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The Impact of Technological Embeddedness on Household Computer Adoption

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ABSTRACT

Technology adoption has been traditionally examined at workplaces, and relatively few studies have been conducted to investigate how technologies are adopted in households. This paper develops the concept of technological embeddedness by extending the social embeddeddness framework of economic actions. It further proposes a new research model for household computer adoption in which technological embeddedness is the key determinant. Moreover, the impact of technological embeddedness is positively moderated by household income and education, and it is particularly stronger on first-time adoption than on repeat purchases. The proposed model is validated using the dataset from the U.S. 1989–2003 Computer and Internet Supplement to the Current Population Surveys (CPS), and the results strongly support the proposed research model. Important policy and managerial implications are also discussed.

Keywords: Household computer adoption, technological embeddedness, digital divide, social networks, decision-making

INTRODUCTION

The digital divide, a term that refers to unequal access to technologies among different groups of individuals and households, has raised concerns from both policy makers and scholars since 1990s. Despite the great efforts of government agencies to bridge the digital divide, the differences between the "haves" and the "have-nots" still remain in both the U.S. and worldwide (e.g., Hsieh, Rai and Keil, 2008). Some analysts and scholars attribute the problem of digital divide largely to economic factors. This line of thought, however, ignores an important factor affecting computer adoption decision: the complex contexts and environments in which a household is embedded. Prior literature suggests that social actors' economic actions are embedded in their social relations, which could facilitate or derail economic exchanges or decision-making (e.g., Granovetter, 1985). Therefore, the process of decision-making is not only one of utility maximization, but also one of social interaction, so that actors' decision-makings are significantly affected by environmental factors such as culture, subculture, reference groups, and situational determinants.

This study intends to examine household computer adoption under the framework of social embeddedness theory (e.g., Zukin and DiMaggio, 1990). Guided by this framework, we develop the concept of technological embeddedness and investigate its impact on household technology adoption, more specifically, the adoption of household computers.

LITERATURE REVIEW AND CONCEPTUALIZATION

Technology adoption and diffusion has been an intriguing and fruitful research area for many years. As technology is rapidly moving into households, there is an urgent need to understand patterns of household technology adoption. To that end, the model of adoption of technology in households, the MATH model, proposes that attitudinal belief and social influence are important factors affecting home computer adoption (Brown and Venkatesh, 2005; Venkatesh and Brown, 2001).

Recent years have witnessed an increasing number of studies focusing on social networks in many disciplines. A key construct in social network theory is social "embeddedness", which refers to the process by which social relations shape economic actions such as economic exchange or decision-making (e.g., Granovetter, 1985). Social embeddedness emphasizes the interplay between the focal actors and their environments, and is considered as the contextualization of economic activities in on-going patterns of social relations. Although the concept takes on many forms, the basic and enduring idea is that economic actors are not atomized individuals and that economic activities cannot be understood as separated from their social contexts.

This research attempts to incorporate social embeddedness theory into current technology adoption theories. We first develop the concept of technological embeddedness and then propose a new research model to study household computer adoption. Examining technology adoption from technological embeddedness perspective helps to understand technology adoption and diffusion as an interactive process, rather than as a single event (Premkumar, Ramamurthy and Nilakanta, 1994).

The key concept in the present study is technological embeddedness, which is developed based on previous social embeddedness research. In their influential manuscript, Zukin and DiMaggio (1990) proposed four types of embeddedness for economic actions: cognitive embeddedness, cultural embeddedness, structural embeddedness, and political embeddedness. Cognitive embeddedness focuses on the cognitive dimension and refers to the ways in which the structured regularities of mental processes limit the exercise of economic reasoning. In contrast, since culture sets limits to economic rationality and proscribes or limits market exchanges, cultural embeddedness is used to refer to the ways shared understandings and meanings come to give forms to individual and organizational activities, structures, and processes (Martin, Knopoff and Beckman, 1998). Structural embeddedness, on the other hand, refers to the way dyadic relations are articulated or the aggregate configuration of those relations in some structural forms. Last, political embeddedness draws attention on how the economic exchange is shaped by the economic actors and nonmarket institutions in their struggle for power (Barnett and Carroll, 1993), especially through legal frameworks, policies, and strategies.

With the advent of the information age and the proliferation of IT, economic actions are increasingly dependent on and influenced by the technological environment in which social actors reside. This is particularly relevant when we consider the adoption and diffusion of IT. In this research, we propose the concept of technological embeddedness, which refers to the extent to which social actors are embedded in the macro technological environment they are situated as well as the ongoing interactions among social actors. Key to understanding the influence of technological embeddedness on technology adoption is the fact that technological embeddedness captures both active and passive aspects of the influencing process. Actors adopt the technology not only because they feel the pressure to conform to others in order to get recognition from their peers, but also because they actively engage in learning and experiencing with the technology through connectivity and interactions with their peers. Deeply embedded actors tend to have more connections with their peers who potentially possess or use the technology, and increased exposure to and interaction with the technology can further increase actors' knowledge with the technology and lower the barriers for adopting the technology, thus facilitating technology adoption.

