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Internet Engagement and Community Participation

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Abstract

During the past decades, scholars have been eager to explain the variances in the adoption, and continued, effective use of the Internet, and pointed out household income and education as the primary predictors. This study contributes to this line of research by showing that social networks formed and maintained within a community (i.e. community participation) are also important to the diffusion and meaningful use of the Internet, even after controlling for income and education. Moreover, we find that the effects of education and income on the extent to which individuals incorporate the Internet into their daily lives are partly mediated by community participation. The implications of these findings for digital inequalities are discussed.

Keywords: Digital Divide, Internet Engagement, Digital Inequalities, Community Participation, Socioeconomic Status

Internet Engagement and Community Participation: Implications for Digital Inequalities

The Internet has become an essential tool for individuals to participate in public spheres, to have access to private markets, to maintain good health, and to become a more productive worker (Boulianne, 2009; DiMaggio and Bonikowski, 2008; Kawachi et al., 2008). Therefore, gaps in access to computers and the Internet between high-socioeconomic status (SES, hereafter) and low-SES groups, i.e. *digital divide,* have long grabbed attention from both scholars and policy makers. Many scholars, however, have argued that most early discussions about the digital divide have adopted a binary, dichotomous view of the Internet and therefore could not accurately and comprehensively describe inequalities in the access to and use of the Internet (DiMaggio et al., 2004; Hilbert, 2011; Talukdar and Gauri, 2011; Tsatsou, 2011; van Deursen and van Dijk, 2010;

Wei, 2012; Zhong, 2011). That is, social inequalities in terms of access to and use of the Internet include much more aspects than just whether one has physical access to the technology or not and thus debates over the digital divide should consider such more subtle disparities that may occur after the initial adoption stage.

In recent years, researchers have tried to go beyond physical access to the Internet or ownership of computers and to examine more qualitative and ecological dimensions of Internet use, such as place and time of Internet use, Internet and computer-related skills, and psychological aspects (e.g. perceived ease of use, perceived importance of the technology) (DiMaggio et al., 2004; Selwyn, 2004; Wei, 2012; Zhong, 2011). In particular, a few groups of scholars (e.g. Jung, 2008; Jung et al., 2012; Jung et al., 2001; Lee, 2009; Leung, 2010, van Deursen et al., 2021) have proposed more comprehensive, holistic indices, such as Internet connectedness and Internet engagement, to capture the extent to which individuals integrate the Internet into their daily lives. Jung and colleagues developed the concept of *Internet engagement*, which consists of the following dimensions: access (i.e. owning computer and Internet access), scope (i.e. the number of activities conducted using the Internet), intensity (i.e. perceived helpfulness of the Internet for achieving one's everyday goals), and centrality (i.e. perceived importance of the Internet in one's daily life). Similarly, Lee proposed the concept of *Internet engagement*, which was constructed using the following six measures: scope of activities using the Internet and computers, Internet- (and computer-) adoption period, frequency of Internet use, comfort level in using the Internet and computers, Internet connection speed, and site scope (i.e. the number of places where one uses the Internet). More recently, van Deursen et al. (2021) argued that the digital divide is being observed in multifaceted forms in society including attitudes, skills, and access to resources, and therefore, more comprehensive approaches are needed to understand the current circumstances. These indices can be understood as an effort to go above and beyond the simplistic and dichotomous conception of the digital divide(s) that have dominated academic works and policy debates.

We argue, however, that one very important question has not been fully addressed in these previous studies: What factors predict Internet connectedness or Internet engagement? To examine the predictors of the Internet engagement in detail, we draw upon communication- and sociological theories, which have been employed to account for individuals' adoption and use of new information and communication technologies (ICTs, hereafter). In doing so, we aim to contribute to this area of research in the following respects. First, we examine the role that individuals' social context, more specifically participation in community group activities (i.e. community participation), may play in the access to and use of the Internet. Although prior studies have primarily focused on the effects of the adoption and use of ICTs on social networks and community participation (e.g. Boulianne, 2009; Hampton et al., 2011), we assume that individuals' Internet use is also heavily influenced by the way in which they engage with other members of their community. Second, in discussing socioeconomic disparities in the spreads and usage of the Internet, previous studies paid little attention to the *social contexts* within which each user is embedded (Agarwal et al., 2009; DiMaggio and Garip, 2011; Rogers, 2003). To directly address this issue, we focus on the potential influences of community participation on the way that individuals are connected to the Internet. Last, but not least importantly, we examine how SES, traditional explanatory factors of Internet adoption and use, is related to community participation, and jointly influences Internet engagement.

