000	-.037	.085
Pre-TTF5	.338	.755	.015	.031	-.034	.253	.009	-.010	-.002
Pre-TTF6	.329	.735	-.102	.085	.078	.260	.071	-.002	.055
CNF2	-.107	-.054	.884	.018	-.036	.173	-.004	-.067	.020
CNF3	-.189	.016	.870	.088	.041	.123	-.003	.029	.069
NICH1	-.002	-.046	-.026	.837	-.056	-.053	.061	.071	.011
NICH2	-.042	.081	.060	.877	-.022	-.087	.055	-.015	-.039
NICH3	-.028	-.085	.009	.884	-.007	-.151	.024	-.001	-.012
NICH4	-.081	.057	.070	.750	-.022	-.157	.158	-.067	-.116
ABD1	-.088	.004	.104	-.063	.826	-.135	-.035	.054	.028
ABD2	.003	-.063	-.063	-.064	.837	-.217	-.070	.063	-.083
ABD3	.029	.033	-.044	.015	.857	-.206	-.005	.054	-.078
Post-TTF2	.149	.111	.110	-.076	-.118	.833	-.027	-.004	.027
Post-TTF3	.102	.118	.058	-.090	-.148	.839	.012	-.013	.048
Post-TTF4	.086	.221	.107	-.197	-.189	.800	.021	.016	.106
Post-TTF5	.106	.261	.009	-.037	-.113	.808	.073	-.097	.015
P0st-TTF6	.084	.153	.037	-.096	-.166	.855	.031	.027	.036
Post-TTF7	.082	-.040	.066	-.083	-.013	.839	.014	.036	.039
FC2	.029	.019	-.045	.125	-.055	.022	.947	.029	-.037
FC3	.043	.039	.038	.150	-.049	.068	.942	.008	-.051
SNdn1	.003	-.038	-.057	.102	.140	-.029	.061	.860	-.017
SNdn2	.050	-.032	.038	-.140	-.061	-.036	.033	.855	-.051
SNin3	-.023	.030	-.021	.033	.085	.047	-.055	.861	-.037
NE1	.056	.001	.013	-.010	-.022	.099	-.007	-.037	.839
NE3	.013	.050	.064	-.051	-.042	.031	-.064	-.001	.863
NE4	-.019	.048	.007	-.068	-.052	.045	-.013	-.063	.855

Note: *NCH: Perceived Niche; ABD: Abandonment; Post-TTF: Post-Adoptive Task-Technology Fit; CNF: Confirmation; Pre-TTF: Pre-Adoptive Task-Technology Fit; IMI: Propensity for imitation; FC: Facilitating Conditions; SN: Subjective Norms; NE: Network effect.*

Table E2. Descriptive statistics and inter construct correlations

	Mean	SD	CR	AVE	NCH	ABD	Post-TTF	CNF	Pre-TTF	IMI	FC	SN	NE
NCH	2.93	1.32	0.878	0.645	**0.803**								
ABD	2.81	1.14	0.837	0.632	-0.258	**0.795**							
Post-TTF	3.58	1.52	0.933	0.700	-0.039	-0.060	**0.837**						
CNF	2.81	.85	0.792	0.656	-0.408	0.528	0.210	**0.810**					
Pre-TTF	3.27	1.08	0.831	0.622	0.089	-0.129	0.015	0.092	**0.788**				
IMI	2.67	1.20	0.878	0.644	-0.062	-0.074	-0.112	-0.036	0.109	**0.802**			
FC	3.50	1.42	0.928	0.868	0.217	0.320	-0.118	0.160	0.107	0.079	**0.931**		
SN	3.57	1.12	0.828	0.616	-0.054	-0.291	0.167	0.055	-0.039	0.018	0.023	**0.785**	
NE	2.35	.98	0.824	0.610	-0.110	0.687	-0.142	-0.039	0.128	0.061	-0.088	-0.097	**0.781**

Notes: Values on the diagonal in the table of inter-construct correlations represent the square root of AVE. Off diagonal elements are the correlations among constructs.
NCH: Perceived Niche; ABD: Abandonment; Post-TTF: Post-Adoptive Task-Technology Fit; CNF: Confirmation; Pre-TTF: Pre-Adoptive Task-Technology Fit; IMI: Propensity for imitation; FC: Facilitating Conditions; SN: Subjective Norms; NE: Network effect.

APPENDIX F
List of Developed Items to measure Perceived Niche:

Table F1. Items for Perceived Niche

Item Wording
Ello is designed for a specific cluster of SNS users.
Ello is distinct from other SNSs.
Ello can be used in a different way compared to other SNSs. *
Other more popular SNSs are not similar to Ello. *
Ello's posts are different from other SNSs.
Using Ello makes me feel different.
There are characteristics that are specific to Ello. *

* The indicated items were dropped after the Q-sorting tests.

CHAPTER 4

Promotion of Explorative IT Learning: A Multilevel Analysis

INTRODUCTION

Information technology (IT) investments continue to account for a significant proportion of spending in organizations (Gartner 2014). However, when introducing novel technologies to their employees and customers, organizations cannot be sure as to whether the technologies will be successfully adopted and used in such a way that efficiency and productivity are actually improved. Recent information systems (IS) research has begun to shift its focus away from whether or not a system will be *adopted*, to investigating *post-adoptive* behaviors; this is because the actual benefits from IT investments accrue from behaviors that users perform in the post-adoption phase of system introduction (Hsieh et al. 2011; Thatcher et al. 2011). Actively revising one's system use, and attempting to discover creative ways of applying that system, result in a better fit between the system and the individual's usage context (Ahuja and Thatcher, 2005; Barki et al. 2007; Sun 2012). The recent focus on post-adoption explorative behaviors is motivated by a recognition that (1) users generally tend to employ only a relatively narrow set of features in their work, resulting in significant under-utilization (Jasperson et al. 2005), and (2) the full benefits of a system are more likely to be realized when users explore and take advantage of a broader range of system features to support their work (Hsieh et al. 2011; Sun 2012). Despite growing interest in understanding users' exploration behavior (in my case, explorative knowledge acquisition), there remain several opportunities to improve our understanding of this phenomenon.

To fully realize the potential benefits expected from a new system, users must acquire the necessary IT skills as well as knowledge of how to employ them. Formal training not only increases individual productivity, but also facilitates communication of the organization's objectives to new employees (Gupta and Bostrom 2013). Hence, it is no surprise that organizations strive to enhance their employees' IT skills through in-house training programs, and spend a considerable amount of money on IT training (Allen and Seaman 2011). According to a recent training industry report, training expenditures in U.S. organizations increased by 15% last year to reach $70 Billion in the US and over $130 Billion worldwide (Bersin 2014). The evidence from surveys and case studies (e.g., Robey et al. 2002; Sun and Bhattacherjee 2011) clearly shows that training has a significant correlation to IS post-adoptive behaviors. Nevertheless, a recent meta-analysis on IT training research has revealed shortcomings in research on the impact of training on IS continuance behaviors (Santhanam et al. 2013). Although the role of user training is more salient as the new system becomes more complex (Te'eni et al. 2007), new system complexity limits the amount of knowledge that individuals can absorb before they can actually begin using the system (Yi and Davis 2003). Therefore, users have to continue to learn and explore new features in the post-adoption stage in order to update the knowledge and skills required for effective long-term usage.

The IT training environment is often characterized by complex, radical systems and observation of the learning behaviors of others. A team oriented learning approach is often applied to enhance learning outcomes in these situations (Gupta and Bostrom 2013). In this sense, the desired outcome of effective team-based IT training is to encourage team members' independent explorative learning behaviors. By independently learning and using more of the technology's available features, learners demonstrate more of an explorative approach in their information search behavior. Such an approach can lead to higher knowledge and mastery of the IT (Barki et al. 2007). In such learning situations, users may extend the scope of the system features that they use in later adoption phases (e.g., extensive usage). Hence, these revisions to initial usage behaviors enable them to exploit the potential of a new system, leading to higher task performance (Jasperson et al. 2005; Tyre and Orlikowski 1994). However, one important observation from a review of the extant literature is that research on user exploration of technology (e.g., Ahuja et al. 2005; Magniet al. 2010; Sun 2012) and IT training (e.g., Santhanam et al. 2013) for the most part has focused exclusively on *individual-level* interventions. Despite providing a solid foundation for future research, the current body of work does not provide much guidance on how to promote such behavior in the case of *team-based* IT learning. This is significant for two reasons.

First, in real life, organizations use teams to manage their operations. In fact, given the increasing complexity of business-related issues today (a result of pressures to make rapid decisions in order to reduce inefficiencies and continually improve work processes (Heerwagen et al. 2007), organizations are increasingly relying on teams as a structure for organizing work. According to recent estimates, over 80 percent of Fortune 500 companies utilize team-based structures for this purpose. Teams are important sources of knowledge when it comes to the learning activities of individual team members, and thus they have a salient role in team members' IT skill acquisition (Ryu et al. 2005). As the team develops a map of knowledge distribution (i.e., "who knows what") and members are able to retrieve knowledge from (and allocate information to) these specialized experts, this leads to overall knowledge gain and improved group efficiency (Child and Shumate 2007). In the same spirit, prior studies have encouraged the adoption of a cross-level perspective in studying individuals’ IS behaviors in order to address the limitations of strictly macro-level studies (i.e., those ignoring mental processes of individuals) and strictly micro-level studies (i.e., those ignoring contextual factors) in understanding technology-related behaviors (Markus and Robey 1988). In sum, team learning has become an integral part of IT training (Franceschi et al. 2009).

Second, a review of the literature points out that current training methods have adopted a more active and team-oriented learning approach (Gupta et al. 2010), referred to as *collaborative learning* (Alavi et al. 1995). While substantial support has been found regarding the significance of collaborative learning outside of IT training research (see Rohrbeck et al. 2003), its role in IT training is unclear. Also, the discrepancy in the findings from the few extant studies on collaborative IT training and education could be due to their cross-sectional design (Gupta and Bostrom 2013). Scholars have argued that the positive effect of collaborative learning is more likely to be observed in longitudinal rather than cross-sectional studies, suggesting the need to emphasize team development over time (Davis and Yi 2004). In addition, training activities, especially in the case of complex systems, are continuous operations, and thus we need to study the associated learning process longitudinally.

To address these considerations, my study adopts a longitudinal design and aims to bridge the gap between the macro and micro domains of post-adoption research by examining how one particular team-level construct -- *team cohesion* -- promotes sustained IT learning in team settings. Team cohesion here refers to an individual's assessments of their relationships with other team members (Chin et al. 1999). Team cohesion promotes trust and knowledge sharing among newly formed teams (Yukl and Mahsud 2010). In addition, high team cohesiveness significantly correlates with frequent intra-group communication and positive evaluation of other team members (Hirunyawipada et al. 2015). Such elements may encourage team members to imitate the risky, but rewarded, explorative learning behaviors of others -- for example, both individuals and their employer might achieve more efficient technology use as a result of exploration (Bandura 2001; Boudreau and Robey 2005).

In team-based learning, there is greater opportunity for observation and imitation (Truman 2009). This paper argues that imitative behavior, i.e., herding, occurs in small team-based training context. The findings of recent research on imitative behavior imply the existence of herd-like decision-making even in small group settings (e.g., in online loan market [Liu et al. 2015]). Applying herd lens can help to explain learners' explorative learning behavior since one can identify the factors of herding, i.e., high levels of observation of team members' learning behavior and uncertainty (Sun 2013) in such setting. Observability of team members' IS behaviors, the high levels of uncertainty not only due to unstructured nature of explorative learning approach, but also due to complexity involved in IT training outcomes, may motivate individuals to imitate their teammates in exploratively learning a system, i.e., to exhibit *herd*-like explorative learning behavior (Lee et al. 2015; Walden and Browne 2009). To study this phenomenon through a herding perspective, my study grounds its arguments in the literature on observational learning (Bandura 1977), which forms the primary theoretical underpinning for understanding herding behavior (Bikhchandani et al. 1998). Due to the highly uncertain outcomes of many technology adoption decisions, individuals are more motivated to overcome the uncertainties through observational learning and imitation of others' behaviors (Walden and Browne 2009). Observational learning occurs when an individual observes the behavior of another individual and infers something about the usefulness of the behavior based on that observation. Research has shown that people use their observations of their peers' behaviors to update their own private beliefs to take actions (Oh and Jeon 2007). Such ‘herded actions’ in a small team setting (e.g., with 3 team members in my research context) may occur where members of the team have more opportunity (compared to a larger community/team) to observe their teammates' exact behaviors (Child and Shumate 2007). The influence of observed group members’ behaviors on "learning by imitation" by other members has been found significant in a number of different group settings (e.g., Leike et al. 2016; Chen et al. 2013). In fact, it has been argued that in such group-oriented learning contexts, peers serve as models to stimulate imitative learning (Gupta et al. 2010). More specifically, in the IT training context in which explorative learning is being encouraged, observational learning is particularly important due to the uncertainty involved in such a learning approach (Gupta and Bostrom 2013).

Hence, I argue that herd behavior, as a mechanism to reduce such uncertainties in an adoption context, has potential to also explain an individual’s post-adoption IS exploration behaviors, including explorative learning. In developing the bridge between herding behavior and individual technology exploration, I draw on recent literature employing the construct of *behavioral expectation* to complement the influence of *behavioral intention* on IS behaviors (Maruping and Magni 2015; Venkatesh et al. 2008). When Venkatesh et al. (2008) introduced behavioral expectation into the IS domain, they emphasized the need for future research to identify its antecedents. Thus, I also contribute to the literature by studying two complementary individual cognitions on continuance of explorative IT learning: intention to continue explorative learning, and expectation to continue explorative learning.

THEORETICAL BACKGROUND

IT Training

Goldstein and Ford (2002) defined *training* as the acquisition of attitudes, skills, knowledge, concepts, or rules that result in enhanced performance in the post-training environment. Training is one of the most common approaches to enhancing individuals' productivity in the workplace (Arthur Jr et al. 2003). Training has been studied from a variety of perspectives in the IS discipline, including collaborative training (Alavi et al. 1995), web-based virtual training (Venkatesh and Speier 2000), co-discovery and self-discovery (Lim et al. 1997), knowledge growth (Chang and Wang 2009), computer skill training methods (Gupta and Bostrom 2013) and behavioral modeling (e.g., the impact of observational learning processes on computer skill training; Truman 2009). The latter form of skill acquisition is of particular relevance to the present study, as it relates to the notion of convergence (i.e., uniform learning behavior by individuals, such as following a role model in making similar decisions) in a group-based training setting. As I will discuss, this is especially important in contexts where system adoption is coupled with uncertainty about that system's value.

IS research has also found that training significantly influences employees' attitudes toward a new system and consequently impacts the success of post-training system usage (Lee et al. 1995; Santhanam et al. 2013; Venkatesh 1999; Venkatesh et al. 2000). Typically, individuals see and interact with a new system for the first time during training sessions. Training is thus considered a significant organizational activity, because it helps form trainees' relevant perceptions about the new technology that may in turn lead to more efficient system usage (Cooper and Zmud 1990; Jasperson et al. 2005). In the same vein, end-user training (Bueno and Salmeron 2008) and the resultant increased levels of IT knowledge (Aggarwal et al. 2015) have been found to be critical factors that affect successful IS implementation. For instance, the quality of the IT training provided has a significant effect on trainees' evaluations regarding the usefulness of a technology (Bueno et al. 2008). Consequently, while early IS training research primarily focused on methods to develop individuals' actual technology skills, later research has started to emphasize the development of affective outcomes of IT training programs, motivational aspects of training, and other contextual factors (Santhanam et al. 2013).

Post-Adoption Behaviors

One dimension of system use, which has been of interest to managers and academics alike, is the post-adoption *patterns of use* that occur at both the individual and collective levels. These patterns of post-adoption usage are described in the literature by such terms as *adaptive use* (Lee et al. 2006; Sun 2012), *innovative use* (Avgerou 2001), and *exploitative use* (Burton-Jones and Straub 2006). To better understand such types of usage, I need to study their antecedents and explore which types of usage have strong relationships with the desired results in a particular organizational setting (Burton-Jones and Straub 2006). One particular form of post-adoption system use that seems worthy of study (i.e., extended use) involves a user expanding the scope of system features (Hsieh et al. 2011). This leads to the discovery of innovative ways of using the system's functions to complete novel tasks or to perform existing tasks in a more creative and efficient way (Sun 2012). This type of usage behavior has the potential to expand the benefits derived from the system's adoption through generating value in ways that were not anticipated when the initial investment in the IT was contemplated (Nambisan et al. 1999).

Technology Exploration

Explorative IS usage behavior emerges once a new system has been installed and made available to users. IS research on explorative behaviors provides a more user- and feature-centric perspective on system usage (Griffith 1999; Truman 2009). It thus provides a finer level of granularity in understanding individuals' IS behaviors. Especially given the increasing levels of re-configurability and complexity of systems today, users' proactive system exploration and selective appropriation of system functions are considered to be important determinants of successful system adoption (Seddon et al. 2010).

Although this research stream has identified several underlying factors that affect individuals' post-adoption usage behaviors, two aspects are more prominent. First, technology acceptance studies argue that at the post-adoption phase, individual usage patterns become more complicated than simply considering an increase in the duration or frequency of use (Jasperson et al. 2005). Thus, by shifting the focus to exploration, research has tried to theoretically and practically enhance my understanding of *how* individuals make use of a particular technology in their work, rather than simply how long or how frequently they use it (Burton-Jones and Straub 2006). Users may proactively seek to further explore a system's attributes to see what other relevant features are available (Sun 2012), and how those features might affect their ability to execute work tasks (Hsieh et al. 2011). Similarly, Barki et al. (2007) have highlighted the value of independent exploration behaviors, which can improve one's knowledge, and mastery of an IT more than a typical training program. Likewise, *explorative* interaction with a new system has been found to positively influence job performance, whereas *exploitative* usage (i.e., routine use of recommended features of an IT to perform a task) has been associated with less efficient performance (Bala and Venkatesh 2015). Liang et al. (2015) also found evidence that IT use and exploration have different natures (i.e., exploration by nature is innovative). They found that IT use is a key component of job requirements, while exploration is more of an extra-role behavior. Other scholars have proposed similar notions, such as technology duality (i.e., technology design and development is influenced by human actors through the different meanings they attach to the technology and the various features they emphasize and use), that highlight how human behavior changes technology over time (Orlikowski and Robey 1991). Hence, users have the ability to adapt a system in various ways to better accomplish their tasks. However, in doing so, they may encounter significant challenges since many of these technologies are complex to use (Sykes et al. 2009) and significant cognitive effort may be required to overcome the knowledge barriers to explorative usage (Sharma and Yetton 2003).

