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CONSUMER BEHAVIOR IN THE ADOPTION OF PEER-TO-PEER TECHNOLOGIES: AN EMPIRICAL EXAMINATION OF INFORMATION CASCADES AND NETWORK EXTERNALITIES

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Abstract

The choice of technology adoption plays a critical role in attracting and maintaining customers. The TAM or TPB related model has dominated in the IS context for explaining an individual user's adoption. However, consumers demand different perspectives in the EC environment to elucidate adoption of EC technologies. In this paper, we develop a conceptual framework for demonstrating adoption of EC technologies. In developing the theoretical model, we draw on the theory of network externalities and information cascading and then synthesize them to conceptualize the salient aspect of EC technology adoption. Specifically, we build upon the framework presented by Li (forthcoming) and postulate testable hypotheses for the effects of information cascades and network externalities in consumer adoption of peer-to-peer technologies. The evidence from our test indicates that information cascades play an important role in the user adoption decision.

Keywords: Information cascade, network externality, consumer behavior, technology adoption, peer-to-peer technology

Introduction

As electronic commerce (EC) matures, there is necessarily a shifting of focus away from technological details, and toward consumer behavior issues. Rather than decisions about server types, code standards, and remote caching being foremost in the organizational agenda, decisions about how to actually make the business work have become more central. One of the primary areas of concern for EC organizations is determining how consumers choose, among competing firms, whom they will do business with. In electronic commerce, *the technology is the business*. Thus, a consumer's choice of firm is a choice of technology adoption.

The issue of information technology (IT) adoption by users in traditional settings is well studied in the information systems (IS) literature. However, as EC research has noted, research should “...not view those who use information systems in the e-commerce context as users in the IS sense, but as customers who have needs and demands different from those fulfilled by traditional information systems (Kauffman and Walden, 2001/p. 86).” In this paper, we apply two different economic perspectives to explain adoption of EC technologies—and hence, EC business models—by typical consumers, rather than organizational IT users.

This work compares the influences of *information cascades* (Anderson, 2001; Bikhchandani, et al., 1992; Bikhchandani, et al., 1998; Li, forthcoming; Walden and Browne, 2002) and *network externalities* (Brynjolfsson and Kemerer, 1996; Katz and Shapiro, 1986; Kauffman, et al., 2000) on consumers' willingness to adopt peer-to-peer (P2P) internet technologies. The results suggest that information cascade theory is an important but previously ignored factor in customer adoption decisions.

The paper is organized as follows: In the next section, we briefly review the literature on network externalities, provide a more in-depth review of information cascade theory, and offer a look at the scant literature on P2P technologies—those technologies

which allow client machines to interact directly with one another. Following that, we outline a model combining these two theories. We then propose hypotheses based on that model. The data collection method is discussed, followed by the data analysis. We conclude with a discussion of our findings, their implications, and suggestions for future research.

Literature Review

Information cascade theory originated with Bikhchandani, Hirshleifer and Welch (1992), hereafter **BHW**, and has not yet been widely applied to IS research. Only two IS articles have examined information cascades and network externalities, jointly. Walden and Browne (Walden and Browne, 2002) offer some initial empirical results suggesting that information cascades play a role in fad-like IT adoption. Li (forthcoming) offers a good description of information cascades in IT adoption and integrates it with network externality theory. It is upon this base that we build. We seek to investigate how (or even, if) individual customers apply these two theories. We are particularly interested in determining the relative strengths of these two effects when they are in conflict with one another.

Network Externalities

Perhaps the most widely invoked economic theory for explaining wide-scale adoption of information technology is network externalities (Katz and Shapiro, 1986). Network externalities occur when the value of membership in a network is a function of the number of members on the network (for a thorough review, see Economides, 1996; Kauffman, et al., 2000). This theory has been used to explain the adoption of technologies ranging from spreadsheet software (Brynjolfsson and Kemerer, 1996; Gandal, 1994) to inter-organizational systems (Riggins, et al., 1994). The causal process basically posits that, as more people adopt the technology, the value of that technology increases, encouraging additional adoption. This virtuous circle continues, causing rapid adoption and leading to markets wherein a single firm promptly emerges as the dominant player (Mantena and Sundararajan, 1999).