Individualistic Account of the Internet Adoption and Use

Most research on the predictors of the diffusion and use of ICTs has focused mainly on a variety of individual characteristics, such as SES, personality traits, and other communication variables. Among others, digital divide studies have consistently pointed out economic capital (e.g. income, financial assets) and human capital (e.g. education, individuals' cognitive abilities in general and technology-specific skills in particular) as key factors that explain individuals' adoption and use of the Internet (Hilbert, 2011; Selwyn, 2004; Tsatsou, 2011; Wei, 2012). Income is of course important in technology use because ICTs are more expensive than other traditional mass media. Also, education plays a significant role in technology adoption and use because effective use of ICTs requires pro-technology attitudes, specific tastes and goals, and a set of technology-related skills and abilities (e.g. skills to operate hardware and software; ability to search, select, process, and apply information; and ability to strategically use technology to achieve one's goals; see van Deursen and van Dijk, 2010), strong correlates with levels of education. For example, Jung and colleagues (Jung et al., 2001, Jung, 2008) reported that income and education were positively associated with Internet connectedness. Likewise, Lee (2009) found that both income and education increases Internet engagement. That is, more educated and affluent people are more likely to establish a long-term, broader, and more intense relationship with the Internet than are their disadvantaged counterparts.

Moreover, previous studies have paid attention to individuals' psychological needs and motivation associated with Internet use since they have emphasized the importance of considering technology users' *perceptions* of that technology in studying why and how people adopt and use new ICTs above and beyond socio-demographics (Po-An Hsieh et al., 2008; Sun et al., 2008; Wei et al., 2011; Zhu and He, 2002). Two theories have been widely used in these studies to identify such crucial psychological variables: the diffusion of innovation theory (see Rogers, 2003) and the technology adoption theory (see Davis, 1989; Park, 2010). Diffusion research has focused on five perceived attributes of innovations, which strongly influence individuals' decisions to adopt a particular product or service or practice: (1) relative advantage (the degree to which an innovation is perceived to be better than its precursors), (2) compatibility (the degree to which an innovation is perceived to be consistent with the existing values, needs, and past experiences), (3) complexity (the degree to which an innovation is perceived to be difficult to use), (4) observability (the degree to which the results of an innovation are observable to others), and (5) trialability (the degree to which an innovation may be experimented with before adoption). Similarly, the technology acceptance model posits that two particular beliefs, that is, *perceived usefulness and perceived ease of use* are very important in studying computer acceptance behavior (Davis, 1989; Park, 2010). Perceived usefulness means potential users' subjective beliefs in the possibility that using a certain technological application will improve their performances, and perceived ease of use represents the extent to which potential users expect the technological applications to be easy to use.

Even though these studies draw our attention to various users' perceptions of attributes of technologies beyond SES and thereby help us better understand the adoption and use of new ICTs, they have relatively ignored the roles of users' *social environments* or *social contexts*. It should be highlighted that such a heavy emphasis on individual-level characteristics found in the Internet diffusion research is not consistent with the original formulation of the diffusion-of-innovation theory. Rogers (2003: 5, Italics added for emphasis) stated that 'Diffusion is the process in which an innovation is communicated through certain channels over time among the members of a *social system*.' Therefore, as Katz (1961, cited in Rogers, 2003: 25, Italics added for emphasis) noted, 'It is unthinkable to study diffusion without some knowledge of the *social structures* in which potential adopters are located as it is to study blood circulation without adequate knowledge of the veins and arteries.' In this vein, Rogers criticized many contemporary diffusion-of-innovation studies for their 'individual-blame bias.' Although it is important to identify individual-level factors, such as income, formal education, media exposure, and needs, scholars should focus on the roles that individuals' network relationships may play in the diffusion process in order to overcome such individual-blame bias.