Second, successful adoption of a system depends on individuals' usage behavior over time. Bhattacherjee(2001) initiated the shift of focus in technology acceptance research from studying initial usage to sustained usage, by highlighting the importance of *IS continuance*. Continued use of a technology is not a one-shot effort; rather, it involves one's ongoing interactions with the same technology over time. Both individuals and organizations should expect to realize tangible benefits from their IT investments only after substantive long-term use, rather than through occasional use at the post-adoption stage (Bhattacherjee 2001). Studies that have followed Bhattacherjee have sought to identify determinants of IS continuance behaviors across a variety of settings including the Internet (Limayem et al. 2007; Venkatesh et al. 2011), enterprise systems (Sykes 2015), e-books (Stone and Baker-Eveleth 2013) and mobile technologies (Venkatesh et al. 2012). IS exploration research, given its focus on post-adoption behaviors, can benefit from this line of research, which emphasizes the cognitions involved in a user's ongoing interaction with technology, and as a result leads to insights about how to fully reap the benefits of using that technology (Maruping et al. 2015). As I am looking at the individual's cognitive process related to explorative learning, adopting a continuance approach would be particularly beneficial since explorative IS usage behaviors require ongoing engagement, such as continuously interacting with different functions, creatively applying them into one's work routines, and discovering new uses for those functions (Hsieh et al. 2011; Sun 2012).

To creatively use and combine the features of a new system at the post-adoption stage, individuals first need to adopt an exploratory approach in learning about the features of the new system (Burton-Jones and Grange 2013). In fact, letting individuals experiment with the system, and control their own pace in discovering its functions, will provide them with a more task-focused learning orientation and will consequently result in more efficient usage (Truman 2009). Since exploration involves both learning and adaptation, exploration in learning becomes an important factor in determining further explorative IS behaviors.

Exploration in IT Training

IT training is a complex skill development activity in which the learner has to develop conceptual knowledge, procedural skills, and motivation to apply the acquired skills (Davis and Yi 2004). The changing nature of technology makes IT training even more complicated. Given the complications involved in IT training and its key role in an individual's subsequent usage behavior, researchers have attempted to discover more efficient training approaches (e.g., Truman 2009). In general, I can identify two different approaches that a person may take in learning a new system. One is to accept the system "as is," and focus on learning its routines and standard functions (i.e., *what* to access and *how* to access it). Alternatively, the individual may build her skills based on absorbing knowledge through revising the system's features and employing them in a more innovative way (i.e., *why* to access it). The latter approach leads to more educated adaptation with greater benefits. This view has much empirical support, with the relevant literature recognizing that the exploration approach to IT training is a more effective way of acquiring the necessary knowledge and skills, as compared to more traditional instructional methods (e.g., lecture). For instance, Carroll and Mack (1984) found that compared to individuals learning through the instructional method, rates of knowledge acquisition are higher for individuals who actively explore a computer system and its functions.

Conceptually, the explorative approach allows an individual to set the pace and direction of their own learning efforts. In sum, explorative IT behavior reflects an individual's willingness to further investigate various features of a technology, together with his or her desire to be involved in active learning and skill acquisition in regard to how best to incorporate the different aspects of the new system into one's tasks. Similarly, Goodman et al. (2004) have characterized exploration as an unstructured method of learning that emphasizes self-discovery and is accompanied by delayed, and less specific, feedback. Thus, each learner may take different paths in this inherently unstructured approach. These specifications allow learners to conduct experimentation with various system features by facilitating "learning by doing" and trial-and-error techniques.

Adopting an explorative approach to learning a new technology may seem complicated and risky. In fact explorative learning is a more difficult training method. In the explorative approach, following formal instruction is discouraged. Instead, a person learns by doing (trying things out), involving more thinking processes (making sense of the system), and finding potentially creative ways of using their new skills and knowledge (Sharma and Yetton 2007). Moreover, the slow pace of the explorative learning progress makes it even more challenging (Truman 2009). Highlighting the importance of explorative IT learning, Burton-Jones and Grange (2013) indicate that in addition to the immediate benefits of learning via exploration, such training also has more efficient distal outcomes (e.g., personalizing the shortcuts of a software package). Such outcomes are typically difficult to predict or appreciate *ex-ante.* Lewis and Seibold (1993) found that explorative training has associations with the levels of uncertainty involved in one's IT usage. They contend that in highly uncertain situations, exploration is more effective since it reflects the coping tactics of individuals for whom the uncertainty associated with IT usage is an important concern.

IS research has also linked the training approach to an individual's subsequent usage behavior by arguing that explorative learning promotes post-training IT usage (Gallego et al. 2015; Vandenbosch and Higgins 1996). In order to develop effective skills as tasks become increasingly complex, one's need to practice explorative learning becomes more critical (Klahr and Dunbar 1988). Similarly, studies have found that individuals typically become frustrated when encountering complex and new technologies (Morris and Venkatesh 2010). The new system may change the nature of their job, which in turn may cause frustration for employees who are satisfied with the status quo. In this situation, offering effective training supports individuals in exploring the new system innovatively and improves their persistence in attempts to creatively employ the system (Baer and Oldham 2006). Such innovative responses could take the form of creatively substituting or combining system features to get more relevant results (Sun 2012).

Observational Learning: Behavioral Modeling

Apart from independent exploration, individual learning behaviors are developed through interactions with other users or IS professionals (Vandenbosch et al. 1996). Learning through observing others is one of the most ubiquitous and useful means of decision making available to humans. Bandura’s (1977) observational learning theory and its extension, social cognitive theory, are the most prevalent theories used to understand people's learning processes both in education and in the IS literature. This school of thought suggests that learning occurs through observation, imitation, and feedback processes. It states that the outcome of learning does not just depend on an individual's exposure to a particular behavior, but also on his/her own endeavors in exploring, modifying, and influencing the environment (Bandura 2001). Observational learning occurs when an individual observes the behavior of someone else and concludes something about the significance of that behavior based on those observations. Put differently, the process begins by a learner observing some behavior performed by a model. The learner subsequently attempts to reproduce that behavior by imitating the model's behavior (Bandura 1977).

The literature has outlined two general components of observational learning: (1) observation of self-actions or *enactive learning*, which emphasizes learning through experience, and (2) observing the actions of others, referred to as *behavioral modeling*, which refers to training by observing a predecessor who exhibits the preferred skill or behavior (Yi and Davis 2001). As Yi et al (2003) pointed out behavioral modeling approach indicates that learners build their mental models based on their observation of others performance of the target behavior. This way, individuals learn the target behavior and absorb cognitive skills through witnessing the actual behavior performed by someone.

Herd-like Behavior

Observational learning is the theory most commonly employed to explain convergence behavior, also referred to as herd behavior (Banerjee 1992; Bikhchandani et al. 1992, 1998). Observational learning is a social learning process in which individuals acquire new information by watching others' actions (Bandura 1977). There are numerous situations in IS research and practice in which members of a community make sequential decisions and can observe others' actions. For example, when asked to evaluate peer-to-peer file sharing technologies, individuals have demonstrated a higher intention to adopt the technologies if they observe others' adoption behaviors, even after controlling for the *number* of the prior adopters (Song et al. 2003). When observing the decisions of predecessors, instead of independently seeking out one's own information, becomes optimal for a person (i.e., it reduces uncertainties involved in decision making), she may prefer to imitate their decisions (Bikhchandani et al. 1992, 1994). The behavior of others is deemed relevant when following them offers some benefits to the individual (Walden et al. 2009). For instance, learners can save a great deal of cognitive effort by inferring that if a peer adopts a behavior (here, explorative IT learning), then her personal information must have suggested that the behavior was worth adopting. In the context where the follower personally knows the predecessors (e.g., they are members of the same group; unlike in more traditional herding settings where the follower does *not* personally know the predecessors (Li et al. 2014), the observation of the actual behavior of the peer predecessor affects the decision of the follower and leads to herd-like decisions (Liu et al. 2015).

Research shows that by mimicking the behavioral decisions of people who came before them, followers may attempt to take a "free ride" and avoid incurring their own information search and experimentation costs (Rao et al. 2001). In other words, when an individual sees others adopting a specific behavior (in my case, explorative IT learning), the observational learning perspective proposes that the individual may conclude that the inherent value of the explorative approach in learning is higher than she previously thought. As this revealed information accumulates, the replication of others' behaviors seems like a rational decision to the follower.

Herding: IT Training

I argue that herding theory can help to explain the imitative behavior that occurs in IT training contexts. I can identify the determinants of herding behavior in a team-based training setting, which considers in-group herding. In such settings, peers have more opportunity to actually observe others' learning behaviors. Members of the group may ignore their own private information and follow the behavior of the successful member (i.e., the one who performs the target behavior) in a learning context (Bandura 1986). Team members can also closely monitor the outcome of the adoption of the target behavior by their peer (i.e., explorative learning behavior) after initiation of the target behavior, thus mitigating the risks involved (such as the moral hazard problem; Arnott and Stiglitz 1991). Hence, in smaller groups (in my research context, these are teams of three to five members) where individuals know each other and can observe each other's (i.e., team members') actions, such behavioral observation can be the source of imitation. Please note that this study conceptualizes and operationalizes the "observation" construct as *the observation of the behavior of the team members*, rather than observation of members of other teams or the general public.

The accessibility to others' learning behaviors and the presence of uncertainty about the values of the new technology are considered the primary antecedents of herding in the IS literature (Duan et al. 2009; Sun 2013). The process starts when an individual encounters a new technology to learn. She may initially be skeptical of the benefits of the new system. The existence of inhibitors such as inertia and high switching costs, coupled with the high complexity involved in most novel systems, make learning such systems both challenging and risky. The level of uncertainty might be particularly high in an IT training context where exploration is being emphasized, given the progress in learning will be less obvious and will be delayed compared to other learning approaches (e.g., instruction based learning) (Truman 2009). Hence, uncertain trainees will be more inclined to observe the results of others' behaviors (specifically, that of their team members, in a team training setting) as they undergo training, and by doing so, infer more information with regard to the value of the behaviors that lead to the similar outcome (Kraatz and Zajac 2001).

Accordingly, I argue that my extension of herd theory to the IT training context is useful because of: (1) the important role of observational learning in today's learning approaches, (2) the significance of uncertainty surrounding the emerging technologies on which individuals are being trained today, (3) the increasing emphasis on efficient technology skill acquisition and explorative IS behaviors, and finally, (4) the fact that although technology adoption (hence training) is mostly mandated within organizations, the individual decision to extend usage of that technology, to explore its features, and to revise its use after formal training is completed is volitional (Ahuja et al. 2005; Sun 2012). Hence, I draw from the herding literature in developing a model (Figure 1) that seeks to improve my understanding of individual IS behaviors in the post-adoption stage.

RESEARCH MODEL

Antecedents of Imitation

Prior research has identified that apart from observation of others' behavior, subjective norms can also be considered as a type of the general "influence of others" (Davis et al. 1989). Fishbein et al. (1975, p. 320) defined subjective norm as "a person's perception that most people who are important to him think he should or should not perform the behavior in question". As Sun (2013) emphasizes, a subjective norm captures the role of social influence, which may also considered as an antecedent of imitative behaviors. It is important to note the difference between "observation of others' behavior" and "subjective norms", as two potential factors of imitative decision-making. The information source in development of subjective norm is a decision maker's reference people who may or may not have made the similar decision, while this study considers observation of others' (i.e., team members') behaviors as the factor of herding (Sun 2013). Therefore, subjective norm primarily depends on messages obtained from others (Thompson et al. 1991), which is deferent from the antecedent of herding that this study is interested in, i.e., observation of the *actual* behavior. Hence, in this study I statistically control for the impact of subjective norm on individual's imitation. Moreover, the study conceptualizes and operationalizes observation as the observation of the *actual* behavior of members of the group, rather than the observed popularity of a behavior within the group, which also can be another factor in developing herd-like behaviors.

Observational Learning Processes

Bandura (1977) posits that observational learning occurs through imitation in four steps. First, attention must be devoted to the individual(s) modeling a behavior, and their ongoing action. Second, the observed behavior and its consequences need to be encoded and memorized. Third, the action is reproduced through imitation. Fourth, imitation (i.e., reproduction) is guided by reward and punishment, i.e., the motivational processes. Bandura posits motivation as a stage in the observational learning process that is responsible for the effects of behavioral modeling-based training. The motivation processes refer to the possibility of replication of observably acquired skills. Crossman et al. (2013) found that the motivational processes have a larger influence on IT skill acquisition, due to the relatively high complexity of such knowledge. Motivational processes, as an important component of the learning process, encourage trainees to direct their attention and efforts toward acquiring and reproducing the observed learning behaviors. This component of observational learning process is particularly important in IT training contexts due to the uncertainty involved in explorative IT learning (Gupta and Bostrom 2013).

Insert Figure 1 here

I can apply a herding lens to better explain individual IT learning behaviors since herding theory also emphasizes the role of motivation in following others. One's desire to reduce decision uncertainty is a key motivational factor that encourages herding behavior. Since following others serves to reduce uncertainty, people will be motivated to imitate observed behaviors when they find themselves in a highly uncertain setting (Bikhchandani and Sharma 2000; Fiol and O'Connor 2003; Lieberman and Asaba 2006; Walden et al. 2009). Drawing from observational learning theories, extant IS research has identified two primary antecedents of herding behavior in IS adoption: 1) uncertainty about the value of a technology and 2) observation of others' adoption behaviors. Accordingly, I posit that these factors will also be important antecedents of herding in the IT training context. However, by highlighting the relevance of the observation of *behavior* (rather than observation of popularity) in team contexts, I will investigate the interactive relationship between these two antecedents. The only IS study, to my knowledge, that has empirically tested the *direct* effects of these two antecedents conceptualized "observation of others' actions" as observed *popularity* (Sun 2013).

As mentioned earlier, the behavioral modeling approach to training emphasizes the role of observing others' actions in skill acquisition (Truman 2009). As Yi et al. (2003) point out, a learner performs similar behavior after observing others' behavior. Put differently, I contend that in a context where individuals are being encouraged to independently explore an IT and creatively use its features, observing others doing the same thing may promote imitation of such explorative learning behaviors. Although prior studies have primarily looked at the instructor as the demonstrator (i.e., the "model"), in today's more prevalent team-based learning environments, a teammate can also act as a model. Accordingly, individuals can influence the learning approach of their teammates, because they can observe and adopt similar learning behaviors. The observation of others' decisions has been found to be an influential determinant of followers' intentions to imitate others in a wide variety of IT and non-IT contexts (e.g., Walden and Browne 2009; Yan-ni and Lei

2013). Thus, I would expect observation of the explorative learning approach of one's team members to lead to its imitation in an IT team-training context.

H1: Observation of team members' explorative IS learning behavior will have a positive impact on one's propensity to imitate team members' behavior.

As previously discussed, uncertainty is another factor that may result in imitative IS behaviors (Sun 2013; Duan et al. 2009). The only IS study that has empirically tested the influence of observation (on imitation) conceptualized and operationalized it as observed popularity, and only looked at the direct effect of "observation" on imitation (Sun 2013). However, basing on the observational learning literature, this paper conceptualizes observation as observed (actual) behavior of the predecessor and posits an interactive effect between these two antecedents of herding.

Milliken (1987) has defined uncertainty as an individual's perceived inability to forecast the future precisely due to a lack of information. The complexity of information technology today, and the presence of imperfect information about it, leads to much uncertainty. For example, one might have doubts about what a particular system is to be used for (state uncertainty) or what skills or needed to use it, they might be uncertain as to its potential benefits (effect uncertainty), or they might be uncertain as to whether they will have to deal with potential changes to the system in the future. As new technologies become ever more sophisticated, individuals are faced with more and more difficulties in evaluating their value (Duan et al. 2009).

Apart from the technology itself, the training method may result in higher uncertainty perceptions for learners. Extant studies indicate that learners perceive the outcomes of explorative learning to be unpredictable (Burton-Jones and Grange. 2013). Compared to other forms of training, the learning process is *slower* (Truman 2009), and the provided feedback is *vague* and *delayed* (Goodman et al. 2004). Thus, trainees may have high perceptions of uncertainty in regard to exploratively learning a new system (Burton-Jones and Grange 2013). In the context of IS training, uncertainty may relate to the required skills to use a new system as well as to training outcomes, and thus can be viewed as the extent to which a trainee is unable to correctly predict the potential benefits of the new system due to a lack of information. Hence, it may appear to be a reasonable strategy to simply follow others' seemingly effective learning strategies. Particularly in an experiential learning setting, where learners are being encouraged to explore the features of the system for themselves, imitation of the observed exploratory behaviors of others may help to reduce one's own uncertainty. In the same vein, Li et al. (2014) argue that in the presence of information incompleteness and asymmetry, decision-makers have more incentives to ignore their private information and engage in informational cascades (i.e., mimicking other's observable actions). In an online P2P loan context, Zhan et al. (2012) showed that lenders not only use existing bidding amounts as a herding signal (i.e., representing observation of others' actions), but lenders are also more likely to herd based on these observations of other lenders' behavior when the loan has unfavorable characteristics (e.g., the borrower is a new member to the P2P lending market). Hence, in settings of higher uncertainty, the observation of others' behaviors is more likely to result in imitation of these behaviors. Thus I posit:

H2: Uncertainty will moderate the relationship between observation of team members and propensity for imitation of team members, such that the relationship is stronger for individuals with higher perceptions of uncertainty.