RESEARCH MODEL AND HYPOTHESES

With the introduction of technological embeddedness, we now propose our research model for household computer adoption. The dependent variable in the model is household computer adoption, which is a binary variable whether a household adopts computers or not. The key independent variable is technological embeddedness. We further propose that the effect of technological embeddedness on household computer adoption is positively moderated by household income and education, two primary factors determining the socio-economic status of a household (Hsieh et al. 2008).

The technological environment in which social actors are embedded can potentially affect the future adoption through several mechanisms. First, technological embeddedness enhances the frequency of communication and interactions between current adopters and potential adopters. In his classic study of the diffusion of hybrid corn, Griliches (1957) found that hybrid corn was adopted more where corn farms were closer together. Innovation diffusion theory suggests that spatial proximity is one of the key determinants of innovation adoption (Wejnert, 2002). Proximity strengthens a local social network and increases the frequency of communication and interactions. As a result, it enhances the spread of information and ideas, and facilitates imitative behavior (Rogers, 1995). In addition to spatial proximity, interaction intensity also plays an important role in promoting the adoption of technologies since it can increase exposure and familiarity with the technologies (Schultze and Orlikowski, 2004). Second, technological embeddedness establishes and enforces social norms related to a technology. If adopters of a particular technology are concentrated in one area, potential adopters in the area are more likely to be influenced by the increased exposure to the technology. In addition, the early adopters create normative pressure for potential adopters to follow the earlier adopters so to adopt the same technology (Markus, 1987). Accordingly, we propose the following hypothesis:

H1: The more deeply a household is technologically embedded, the more likely the household will adopt computers at home.

Prior literature suggests that absence of resources and knowledge can inhibit both the intent and the actual performance of a behavior (Venkatesh and Brown, 2001). Recent studies also suggest that income and education levels are the two most significant factors that determine one's socio-economic status and distinguish adopters from non-adopters (e.g., Hsieh et al., 2008). It is well known that household income is a critical factor in household purchase decision (Murthi and Srinivasan, 1999; Nelson, 1990). Here, we propose that income also significantly moderates the impact of technological embeddedness on household computer adoption. First, households of various income levels could be exposed to different social influence and learning opportunities (Rogers, 1995). Second, given the same level of social influence and learning opportunities, households' susceptibilities to new technologies may differ substantially. Wealthy households have more slack resources at their disposal and, when influenced by their peers, are more susceptible to peers' influence regarding new technologies. This also holds for household computer adoption—as computers are getting more and more popular, households with more disposable income will be more likely to purchase computers at home as a result of peer influence. In contrast, households with tight budgets may be reluctant to try new technologies. Moreover, lower income also negatively affects households' attitude toward new technologies, dampening the social influence and learning effect (Murthi and Srinivasan, 1999; Nelson, 1990). The above analysis reveals that household income plays the role of enabler or catalyst for technological embeddedness to take effect. Thus we propose:

H2a: The impact of technological embeddedness is stronger on households that have higher income.

Education is another important moderator on the effect of technological embeddedness. Education has often been found to increase the chance of IT adoption due to its positive correlation with income (Rogers, 1995). Yet the role of education in facilitating learning and shaping attitudes toward technologies is largely underexplored. Education not only improves the ability to understand information but it enhances the ability to learn from experience and observation. In the process of technology adoption, learning, especially absorbing and comprehending information emanating from the networks is critical. More educated individuals are more responsive, more ready to accept and comprehend information signals related to new technologies (Rogers, 1995). Furthermore, more educated individuals tend to possess a more positive attitude towards technologies (Nelson, 1990). Based on the above analysis, it is reasonable to suggest that education makes a difference for technological embeddedness to take effect. Specifically, more educated households are more likely to accept new ideas and try new technologies than their less educated counterparts (Murthi and Srinivassan, 1999). Accordingly, we propose:

H2b: The impact of technological embeddedness is stronger on more educated households.