In addition to the diffusion of innovation theory, communication scholars from its early days have emphasized the importance of adopting a system, ecological perspective when studying media use and effects (for an overview, see Chen et al., 2012; Hayden and Ball-

Rokeach, 2007). The *media system dependency theory*, for instance, assumes that a media system, as a crucial part of a society, is closely connected to individuals, institutions, and social environment, and thus posits that any relationships that individuals shape with media channels depend not only on individuals' goals but also on resources available in media system and social system (Ball-Rokeach, 1985). More recently, Ball-Rokeach et al. (2001) revised the media system dependency theory, and proposed the *communication infrastructure theory* to more explicitly theorize the roles of people's personal- and social environments in how individuals interact with other community residents, local media, and community groups, and in the extent to which they develop relationships with a variety of media channels including the Internet.

Despite the aforementioned, long history of ecological, system approach in commu nication, most digital divide studies have adopted an individualistic or psychological perspective. To redress this oversight, we aim to identify social contextual factors that may be crucial in individuals' Internet adoption and use. To be more specific, we focus on community participation as a social, contextual predictor of Internet engagement.

The Role of Community Participation in the Internet Adoption and Use

Unlike a predominant majority of previous studies in this area, a few scholars have noted the role of social contexts in the adoption and use of new ICTs (e.g. Agarwal et al., 2009; DiMaggio and Garip, 2011; Jung, 2008; Jung et al., 2005; Po-An Hsieh et al., 2008). That is, they have focused on the effect of *social networks* on the Internet use and adoptions, and examined whether and how individuals' primary social networks, such as family and friends, may affect their adoption and usage of the Internet. For example, a few studies demonstrated that when there are more computers in the household and when other family members are experienced, advanced Internet users, people are more likely to use the Internet for more purposes and have better Internet use skills (Hargittai, 2003; Hargittai and Hinnant, 2008). Also, another group of studies have focused on some structural characteristics of individuals' technology-specific social networks or individuals' perceptions of their network members in studying the diffusion of the Internet, and reported that those with someone to rely upon for a variety of supports (e.g. offering technical expertise, sharing hardware and software, providing encouragement) learn new communication technologies more quickly, use these for more diverse purposes, and show sustained use of them (Agarwal et al., 2009; DiMaggio et al., 2004; Selwyn, 2004; Zhong, 2011). In contrast, those without these social supports are less likely to employ and continuously use the Internet than their socially resourceful counterparts.

Although these previous studies are all based on strong theorizations and make invaluable contributions, we take a slightly different approach from them by situating the relationship between individuals and the Internet within a broader social context, i.e. individuals' community, above and beyond their immediate social contexts (e.g. family and friendship ties), and by focusing on the role of community participation. The importance of community participation in the technology adoption and use derives from the concept of *social capital* as an important social contextual factor for individuals or collectives to achieve their goals (Coleman, 1988; Kikuchi and Coleman, 2012; Putnam, 2000). Recent research showed that social capital helps people to increase their digital capital by means of social practices and social supports (Calderon Gomez, 2021). At an individual level, social capital has been measured as community participation (e.g. the number of formal group activities), social trust, or sometimes informal socializing (Kikuchi and Coleman, 2012; Putnam, 2000). Thus, community participation lies at the heart of the concept of social capital.

We hypothesize that community participation is important to Internet engagement even after controlling for income and education (Hypothesis 1) based the following considerations. First, people can learn about costs and benefits associated with Internet use from other community residents, who may have different backgrounds and thus are more likely to play a crucial *informational* role for potential or occasional Internet users. As Rogers (2003: 23) stated, for example, 'The nature of diffusion demands that at least some degree of heterophily be present between the two participants in the communication process.' Because the homophily governs the primary social ties such as family and friends (McPherson et al., 2006), by interacting with community members rather than with primary social groups, can people experience heterophily and thus be likely to adopt and use ICTs. Also, some technology-savvy community members may serve as role models that one can try to emulate in terms of the use of computers or the Internet. In addition, many technical difficulties that one might encounter could be solved with the informational support from his or her community residents.

Second, community members can be a source of *normative influences*. For example, if one finds out that most of the community residents are using computers or the Internet through interacting with their community residents in a form of community participation, he or she may feel pressured to use these technologies. Perception of how others in one's community behave may signal what is acceptable and even right in that community (descriptive social norm; see Rimal and Real, 2003). Many studies have demonstrated that individuals are likely to have favorable attitudes toward ICTs, such as personal computers, mobile phones, and the Internet, and adopt those technologies when they are surrounded by others who started to use those technologies before them (e.g. DiMaggio and Garip, 2011; Hargittai, 2003).