Team Level Effects: Team Cohesion

The group-training context offers individuals the opportunity to observe, comprehend, and imitate other team members' thoughts and ideas (Benbunan-Fich and Hiltz 2003). Extant herding research mostly assumes that one's predecessors are unknown to the follower, and ignores the possibility of social relations between preceding and following decision makers (Liu et al. 2015). This is not the case in team-based learning settings, where there is a social connection among team members that allows individuals to track and observe their teammates' activities. In this section, I discuss one specific characteristic of teams, *team cohesion*, and its link to imitative learning behaviors within teams.

Team cohesion is one of the most extensively studied constructs in the team literature. It represents the extent to which team members demonstrate a sense of belonging to the team, and the strength of their interpersonal relationships (Bolen and Hoyle 1990; Carless and De Paola 2000). In team-based IT learning, team cohesion refers to an individual's affective and cognitive assessments of her relationships with other members (Chin et al. 1999). Team cohesion has been used as an indicator of social integration in prior team-based research, and underlines the importance of interpersonal ties (Hoegl and Proserpio 2004). Put differently, in a cohesive team, members are committed to each other and are motivated to stay in the group. As Janssen and Huang

(2008) indicate, people identify more intensely with a team when they have a sense of emotional involvement within the team and perceive more positive value attached to team membership. This sense of 'oneness' within the team stimulates individual team members to perform in team-oriented ways to promote their collective social identity (Haslam et al. 2000).

Extant research has found team cohesion to be correlated with the degree of perceived emotional safety in relationships and its consequences, e.g., trust and openness within the team (Joo et al. 2012). According to Pinto (2007), trust is a common characteristic of cohesion. Especially in the case of a newly formed team, team cohesion induces a sense of trust and comfort among its members, and promotes a perception that the team can successfully resolve internal conflicts (Yukl et al. 2010). It is reasonable to argue that higher degrees of trust within a team can strengthened the importance of observation of members' behavior in making imitative decisions. Put it differently, one may argue that the observation of the members' learning behavior, in a team setting where members have stronger inter-personal relationships and higher degrees of trust, will more likely to result in herding behaviors.

In addition, when individuals are confronted with a new technology, they seek out more information about it. Information searches can be costly and consume much time and energy (Rao et al. 2001). Particularly in an explorative learning context in which individuals must independently seek out information on how to learn a technology, this cost might seem higher. Some individuals might want to depend on other team members (e.g., replicate their behaviors) in order to mitigate the related costs (Rom and Mikulincer 2003). In particular, belonging to a cohesive team, in which members are more accepting and trusting, might lead individual members to attempt to reduce the costs related to independently conducting an exploration of the technology. Hence, a sensible approach to reduce one's exploration costs is to weigh more on the observation of the actions of the trusted members in replicating those exploration decisions (Brockman et al. 2010).

The risk-reducing nature of herding behavior (Banerjee et al. 1992) acts as a driver of imitative behaviors in team settings. This argument is in line with the reputational-based herding literature (Bikhchandani et al. 2000), which argues that even if an individual makes an incorrect decision by following others (e.g., investing in a less profitable stock), the follower “shares the blame” with her/his predecessors. Obviously, people do not want to be the only one who makes a wrong decision. Research indicates that in a cohesive team, members are highly motivated to contribute to the team goals due the higher sense of “oneness” (Joo et al. 2012). This is especially true for less skillful team members, who follow others’ learning behaviors in order to demonstrate and enhance their contributions (Tsang 2013). Such tendency to demonstrate contribution is higher in the context of explorative learning, which could be perceived as a risky and challenging learning approach (Truman 2009). Hence, one reasonable approach to reducing this risk and also satisfying the tendency of a learner to demonstrate his/her contribution in a cohesive environment (Joo et al. 2012) is to imitate others. In this case, even if the adopted approach is not fruitful, they will share this mistake with other team members and avoid damage to their reputation (Chevalier et al. 1999).

Bandura (1977) developed a model of imitative learning in which he argues that reward and other motivational processes guide imitation. Individuals need to first observe an action then they may imitate to learn it. However, it is also required that they receive reward/punishment to engage in those imitative learning behaviors. As argued above, higher team cohesiveness may provide the needed motivation for a member to imitate the observed behavior (i.e., to improve contribution to the team and to share the blame). Therefore, the level of perceived team cohesiveness, as a motivational factor, can significantly strengthen the extant relationship between observation and imitation for a learner. Thus, I hypothesize that:

H3: Team cohesion will moderate the relationship between observation of team members and propensity for imitation of team members, such that the relationship is stronger for individuals with higher levels of team cohesiveness.

Explorative IS Learning

Extant research has found that individuals often develop distinct patterns of interacting with a system (Sun 2012). Information systems nowadays are more flexible than in the past, and often provide individuals with a number of different ways to carry out similar tasks (Burton-Jones and Grange 2013). For instance, in the case of the statistical package JMP, learners can use a number of different functions to generate the same descriptive statistics for a given data set. Moreover, since many employees today are unwilling to attend IS training courses, they are encouraged to self-select a more explorative learning approach and update their IS knowledge independently (Agarwal et al. 2015). The existence and observability of different patterns of IS exploration provide a rich opportunity for individuals to learn from each other through imitation. In addition, research reveals that individuals are more motivated to imitate their peers (Ryu et al. 2005), particularly the most salient ones (Boudreau et al. 2005), when they encounter a complex system. Literature shows that imitation can influence an individual's decisions. For instance, Sun (2013) found that those who imitate their predecessors' IS behavior are more likely to sustain that behavior in the post-adoption stage. I expect the same phenomenon to apply to my research setting. I.e., when a trainee imitates exploration behaviors, the previously highly challenging task of exploration may seem more feasible, and she may adopt a similar approach to learning afterwards.

Imitating the actions of others through the observational learning process has also been found to increase one's post-training self-efficacy (Yi et al. 2003). In fact, Bandura (1977) postulates that observation of others' behavior is one of the principal information sources for improving one's self-efficacy. Two recent meta-analyses of training studies have found that trainees' self-efficacy is a key variable influencing training outcomes (Colquitt et al. 2000; Santhanam et al. 2013). In the context of IT learning, recent research has found that higher post-training self-efficacy significantly increases post-adoption willingness to further learn and explore a system (Chou et al. 2014; Darban et al. 2016). In fact, development of higher post-training self-efficacy encourages the individual to have higher expectations from herself to overcome barriers (Bandura 1977). Therefore, through influencing self-efficacy levels, imitation can lead to continued explorative learning.

Alongside the elements of observation and imitation, the observational learning literature emphasizes the role of feedback as its third operative mechanism supporting learning (Bandura 1977). One of the more salient characteristics of explorative learning is that feedback is typically delayed and less specific (Goodman et al., 2004). Hence, individuals have to independently seek out supplemental mechanisms as feedback. By imitating successful explorative practices and realizing the ensuing benefits, one may be more likely to continue further exploration in learning a new system. Put differently, in a learning setting where exploration is being rewarded, a person would imitate this approach more willingly if the resultant outcomes, as a form of feedback, were favorable. Such an imitation, when it is accompanied by positive outcomes, could work as a reward for followers to replicate a similar explorative learning approach in the future. However, I should differentiate this form of feedback from the more accurate and continuous form of feedback that a supervisor may provide for a user. It takes time and effort to seek out information and achieve results through explorative learning (Goodman et al. 2004). In this case, imitation may work as a driving factor since individuals have a tendency to avoid the seemingly wrong decision of not following a more effective peer's IS behavior (Boudreau et al. 2005). Therefore, followers behave with tenacity and persistence in the face of obstacles and difficulties when they follow in the footsteps of efficient learners in learning and exploring a system, and this stimulates their expectation of overcoming such obstacles. Imitation not only acts as a mechanism to reduce their learning uncertainty, but also acts as a motivational factor to encourage experimentation with the system. Prior research has found that an individual's level of motivation plays a significant role in the success of the imitative learning process (Bandura 1986). Recent models of imitative learning support this notion by highlighting the goal-oriented and intentional nature of imitations in learning. Thus, in this research I argue that imitation works as mechanism to encourage individuals to proactively explore the system and learn innovative ways of applying the system to best support their daily job tasks.

The focal technology in my study, JMP, is a statistical package that provides a wide spectrum of features for users to explore. Users must expend significant cognitive resources to overcome the knowledge barriers to use JMP effectively. Adding to this challenge, system exploration is usually not clearly specified in job descriptions and depends largely on the initiative of individual users. These characteristics lead individuals to perceive IS exploration behaviors as being highly risky with uncertain outcomes. However, research has found that imitating the learning behaviors of others might instill an individual with higher motivation levels in order to perform on par with them, particularly in a context of doing complex tasks (Benbunan-Fich and Hiltz 2003). The relationship between explorative IS behaviors and motivation has been studied in the past, with results indicating that a motivated user is more likely to be interested in further discovering and learning system features, which in turn will drive her to be open to challenges and willing to take risks (Ke et al. 2012). Jasperson et al. (2005) argue that encountering unfamiliar features triggers active thinking. To achieve this level of thinking, which is required for exploration, individuals should be highly motivated (Liang et al. 2015). Arguing that imitation is a pillar of the learning process (Bandura 1977), I may link it with learners' post-adoptive behaviors. In the next section, I will differentiate between two distinct cognitions that determine an individual's explorative IS behavior.

Intended vs. Expected Exploration in Learning

Intention and expectation represent two distinct cognitions that drive behavior (Venkatesh et al. 2006). Given my focus on sustained post-adoption behavior, I expand the notion of intention and expectation into the continuance domain of IS exploration. I define "*intention to continue* e*xplorative learning"* as a user's conscious plans to engage in continued learning of a system to develop personalized and innovative ways of using it over time. I further define "*expectation to continue explorative learning"* as a user's subjective probability of continuing learning a system exploratively, and finding creative uses based on his or her appraisal of the volitional and non-volitional behavioral determinants. Although these two forms of cognitions are each expected to influence technology exploration, they do so based on fundamentally different orientations, as explained next.

Fishbein and Ajzen (1975) originally described intentions as "people's expectancies about their own behavior in a given setting" (p. 288) and operationalized intentions as the probability that one intends to act. Warshaw and Davis (1985) argued that this conceptualization of intentions does not recognize the common sense notion of intentions held by most people. Accordingly, they re-defined behavioral intention as "the degree to which a person has formulated conscious plans to perform or not perform some specified future behavior" (Warshaw et al. 1985, p. 214). They suggested that intentions correspond most closely to whether an individual has formulated conscious plans to act. This conceptualization of intention takes into account an individual's ability to act and evaluation of the situation in which they must act, in terms of impediments to, or facilitators of, action. They further argued that one's expectations that he or she will act should be a better predictor of actual behavior. Intentions largely tend to focus on one's *internal* beliefs and motivations (Venkatesh et al. 2006), in the presence of volitional factors (Warshaw et al. 1985) that drive behavior. Following this description, "*intention to continue* e*xplorative learning"* reflects a user's internally formulated desire and plan to engage exploratively with the technology over a period of time, which is driven by volitional factors. Prior work has suggested that post-adoption behaviors such as IS exploration tend to be volitional in nature (Ahuja et al. 2005; Magni et al. 2010) although not exclusively so (Jasperson et al. 2005; Thatcher et al. 2011), and are influenced by internally oriented cognitions (Magni et al. 2010).

Empirical studies have demonstrated that while behavioral intention is an important determinant of many behaviors, including system use (see Venkatesh et al. 2003 for a review), it cannot fully account for external elements that may affect the performance of a behavior. The construct of facilitating conditions was thus proposed in order to address the role of external factors (Todd 1995). Facilitating conditions reflects an individual's perceived control over her/his behavior, and thus has considerable overlap with the perceived behavioral control construct from the theory of planned behavior (TPB; Ajzen 1991). Hence, to better evaluate relevant external factors in their unified theory of acceptance and use of technology (UTAUT), Venkatesh et al. (2003) conceptualized facilitating conditions in a much broader fashion by combining constructs from the theory of planned behavior (e.g., perceived behavioral control) and the model of personal computer utilization (e.g., facilitating conditions) (Thompson et al. 1994).

Despite the ability of this more comprehensive, integrative view of "facilitating conditions" to better reflect external elements, the construct suffers from some shortcomings. Specifically, scholars have argued that it does not recognize the incompleteness of information (Sheeran et al. 2003). In other words, in predicting an individual's behavior based on the presence of facilitating conditions, the individual's perceptions of these conditions must accurately and realistically reflect their actual control over that individual's behavior. This is not the case in situations where individuals are faced with incomplete information and/or uncertainty regarding the focal behavior. There are many situations in which one's ability to perform an intended behavior, given total effort, is uncertain. For instance, individuals are faced with incomplete information and uncertainty when they learn and adopt a new technology. It is reasonable to argue that this lack of information is more obvious in explorative IS learning behaviors, in which users must independently engage with the system and the process is unstructured by its very nature (Burton-Jones and Grange 2013).

Furthermore, uncertainty regarding a behavior is stronger when behavioral intentions are formed well in advance of the intended behavior, such that ensuing and unexpected impediments may change one's original intentions (Venkatesh et al. 2006). Decisions to conduct exploration are frequently made at a point in time significantly before the actual explorative behavior takes place, as a person may decide to conduct explorative learning but must first gain the basic knowledge and actual experience through training, and then can continue to learn the system exploratively (Jasperson et al. 2005). This same pattern may occur in my research setting, in that individuals may first observe similar behaviors and imitate them, then may be motivated to conduct more explorative learning on their own at some point in the future. However, while they may intend to conduct explorative learning, the opportunity to do so will arise farther in the future since explorative learning is unstructured with delayed feedbacks and slow progress patterns (Truman 2009). In sum, research indicates that intentions, even in combination with facilitating conditions, may not be a good predictor of behavior in such conditions (Ajzen 1991; Sheeran et al. 2003).

Behavioral expectation – defined as "an individual's self-reported subjective probability of his or her performing a specified behavior, based on his or her cognitive appraisal of volitional and non-volitional behavioral determinants" (Warshaw et al. 1984,

p. 111) – has been incorporated in more recent IS studies to address the limitations of behavioral intention and facilitating conditions in accounting for external factors (Venkatesh et al. 2006; 2008; Maruping et al. 2015). To estimate the probability of performing explorative learning (i.e., the target behavior in my context), individuals evaluate all of the relevant information available to them about the external elements that would affect their likelihood of conducting explorative approach to learning a system. For instance, although an individual may form an intention to continue expending time and effort to discover more innovative ways of using a system, she might abandon this exploration, simply due to a non-supportive working environment (e.g., high workload). Thus, the evaluation of external factors lowers the probability of actually carrying out the intended behavior. Drawing on the above discussions on the role of imitating others' explorative IS behaviors in the presence of external and internal barriers, and also differentiating between two cognitions, I hypothesize that:

H4: *One's propensity to imitate the explorative IS learning behavior of team members will have a positive impact on intention to continue explorative learning.*

H5: *One's propensity to imitate the explorative IS learning behavior of team members will have a positive impact on expectation to continue explorative learning.*

METHODOLOGY

Sample and Participants

To test my research hypotheses, I collected data in the context of an actual team-based IT learning environment. The subjects were undergraduate business students at a large public university in the United States, who had registered in a required course on the fundamentals of business statistics. This course had two main components: lectures and lab sessions. In the lecture sessions, students were learning the basic concepts of statistics and data analysis. Throughout the semester, they attended computer labs to learn a new statistical software package (JMP), and used it to conduct a team-based project that must be completed within the semester. Students were randomly assigned into teams of three to five by the instructor. The objective of the team project was to teach the application of JMP to practical problems. Instructors asked students to use available data sets and prepare them for analysis. Each team came up with their own research questions and hypotheses, and used JMP functions to test them. Teams then reported the output of the JMP functions and discussed the results. Some of the statistical analyses carried out during the project include generation of descriptive statistics, correlation tables, and various plots to visualize relationships, outlier analysis, regression, and ANOVA.

The focal technology was designed to support the development of individuals' data analysis and data interpretation skills. The JMP software package offers a number of different functions and features that produce similar output. For example, there are multiple ways of producing box-plots in JMP (e.g., students could use the "Graph" function that gives only the plot, or they could apply the "Distribution" function that produces the plot as well as other summary statistics).

JMP can also be customized based on a user's needs. For example, users can customize the toolbars and menus to show only the commands that they need, such as removing the SAS option in the File menu if they do not use SAS. Or they might assign a shortcut key to run any command. Another way to customize JMP is to use "add-ins," which simplify deploying and using complicated analyses. The course lab introduced this functionality of JMP and provided students with some examples. For instance, the statistics calculator add-in provides calculators for confidence intervals and hypothesis tests, etc. However, students needed to search for and identify these alternative and more straightforward functions of JMP. These characteristics of JMP made it possible for us to observe students' explorative learning behaviors. Instructors primarily covered the basic concepts of statistics and basic functions of JMP during class sessions. Hence, students should use those basic functions to discover more relevant and personalized features on their own.

Procedure

Data was collected in two phases. In the first phase, which took place in the 8th week after the initial introduction of the system, students were invited to participate in an online survey. At the beginning of the survey, each student was asked to conduct a simple task to situate them in an explorative learning context. This way, they became aware of some of the explorative learning behaviors that they had performed previously (Orlikowski and Yates 2002). Adapting the approach used in Sun's 2012 study, I designed a task that asked participants to write out one instance in which they changed their use of JMP features (see Appendix A for details of the situating task). Students then responded to the questionnaire based on that instance. The survey included items covering individual level constructs including observation, uncertainty, and propensity for imitation. The team-level construct, team cohesion, was also measured in this phase. Control variables captured at this time included subjective norm, personal innovativeness, self-efficacy, and facilitating conditions. The second phase of data collection was conducted eight weeks after the first survey, near the end of the semester. In this phase, students answered questions about the outcome variables (i.e., intention to continue explorative learning, and expectation to continue explorative learning), which measured their propensity to perform sustained exploration of JMP.

Measurement

Individual Level Constructs

The study used previously validated seven-point Likert-type scales. The practice of employing previously validated and published measures of a construct has been commonly used within the IS research community since its earliest days and is widely accepted (Marakas et al. 2007). This practice has been identified as an important path toward building a more rigorous research tradition (Keen 1980), and also ensures content validity (McLaren et al. 2011). I tried to preserve the exact wording of the original items, and as such, only replaced the name of the focal technology with my own (i.e., JMP).