Information Cascades

Recent research has shown that firms often choose technologies identical to those chosen by other firms in the same industry, even if those technologies are inferior (Tingling and Parent, 2003). This result is attributed to mimetic isomorphism, a process wherein firms achieve legitimacy in their community by mimicking other firms in the community (Deephouse, 1996; DiMaggio and Powell, 1983; Haveman, 1993). Mimetic isomorphism is an institutional theory, describing how organizations make decisions. However, our focus here is on explaining how individual consumers make adoption decisions. Similarly, mimetic isomorphism is a behavioral theory, while this work focuses on economic theory. Luckily, the behavioral suggestions of mimetic isomorphism from an economic consumer viewpoint are captured in information cascade theory.

Information cascade theory (Bikhchandani, et al., 1992; Bikhchandani, et al., 1998) takes into account both value propositions of the technology and the uncertainty of those propositions, with respect to novel technologies. Information cascade theory explains how the uncertainty about value propositions can lead to fad-like behavior in the adoption of novel technologies. This work proposes that information cascade theory offers an excellent description of the adoption decision for novel technologies, because it takes into account the uncertainty in the decision.

The Applicability of The Theories to the Study of P2P

Recent research suggests that the economic theories presented here are very important to consumer's perceptions of P2P networks (Lee, 2003). Information cascade theory is focused on inferring information about the quality of a product from prior adoptions. Thus, information cascade theory speaks to *experiential* qualities—those qualities which one can only determine *after* using the product. Information cascade theory informs consumer adoption, relative to features that can only be determined after making the adoption decision. Network externality theory puts forth that adoption is driven by the size of the network, which is something that is clearly observable before the adoption decision.

Lee (2003) has offered a user ranking of the importance of P2P features. We duplicate the top 10 features by order of importance from that study in Table 1. Perusal of this list shows that the most important feature is monetary cost. However, the next three

items are experiential features, which should be informed by information cascade theory. It is not until the sixth and eighth feature that users rank network externalities. Thus, it is reasonable to believe that the addition of information cascade theory to network externality theory will greatly enhance the understanding of economic theories of adoption of P2P technologies.

Table 1. Importance of P2P Features as Reported in Lee (2003)

Feature	Rank	Theory
Charges no fee	1	Directly observable before adoption
Is fast	2	Info Cascade
Is stable	3	Info Cascade
Is reliable	4	Info Cascade
Can resume loading	5	Directly observable before adoption
Has large file selection	6	<i>Network Externality</i>
Can exit nicely	7	Info Cascade
Has large user base	8	<i>Network Externality</i>
Has good search features	9	Info Cascade
Gives error message	10	Directly observable before adoption

In sum, prior literature suggests that both network externalities and information cascades are viable explanations of IT adoption. While network externality theory is far better known, current research on P2P technologies suggests that information cascades may play a larger role in consumer adoption decisions.

Research Model

We posit a basic model in which network externalities, as measured by absolute adoption level, and information cascades, as measured by recent adoptions, impact a user's likelihood of adopting a P2P technology. This simple model is illustrated in Figure 1 and is essentially the model of Li (forthcoming).

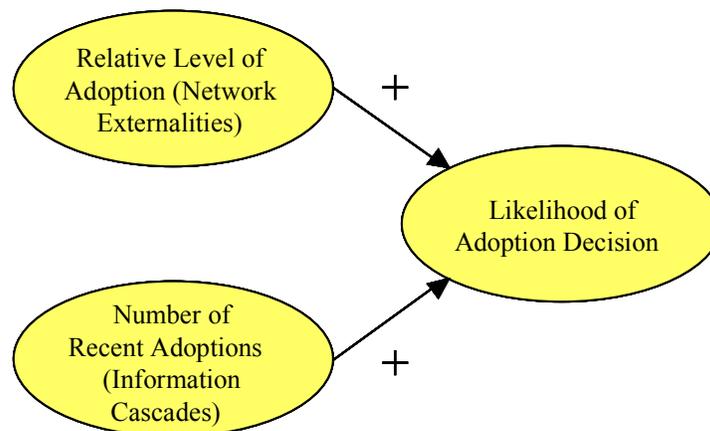


Figure 1. Simple Model of Effects of Network Externalities and Information Cascades