So far, our analysis has been restricted to first-time adoption only. Our next hypothesis investigates the differential effect of technological embeddedness on first-time adoption versus repeat purchases. Brown and Venkatesh (2003) proposed that early and late adopters might react differently to such factors as hedonic outcomes, utilitarian outcome, social influence, and various barriers. We expect that technological embeddedness affects first-time adoption differently from repeat purchases: potential first-time adopters are more likely to be influenced by the technological embeddedness. Studies have shown that first-time adopters tend to be more skeptical and need to overcome technical barriers (Rogers, 1995), while repeat purchases are more closely related to prior consumption experiences, personal needs, and consumption habits (Ouellette and Wood, 1998). Therefore, social norms and pressure arising from technological embeddedness will be stronger on potential first-time adopters, since technological embeddedness is more helpful to potential first-time adopters in acquiring computer skills and knowledge. Thus, we hypothesize:

H3: The impact of technological embeddedness is stronger on potential first-time adopters than on repeat purchases.

DATA AND METHODOLOGY

The data used in this study is obtained from the Current Population Surveys (CPS) administered by the U.S. Census Bureau and the Bureau of Labor Statistics. In 1989, 1993, 1997, 2001, and 2003, five CPS surveys related to computer and Internet use were conducted. Questions about computer ownership, accesses to as well as general uses of computers and the Internet are asked. From these surveys, we identified 96,821 households in total; 56,425 of them did not own any computers at the beginning of the survey years and are identified as potential first-time adopters.

The dummy variable *household computer purchase* (D_i) represents whether household *i* purchased a computer in the survey year; it equals 1 if the households did purchase computers in the year, and 0 otherwise. In other words, D_i represents first-time adoption as well as repeat purchases of computers during the survey year. Since the surveys identify whether or not a household owned a computer prior to the survey year, we can easily obtain the second dependent variable *household computer adoption* (Y_i); Y_i indicates if household *i* purchased their *first* computer in the survey year; it equals 1 if a household purchased its first computer in the year, and 0 otherwise.

The dummy variable *potential first-time adopters* (F_i) identifies those households that did not have computers before the survey years. *Household income* is calculated as the per capita income for a household (in $10,000). Other demographic variables such as *education* (in years), *number of household members*, *minority*, and *married households* are directly obtained from the CPS. We also control for the *presence of school-going kids* for a household, and the geographical regions where the households locate. Finally, we obtain the computer price index from the US Bureau of Economic Analysis (BEA) of Department of Commerce.

Technological embeddedness is measured in three ways in this study: First, we use the percentage of household computer ownership (C_i) for a Metropolitan Statistical Area (MSA). For each household i, C_i is calculated as the fraction of the number of households that own computer(s) to the total number of households in that MSA. The intuition is that social actors tend to learn and exchange information more from their local network than from remote networks, and social norms will be stronger from local neighborhood than remote ones. Second, the surveys also identify two venues of computer usage by each household across all years: computer use at work and computer use at school. From these two venues we derive the number of computer use venues outside home (V_i). Thus V_i = 2 if household members use computers both at work and at school, V_i = 1 if use computers at only one of these two venues, and finally V_i = 0 if use computers at neither of these two venues. Therefore our second measure of technological embeddedness is the number of computer use venues outside of home, V_i. However, a potential problem of using V_i as a proxy for technological embeddedness is that V_i does not account for the intensity of the social interactions. Thus we adopt a third measure, the number of computer applications the household member use at workplace, (W_i). In the CPS surveys, for any household members who use computer at work, we can identify if they use any of the following six computer applications recorded in the surveys: word processing, Internet/email, schedule/calendar, database/spreadsheet, graphics/design, and programming. We count the total number of the applications as W_i, thus W_i ranges from 0 to 6. Since the dependent variables are binary, we use Probit model (Greene, 2003) for the estimation.

ESTIMATION RESULTS

The estimation results for H1, H2a, and H2b are listed in Table 1. Model 1 is the base model, which does not include any proxy variables for technological embeddedness. Models 2 to 4 use the three measurements for technological embeddedness respectively, and the McFadden's Pseudo-R^2 are much higher than that in Model 1, suggesting better model fit (Greene, 2003). More importantly, the coefficients on all three measures of technological embeddedness are positive and highly significant (p<0.01) in Models 2 to 4, thus H1 is strongly supported. Model 5 to Model 7 show the results of H2a and H2b, the moderating effects of income and education. Across all three models, the interactions between income and the proxies for technological embeddedness are positive and significant, therefore supporting H2a (Jaccard and Turrisi, 2003). But the interactions between education and the proxies for technological embeddedness are not significant, therefore H2b is not supported. The results for H3 are listed in Table 2. The interaction between first-time adopters and the technological embeddedness is positive and highly significant (p<0.01) in all three models, thus supporting H3.

In addition, throughout all models, the coefficients on income and education are all positive and significant, confirming prior results that these two variables are important determinants for household computer adoption (Murthi and Srinivasan, 1999; Nelson, 1990).