The three items that were used for measuring observation were adapted from Sun (2012). This scale was recently developed for measuring the observation of others' usage behaviors in an IS setting in which individuals are engaging with a new system. I used three items from Sun and Fang (2010) to measure uncertainty. Milikan's seminal 1978 paper conceptualized uncertainty in three dimensions (i.e., state, effect, and response). Basing on this conceptualization, Sun and Fang developed a three-item scale to measure an individual’s perceptions of uncertainty in an IS environment. Each item represents one dimension of the reflectively measured uncertainty construct. I adapted scales from Sun

(2013) to assess propensity for imitation, which Sun simply called "imitating others." These items were developed and validated specifically for use in an IS herding setting.

The two ultimate outcome variables, intention to continue explorative learning and expectation to continue explorative learning, were measured with items taken from Nambisan et al. (1999) and Venkatesh et al. (2008), respectively. To measure intention to continue exploration, Nambisan et al. (1999) developed a scale that captures the extent to which an individual has plans to conduct explorative IS behavior as part of her ongoing routine activities in interacting with a system. This coincides with my conceptualization of this construct, which reflects the person's willingness to continue to exploratively learn ways in which the technology can be incorporated into her tasks. The measures for expectation to continue explorative learning were originally created by Venkatesh et al. (2008) and adapted to fit the IS context. Their study, like mine, bases the conceptualization of this construct on Warsaw et al.'s (1985) definition of behavioral expectation. Maruping et al. (2015) have also used this scale in an IS exploration context. Hence, the scale captures an individual's subjective probability of exploring the technology for application in her tasks on an ongoing basis. The original behavioral expectation scale was adapted to reflect continued explorative learning as the referent behavior.

Team-Level Construct

To measure team cohesion, I used Chin et al.'s (1991) survey questions, which they adapted for use in an IS learning setting based on Bollen and Hoyle's (1990) original scale. I adapted this scale since it has the same focus as I have in my study, which is capturing team members' sense of belonging and their emotional response to such sense. Chin et al. used the scale specifically to test its validity in the context of small student teams (i.e., those with 3 to 5 members) that were learning and using a new technology. The scale demonstrated acceptable psychometric properties when adapted to the small group context.

Team cohesion is a bottom-up emergent phenomenon that results from the interpersonal interactions within groups (Carless and De Paola 2000). Team cohesion results from emergence from the attributes of individual level perceptions of team cohesiveness (Bélanger et al. 2014). In fact, theoretically, team cohesion emerges from the collective cohesiveness of team members, despite the fact that they may have different levels of cohesiveness perceptions (Kozlowski and Chao 2012). Hence, I measured all items at the individual level and then aggregated them to the team level. Aggregating individual-level metrics to create team-level scales is consistent with prior research, both in IS (e.g., Maruping et al. 2015) and psychology (e.g., Ilies et al. 2007). Further, several studies have applied the aggregation approach specifically to measure team cohesion in the past (e.g., Chang et al. 2014; Jong et al. 2014; Kristof-Brown et al. 2014). To garner the aggregated scores, I employed a referent shift consensus approach in wording the items for the team-level construct (Chan 1998). Referent-shift consensus models require individual group members to respond to survey items in reference to a higher-level unit (e.g., team) (Chan, 1998). Thus, rather than asking followers about their individual perceptions, referent-consensus models incorporate a different referent (here the team as a whole). For instance, I asked participants to rate the degree to which they agree with the statement: "Members of my team feel that they belong to this team". I measured team cohesion at the individual level and then aggregated the scores to the team level as this approach has been applied in similar studies (e.g., Venkatesh et al. 2012).

Control Variables

I controlled for the effect of several other constructs at both the individual and team levels of analysis. Previous studies have shown that subjective norms, facilitating conditions, self-efficacy, and personal innovativeness in IT (PIIT) can all have an impact on individuals' IS behaviors (Li 2004; Venkatesh et al. 2003). Despite essential differences with the herding concept, subjective norms (which represent how an individual believes that those important to her will view her as a result of performing the referent behavior) (Thompson et al. 1991; Venkatesh et al. 2003), can also influence a person's decisions. Subjective norms are commonly decomposed into the two aspects of injunctive and descriptive norms. Injunctive norms refer to normative influences in which a behavior is approved by others, whereas descriptive norms refer to normative influences in which a behavior is typically performed by others (Cialdini et al. 1990). To statistically control for the influence of both of these components, four items for injunctive norms and four items for descriptive norms were derived from Rhodes and Coureneya (2003) and Hagger and Chatzisarantis (2005); these scales have previously been used and validated in several IS studies. (e.g., Lazuras et al. 2013; Schmitz et al. 2015). The original survey items have been modified by replacing the name of the focal technology (JMP).

Facilitating conditions, which reflect the availability of resources required to engage in a behavior (Triandis 1979) is an important predictor of individual IS behaviors (Venkatesh et al. 2003), and has been proposed as a construct that partially addresses the role of external factors (Venkatesh et al. 2008). I used the three-item scale that was originally developed and validated by Thompson et al. (1991) specifically for an IS setting.

These items have been further used and validated in prior IT training studies (e.g., Nagai et al. 2007; Teo 2009).

Prior research has also suggested that personal factors may influence individual IS behaviors. Social cognitive theory (Bandura 1977), as one of the most powerful theories of human behavior, identifies self-efficacy as one of the more important personal factors impacting individuals' behavioral intentions. Self-efficacy, defined as "people's judgments of their capabilities to organize and execute courses of action required to attain designated types of performances"(Bandura 1986, p. 391), has been adapted for use in the IS field by Compeau and Higgins (1995), under the name of computer self-efficacy. Their conceptualization of self-efficacy refers to one's judgments of their ability to apply skills in the future. I adapted Compeau and Higgins' (1995) original ten-item scale, which was originally developed for use in an IT training context. Thatcher et al. (2008) conducted a multi-study analysis that found that a six-item scale of self-efficacy (i.e., one that dropped four items from the original set of Compeau et al. (1995) yielded better measurement fit. Hence, I used their same six-item scale to measure an individual's self-efficacy in relation to JMP.

Personal innovativeness in information technology (PIIT) represents "the willingness of an individual to try out any new information technology" (Agarwal and Parsad 1998, p. 206). In the context of IS, higher PIIT levels have been linked with higher usage intentions (Agarwal et al. 2000). Agarwal and Prasad's (1998) four-item scale was used to measure this construct.

At the team level, I controlled for team size, as the number of members on a project team constitutes an important structural variable with potential influences on its social and task processes (Campion et al. 1993). It might be reasonable to assume that in larger teams, members may have more opportunity to observe each other's behavior and consequently imitate each other. However, some research has shown a negative effect of increased team size that makes interactions between team members difficult (Riopelle et al. 2003). Therefore, the role of team size is not clear in my context; hence, I control for its effect on propensity for imitation. Existing research suggests that gender diversity within teams has an influence on team members' communication levels, and on their attitudes and behaviors during group interactions (Bear and Woolly 2011). Moreover, it has been found that women are significantly more interpersonally oriented than man (Eagly and Johnson 1990), which may help to explain the positive effect of gender diversity on team processes and within-team communication. Therefore, I statistically controlled for the influence of the gender makeup (proportion) within each team on propensity for imitation.

Data Analysis

To evaluate the measurement model, I conducted a confirmatory factor analysis (CFA) using AMOS 24.0. I examined the validity and reliability of the scale to further assess the psychometric properties of the measures (Fornell and Larcker 1981). To demonstrate the internal consistency of constructs, composite reliability (CR) values have to be greater than 0.7 (Hair et al. 2009). To evaluate the results of the CFA, several commonly used goodness-of-fit indices were examined (commonly accepted thresholds are shown in parentheses): root mean square error of approximation (RMSEA: between .05 and .08),, comparative fit index (CFI: ≥ .95), normed-fit index (NFI: ≥ .90), Tucker-Lewis index (TLI: ≥ .95), and standardized root mean squared residual (SRMR: ≤ .08) (Hair et al. 2009).

Multi-Level Approach

My study investigates both individual- and team-level factors; therefore, I applied a multilevel approach to testing the research model. Moreover, because individuals belonged to different teams, they were considered to be nested. Given the hierarchically nested structure and the cross-level relationships in the proposed model, hierarchical linear modeling (HLM) is the preferred analytical technique, since it can handle non-independence of observations and can account for variance at different levels of analysis simultaneously, unlike ordinary least square (OLS) techniques (Klein and Kozlowski 2000). HLM has been employed extensively in the management literature and has recently become more popular in IS research (e.g., Rai et al. 2009; Kang et al. 2012; Maruping et al. 2015). HLM enables us to create sub-models for each of the levels of nested data, after which I can assess the impact of each of the levels on the dependent variables.

RESULTS

I distributed surveys to 242 students, representing 78 teams. Out of these 242 respondents, eight marked similar scales throughout, thirteen failed to answer the bogus questions correctly and eleven did not complete the survey. These 32 individuals were thus eliminated from further statistical analysis. In total, 210 surveys in 71 teams from nine classes were judged appropriate for hypothesis testing. In each class, the participants were randomly assigned to seven or eight teams, with each team made up of three to five students. The sample was comprised of approximately 43% females. The average age was 20.7 years, and the average team size was three.

I also checked assignment bias to rule out a possible confounding effect by using the key construct, propensity for imitation. There were no significant differences in propensity for imitation across the classes ($F = 1.48$, $p = 0.19$) or team size ($F = 1.38$, $p = 0.25$). This suggests that there was no assignment bias in terms of class assignment or team size.

The results are presented into two parts. First, I discuss the measurement model to confirm the convergent and discriminant validity, as well as the reliability, of the constructs. I also demonstrate the appropriateness of aggregating the data at the team level and the test for possible common method bias. Then, I discuss the structural model to test the hypothesized relationships among the constructs.

I tested the measurement model using AMOS 24 statistical software, with maximum likelihood estimation. The reliability and validity of the scales were examined via confirmatory factor analysis (CFA), while the strength and direction of the hypothesized causal paths among the constructs were analyzed via hierarchical linear modeling using HLM7 statistical software. Tests for skewness and kurtosis indicated acceptable univariate normality, and no significant outliers were detected (Hair et al. 2009).

Measurement Model

I performed a CFA to assess the psychometric properties of the scales. I evaluated model fit based on multiple fit criteria. As shown in Table B1 in the Appendix, all constructs had composite reliability (CR) scores above the commonly accepted threshold of 0.70, as well as values for average variance extracted (AVE) exceeding 0.50, indicating acceptable convergent validity. Discriminant validity was established based on the square root of AVE for each construct exceeding its correlations with other constructs in the model (Fornell and Larcker, 1981; Hair et al., 2009). To evaluate the overall fit of the CFA model, I checked several commonly used goodness-of-fit indices (Table 1). Values of all indices fell within the accepted thresholds, indicating satisfactory model fit (Hu and Bentler, 1999).

Insert Table 1 here

Common Method Bias

I adopted a longitudinal design for this study which can reduce the impact of common method bias (CMB) to some degree. Compared to cross-sectional design, longitudinal studies are less subject to CMB (Sharma et al. 2009). Also, some prior research has found that the influence of CMB is less severe in a multilevel than in a single-level data set (e.g., Liao and Rupp 2005). Consistent with this view, Ostroff et al. (2002) reported that the influence of CMB appears to be less serious for cross-level correlations. However, following Podsakoff et al. (2003), I took several precautions, both procedural and statistical, to minimize and investigate the potential effect of CMB, and did not find any significant threats of such biases in the data.

First, to increase response candidness, I presented the respondents with detailed information about the precautions taken to ensure the confidentiality of their individual responses. Furthermore, to decrease respondent evaluation apprehension, we assured the respondents that there were no right or wrong answers to the items in the survey. Also, the participants were informed that their responses would be anonymous, assured that there were no right or wrong answers, and requested that they answer questions as honestly as possible. This way I was able to protect respondent anonymity and reduce evaluation apprehension. Second, As Straub (et al. 2004) suggested by randomizing survey items within each survey block, , and also randomized the survey blocks themselves, I counterbalanced them(Straub et al. 2004).

Next, as a statistical procedure, I applied Harman's one-factor test to the data (Podsakoff and Organ 1986). This test includes all observed variables in a single 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), CMB 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 items. No single factor was observed, and no single factor accounted for a majority of the covariance in the variables, suggesting that common method bias is not a major concern in the present study. The emergent factor explained only 12 percent of the variance, indicating no serious problems with method bias.

Since the Harman's test is considered a weak method of determining the extent of CMB (Schwarz et al. 2017), I also added a latent method factor to my CFA, allowing all self-reported items to load on both their respective theoretical constructs and the method factor (Bagozzi 2011). The analysis indicated that the common variance is less than 14 percent. Further, the item loadings on the method factor were statistically insignificant and much lower than the loadings on their respective constructs. The model fit remained essentially similar after the inclusion of a common latent factor (model without common latent factor: $\chi 2$ /d.f. = 1.26, model with common latent factor: $\chi 2$ /d.f. = 1.24).

In order to further investigate CMB, the standardised item loadings of the latent constructs were assessed and compared across the two measurement models, i.e., a model with a common latent factor included and a model without it. Normally, the path estimates in the measurement model without the presence of a common latent factor are higher, as CMB tends to inflate the estimates. CMB is deemed problematic if there are differences in the standardized estimates between the two models which exceed a value of 0.20 (Gaskin 2012). The differences were found to be marginal (<0.20), and thus problematic levels of CMB were ruled out in this study.

Multilevel Validity Testing

As mentioned earlier, the study measured all items of the team level construct at the individual level, and aggregated them to the team level. In order to make certain that I can aggregate individual responses at the team level, I calculated inter-rater reliability using the interclass correlation coefficient (ICC) (Shrout and Fliess 1979) and James' index ($r_{wg(j)}$) (James et al. 1993). The $r_{wg(j)}$ indicates the extent to which within-group agreement among team members is greater than what would be expected by chance (James et al. 1984).

ICCs ensure that there is sufficient between-team variability in the response to survey questions. ICC(1) measures the proportional consistency of total variance in the dependent variable that is accounted for by teams. More specifically, we computed ICC(1) to compare the variance between teams with the variance within teams using the individual responses. ICC(2) assesses the reliability of the team-level means as aggregated from the individual level measures (Bliese, 1998, 2000). Adequately high ICC values demonstrate that a proportion of total variance in a given variable could be accounted for by group membership (i.e., ICC[1]), and that the team-level means were reliable (i.e., ICC[2]) (Bliese 2000). ICC(1) values as low as .06 and ICC(2) values greater than .50 are commonly accepted thresholds (Liao and Chuang 2004).

For our study, the ICC(1) for Team Cohesion was 0.69, suggesting sufficient between-team variation. In addition, the ICC(2) for Team Cohesion was 0.94, indicating excellent reliability of team means. Also, the $r_{wg(j)}$ was 0.93, suggesting good within-group agreement, since it exceeded the value of 0.7, as recommended by James et al. (1984). Overall, the aggregation of individual Team Cohesion to group level is justifiable.

I also calculated the deviance values of the null model (i.e., the model without the team level construct, that creates the baseline for comparing later complex models), and the full model (i.e., the model that includes the team level construct). The value significantly decreased from 597.40 (for the null model) to 502.89 (for the full model). According to Luke (2004), the null model and full model can be compared using the change in deviance values, with reduction in these values signifying better fit.

Moreover, Luke (2004) suggests running a null model to determine if there is enough between-group variance in to justify using such a model. In my null model, Propensity for imitation was used as the dependent variable, with no predictor variables. The null model equation was:

$$\textit{Propensity for imitation}_{ij} = \gamma_{00} + u_{0j} + r_{ij}$$

Where γ_{00} is the random intercept at level 2, u_{0j} is the random error associated with the intercept and r_{ij} the level 1 residual error term. The intra-class coefficient of the null model was 74% with significant intercept component. The fact that the intercept component is significant means that the intraclass correlation coefficient, ICC, is also significant, indicating that a multilevel model is appropriate and needed (Garson 2012).

Hypothesis Testing

I employed HLM to test the cross-level models (H1, H2, and H3) and employed ordinary least squares (OLS) regression to test the individual-level models (H4 and H5). HLM does not allow a multistage approach in testing the models and rather requires separate analyses similar to regression analysis. I utilized the intercepts-as-outcomes model (Model 1 in Table 2) in order to test H1, 2 and 3 using the following cross-level equations:

$$\text{Propensity for imitation} = \beta_{0j} + \beta_{1j}\,(\text{Gender}_{ij}) + \beta_{2j}\,(\text{Age}_{ij}) + \beta_{3j}\,(\text{Self-efficacy}_{ij}) + \beta_{4j}\,(\text{PIIT}_{ij}) + \beta_{5j}\,(\text{SN}_{ij}) + \beta_{6j}\,(\text{FC}_{ij}) + \beta_{7j}\,(\text{Observation}_{ij}) + \beta_{8j}\,(\text{Uncertainty}_{ij}) + \beta_{9j}\,(\text{Uncertainty*Observation}_{ij}) + \varepsilon_{ij}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01}\,(\text{Team cohesion}_{j}) + \gamma_{02}\,(\text{Team-size}_{j}) + \gamma_{03}\,(\text{Gender proportion}_{j}) + u_{0j}$$

$$\beta_{7j} = \gamma_{70} + \gamma_{71}\,(\text{Team cohesion}_{j})$$

The results of my hypothesis testing show that all three of the proposed antecedents to propensity for imitation had significant associations with it as hypothesized (Table 2 and Figure 2). Observation (H1: $\beta = 0.49$; $p < 0.00$) had a significant direct effect on propensity for imitation, supporting H1. H2 and H3 posited that high levels of team cohesion and uncertainty would magnify the positive effect of observation on propensity for imitation. Model 1 indicated that there was a significant cross-level interaction for team cohesion on the relationship between observation and propensity for imitation (H2: $\beta = 0.14$; $p < 0.04$).