To this basic model, we add a number of extensions. First, as we note in the hypothesis section, the effect of the absolute adoption level will not be linear. Rather, the effect will virtually be non-existent for very large markets. This is a direct implication of the nature of the network externality for P2P technologies, and it directly addresses Kauffman and Walden's (2001) suggestion that, "[o]ne important caution for researchers is to be clear about the source of the externality and to whom the benefits accrue (p. 64)."

A second contribution of this work is to offer an explanation of the relative size of the impacts of network externalities and information cascades. This is a direct result of the fact that we examine this issue specifically in the e-commerce customer adoption intention. By looking at a specific adoption decision, we are able to develop more reliable, but less generalizable theory. Specifically, we claim that P2P adoption is a relatively uncertain environment, which lends itself to information cascades. Prior literature shows that information cascades only make sense in uncertain environments (Bikhchandani, et al., 1992; Bikhchandani, et al., 1998; Walden and Browne, 2002). If the correct decision is known, then cascades will not occur. Conversely, network externality theory requires full knowledge on behalf of market participants, so that they may effectively evaluate the value of the externality. Thus, given the novelty of the P2P situation, information cascades seem very likely, while high precision estimates of network externalities are problematic. Thus, we posit that consumers will place more value on information present in recent adoption decisions than in information present in absolute adoption levels.

In addition, we provide an empirical examination of the questions, and thus, add a number of control variables to account for individual differences.

Hypothesis Development

Network Externalities

The basic impact of network externalities should be, simply, that a customer adopts the technology with the larger network. However, it is important to define the nature of the externalities (Kauffman and Walden, 2001). We focus on the adoption intention of P2P technologies. The value of the externality comes from the fact that each member sharing files has some probability of having the file a new adopter desires. As the number of members in the network increases, the probability of finding the desired file increases. Note that this is not a linear increase, as the value of multiple copies of the same file is nil.

The value of adopting a P2P network, characterized by network externalities, is a gradually increasing function of the number of prior adopters. The steepness of the curve is determined by the probability that any given user has a file.

This discussion leads to hypothesis 1.

Hypothesis 1: Consumer's likelihood of adopting a P2P technology increases as the relative difference between network sizes increases.

Information Cascades

Information cascades' probabilities are considerably more complex to derive. They depend upon the base rate of the occurrence, the strength of private signals and the actual decisions made in the sequence. For the derivation of the formula and the assumptions leading up to it, we refer the reader to (Bikhchandani, et al., 1992 / pp. 995-998). The net result is that more prior adoptions make it more likely that the current decision maker will decide to adopt. Thus, we hypothesize.

Hypothesis 2: Consumer's likelihood of adopting a P2P technology increases as the number of consecutive recent adoptions increases.

The important issue is that the probability of an information cascade as a function of the number of adopters increases much more quickly than the probability of finding the file one desires. This would suggest that if customers adopted due to information cascades, they would make much stronger decisions in earlier periods. In fact, after a very few adoptions, cascades are almost certain to form, while it may take significant (thousands or millions) adoptions before network effects become strong enough to influence adoption. Note that this is not exactly a direct comparison. The point is that, for information cascades to cause herd-like behavior, much fewer adopters are required than are required for network externalities to cause herd-like behavior. This difference in relative strength of the effects leads to a third hypothesis.

Hypothesis 3: Recent consecutive adoptions increase a consumer's likelihood of adopting more than do increases in absolute market size.

In addition to these theoretical contributions, we make several empirical contributions. The first is simply in offering an empirical test. The second empirical contribution occurs because we include a variety of control variables. This not only lends more credence to the results, but also may offer some additional insights, depending upon the effects of those variables. These control variables and the enhanced model based on them is shown in Figure 4.