DISCUSSIONS AND CONCLUSION

In this study, we develop the concept of technological embeddedness and propose a new research model to investigate the impact of technological embeddedness on household computer adoption. Several insightful implications can be drawn from the results. First, technological embeddedness plays an important role in household computer adoption. As discussed earlier, households that are more deeply embedded in technological environments are more likely to adopt new technologies. Therefore, to induce adoption of computers, we need to immerse the focal households in an environment or community that can facilitate the flow and exchange of computer-related knowledge. Second, as expected, income emerged as a significant moderator of the effect of technological embeddedness. The impact of technological embeddedness is more pronounced on households with higher income. This finding indicates that it is a tougher task to induce household computer adoption among low-income households, which may need more assistance from governments and organizations.

Table 1. Estimation Results for Computer Adoption

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Household income ($Income_i$)	0.140**	0.139**	0.127**	0.107**	0.095**	0.112**	0.113**
Education (Edu_i)	0.103**	0.102**	0.083**	0.082**	0.097**	0.080**	0.084**
Percentage of household computer ownership (C_i)		2.140**	———	———	1.823**	———	———
Number of computer use venues outside home (V_i)			0.356**	———		0.265**	———
Number of computer usages at work (W_i)				0.141**			0.170** (0.027)
$C_i \times Income_i$					0.112**		
$C_i \times Edu_i$					0.010		
$V_i \times Income_i$						0.027*	
$V_i \times Edu_i$						0.004	
$W_i \times Income_i$							0.008**
$W_i \times Edu_i$							0.001
Log likelihood	−13168.07	−13099.03	−12851.56	−12811.78	−13092.64	−12848.36	−12810.79
McFadden's Pseudo-R^2	0.205	0.209	0.224	0.227	0.210	0.225	0.228

Notes: N = 56,425. Dependent variable is household computer adoption (Y_i). Other independent variables include price, number of household members, minority, school-going kids, married households, 3 region dummies, 4 year dummies, and 280 MSA dummies. *p<0.05, **p<0.01.

Third, the effect of technological embeddedness is stronger on first-time adopters compared to repeat purchases. For computer vendors who target first-time household computer buyers, their promotional strategies and messages should emphasize the aspect of social relations in technology adoption. Since repeat purchases are made usually by earlier adopters, it is worthwhile to note that technological embeddedness is more meaningful to the laggard segment than to early adopters. Finally, as discussed earlier, technological embeddedness emphasizes the adoption process rather the single adoption event (Premkumar et al., 1994). Promoting an environment that is deeply embedded technologically is an ongoing process and will create a virtual cycle. The more households have adopted home computers, the more enticing the environment becomes, which in turn contributes to increased adoption. In a large scheme, this virtual circle will contribute to bridging the "digital divide" and promote equal opportunities for all households.

However, there are several limitations associated with this study. First, the measurement of technological embeddedness used in this study may not capture the richness of the concept. In particular, due to data limitations, our research does not examine at a micro-level how individuals interact with each other within the social networks. Future studies could focus on the networks of friends and relatives, etc. to study their influence in shaping an individual's attitude towards household computer adoption. Second, this study only examines the impact of technological embeddedness on the adoption of household computer in the U.S. Future research can test the applicability of the concept in adoption of other new technologies (e.g., cell phone, PDA, digital cameras, online social networking services), as well as in other countries, especially developing markets where new technology adoption is still in its early stage. Third, this study only compares the effect of technological embeddedness between two broad consumer segments: first-time adopters and repeat purchasers. Given the heterogeneity of consumer segments, investigating whether technological embeddedness will exert the same influence on more detailed segments would be an interesting extension of this study.

Table 2. Estimation Results for Computer Purchase

Independent Variables	Model 1	Model 2	Model 3
Potential first-time adopters (F_i)	0.023	0.372**	0.476**
Household income	0.109**	0.106**	0.087**
Education	0.083**	0.067**	0.065**
Percentage of household computer ownership (C_i)	0.667**	_____	_____
Number of computer use venues outside home (V_i)	_____	0.164**	_____
Number of computer usages at work (W_i)	_____	_____	0.080**
Percentage of computer ownership × Potential first-time adopters ($C_i \times F_i$)	0.936**	_____	_____
Number of computer use places outside home × Potential first-time adopters ($V_i \times F_i$)	_____	0.231**	_____
Number of computer usages at work × Potential first-time adopters ($W_i \times F_i$)	_____	_____	0.079**
Log likelihood	–26030.43	–25697.75	–25557.49
McFadden's Pseudo-R^2	0.212	0.223	0.226

Notes: N = 96,821. Dependent variable is household computer purchase (D_i). Other independent variables include price, number of household members, minority, school-going kids, married households, 3 region dummies, 4 year dummies, and 280 MSA dummies. ***p*<0.01.

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