I calculated the simple slopes of the interaction effects one standard deviation below and above the mean to assess the nature of the significant interactions (Aiken and West 1991). Simple slope tests show that the simple slope for team members with high levels of team cohesion perceptions ($b = 0.61$; $p < 0.001$), and also the slope for members with low levels of team cohesion perceptions ($b = 0.23$; $p < 0.05$) were both significant, confirming the study's second hypothesis.

In addition, there was a significant moderating effect for uncertainty on the relationship between observation and propensity for imitation (H3: $\beta = 0.11$; $p < 0.02$). The results of the simple slope test indicate that at high levels of perceived uncertainty, the relationship between observation and propensity for imitation is significant ($b = 0.39$; $p < 0.001$), while the slope for individuals with low levels of perceived uncertainty is not ($b = 0.08$; $p = .38$), confirming the third hypothesis that high levels of uncertainty strengthen the positive relationship between observation and propensity for imitation. Figures 3a and 3b graphically illustrate the nature of these interactions.

Next, I used Ordinary Least Squares (OLS) for Model 2&3. Controlling for several variables, propensity for imitation was a significant predictor of both ICE (H4: $\beta = 0.40$; $p < 0.00$) and ECE (H5: $\beta = 0.50$; $p < 0.00$).

Insert Table 2 here

Insert Figure 2 here

It is worth noting that it is not customary to report R^2 values in HLM studies, and HLM software does not display R^2 values in its output (Kang et al. 2012). However, to provide an estimate, one can compare the error terms in the null model (i.e., model with no predictors) and the tested model to obtain the proportion of variance explained by the model. Following the formula suggested by Snijders and Bosker (1999), I found that the change in R^2 for propensity for imitation was 17% (from 52% when only individual level variables were included, to 69% when Team cohesion was added). The change in R^2 represents the proportion of total variance at the individual level (i.e., both within and between groups) that was explained by addition of the group-level factor. Also, Xu (2003) proposed an overall measure of variance accounted for and unlike the above-mentioned approach it does not require specific reference to level-1 or level-2 predictors or outcomes. I found that my cross-level model explains 45% of the variance in propensity for imitation. In addition, 22% of the variance in "Intention to continue explorative learning" and 29% of the variance in "Expectation to continue explorative learning " is explained by the model.

Insert Figure 3 here

DISCUSSION

Organizations reap the benefit of information systems investments from their individual employees' post-adoptive IS behaviors. (Hsieh et al. 2011). Explorative IS behaviors, in which individuals actively revise their usage and discover creative ways of applying the system, extend the potential of the system and enhance task performance (Barki et al. 2007). Accordingly, IS researchers have begun to pay a great deal of attention towards understanding individuals' explorative IS behaviors (e.g., Sun 2012; Maruping et al. 2015). This growing interest in this particular post-adoptive IS behavior is one of the most welcome developments in recent IS scholarship (Ortiz de Guinea et al. 2009). My study has developed a specific concept of explorative system behavior -- explorative IS learning -- to describe users' post-adoptive system use, and has also identified individual and team level triggers to explain development of intention to learn new system, exploratively. The results of my empirical analysis indicate that learners develop intentions to use system features exploratively in response to triggers, under the influence of herding factors.

Major Findings and Contributions

Drawing on the herd behavior literature, I developed a framework (Figure 1) and conducted an empirical test to advance understanding of the determinants of IS explorative learning and, importantly, how a herding context facilitates learners' post-adoptive behaviors. Integrating individual-level technology adoption research with the herd literature, my model considers both individual- and team-level factors that affect individual IS behavior. A series of hypotheses regarding observation, propensity for imitation, and the moderating roles of team cohesion and uncertainty were generated. Drawing from observational learning theory (Bandura 1977), I theorized and studied herd behaviors in small team settings.

All of my hypotheses were supported by the data in my sample. In line with previous research on herding (Sun 2013), I found that higher levels of the observation of others' behavior can lead a team member to imitate them. In addition, I found that the herded actions in a *small* team setting (e.g., with three to five team members in my research context) occur where an individual has more opportunity to observe members' exact behavior. This finding is also consistent with the recent literature on IS herding behavior where, unlike classic herding settings where adopters are anonymous to each other (Li et al. 2014), the follower personally knows the predecessor (Liu et al. 2015).

Uncertainty with respect to exploring a new technology influences the relationship between observation and propensity for imitation. The outcome of IS explorative learning, compared to other forms of learning, is full of uncertainties for a learner, hence observational learning is particularly influential (Gupta et al. 2013). Consistent with this line of research, I found individuals employed herding as a mechanism to mitigate uncertainty. In other words, learners with higher uncertainty perceptions put more weight on the relationship between observation and propensity for imitation.

The significant positive moderating effect of team cohesion on the relationship between observation and propensity for imitation indicates that individuals give more weight to their observations when they have higher team cohesion perceptions. The finding regarding the role of the team-level construct (team cohesion) on the relationship between the individual-level constructs (observation and propensity for imitation) is an important one and warrants further attention. As today's organizational work environment increasingly becomes more collaborative and team-oriented, and as technology training likewise becomes more team-oriented (Senthanam et al. 2013), team level determinants are becoming more relevant. Therefore, team-level factors need to be taken into consideration to better understand and explain individual members' learning and post-adoptive IS behaviors.

My study found significant relationships between propensity for imitation and the individual's behavioral cognitions in the post-adoption phase (i.e., the two ultimate outcomes in my research model). Specifically, the findings revealed the role of herding in individuals' post-adoption explorative IS learning behavior. In a herding setting, propensity for imitation has a significant positive effect on both types of behavioral cognitions, behavioral expectation and behavioral intentions, which are the two distinct drivers of individuals' behaviors (Warsaw et al. 1985). Consistent with prior empirical findings, propensity for imitation had a larger impact on behavioral expectations of the sampled learners, compared to its impact on behavioral intentions. Prior IS studies have likewise argued that contextual and environmental factors (here, herding) have stronger effects on the development of individuals' behavioral expectations in IS settings (Venkatesh et al. 2006).

Theoretical Contributions and Implications for Research

My results also have significant implications for research on herding and its impacts, as I found that the determinants of herding have significant effects on individuals' post-adoptive IS learning behaviors. With these findings, I make important theoretical and practical contributions.

Extant IS adoption research has primarily highlighted the role of an individual's own beliefs on her IS behaviors, and, as a result, does not clearly explain herd behavior (Sun 2013). My study depicts the significance of considering the direct impact of imitation on the development of intentions in the later post-adoptive stage, i.e., exploration. It extends theory and research on herding (e.g., Banerjee 1992; Bikhchandani et al. 1992) by identifying herding in small team settings, where trainees are likely to follow the "wisdom of crowds" when those crowds include their own team members.

My research also has implications for IS post-adoption research, specifically exploration of technology literature. Prior research on exploration intentions has called for more work to identify the antecedent conditions that facilitate its development (e.g., Nambisan et al. 1999; Magni et al. 2010). By theorizing and analyzing the effects of herd factors, I have shown how individual-level cognitions can be shaped by both individuals' personal perceptions and also the team environment in which an individual is embedded. Such a finding is particularly relevant for the stream of research on IS continuance. Indeed, I contribute to the call by Limayem et al. (2007), who pointed to the need for studies that provide a better understanding on how to promote and sustain continued behaviors that may facilitate the exploration of system features in the long run. The contribution of my study in addressing this call is twofold. First, I showed that a motivational state at the team level (i.e., team cohesion) can play an important role in triggering continuance intentions and expectations in individuals, thus demonstrating that contextual characteristics foster long-lasting cognitions that go beyond a one-time event. Second, my study shows how the interactive effect of the factors of herding behavior (i.e., observation and uncertainty) can ultimately lead to formation of the continuance cognitions that have been recognized to be critical for the long-term viability of the system and for the realization of the expected benefits (Li et al. 2013).

Hence, by investigating explorative IS behaviors through the lens of herd theory, the study improves my understanding of such behaviors. In recent years, a considerable amount of attention has been given to investigating post-adoptive behaviors (e.g., Bhattacherjee 2001; Burton-Jones et al. 2006; Limayem et al. 2008; Schmitz et al. 2016). Researchers have applied various perspectives to explain the link between initial adoption and post-adoptive behavior (e.g., belief updating [Kim et al. 2005] and expectation–confirmation [Bhattacherjee 2001]). My study adds to the existing research by presenting a new mechanism by which initial adoption and post-adoptive behavior are connected: propensity for imitation can form post-adoptive explorative behaviors.

Benbasat et al. (2007) indicate that the extant studies on IS adoption are only focused on explaining a single IS behavior as the outcome, i.e. IS use. The extant literature has largely ignored the fact that the ultimate goal of adopting a technology is to improve efficiency, and has rather mostly stopped at investigating the usage phase (Bagozzi, 2007). A better conceptualization of system use has been encouraged, which I am addressing by examining explorative learning behaviors and focusing on the final phase of the IS life cycle (Furneaux et al. 2011).

My results add to the nascent empirical research on IT training and its determinants. Several researchers have suggested that IT training must be viewed from a *process* perspective and have put forth stage-based training frameworks (Compeau et al., 1995; Sein et al., 1997). These frameworks view training as a continuous process where IT training happens at three stages: (1) training that takes place *before* a formal training workshop forms part of the pre-training stage; (2) the training that takes place *during* the formal training stage; and (3) the training that takes place after formal training and belongs to the *post*-training stage. The post-training stage involves exploration of the features of the new technology to improve its usage performance. The process of such explorative learning at the post-training stage has not been examined (Gupta et al. 2013). My study integrates the literature on behavioral modeling, which emphasizes the role of observing others' actions in skill acquisition (Truman 2009) and herd theory to provide a clearer picture of the process of the IS explorative learning at the post-training stage. The significant positive relationships between propensity for imitation and the outcome variables in my research model reveal the importance of (the drivers of) herding as the encouraging factors of exploratively learning. In addition, the longitudinal design of my research has helped to identify and examine the positive impact of behavioral modeling on the later stage of learning through the lens of herding.

Moreover, my study contributes to the IS post-adoption literature by examining the determinants of technology exploration in a *team* context. Recent research has been drawing attention to the importance and benefits of exploration in post-adoption phase (e.g., Hsieh et al. 2011; Li et al. 2013; Magni et al. 2010; Sun 2012), but these efforts have been focused exclusively at the individual level. It is surprising that there were not more explicit quantitative multilevel studies on continued IS behaviors (e.g., Bélanger et al. 2014) given several calls for such research (e.g., Tilson et al. 2010; Yoo, 2010). Examinations of IS behaviors in team settings require consideration of the team environment as well as the individual cognitions that shape post-adoption behaviors such as exploration. Excepting a few research studies, IT research has for the most part focused on individual learning (Santhanam et al. 2013). Hence, adopting a multilevel approach, this study extends earlier IS research by introducing herd theory to the area of team learning.

I identified team cohesion as an important team-level moderator of increased imitation in a herding setting. Specifically, I found that individuals embedded in teams with high levels of team cohesion tended to engage in more imitative explorative behaviors when observing others' similar behaviors compared to individuals embedded in teams with lower levels of team cohesions. These results show that the collective motivation reflected in team cohesion helps to shape individuals' post-adoption behavior and underscores the important role of team context in shaping how individuals interact with technology at the later post-adoption stage. It further reinforces Orlikowski's et al. (1991) argument that people do not work in a vacuum, but instead are influenced by properties of the context in which they operate.

Given my focus on sustained post-adoption behavior, I further expand the notion of intention and expectation into the continuance domain of IS exploration. In introducing behavioral expectation into the IS domain, Venkatesh et al. (2008) emphasized the need for future research to identify antecedents of the construct. My study introduces two pathways through which "imitation" influences two distinct cognitive orientations, (i.e., intentions and expectations to continue explorative learning) in a herding setting at a later IS lifecycle phase. Through the "intentions to continue explorative learning" pathway, propensity for imitation leverages the internally oriented drivers toward engaging with the technology (Venkatesh et al. 2008; Venkatesh et al. 2006). On the other hand, "expectations to continues explorative learning" represents a pathway that incorporates consideration of the external environment that can affect one's probability of engaging with the technology. The results indicate that propensity for imitation is a significant antecedent of both cognitions. Also, propensity for imitation mediates the direct and interactive effects of individual and cross-level drivers of herding on these two cognitions. Hence, the study uncovers a cross-level chain that incorporates both individual and team level determinants of individual's IS exploration behaviors.

As the results of my analysis have shown, my cross-level model explains more variance in “expectation to continue explorative learning”, i.e., 29%, than in “intention to continue explorative learning”, i.e., 22%. This suggests that the investigated factors of herding appear to have a stronger influence on the externally oriented dependent variable (expectation to continue explorative learning) than they do on the internally oriented dependent variable (intention to continue explorative learning). This finding is particularly important because it complements the results of recent research showing that innovative post-adoptive behaviors are more likely to be triggered by external motivational drivers, alongside internal drivers (Li et al. 2013).

Limitations and Directions for Future Research

As with any study, mine has several limitations that must be acknowledged. First the study used survey methods to measure the variables in the model. Naturally, this raises concerns about common method variance. However, I followed several steps in my study design to attempt to alleviate these concerns. One of the variables in the model (team cohesion) was measured using multiple respondents within each team. I also adopted a longitudinal model and separated the measurement of some of the variables in time (Sharma et al. 2009). Moreover, I ran CFA with an unmeasured latent factor to investigate the impact of CMB. However, the study could not completely partial out the potential effect of CMB. Second, while I controlled for a variety of constructs at both the individual and team levels of analysis, there is always the possibility that other factors, for which I did not account, could influence my outcome variables. I believe that the factors the study controlled for at both levels of analysis are theoretically relevant to out research model. Finally, I used a student sample. The homogeneity of background and age in the sample constitutes another limitation. I cannot say whether similar effects would have resulted when examining other age groups.

The findings in this study provide a useful foundation for future research. In this research, I found that herding in smaller team settings can lead to post-adoptive explorative behavioral intentions and expectations. Future research should begin to examine the effect of herding on the later phase of the IS life cycle i.e., the actual explorative behaviors. Further, in this study, I have only investigated the role of one team level construct in studying herding in IT training. Team level constructs have rarely been studied in the IT training context (Santhanam et al. 2013). Thus my study points to a new direction to examine explorative learning in team contexts. Subsequent studies may consider other important team level constructs (e.g., collective efficacy and team empowerment), which have been found to have significant impacts on individuals' explorative behaviors (e.g., Maruping et al. 2015).

Practical Implications

The findings from this research have important practical implications as well. First of all, IT practitioners should be aware of the importance of trainees' team context in shaping their learning behaviors. The trainee's environment plays a key role in determining her/his subsequent IS learning behaviors to explore technology for higher performance (Markus and Silver 2008). Identifying such determinant factors provides a guideline for practitioners to recognize how learners learn and explore a new system that may lead to further performance improvements.

The results further suggest that IT practitioners should consider developing training interventions based on herding behaviors, which address group cognitions and collaborative learning. Employees could be first trained on the basics of complex and new systems in groups of three to five members. Then, these initial collective learning practices can be followed by individual's explorative learning behaviors.

By theorizing and analyzing the effects of team elements, I add to the herding literature by showing how the individual-level cognitions—intention to continue learning and expectation to continue exploration— can be triggered through initiating imitative behaviors. Limited consideration has been given to the mechanisms through which managers can foster desirable explorative learning behaviors. It is possible that by encouraging imitative behaviors, employers can positively influence further explorative learning, which in turn promotes efficiency and performance.

REFERENCES

Abrahamson, E. (1991). Managerial fads and fashions: the diffusion and rejection of innovations. *Academy of Management Review, 16*(3), 586-612.

Abrahamson, E., & Rosenkopf, L. (1993). Institutional and competitive bandwagons: Using mathematical modeling as a tool to explore innovation diffusion. *Academy of Management Review, 18*(3), 487-517.

Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. *Information Systems Research, 9*(2), 204-215.

Aggarwal, R., Kryscynski, D., Midha, V., & Singh, H. (2015). Early to Adopt and Early to Discontinue: The Impact of Self-Perceived and Actual IT Knowledge on Technology Use Behaviors of End Users. *Information Systems Research, 26*(1), 127-144.

Ahuja, M. K., & Thatcher, J. B. (2005). Moving beyond intentions and toward the theory of trying: effects of work environment and gender on post-adoption information technology use. *MIS Quarterly, 29*(3), 427-459.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211.

Alavi, M., Wheeler, B. C., & Valacich, J. S. (1995). Using IT to reengineer business education: An exploratory investigation of collaborative telelearning. *MIS Quarterly*, 293-312.

Allen, I. E., & Seaman, J. (2011). *Going the distance: Online education in the United States, 2011*: ERIC.

Anderson, P. H., & Lawton, L. (2009). Business simulations and cognitive learning: Developments, desires, and future directions. *Simulation & Gaming*, *40*(2), 193-216.

Arnott, R. & Stiglitz, J.E. (1991). Moral hazard and nonmarket institutions: Dysfunctional crowding out of peer monitoring?. *The American Economic Review*, *18*(1),179-190.

Arthur Jr, W., Bennett Jr, W., Edens, P. S., & Bell, S. T. (2003). Effectiveness of training in organizations: a meta-analysis of design and evaluation features. *Journal of Applied Psychology, 88*(2), 234-245.

Ashleigh, M., & Prichard, J. (2012). An integrative model of the role of trust in transactive memory development. *Group & Organization Management, 37*(1), 5-35.

Avgerou, C. (2001). The significance of context in information systems and organizational change. *Information Systems Journal, 11*(1), 43-63.

Baer, M., & Oldham, G. R. (2006). The curvilinear relation between experienced creative time pressure and creativity: moderating effects of openness to experience and support for creativity. *Journal of Applied Psychology, 91*(4), 963-970.

Bala, H., & Venkatesh, V. (2015). Adaptation to information technology: A holistic nomological network from implementation to job outcomes. *Management Science*, *62*(1), 156-179.

Baldwin, T. T. (1992). Effects of alternative modeling strategies on outcomes of interpersonal-skills training. *Journal of Applied Psychology, 77*(2), 147-154.