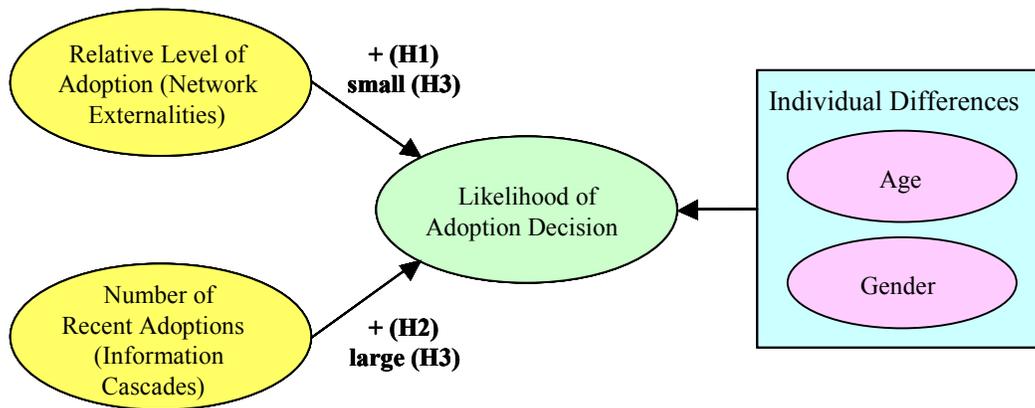


Figure 4. Empirical Model

Experimental Design

We carried out a study prior to administering the main survey. The objective of the study was to ensure the clarity of the instruction in the study. The subjects in this study are undergraduate and graduate students at a large southwestern university. Frequently, in IS research, student subjects are used as a convenience sample and questions arise about the generalizability to more appropriate populations. However, in this case, college students are very representative of the population of P2P adopters. For example, Lee (2003) reports that more than half of the bandwidth utilization at Cornell University is devoted to the P2P technology “KaZaA”. The experiments of the study lasted approximately 10-15 minutes per task. The profiles of participants are reported in Table 2.

Table 2. Profiles of Participants (n=121)

Age	Mean	23.12
	Median	22.00
Gender	Male	84.3%
	Female	15.7%
Experience to use P2P technologies (years)	Mean	2.77
	Median	3.00

The subjects were randomly given a scenario in which they were asked to choose between two competing P2P technologies—technology A and technology B—for sharing academic files (see appendix A). Several characteristics of each technology were given in a side-by-side comparison, with the only difference being the current size of the network. The subjects were also informed that some number of people they personally spoke to on the subject had actually chosen to use the smaller network. Technology A always had a larger network size and technology B always had recent consecutive adoptions. Both technologies were free. The subjects were then asked to indicate, on a seven point likert scale, their likelihood of adopting each technology. The levels of the variables are displayed in Table 3.

Table 3. Manipulation Variables

		Technology A Count	Technology B Count	Relative Difference
Network Size Differences	Large	1,000,000	1,000	1000
	Medium 1	100,000	10,000	10
	Medium 2	6,000	5,000	1.2
	Small	1,006,000	1,005,000	1.0001
Recent Adoptions	Single	0	1	n/a
	Double	0	2	

These different levels of the variables yield eight cells with counts as shown in Table 4.

Table 4. Independent Variable Counts (number of subjects)

		Network Size Difference			
		Large	Medium1	Medium2	Small
Recent Adoptions	Single	19	24	8	8
	Double	23	23	8	8

Analysis

The analysis in this case is not straightforward, because of the ordered nature of the responses. Our theory suggests that the model we wish to estimate is:

$$\text{Likelihood of adopting} = f(\text{REL_DIFF}, \text{RECENT}, \text{GENDER}, \text{AGE}).$$

Here, REL_DIFF is the relative difference, RECENT is the count of the number of recent adoptions, and GENDER and AGE are control variables.

The problem arises because the likelihood of adopting is an ordered categorical variable. Namely, it is a whole number between one and seven, inclusive. At the same time, the order is important, so that moving up categories from lesser to greater indicates an increasing likelihood of adopting B and a decreasing likelihood of adopting A. To estimate such a dependent variable, we apply ordered (cumulative) logit.