Third, the effect of community participation on the adoption and use of ICTs can be explained by the concept of *network externalities*, which means that values of products, services, or behaviors rely upon the number of people who use the same products or services or engage in the same behaviors (Katz and Shapiro, 1985). Costs and risks of Internet use decreases but its benefits increase as the number of Internet users goes up in their social networks. This leads to the expectation that people are more likely to incorporate the Internet into their daily lives if they realize through their interactions with other community residents that more and more people have adopted the Internet and widely used it in their lives. That is, as DiMaggio and Garip (2011: 1985) pointed out, 'Internet diffusion is a conventional instance of new-product adoption in which network effects directly enhance the technology's value (i.e. its value of the network to which the technology provides access) to the agent.'

Theorizing the Relationship between Community Participation and Socioeconomic Status

Besides testing the main effects of community participation on Internet engagement, we examine the relationship between community participation and SES. Many scholars (e.g. Coleman, 1988; McLeod et al., 1999; Perkins et al., 1996; Putnam, 2000) have suggested that community participation and SES are interlinked with each other, rather than being independent from one another. It was found that education and income are positively related to social capital, measured by community engagement and social trust. That is, those with high levels of education and income tend to actively participate in community groups. This may be partly because highly educated people are more than their less educated counterparts likely to be more knowledgeable about community affairs, to have higher levels of social skills, and to be more efficacious about politics (McLeod et al., 1999). Also, it is plausible that high-SES people have more reasons than low-SES people to participate in community activities in order to protect their economic resources, take control of their neighbors, and acquire better services (Perkins et al., 1996). In line with these previous studies, we hypothesize that education and income both are positively associated with community participation (Hypotheses 2 & 3).

By theorizing the effects of SES on community participation, one can have a better understanding of the underlying mechanisms by which SES influences the adoption and use of the Internet. We contend that those with high levels of formal education and household income are more likely than their low-SES counterparts to integrate the Internet into their daily lives partly because of their higher levels of community participation (Hypothesis 4). Notably, this hypothesized mediation model is different from the psychological models proposed in previous research (e.g. Wei et al., 2011). That is, we provide a sociological perspective regarding why high-SES people form and maintain closer, stronger relationship with the Internet than their low-SES counterparts by focusing on community participation.

Method

Data Source

We used a cross-sectional survey data, entitled the 2010 ANHCS. The ANHCS was designed to collect a nationally representative sample of 250 respondents each month to monitor the American public's health-related media exposure, behavior, knowledge and beliefs, and policy preferences. The ANHCS featured a national probability sample of civilian, noninstitutional adults (18 and above) in the United States. Knowledge Networks (KN) recruited a panel of respondents (panel recruitment rate = 18%) using random digit dialing (RDD) procedures. Selected households who did not already have home Internet access were provided with free hardware (Web TV) and Internet access. The 2010 ANHCS were conducted from January 2010 to December 2010. Of those who were in the panel and were asked to participate, 56.0% agreed to participate in the ANHCS survey. Thus, the response rate for the 2010 ANHCS data was 10.1%, the product of the panel recruitment rate (18) and the cooperation rate (56). The sample size for the 2010 ANHCS data was 3,582.

Measures

Dependent Variable: Internet Engagement

Internet engagement consists of the following six measures: scope of activities using the Internet and computers, Internet- (and computer-) adoption period, frequency of Internet use, comfort level in using the Internet and computers, Internet-connection speed, and site scope.

First, *scope of activities using the Internet and computers* was operationalized as an additive index of 17 dichotomous items, asking respondents to indicate if they engaged in the following online activities: (1) audio or video editing; (2) finances (e.g. banking or paying bills); (3) checking news, weather, or sports; (4) creating web pages; (5) educational purposes; (6) job searches; (7) listening to or downloading music; (8) making phone calls; (9) participating in chat rooms or message boards; (10) playing games; (11) reading newsgroups; (12) searching for information; (13) sending instant messages; (14) shopping; (15) stocks (buying/selling, looking up quotes, etc.); (16) word processing; and (17) work purpose (KR-20 = .77; M = 6.03, SD = 3.35).