Bandura, A. (1977). *Social learning theory.* Englewood Cliffs, NJ: Prentice-Hall.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*: Prentice-Hall, Inc.

Bandura, A. (2001). Social cognitive theory: An agentic perspective. *Annual review of psychology, 52*(1), 1-26.

Banerjee, A. V. (1992). A simple model of herd behavior. *The quarterly journal of economics*, *107*(3), 797-817.

Barki, H., Titah, R., & Boffo, C. (2007). Information system use-related activity: An expanded behavioral conceptualization of individual-level information system use. *Information Systems Research, 18*(2), 173-192.

Bear, J.B. and Woolley, A.W. (2011). The role of gender in team collaboration and performance. *Interdisciplinary Science Reviews*, *36*(2), 146-153.

Beaudry, A., & Pinsonneault, A. (2005). Understanding user responses to information technology: A coping model of user adaptation. *MIS Quarterly*, *29*(3), 493-524.

Bélanger, F., Cefaratti, M., Carte, T., & Markham, S. E. (2014). Multilevel research in information systems: Concepts, strategies, problems, and pitfalls. *Journal of the Association for Information Systems*, *15*(9), 614-650.

Benbunan-Fich, R., & Hiltz, S. R. (2003). Mediators of the effectiveness of online courses. *IEEE Transactions on Professional Communication, 46*(4), 298-312.

Bhattacherjee, A. (2001). Understanding information systems continuance: an expectation-confirmation model. *MIS Quarterly*, 25(3), 351-370.

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of political Economy*, *100*(5), 992-1026.

Bikhchandani, S., Hirshleifer, D. & Welch, I. (1998). Learning from the behavior of others: Conformity, fads, and informational cascades. *The Journal of Economic Perspectives*, *12*(3),151-170.

Bikhchandani, S., & Sharma, S. (2000). Herd behavior in financial markets. *IMF Staff papers*, *47*(3), 279-310.

Bliese, P. D. (2000). Within-group agreement, non-independence, and reliability: Implications for data aggregation and analysis. In K. J. Klein, & S. W. J. Kozlowski (Eds.), Multilevel theory, research, and methods in organizations (pp. 349–381). San Francisco, CA: Jossey-Bass

Bollen, K. A., & Hoyle, R. H. (1990). Perceived cohesion: A conceptual and empirical examination. *Social forces*, *69*(2), 479-504.

Boudreau, M.-C., & Robey, D. (2005). Enacting integrated information technology: A human agency perspective. *Organization Science, 16*(1), 3-18.

Brockman, B. K., Rawlston, M. E., Jones, M. A., & Halstead, D. (2010). An exploratory model of interpersonal cohesiveness in new product development teams. *Journal of Product Innovation Management, 27*(2), 201-219.

Bueno, S., & Salmeron, J. L. (2008). TAM-based success modeling in ERP. *Interacting with Computers, 20*(6), 515-523.

Burton-Jones, A., & Grange, C. (2013). From use to effective use: a representation theory perspective. *Information Systems Research, 24*(3), 632-658.

Burton-Jones, A., & Straub Jr, D. W. (2006). Reconceptualizing system usage: An approach and empirical test. *Information Systems Research, 17*(3), 228-246.

Campion, M.A., Medsker, G.J. & Higgs, A.C. (1993). Relations between work group characteristics and effectiveness: Implications for designing effective work groups. *Personnel Psychology*, *46*(4), 823-847.

Carless, S. A., & De Paola, C. (2000). The measurement of cohesion in work teams. *Small group research, 31*(1), 71-88.

Carroll, J.M., & Mack, R.L. (1984). Learning to Use a Word Processor: By Doing, By Thinking and By Knowing. *Human Factors in Computer Systems,* J.C. Thomas and M.L. Schneider (eds.), Ablex, Norwood, NJ, 13-51.

Chan, D. (1998). Functional relations among constructs in the same content domain at different levels of analysis: A typology of composition models. *Journal of Applied Psychology, 83*(2), 234-246.

Chang, S., Jia, L., Takeuchi, R., & Cai, Y. (2014). Do high-commitment work systems affect creativity? A multilevel combinational approach to employee creativity. *Journal of Applied Psychology*, *99*(4), 665-680.

Chang, T.-H., & Wang, T.-C. (2009). Using the fuzzy multi-criteria decision making approach for measuring the possibility of successful knowledge management. *Information Sciences, 179*(4), 355-370.

Chen, Z., Takeuchi, R. & Shum, C., 2013. A social information processing perspective of coworker influence on a focal employee. *Organization Science*, *24*(6), pp.1618-1639.

Child, J. T., & Shumate, M. (2007). The impact of communal knowledge repositories and people-based knowledge management on perceptions of team effectiveness. *Management Communication Quarterly, 21*(1), 29-54.

Chin, W. W., Salisbury, W. D., Pearson, A. W., & Stollak, M. J. (1999). Perceived cohesion in small groups adapting and testing the perceived cohesion scale in a small-group setting. *Small Group Research, 30*(6), 751-766.

Chou, H.-W., Chang, H.-H., Lin, Y.-H., & Chou, S.-B. (2014). Drivers and effects of post-implementation learning on ERP usage. *Computers in Human Behavior, 35*, 267-277.

Colquitt, J. A., LePine, J. A., & Noe, R. A. (2000). Toward an integrative theory of training motivation: a meta-analytic path analysis of 20 years of research. *Journal of Applied Psychology, 85*(5), 678-707.

Cooper, R. B., & Zmud, R. W. (1990). Information technology implementation research: a technological diffusion approach. *Management Science, 36*(2), 123-139.

Darban, M., Kwak, D.H.A., Deng, S.L., Srite, M. & Lee, S., 2016. Antecedents and consequences of perceived knowledge update in the context of an ERP simulation game: A multi-level perspective. *Computers & Education*, *103*, 87-98.

Davis, F. D., & Yi, M. Y. (2004). Improving computer skill training: behavior modeling, symbolic mental rehearsal, and the role of knowledge structures. *Journal of Applied Psychology, 89*(3), 509-523.

Eagly, A.H. & Johnson, B.T. (1990). Gender and leadership style: A meta-analysis. *Psychological Bulletin*, *108*(2), 233-256.

Fiol, C. M., & O'Connor, E. J. (2003). Waking up! Mindfulness in the face of bandwagons. *Academy of Management Review, 28*(1), 54-70.

Fishbein, Martin & Icek Ajzen (1975), *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research*. Reading, MA: Addison-Wesley.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39-50.

Franceschi, K., Lee, R. M., Zanakis, S. H., & Hinds, D. (2009). Engaging group e-learning in virtual worlds. *Journal of Management Information Systems, 26*(1), 73-100.

Furneaux, B., & Wade, M. (2011). An Exploration of Organizational Level Information Systems Discontinuance Intentions. *MIS Quarterly 35*(3), 573-598.

Gallego, M. D., Bueno, S., Racero, F. J., & Noyes, J. (2015). Open source software: The effects of training on acceptance. *Computers in Human Behavior, 49*, 390-399.

Garson, G. D. (2012). *Hierarchical linear modeling*. Thousand Oaks, CA: SAGE Publications, Inc.

Gaskin, J., (Year video uploaded). *Common method bias using common latent factor,*

Gaskination's Statistics. http://youtube.com/Gaskin

Goldstein, I. L., & Ford, J. K. (2002). *Training in organizations: Needs assessment, development, and evaluation*. Belmont, CA: Wadsworth.

Goodman, J. S., Wood, R. E., & Hendrickx, M. (2004). Feedback specificity, exploration, and learning. *Journal of Applied Psychology, 89*(2), 248-272

Griffith, T. L. (1999). Technology features as triggers for sensemaking. *Academy of Management Review, 24*(3), 472-488.

Gupta, S., & Bostrom, R. (2013). Research Note-An Investigation of the Appropriation of Technology-Mediated Training Methods Incorporating Enactive and Collaborative Learning. *Information Systems Research, 24*(2), 454-469.

Gupta, S., Bostrom, R. P., & Huber, M. (2010). End-user training methods: what we know, need to know. *ACM SIGMIS Database, 41*(4), 9-39.

Haslam, S. A., Powell, C., & Turner, J. (2000). Social identity, self-categorization, and work motivation: rethinking the contribution of the group to positive and sustainable organisational outcomes. *Applied Psychology, 49*(3), 319-339.

Heerwagen, J., Kelly, K. & Kampschroer, K. (2007). The Changing Nature of Organisations, Work, and Workplace. *Holland (http://www. wbdg. org/design/chngorgwork. php)*.

Hirunyawipada, T., Paswan, A. K., & Blankson, C. (2015). Toward the development of new product ideas: asymmetric effects of team cohesion on new product ideation. *Journal of Business & Industrial Marketing, 30*(7), 855-866.

Hoegl, M., & Proserpio, L. (2004). Team member proximity and teamwork in innovative projects. *Research Policy, 33*(8), 1153-1165.

Hsieh, J. P.-A., Rai, A., & Xu, S. X. (2011). Extracting business value from IT: A sensemaking perspective of post-adoptive use. *Management Science, 57*(11), 2018-2039.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1-55.

Hülsheger, U. R., Anderson, N., & Salgado, J. F. (2009). Team-level predictors of innovation at work: a comprehensive meta-analysis spanning three decades of research. *Journal of Applied Psychology, 94*(5), 1128-1145.

Ilies, R., Wagner, D. T., & Morgeson, F. P. (2007). Explaining affective linkages in teams: individual differences in susceptibility to contagion and individualism-collectivism. *Journal of Applied Psychology, 92*(4), 1140-1148.

James, L. R., Demaree, R. G., & Wolf, G. (1984). Estimating within-group interrater reliability with and without response bias. *Journal of Applied Psychology, 69*(1), 85-98.

Janssen, O., & Huang, X. (2008). Us and me: Team identification and individual differentiation as complementary drivers of team members' citizenship and creative behaviors. *Journal of Management, 34*(1), 69-88.

Jasperson, J. S., Carter, P. E., & Zmud, R. W. (2005). A comprehensive conceptualization of post-adoptive behaviors associated with information technology enabled work systems. *MIS Quarterly, 29*(3), 525-557.

Jong, J. P., Curşeu, P. L., & Leenders, R. T. A. (2014). When do bad apples not spoil the barrel? Negative relationships in teams, team performance, and buffering mechanisms. *Journal of Applied Psychology*,*99*(3), 514-522.

Joo, B. K. B., Song, J. H., Lim, D. H., & Yoon, S. W. (2012). Team creativity: the effects of perceived learning culture, developmental feedback and team cohesion. *International Journal of Training and Development, 16*(2), 77-91.

Kang, S., Lim, K. H., Kim, M. S., & Yang, H.-D. (2012). Research Note-A Multilevel Analysis of the Effect of Group Appropriation on Collaborative Technologies Use and Performance. *Information Systems Research, 23*(1), 214-230.

Kazanjian, R. K., Drazin, R., & Glynn, M. A. (2000). Creativity and technological learning: the roles of organization architecture and crisis in large-scale projects. *Journal of Engineering and Technology Management, 17*(3), 273-298.

Ke, W., Tan, C.-H., Sia, C.-L., & Wei, K.-K. (2012). Inducing intrinsic motivation to explore the enterprise system: The supremacy of organizational levers. *Journal of Management Information Systems, 29*(3), 257-290.

Klahr, D., & Dunbar, K. (1988). Dual space search during scientific reasoning. *Cognitive Science, 12*(1), 1-48.

Klein, K. J., & Kozlowski, S. W. (2000). From micro to meso: Critical steps in conceptualizing and conducting multilevel research. *Organizational Research Methods, 3*(3), 211-236.

Kozlowski, S. W., & Chao, G. T. (2012). The dynamics of emergence: Cognition and cohesion in work teams. *Managerial and Decision Economics*,*33*(5-6), 335-354.

Kraatz, M. S., & Zajac, E. J. (2001). How organizational resources affect strategic change and performance in turbulent environments: Theory and evidence. *Organization Science, 12*(5), 632-657.

Kristof-Brown, A. L., Seong, J. Y., Degeest, D. S., Park, W. W., & Hong, D. S. (2014). Collective fit perceptions: A multilevel investigation of person–group fit with individual-level and team-level outcomes. *Journal of Organizational Behavior*, *35*(7), 969-989.

Lazuras, L., Barkoukis, V., Ourda, D. & Tsorbatzoudis, H. (2013). A process model of cyberbullying in adolescence. *Computers in Human Behavior*, *29*(3), 881-887.

Lee, G., DeLone, W., & Espinosa, J. A. (2006). Ambidextrous coping strategies in globally distributed software development projects. *Communications of the ACM, 49*(10), 35-40.

Lee, Y. J., Hosanagar, K., & Tan, Y. (2015). Do I follow my friends or the crowd? Information cascades in online movie ratings. *Management Science*, *61*(9), 2241-2258.

Lieke, L., Johns, G., Lyons, B.J. & ter Hoeven, C.L. (2016). Why and when do employees imitate the absenteeism of co-workers?. *Organizational Behavior and Human Decision Processes*, *134*, 16-30.

Lewis, L. K., & Seibold, D. R. (1993). Innovation modification during intraorganizational adoption. *Academy of Management Review, 18*(2), 322-354.

Li, X., Kauffman, R.J., Yu, F. & Zhang, Y. (2014). Externalities, incentives and strategic complementarities: understanding herd behavior in IT adoption. *Information Systems and e-Business Management*, *12*(3), 443-464.

Liang, H., Peng, Z., Xue, Y., Guo, X., & Wang, N. (2015). Employees' Exploration of Complex Systems: An Integrative View. *Journal of Management Information Systems, 32*(1), 322-357.

Liao, H. & Subramony, M. (2008). Employee customer orientation in manufacturing organizations: joint influences of customer proximity and the senior leadership team. *Journal of Applied Psychology*, *93*(2), 317-328.

Lieberman, M. B., & Asaba, S. (2006). Why do firms imitate each other? *Academy of Management Review, 31*(2), 366-385.

Lim, K. H., Ward, L. M., & Benbasat, I. (1997). An empirical study of computer system learning: Comparison of co-discovery and self-discovery methods. *Information Systems Research, 8*(3), 254-272.

Limayem, M., Hirt, S. G., & Cheung, C. M. (2007). How habit limits the predictive power of intention: the case of information systems continuance. *MIS Quarterly*, 705-737.

Liu, D., Brass, D., & Chen, D. (2015). Friendships in Online Peer-to-Peer Lending: Pipes, Prisms, and Relational Herding. *MIS Quarterly, 39*(3), 729-742.

Luke, D. A. (2004). *Multilevel modeling* (Vol. 143). Thousand Oaks: Sage Publications.

McLaren, T.S., Head, M.M., Yuan, Y. & Chan, Y.E. (2011). A multilevel model for measuring fit between a firm's competitive strategies and information systems capabilities. *MIS Quarterly*, *35*(4), 909-929.

Magni, M., Taylor, M. S., & Venkatesh, V. (2010). 'To play or not to play': A cross-temporal investigation using hedonic and instrumental perspectives to explain user intentions to explore a technology. *International Journal of Human-Computer Studies, 68*(9), 572-588.

Markus, M. L., & Robey, D. (1988). Information technology and organizational change: causal structure in theory and research. *Management Science, 34*(5), 583-598.

Maruping, L. M., & Magni, M. (2015). Motivating Employees to Explore Collaboration Technology in Team Contexts. *MIS Quarterly, 39*(1), 1-16.

Mikulincer, M., & Shaver, P. R. (2007). Boosting attachment security to promote mental health, prosocial values, and inter-group tolerance. *Psychological Inquiry, 18*(3), 139-156.

Milliken, F. J. (1987). Three types of perceived uncertainty about the environment: State, effect, and response uncertainty. *Academy of Management Review, 12*(1), 133-143.

Morris, M. G., & Venkatesh, V. (2010). Job characteristics and job satisfaction: understanding the role of enterprise resource. *Management Information Systems Quarterly, 34*(1), 143-161.

Mullen, B., & Copper, C. (1994). The relation between group cohesiveness and performance: An integration. *Psychological Bulletin, 115*(2), 210-227.

Ngai, E. W. T., Poon, J. K. L., & Chan, Y. H. C. (2007). Empirical examination of the adoption of WebCT using TAM. *Computers and Education*, 48(2), 250–267

Nambisan, S., Agarwal, R., & Tanniru, M. (1999). Organizational mechanisms for enhancing user innovation in information technology. *MIS Quarterly*, 365-395.

Oh, W. & Jeon, S. (2007). Membership herding and network stability in the open source community: The Ising perspective. *Management Science*, *53*(7), 1086-1101.

Orlikowski, W. J., & Robey, D. (1991). Information technology and the structuring of organizations. *Information Systems Research, 2*(2), 143-169.

Orlikowski, W. J., & Yates, J. (2002). It's about time: Temporal structuring in organizations. *Organization Science, 13*(6), 684-700.

Ostroff, C., Kinicki, A.J. & Clark, M.A. (2002). Substantive and operational issues of response bias across levels of analysis: an example of climate-satisfaction relationships. *Journal of Applied Psychology*, *87*(2), 355–368

Pelled, L. H., Eisenhardt, K. M., & Xin, K. R. (1999). Exploring the black box: An analysis of work group diversity, conflict and performance. *Administrative Science Quarterly, 44*(1), 1-28.

Pinto, J. K. (2007). *Project management: achieving competitive advantage, 6* (4), 570-572.

Rao, H., Greve, H. R., & Davis, G. F. (2001). Fool's gold: Social proof in the initiation and abandonment of coverage by Wall Street analysts. *Administrative Science Quarterly, 46*(3), 502-526.

Robey, D., Ross, J. W., & Boudreau, M.-C. (2002). Learning to implement enterprise systems: An exploratory study of the dialectics of change. *Journal of Management Information Systems, 19*(1), 17-46.

Rohrbeck, C. A., Ginsburg-Block, M. D., Fantuzzo, J. W., & Miller, T. R. (2003). Peer-assisted learning interventions with elementary school students: A meta-analytic review. *Journal of Educational Psychology, 95*(2), 240-257.