This model specifies that:

$$f(\text{Pr}(Y < j)) = \alpha_j + \beta X \text{ for } j = 1 \dots k$$

where $k+1$ is the number of categories, Y is the categorical response, α_j is a separate intercept for each threshold, X is a vector of observations, and β is a vector of parameters to be estimated.

Because the probability being estimated is the probability of being in a lower category, the signs of all of the coefficients will be opposite from what is intuitive. In other words, smaller values of the dependant variable are associated with a greater preference for technology A. Thus, a positive coefficient indicates a higher probability of a lower value and hence, an increased preference for technology A. The hypothesized signs of the coefficients are given in Table 5.

Table 5. Hypothesized Signs of Coefficients

Hypothesis	Coefficient	Explanation
H1	$\beta_1 > 0$	Increased relative difference leads to increased probability of the dependant variable being smaller, which implies great preference for technology A.
H2	$\beta_2 < 0$	Increased number of recent adoptions leads to decreased probability of the dependant variable being smaller, which implies great preference for technology B.
H3	$ \beta_2 > \beta_1 $	The impact of recent adoptions is greater than the impact of relative market size.
N/A	$\beta_3 \geq 0$ $\beta_4 \geq 0$	No hypothesized sign on control variables

Functional form

$$f(\Pr(Y < j)) = \alpha_j + \beta_1 REL_DIFF + \beta_2 RECENT + \beta_3 AGE + \beta_4 GENDER$$

The results of the ordered logit analysis are given below in Table 6. These results seem to support our hypothesis. The coefficient on the relative difference is not significant, but does have the correct sign. The coefficient on recent adoptions both has the correct sign and is statistically significant, thus supporting hypothesis 2. Hypothesis 3 is also supported. While the coefficient on age is not significant, the coefficient on gender is, suggesting that females have a preference for technology A—the network externality technology.

Table 6. Ordered Logit Results
(positive indicates preference for A negative indicates preference for B)

Coefficient	Estimate	P-value	Odds Ratio
<i>REL_DIFF</i>	0.000	0.211	1.00
<i>RECENT</i>	-1.043	0.003	0.35
<i>GENDER</i> (F)	-1.023	0.042	0.36
<i>AGE</i>	-0.028	0.418	0.97
Intercept 1	1.178	0.412	
Intercept 2	4.219	0.004	
Intercept 3	4.294	0.004	
Intercept 4	5.135	0.001	
Intercept 5	5.285	0.000	
Intercept 6	7.494	0.000	
Log-likelihood	-165.076	0.005	

Discussion

Implications/Extensions

This research article has been aimed at addressing the question of IT adoption by economic agents, specifically by potential customers of P2P technologies. As such, it takes the perspective that individuals adopted a technology because of the actual value of the technology. This is in contrast to the premier model of technology adoption—the technology acceptance model (**TAM**)—which posits that adoption is based on perceptions. Economic models implicitly assume that agents' perceptions of reality are based on reality, while TAM, a psychological model, does not require perceptions to be matched to reality.

We examine two economic models. The first, network externality theory, assumes full information on behalf of the potential adopters. Thus, reality and perceptions of reality are perfectly correlated. However, we fail to find that potential adopters' behavior in accordance with this model.

The second model, information cascade theory, relaxes the assumption of perfect information. It assumes that, while agents are fully rational, they do not have access to complete information, and thus must compensate for that by inferring additional information from the adoption decisions of others. In this sense, information cascade theory bridges a gap between pure, full information, economic theory and psychological theory. More to the point, it bridges a gap between TAM and network externality theory.

Information cascade theory takes into account the actual value propositions of technology adoption, but also allows for perceptions of the value to be different than the reality of the value. In accordance with network externality theory, information cascade theory posits that adopters are influenced by other adopters. At the same time, in accordance with TAM, information cascade theory recognized that agents must behave based on perceptions that may be imperfectly correlated with reality. Not surprisingly, decision makers do seem to behave in accordance with information cascade theory.

Empirical tests of network externality theory are usually operationalized by setting the current period's adoption decision as a function of the number of adopters in the prior period. The empirically testable hypothesis is then that the current period's adoption decision is a function of the prior period's adoption decision. Interestingly, this is exactly the same empirical prediction that would be generated by information cascade theory. Thus, the vast majority of empirical tests of network externality theory are also empirical tests of information cascade theory. Therefore, the large body of empirical support for network externality theory is also a large body of empirical support for information cascade theory. This brings up a very important question.