Second, *Internet- (and computer-) adoption period* was measured by asking respondents on a five-point scale how long they have been using (1) computers, (2) email, and (3) the Internet other than email. After these items were recoded into interval-level variables (i.e. less than 6 months = 6, 6 to 12 months = 9, 1 to 2 years = 18, 3 to 4 years = 42, and 5 or more years = 60), the answers to these three questions were averaged (α = .89; M = 55.32, SD = 10.93).

Third, *frequency of Internet use* was measured by asking respondents the following question: 'In the past seven days, on how many days did you use the Internet?' (M = 4.79, SD = 2.59).

Fourth, *comfort level in using the Internet and computers* is an averaged value of three 5-point items (1 = 'very uncomfortable' to 5 = 'very comfortable') that asked how comfortable respondents felt in using (1) computers, (2) email, and (3) the Internet other than for email (α = .95; M = 4.16, SD = 1.16).

Fifth, *Internet-connection speed* was measured by asking respondents what kinds of Internet connection they had at home other than the Internet access that Knowledge Networks provided using a three-point scale (i.e. 1 = 'no Internet connection,' 2 = 'Internet connection through a telephone modem,' 3 = 'Internet connection through advanced-quality device such as cable or satellite modem, DSL modem, and T1/T3 line'; M = 2.63; SD = .61).

Sixth, *site scope* was measured as the number of places where respondents use computers, based on the fact that most Internet users rely on computer as their main platform (DiMaggio et al., 2004; van Deursen and van Dijk, 2010). By asking whether respondents use the Internet at home, at work, and somewhere else (e.g. library and friends' house) respectively, dichotomous variables for each place were created and then added up (M = 1.45, SD = .64).

These final scale scores were entered into a principal component factor analysis. All six measures loaded on the first principal component (.77, .72, .58, .59, .59, and .63, respectively). Thus, each of these six measures was standardized and then summed to compose an overall scale of *Internet engagement*.

Mediating Variable: Community Participation

Community participation was measured by asking respondents the following question: 'People may be involved in their communities in many different ways. In the past 12 months, have you…' This was operationalized as an additive index of eight dichotomous items, asking respondents to indicate if they engage in the following types of community participation: (1) participate in neighborhood association or community group; (2) attend a PTA/school group meeting; (3) attend a community group meeting; (4) donate blood; (5) give money to a charity; (6) work for a charity or your church; (7) serve on a community board; and (8) work with others to solve a community problem.[1)]

Independent Variables: Socioeconomic Status

Our independent variables include household income and formal education years. *Education* was measured by asking respondents their highest grade or level of school completion using a 12-point scale (1 = no formal education; 2 = 1st, 2nd, 3rd, or 4th grade; 3 = 5th or 6th grade; 4 = 7th or 8th grade; 5 = 9th grade; 6 = 10th grade; 7 = 11th grade; 8 = 12th grade, no diploma or high school graduate or equivalent; 9 = some college, no degree or associate degree; 10 = bachelor's degree; 11 = master's degree; 12 = professional or doctoral degree). Education was then recoded as a ratio variable, which represents the number of years typically required to obtain a degree (e.g. 1 to 0, 2 to 2.5, 3 to 5.5, 4 to 7.5, 5 to 9, 6 to 10, 7 to 11). *Household income* was originally measured on a 19-point scale (i.e. 1 = less than \$5,000; 2 = \$5,000 to \$7,499; 3 = \$7,500 to \$9,999; …; 19 = \$175,000 or more). We recoded this into a ratio variable by adopting the midpoint of the lower and upper bounds of most categories (i.e. 1 to 5, 2 to 6.25, 3 = 8.75, …, 19 to 175). Although it is quite common to treat ordinal variables as interval variables in regression analyses, we tried to meet the assumption of regression analyses by making this analytical decision (Asher, 1983).

See Table 1 for descriptive statistics of these theorized variables and their correlations.

Table 1 Descriptive Statistics and Bivariate Correlations

Antecedent	Means (SD)	1	2	3	4
1. Household Income (\$)	61,725 (42,581)				
2. Formal Education Years	13.98 (2.56)	.41***			

1) This is a positively skewed variable. Thus, we square rooted this variable and then conducted the same analysis. The result was essentially the same.