Rom, E., & Mikulincer, M. (2003). Attachment theory and group processes: the association between attachment style and group-related representations, goals, memories, and functioning. *Journal of Personality and Social Psychology, 84*(6), 1220-1235.

Ryu, C., Kim, Y. J., Chaudhury, A., & Rao, H. R. (2005). Knowledge acquisition via three learning processes in enterprise information portals: learning-by-investment, learning-by-doing, and learning-from-others. *MIS Quarterly*, *29*(2), 245-278.

Santhanam, R., Yi, M. Y., Sasidharan, S., & Park, S.-H. (2013). Toward an Integrative Understanding of Information Technology Training Research across Information Systems and Human-Computer Interaction: A Comprehensive Review. *AIS Transactions on Human-Computer Interaction, 5*(3), 134-156.

Schmitz, B., Schuffelen, P., Kreijns, K., Klemke, R. & Specht, M. (2015). Putting yourself in someone else's shoes: The impact of a location-based, collaborative role-playing game on behaviour. *Computers & Education*, *85*, 160-169.

Schmitz, K., Teng, J. T., & Webb, K. (2016). Capturing the Complexity of Malleable IT Use: Adaptive Structuration Theory for Individuals. *MIS Quarterly*, *40*(3), 663-686.

Seddon, P. B., Calvert, C., & Yang, S. (2010). A multi-project model of key factors affecting organizational benefits from enterprise systems. *MIS Quarterly, 34*(2), 305-328.

Sethi, R., & Nicholson, C. Y. (2001). Structural and contextual correlates of charged behavior in product development teams. *Journal of Product Innovation Management, 18*(3), 154-168.

Sharma, R., & Yetton, P. (2003). The contingent effects of management support and task interdependence on successful information systems implementation. *MIS Quarterly*, 533-556.

Sharma, R., & Yetton, P. (2007). The contingent effects of training, technical complexity, and task interdependence on successful information systems implementation. *MIS Quarterly*, 219-238.

Sheeran, P., Trafimow, D., & Armitage, C. J. (2003). Predicting behaviour from perceived behavioural control: Tests of the accuracy assumption of the theory of planned behaviour. *British Journal of Social Psychology, 42*(3), 393-410.

Schwarz, A., Rizzuto, T., Carraher-Wolverton, C., Roldán, J.L. & Barrera-Barrera, R. (2017). Examining the Impact and Detection of the Urban Legend of Common Method Bias. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems*, *48*(1), 93-119.

Song, J. and Walden, E. (2003). Consumer behavior in the adoption of peer-to-peer technologies: an empirical examination of information cascades and network externalities. *AMCIS 2003 Proceedings*, 1801-1810.

Souder, W. E., & Moenaert, R. K. (1992). Integrating Marketing And R&D Project Personnel Within Innovation Projects: An Information Uncertainty Model. *Journal of Management Studies, 29*(4), 485-512.

Stone, R. W., & Baker-Eveleth, L. (2013). Students' expectation, confirmation, and continuance intention to use electronic textbooks. *Computers in Human Behavior, 29*(3), 984-990.

Sun, H. (2012). Understanding user revisions when using information system features: adaptive system use and triggers. *MIS Quarterly, 36*(2), 453-478.

Sun, H. (2013). A longitudinal study of herd behavior in the adoption and continued use of technology. *MIS Quarterly, 37*(4), 1013-1041.

Sun, H., and Fang, Y. (2010). Toward a Model of Mindfulness in Technology Acceptance," in *Proceedings of the 31st International Conference on Information Systems* (ICIS). St. Louis, MO.

Sun, Y., & Bhattacherjee, A. (2011). Multi-level analysis in information systems research: the case of enterprise resource planning system usage in China. *Enterprise Information Systems, 5*(4), 469-494.

Sykes, T. A. (2015). Support Structures And Their Impacts On Employee Outcomes: A Longitudinal Field Study Of An Enterprise System Implementation. *MIS Quarterly, 39*(2), 473-495.

Sykes, T. A., Venkatesh, V., & Gosain, S. (2009). Model of acceptance with peer support: A social network perspective to understand employees' system use. *MIS Quarterly*, (33:2), 371-393.

Taylor, P. J., Russ-Eft, D. F., & Chan, D. W. (2005). A meta-analytic review of behavior modeling training. *Journal of Applied Psychology, 90*(4), 692-709.

Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. *Information Systems Research, 6*(2), 144-176.

TE'ENI, D., Carey, J., & Zhang, P. (2007). Human Computer Interaction: Developing Effective Organizational Information Systems. John Wiley& Sons. New York, NY.

Teo, T. (2009). Modelling technology acceptance in education: A study of pre-service teachers. *Computers & Education*, *52*(2), 302-312.

Thatcher, J. B., McKnight, D. H., Baker, E. W., Arsal, R. E., & Roberts, N. H. (2011). The role of trust in postadoption it exploration: An empirical examination of knowledge management systems. *IEEE Transactions on Engineering Management, 58*(1), 56-70.

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1994). Influence of experience on personal computer utilization: testing a conceptual model. *Journal of Management Information Systems*, *11*(1), 167-187.

Tilson, D., Lyytinen, K., & Sørensen, C. (2010). Research commentary—Digital infrastructures: The missing IS research agenda. *Information Systems Research*, *21*(4), 748-759.

Truman, G. E. (2009). Behaviour modelling, instruction and exploration training approaches in group and individual contexts. *Behaviour & Information Technology, 28*(6), 493-524.

Tsang, A. K. T. (2013). *Learning to Change Lives: The Strategies and Skills Learning and Development Approach*. University of Toronto Press.

Tyre, M. J., & Orlikowski, W. J. (1994). Windows of opportunity: Temporal patterns of technological adaptation in organizations. *Organization Science, 5*(1), 98-118.

Vandenbosch, B., & Higgins, C. (1996). Information acquisition and mental models: An investigation into the relationship between behaviour and learning. *Information Systems Research, 7*(2), 198-214.

Venkatesh, V., Brown, S. A., Maruping, L. M., & Bala, H. (2008). Predicting different conceptualizations of system use: the competing roles of behavioral intention, facilitating conditions, and behavioral expectation. *MIS Quarterly*, 32(3), 483-502.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425-478.

Venkatesh, V., & Speier, C. (2000). Creating an effective training environment for enhancing telework. *International Journal of Human-Computer Studies, 52*(6), 991-1005.

Venkatesh, V., Thong, J. Y., Chan, F. K., Hu, P. J. H., & Brown, S. A. (2011). Extending the two-stage information systems continuance model: incorporating UTAUT predictors and the role of context. *Information Systems Journal, 21*(6), 527-555.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157-178.

Venkatesh, V. & Windeler, J.B., 2012. Hype or help? A longitudinal field study of virtual world use for team collaboration. *Journal of the Association for Information Systems*, *13*(10), 735-771.

Walden, E. A., & Browne, G. J. (2009). Sequential adoption theory: a theory for understanding herding behavior in early adoption of novel technologies. *Journal of the Association for Information Systems, 10*(1), 31-62.

Warshaw, P. R., & Davis, F. D. (1985). Disentangling behavioral intention and behavioral expectation. *Journal of Experimental Social Psychology, 21*(3), 213-228.

Xu, R. (2003). Measuring explained variation in linear mixed effects models. *Statistics in Medicine*, *22*(22), 3527-3541.

Yi, M. Y., & Davis, F. D. (2001). Improving Computer Training Effectiveness for Decision Technologies: Behavior Modeling and Retention Enhancement*. *Decision Sciences, 32*(3), 521-544.

Yi, M. Y., & Davis, F. D. (2003). Developing and validating an observational learning model of computer software training and skill acquisition. *Information Systems Research, 14*(2), 146-169.

Yoo, Y. (2010). Computing in everyday life: a call for research on experiential computing. *MIS Quarterly*, *34*(2), 213-231.

Yukl, G., & Mahsud, R. (2010). Why flexible and adaptive leadership is essential. *Consulting Psychology Journal: Practice and Research, 62*(2), 81-93.

APPENDICES

Table 1. Goodness-of-Fit indicators of proposed model

Measure	MIN/DF	CFI	SRMR	RMSEA	PClose	TLI
Threshold	Between 1 and 3	>0.95	<0.08	<0.06	>0.05	>0.95
Estimate	1.26	0.975	0.05	0.035	0.993	0.97

Table 2. Results of Hypothesis Testing

Independent variables	Dependent variables											
	Model 1 Propensity for imitation				Model 2 Intention to continue explorative learning				Model 3 Expectation to continue explorative learning			
	Coef.	SE	*t*-ratio	*p*	Coef.	SE	*t*-ratio	*p*	Coef.	SE	*t*-ratio	*p*
Intercept	5.11	0.09	51.22	0.000								
Team level effects												
Team cohesion	0.25	0.06	3.92	0.000								
Observation * Team Cohesion	0.14	0.03	2.04	0.043[b]								
Team size	0.17	0.17	0.98	0.331								
Gender proportion	-0.77	0.42	-1.81	0.075								
Individual level effects												
Propensity for imitation					.40	0.6	6.19	0.000[d]	.50	.06	8.32	0.000[e]
Observation	0.49	0.03	13.07	0.000[a]								
Uncertainty	0.43	0.045	9.59	0.000								
Observation * Uncertainty	0.11	0.04	2.36	0.020[C]								
Gender (0 = female)	0.08	0.08	1.04	0.296	-0.02	0.12	-0.32	0.751	-0.03	.11	-0.61	0.541
Age	-0.00	0.02	-0.19	0.845	-0.02	0.03	-0.36	0.717	0.02	0.03	0.35	0.726
Self-efficacy	-0.00	0.02	-0.25	0.800	-0.02	0.06	-0.35	0.725	0.02	0.05	0.36	0.721
Personal Innovativeness	-0.01	0.04	-0.41	0.674	0.12	0.06	2.03	0.043	0.07	0.06	1.21	0.228
Subjective Norms	0.00	0.04	-0.08	0.936	-0.01	0.05	-0.15	0.870	0.08	0.06	1.23	0.219
FC	0.05	0.03	-1.53	0.127	0.15	0.06	2.37	0.019	0.10	0.06	1.77	0.079
Model type	HLM				OLS				OLS			
Deviance	502.89[f]				-				-			

Notes: FC: Facilitating Conditions; N = 71 (Team level), N = 210 (Individual level)
[a] Statistics for testing H1.
[b] Statistics for testing H2.
[c] Statistics for testing H3.
[d] Statistics for testing H4.
[e] Statistics for testing H5.
[f] Deviance for null model = 597.40

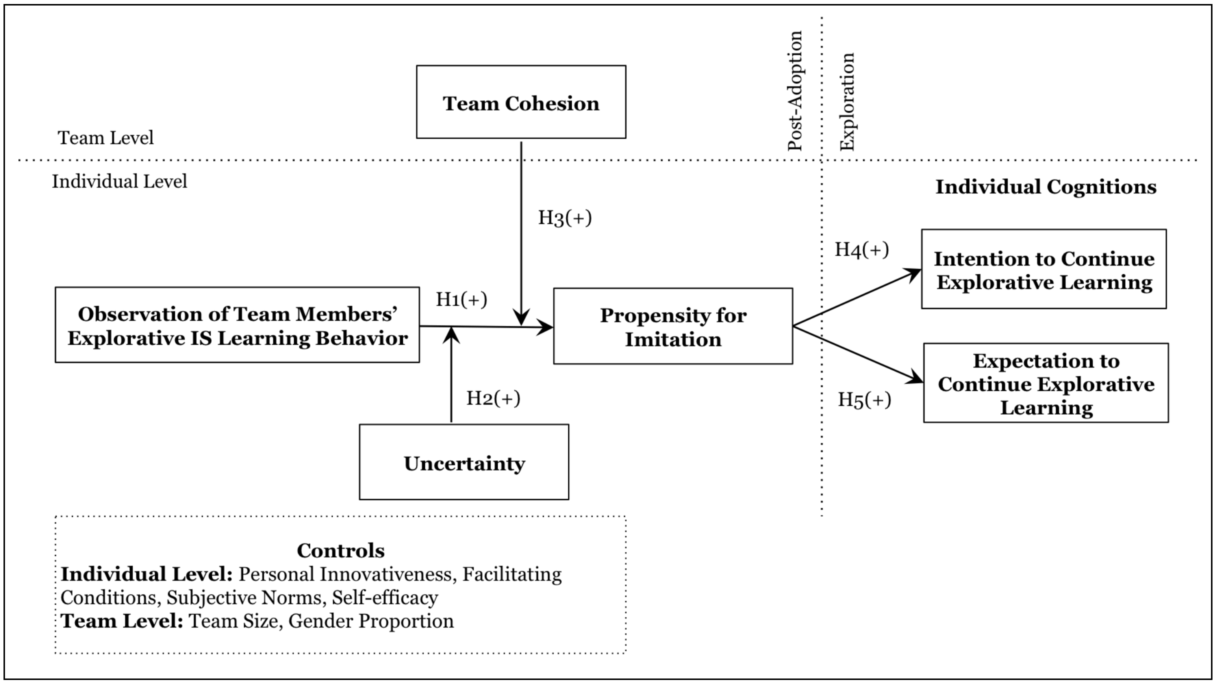


Figure 1. Research Model

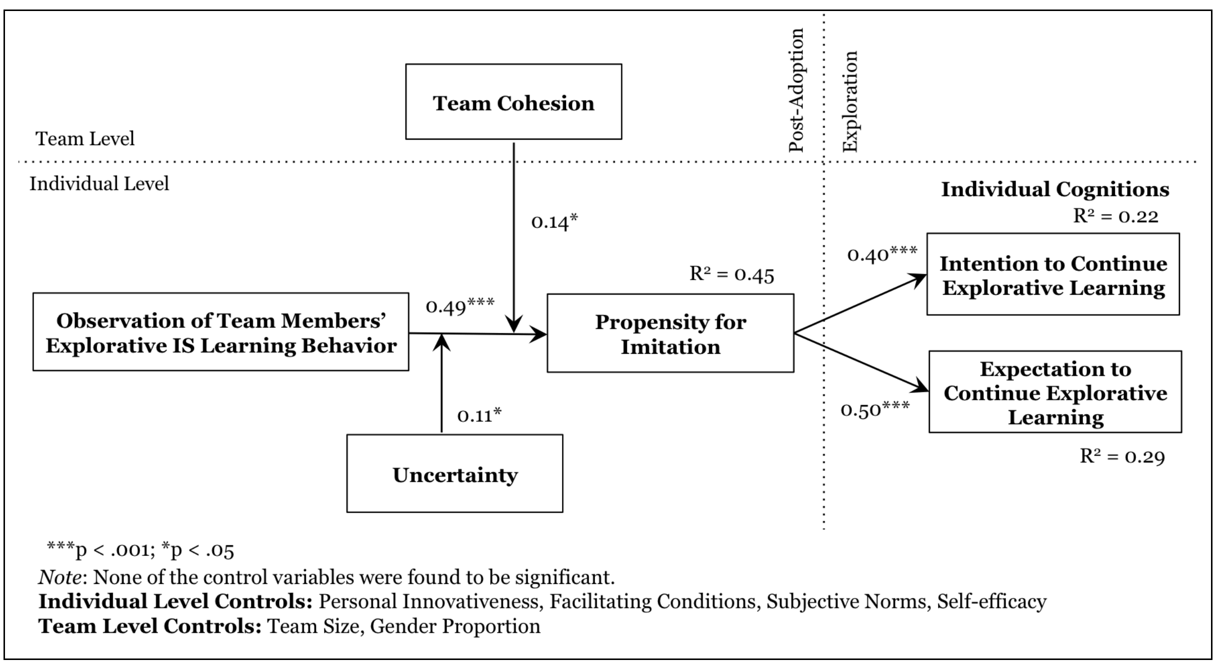
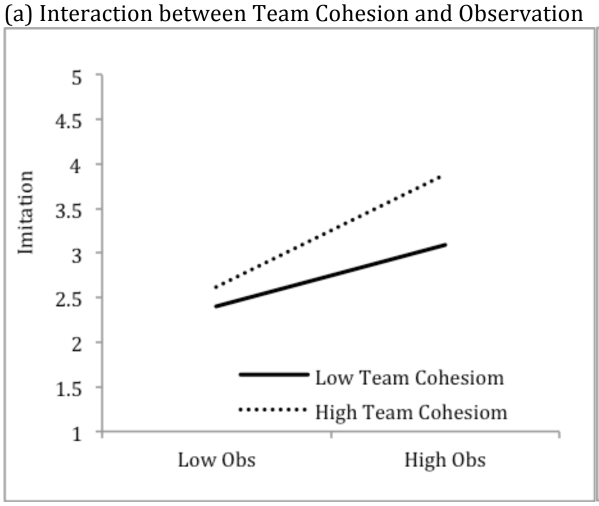


Figure 2. HLM Results

(a) Interaction between Team Cohesion and Observation (b) Interaction between Uncertainty and Observation



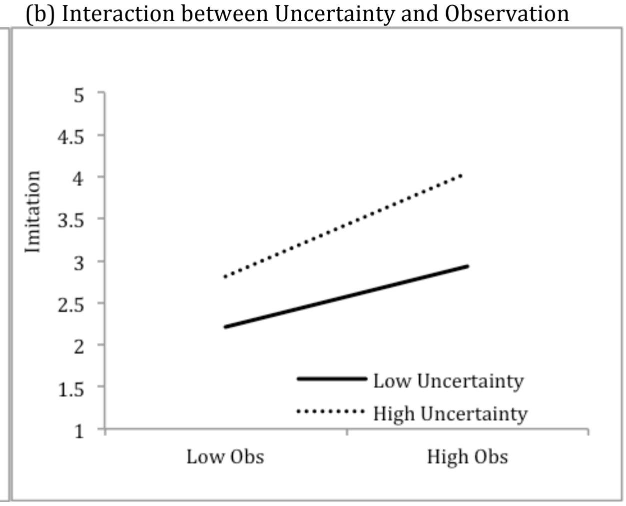


Figure 3. Moderation Effects

APPENDIX A
Wording of Proposed Scale Items

<u>Items for 1nd phase (TIME ONE)</u>

Please complete the following:

- Age: _____ Years
- Gender M F

Prior Experience (adapted from Kim and Malhotra 2005)
Have you used JMP before taking this course? Yes No

The Situating Task

In this survey, I define ***features*** as the building blocks of the JMP software package. You know them as functions such as the "distribution," "fit X by Y," and "fit model" functions in JMP.