What if information cascade theory, rather than network externality theory, is the operative theory in IT adoption?

The main implication would be that potential adopters actually adopt based on the information received from a few individuals rather than based on the cumulative value generated by all prior adopters. From a marketing perspective, this would suggest that it would be more important to get a wide breadth of heterogeneous adoptions rather than a single large group.

Taking this a step further, one could construct models in which a population was made up of smaller social networks that were loosely coupled. Adoption decisions would be made by individuals based on the observed behavior at the social network level rather than at the population level. Thus, rather than having the typically theorized single S curve of adoption, we would instead have multiple small S curves for each social network. Cumulatively, this would appear to generate a single large S curve, but when viewed at the proper level, it would become apparent that adoption information was gathered at the social network level rather than the population level. This would imply that the impact of adoption by a group would depend, not on the size of the group, but on the connectedness of the group.

Another issue that arises is, what information, exactly, is being inferred from the decisions of others. Are decision makers inferring information about qualitative aspects such as user friendliness, aesthetics and other issues, or are they inferring information about the level of network externalities. The value of network externalities is a function, not only of the number of users, but also of the volume and variety of sharing done by those users. Thus, decision makers may be inferring those variables from prior decision makers' adoption decisions.

In sum, this work opens a whole new stream of research that can greatly enhance our understanding of consumer adoption. However, it requires that the research actually be done. First, more confirmation about information cascade theory must be fulfilled. More exploration about the differences of information cascade theory and network externality theory is called for, and refinement of the models is necessary.

Conclusion

Overall, the results suggest that potential adopters of P2P technologies place considerable weight on recent adoptions and very little weight on relative network size, when making their own adoption decisions. While these are preliminary results, they have profound implications for the state of IS knowledge. Simply stated, these results suggest that information cascade theory, rather than network externality theory, explains adoption behavior for novel technologies. This is very important, because to date, only one other study (Walden and Browne, 2002) has empirically examined both of these theories and that study also found that information cascade theory better explained adoption behavior than did network externality theory.

Prior to these two pieces of work, network externality theory has been widely tested and validated. However, network externality theory and information cascade theory produce empirically identical behavior, in most instances. While we do not endorse abandoning network externality theory, it is imperative that researchers consider the possibility that information cascades are, in fact, the operative theory.

Why might it be the case that information cascade theory better explains adoption than network externality theory? There are many candidate explanations, but it seems intuitively satisfying that, in the case of novel technologies, the presumption of full information is unrealistic. Information cascade theory is based on noisy information, while network externality theory is based on full information.

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Appendix 1. Experimental Task

Last week, you saw a presentation on two new peer-to-peer (P2P) technologies for sharing academic and job related materials. Both of the technologies work by creating a folder with a student's network drive, which is accessible via the P2P interface. Each of the technologies has a similar interface with the following capabilities:

Capability	Technology A	Technology B
Search	Full text, subject, and keyword.	Full text, subject, and keyword.
Retrieval	Save to network drive, save to other hard drive, view from current location.	Save to network drive, save to other hard drive, view from current location.
Indexing	Naming, keyword specification, subject specification	Naming, keyword specification, subject specification
Messaging	Direct and asynchronous	Direct and asynchronous
Current Number of Users	<u>1,000,000</u> or <u>100,000</u> or <u>1,006,000</u> or <u>6,000</u>	<u>1,000</u> or <u>10,000</u> or <u>1,005,000</u> or <u>5,000</u>
Cost	Free	Free

During the presentation you asked the presenter which technology she used. She said that she used technology **B** and had never actually tried technology **A**. This week, you meet someone who was in the audience with you and asked them which technology they choose. They also indicated that technology **B** was their choice and they had not yet tried technology **A**. Given this information please answer the following questions.

If you were to try one of these P2P technologies which would you choose?

Definitely A Most likely A Less likely A Undecided Less likely B Most likely B Definitely B

Explain why? _____