To begin, please recall one specific incident in which you learned JMP's functions by exploring them to get the needed report/analysis. By "**exploring**," I mean that you either discovered new ways of producing similar outputs in JMP, or you changed the way that you used specific JMP features. For example: you may have tried new features, combined some features for the first time, or applied features to tasks that they are not meant for (e.g., you used the "Graph Builder" function instead of the "Sorting" function to get the largest/smallest values). I refer to this learning behavior as **explorative learning** (i.e., learning through exploring JMP's functions).

Next, please indicate to what extent you agree with each of the following statements about the incident you reported above, by selecting a number from 1 to 7, where 1 indicates that you strongly *disagree* with the statement, 4 indicates that you are *neutral* in regard to the statement, and 7 indicates that you *strongly agree* with the statement.

Observation (adapted from Sun 2012)**:**

OBS1. I saw my team members were using that feature.

OBS2. The members of my team showed me a new feature.

OBS3. The members my team showed me a new way of using a feature I knew.

Uncertainty (UNC) (adapted from Sun & Fang, 2010)

UNC1. I am *NOT* sure what JMP is about and what it could do for me in the future.

UNC2. I feel uncertain as to whether my future projects' needs could be met by using JMP in the future.

UNC3. I feel uncertain as to whether I would be able to respond appropriately to the new versions and features in of JMP.

Propensity for Imitation (Time 1) (adapted from Sun, 2013)

IMI1. I will follow others in learning JMP through exploring it .

IMI2. It is a good idea to follow others in learning JMP by exploring its features.

IMI3. I like the idea of learning JMP by exploring it, since other students are also doing it.

IMI4. It is pleasant to follow others in discovering new features in JMP.

<u>Control Variables</u>

Individual Level Controls:

Gender
Age

Facilitating Conditions (Thompson et al. 1991)

FC1. A specific person is available for assistance with JMP's difficulties.

FC2. Guidance is available to me when I need to use JMP.

FC3. Specialized instruction is available to help me with JMP's difficulties

Personal Innovativeness with IT (Agarwal and Prasad 1998)

PIIT1. If I heard about a new information technology, I would look for ways to experiment with it.

PIIT2. Among my peers, I am usually the first to try out new information technologies.

PIIT3. In general, I am hesitant to try out new information technologies.[reverse-scored item]

PIIT4. I like to experiment with new information technologies.

Subjective Norm: Two aspects

Aspect one: Descriptive Norm (DN) (adapted from Hagger and Chatzisarantis 2005)

DN1. Most of my friends are using JMP.
DN2. Most of my co-workers are using JMP.
DN3. Most people I know are using JMP.
DN4. Most people who are important to me use JMP.

Aspect two: Injunctive Norm (IN) (adapted from Rhodes and Coureneya 2003)

IN1. Most people in my social circle want me to use JMP.
IN2. Most people in my social circle approve of my using JMP.
IN3. Most people who are important to me would want me to use JMP.
IN4. Most people I know think I should use JMP.

Self-efficacy (SEF): (adapted from Compeau et al,1995; 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.")

SEF1. I could use JMP if there was no one around to tell me what to do.
SEF2. I could use JMP if I had never used a software program like it before.
SEF3. I could use JMP if I had only the online help for reference.
SEF4. I could use JMP if I had someone else helped me get started.
SEF5. I could use JMP if I could call someone for help if I got stuck.
SEF6. I could use JMP if someone showed me how to do it first.
SEF7. I could use JMP if I had just the built-in help facility for assistance.

Team Level Controls: Team Size, Gender Proportion

Bogus Items

7. I have been to every country in the world.
8. I have never brushed my teeth.
9. All my friends are aliens.

Team Level Construct

Team Cohesion (Bollen and Hoyle 1990; Chin et al. 1991)

COHS1. Members of my team feel that they belong to this team.
COHS2. Members of my team feel that they are members of the team.
COHS3. Members of my team see themselves as part of the team.

Situating Task (Time Two)

Please Read Carefully

Please recall one specific incident in which you learned JMP's functions by exploring them to get the needed report/analysis. By "exploring," we mean that you either discovered new ways of producing similar outputs in JMP, or you changed the way that you used specific JMP features. For example, you might have applied functions to tasks that they are not meant for (e.g., you used the “Graph Builder” function instead of the “Sorting” function to get the largest/smallest values). We refer to this learning behavior as **explorative learning** (i.e., learning through exploring JMP’s functions).

Items for 2nd phase (TIME TWO)

Intention to Continue Explorative Learning (adapted from Nambisan et al. 1999; Maruping and Magni 2015)
ICE1. I intend to continue learning how *JMP* can be used in new ways in my future tasks.
ICE2.I intend to continue exploratively learning other ways that *JMP* may enhance my work effectiveness.
ICE3.I intend to continue spending time and effort in exploring *JMP* to learn potential applications to my work.

Expectation to Continue Explorative Learning (adapted from Venkatesh et al. 2008; Maruping and Magni 2015)
ECE1.I expect to continue learning how JMP can be used in new ways in my work tasks.
ECE2.I am likely to continue making an effort to explore JMP features for potential applications to my work.
ECE3.I am going to continue exploratively learning how JMP can be used in my work tasks.
ECE4.I will continue discovering new ways of using JMP.

APPENDIX B
Correlations and Item Loadings

Table **B1.** Descriptive statistics and inter construct correlations

	Mean	SD	CR	AVE	OBS	UNC	IMI	COH	ECE	FC	SEF	PIIT	ICE	SN
OBS	4.83	1.52	0.908	0.767	**0.876**									
UNC	4.80	1.30	0.711	0.551	-0.339	**0.743**								
IMI	5.09	1.33	0.808	0.677	0.697	0.540	**0.823**							
TCO	3.91	1.63	0.895	0.741	-0.240	0.359	0.141	**0.861**						
ECE	4.34	1.19	0.720	0.563	0.463	0.209	0.612	-0.017	**0.750**					
FC	3.79	1.25	0.893	0.737	0.045	0.035	0.070	0.073	0.154	**0.858**				
SEF	5.40	1.90	0.887	0.723	-0.087	0.002	-0.188	-0.072	-0.110	-0.037	**0.850**			
PIIT	4.02	1.25	0.846	0.649	0.100	0.078	0.130	0.120	0.196	0.008	-0.023	**0.805**		
ICE	4.33	1.44	0.807	0.676	0.211	0.289	0.527	0.033	0.662	0.188	-0.110	0.216	**0.822**	
SN	3.78	1.17	0.896	0.592	0.177	0.006	0.194	0.031	0.198	0.250	-0.071	0.082	0.094	**0.769**

Notes: Values on the diagonal in the table of inter-construct correlations represent the square root of AVE. OBS: Observation; UNC: Uncertainty; IMI: Propensity for imitation; Coh: Team Cohesion; ECE: Expectation to Continue Explorative Learning; FC: Facilitating Conditions; SEF: Self-efficacy; PIIT: Personal Innovativeness; ICE: Intention to Continue Explorative Learning; SN: Subjective Norms.

Table **B2.** Items and Factor Loadings

Construct	Item		Loading
Observation	OBS1.	I saw my team members were using that feature.	.847
	OBS2.	The members of my team showed me a new feature.	.907
	OBS3.	The members my team showed me a new way of using a feature I knew.	.873
Uncertainty	UNC1.	I am *NOT* sure what JMP is about and what it could do for me in the future.	.725
	UNC2.	I feel uncertain as to whether my future projects' needs could be met by using JMP in the future.	.760
Imitation	IMI2.	It is a good idea to follow others in learning JMP by exploring its features.	.810
	IMI3.	I like the idea of learning JMP by exploring it, since other students are also doing it.	.836
Team Cohesion	COH1	Members of my team feel that they belong to this team.	.739
	COH2	Members of my team feel that they are members of the team.	.973
	COH3	Members of my team see themselves as part of the team.	.804
Expectation to Continue Explorative Learning	ECE1	I expect to continue learning how JMP can be used in new ways in my work tasks.	.702
	ECE2	I am likely to continue making an effort to explore JMP features for potential applications to my work.	.796
Intention to Continues Explorative Learning	ICE1	I intend to continue learning how *JMP* can be used in new ways in my future tasks.	.808
	ICE2	I intend to continue exploratively learning other ways that *JMP* may enhance my work effectiveness.	.837
Facilitating Condition	FC1.	A specific person is available for assistance with JMP's difficulties.	.836
	FC2.	Guidance is available to me when I need to use JMP.	.940
	FC3.	Specialized instruction is available to help me with JMP's difficulties	.792
Self-Efficacy	SEF2.	I could use JMP if I had never used a software program like it before.	.832
	SEF3.	I could use JMP if I had only the online help for reference.	.872
	SEF4.	I could use JMP if I had someone else helped me get started.	.864
Innovativeness	PIIT1.	If I heard about a new information technology, I would look for ways to experiment with it.	.734
	PIIT2.	Among my peers, I am usually the first to try out new information technologies.	.919

	PIIT3.	In general, I am hesitant to try out new information technologies.[reverse-scored item]	.749
Subjective Norms	IN1.	Most people in my social circle want me to use JMP.	.736
	IN2.	Most people in my social circle approve of my using JMP.	.902
	IN3.	Most people who are important to me would want me to use JMP.	.841
	IN4.	Most people I know think I should use JMP.	.733
	DN2.	Most of my co-workers are using JMP.	.733
	DN3.	Most people I know are using JMP.	.705

CHAPTER 5

CONCLUSION

Technology adoption is prone to a complex decision making process which makes it difficult to predict whether that adoption will ultimately be successful. Adoption of less efficient alternatives may lead to incorrect resource allocations. For this reason, IS scholars have been investigating the factors impacting IT adoption since the mid-1980s. The modern era of technology use requires us to provide a fresh and more relevant understanding of individuals' IS behaviors. Prior research has rarely discussed the role of contextual factors in adopters' decision-making processes. The rapid development of Internet technologies, and the associated tools that make information free and easy to acquire, provides potential adopters with previously unknown opportunities to observe others' ideas and behaviors about new technology products. Furthermore, one may witness the increasing complexity and uncertainty involved in adoption decisions due to concerns such as overload of information, privacy and security of data. Hence, we can see numerous situations where potential adopters observe the decisions of others, and imitate their adoption behaviors and join the herd of those prior adopters.

This dissertation examined individuals' different IS behaviors at the adoption and post-adoption phases of the IS lifecycle, applying the lens of herding theory. In order to depict a comprehensive picture of the determinants and dynamism of decision making in the highly uncertain context of technology adoption, I not only focused on *technology adoption* behaviors, but also on *technology abandonment* and *technology exploration*, as lines of inquiry into IS continuance behaviors.

ESSAY ONE

Prior research on the role of herd behavior in IS adoption has primarily looked at the direct influence of the factors of herding (Sun 2013). These studies have not realized the probable impact that differing characteristics of individuals and technologies may have on the initiation of herding behavior. Hence, they might have overemphasized the role of those direct antecedents of herding (i.e, observation and uncertainty) and thus provided only a limited understanding of the development of such behaviors. In order to improve our knowledge of *en mass* IS adoptions, I investigated the moderating influence of user and technology characteristics with herding behavior in predicting IS usage intentions.

The results of my online experiment revealed that there is a significant influence of herd behavior in the context of technology adoption, more specifically SNS adoption. By employing an SNS, i.e., Ello, as the focal research technology, I was able to further detect and isolate the effect of herding despite the existence of network effects (which is typically an important determinant of SNS growth). My findings that levels of PIIT and RA impact individuals' tendencies to join a herd address the question of why factors of herding (i.e., observation and uncertainty) do not always lead to herd like behaviors (Walden et al. 2009). By identifying the moderating roles of PIIT and RA on the relationships between the antecedents of herding and one's propensity for imitation, my study defines boundary conditions for IS herd behavior.

Personal Innovativeness

My results show that higher levels of PIIT weaken the probability of herding in the presence of the key factors of herding. Hence, an individual's natural inclination to try out a new technology (i.e., PIIT) plays a crucial role in determining adopters' herd-like behavior in IT adoption contexts. This finding supports the argument that ignoring personality variables in the context of herding may result in a more naïve description of an adopter's decision making processes than what actually exists (Aldas-Manzano et al. 2009).

Relative Advantage

My study found a significant moderating effect of relative advantage, as the key technology- related characteristic introduced by IDT, in the relationship between uncertainty and propensity for imitation. This shows the value of combining notions from the IT herding and IDT literatures to offer a more comprehensive model for explaining and testing technology adoption. Furthermore, the study introduced a technology-related attribute, and found proof for the argument that the initiation of herd-like behavior can be better explained not only by considering user-related characteristics such as PIIT, but also by considering technology characteristics such as RA. In other words, this result highlights the importance of an individual’s psychological perceptions (i.e. PIIT) and her utilitarian needs (i.e., RA) in the creation of a herd like behavior.

ESSAY TWO

The final phase of the IS lifecycle, i.e., the termination phase (Furneaux and Wade 2011), is the period in which many individuals may develop abandonment intentions (Turel 2015). Although the later phases of IS adoption are the major sources of benefits for individuals and organizations (Hsieh et al. 2011), the phenomena related to these phases have rarely been studied (Maier et al. 2015). By developing a herding model, my second essay investigates the determinants of abandonment intentions. The results of my longitudinal study provide a clearer understanding of *en mass* abandonments, which may happen after an initial *en mass* adoption.

Abandonment

By finding a moderating effect related to observing a smaller (compared to a larger) mass of adopters in the IS termination phase, my study enriches the understanding of the current argument that IS abandonment and continuance are two different theoretical phenomena (Pollard 2003;Turel 2015; Maier et al. 2015). Based on this finding, I add to the literature that encourages researchers to not only focus on continued use, as a key phenomenon, but also to pay attention to the theoretical development of abandonment intentions.

Task Technology Fit

Prior studies of IS continuance have primarily focused on the cognitive processes of adopters in the later phases of the IS lifecycle, while I extend this approach by including a dynamic conceptualization of task-focused perspective (i.e., TTF). My study integrates pre- and post-TTF constructs in a herd model to adopt a utilitarian lens in investigating herding decisions. Hence, my study enriches understanding of herd-like post-adoption behaviors from a task-oriented perspective. The findings support my argument that the formation of TTF perceptions at the post-adoption stage, after a period of use, may lead to the formation of conflicts between the expected and offered capabilities of the technology, which in turn may lead to the creation of abandonment intentions.

Niche Technology

Reviewing the relevant literature indicates that technology adoption studies have not differentiated the niche vs. mainstream technology adoption behaviors of adopters. Drawing from research on conspicuous consumption, my study integrates the concept of niche IS into the IS adoption literature. This is a topic worth studying since we can observe the recent increase in popularity of niche systems, such as niche SNSs (e.g., Ello, Dribbble, Diaspora). By introducing the concept of niche technology adoption, my study has identified *anti*-herding behavior in such a context. It is the first IS study that investigates the anti-herding phenomenon in IS field, although it has been acknowledged in other disciplines, for instance in finance and economics (Babalos and Stavroyiannis 2015; Bohl et al. 2017).

Also, my study finds that higher levels of perceived niche mitigate the influence of the observation of abandoners and the potential influence of low post-adoptive TTF on abandonment intentions. This is in line with the arguments of the coping model of user adaptation (CMUA), which discussed the development of adaptation strategies in unwelcomed situations (Beaudry and Pinsonneault, 2005). My study adds to that realm of research by introducing perceived niche as a potential adaptation strategy in a herding setting where decisions tend to be fragile. Therefore system designers, by developing and better communicating unique functions of their systems, might be able to strengthen the positive impact of higher post-adoptive TTFs and create sustained usage behaviors.

ESSAY THREE

My third essay examined the determinants of explorative IS behavior (i.e., explorative IS learning), where the actual benefits from an IT investment accrue (Hsieh et al., 2011). Extant IS adoption research on the later phases of the IS lifecycle is mostly limited to focusing on the role of an individual's own beliefs on her IS behaviors, and, as a result, does not clearly explain herd behavior (Sun 2013). I adopted a longitudinal research design and a cross-level perspective. By developing a two-level model of herding, my study extends theory and research on herding (e.g., Banerjee 1992; Bikhchandani et al. 1992). More specifically, I was able to detect herding in small team settings, where trainees are likely to follow the "wisdom of crowds" when those crowds include their own team members.

A review of the relevant literature on user exploration of technology and IT training reveals that for the most part, researchers have focused exclusively on individual-level interventions (e.g., Magni et al., 2010; Sun 2012; Senthanam et al. 2013). However, within organizations, most operations and training take place within teams (Gupta and Bostrom 2013). My multilevel research design enables me to extend herd theory to the area of team learning and introduce an upper level factor of herding, i.e., team cohesion. My findings suggest that IT practitioners should consider developing training practices that enhance cohesiveness within teams, which may help to initiate herd-like IT learning behaviors in the long term.

Most IS adoption research has assumed that the ultimate goal of adoption is usage. However, these studies ignore the fact that the ultimate goal of adoption should be to improve the performance of the user. Hence, researchers should switch their focus to the phases beyond usage (i.e., ways of using a system) rather than stopping their investigation at the usage phase (Bagozzi 2007). By investigating explorative IS behaviors (i.e., the outcome variable in my research model) in a herd model, I have shown that teams' motivational states (i.e., team cohesion) trigger individual team members' continuance expectations and intentions, which in turn develop long lasting cognitions. In the same vein, my finding that the interactive effect of herding factors (i.e., observation and uncertainty) is significant determinants of the development of explorative cognitions of the trainees contributes to the growing body of research on post-training behaviors. Managers can promote desirable post-training behaviors in high uncertainty contexts of IT implementations by designing collective learning initiatives that facilitate observations within teams, which in turn promotes efficiency and performance.