3. Community Participation	1.65 (1.55)	.23***	.32***	.62	
4. Internet Engagement	.17 (3.83)	.30***	.30***	.14***	.72

Note. *** $p < .001$. Cronbach's alpha or KR-20 coefficients are included in the diagonal for multi-item scales. Community participation ranges from 0 to 8. Internet engagement ranges from -15.81 to 8.31.

Control Variables

Previous studies have identified several demographic factors that are associated with the Internet adoption and use (see Hargittai and Hinnant, 2008; Wei, 2012). We thus measured a variety of demographic variables to control for factors that might influence Internet engagement, SES, and community participation, including age (M = 49.48, SD = 16.56), gender (54.6% female), race/ethnicity (79% White, 7% African American, 8% Hispanic, 5.9% Other), marital status (57% married) and working status (53% employed). We also included two media use variables that might be associated with Internet use patterns, SES, and community participation. We first constructed TV watching hours per day (M = 4.95, SD = 3.89) by combining responses to the following two questions: 'On a typical weekday, about how many hours do you watch TV each day?' and 'During a typical weekend, about how many total hours do you watch TV?' In addition, to control for influences of newspaper reading (M = 2.81, SD = 2.85) and radio listening (M = 2.31, SD = 2.63) on Internet engagement, we asked respondents 'In the past seven days, on how many days did you read newspaper (and radio talk shows or news)?'

Analysis Summary

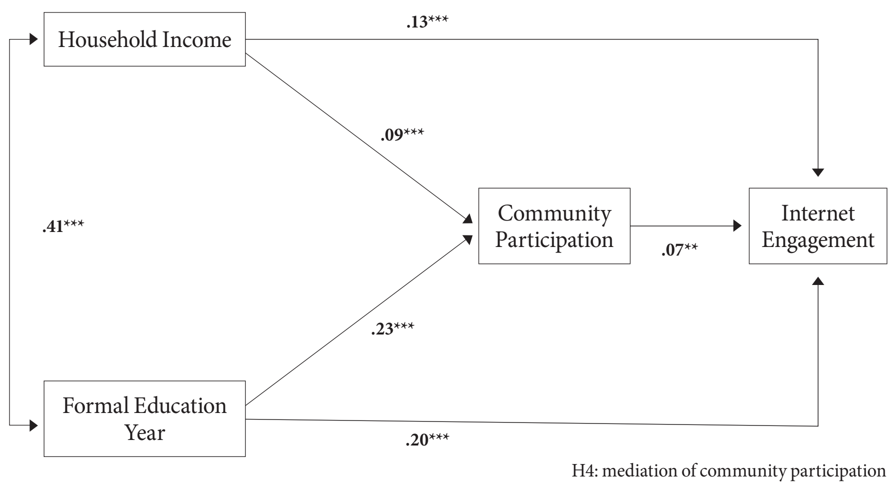
In order to test our hypotheses, we conducted a path analysis using M*plus* 5.21. We evaluated our path model based on Hu's and Bentler's (1999) model fit criteria. A well-fitting model should have a comparative fit index (CFI) ≥ .95, a root mean square error of approximation (RMSEA) ≤ .06, and the Tucker-Lewis Index (TLI) should be ≥ .90. To handle the missing data, listwise deletion was not employed because it does not allow for enough statistical power and may produce biased parameter estimates. Instead, we used the full information maximum likelihood method (FIML), which uses respondents' raw data and incomplete cases to calculate the parameter estimates and standard errors (Graham, 2009).

We tested indirect effects proposed in H4 by employing the bootstrapping mediation analyses to obtain the asymmetric 95% confidence intervals (CIs). As Preacher and Hayes (2008) pointed out, the bootstrapping method does not make any assumption about the shape of the sampling distribution of the indirect effect. The number of bootstrapping was set to be 5,000. Indirect effects were considered statistically significant at the .05 level when zero was not within the 95% asymmetric CI.

Results

As seen in Figure 1, the hypothesized model fit the data well: [CFI = 1.00; TLI = 1.02; RMSEA = 0.00]. Since chi-square is sensitive to large sample size and is often significant in such cases (Hu and Bentler, 1999), the chi-square is not a good indicator for model fit, particularly in the current study with its sample size of 3,582 adults. Thus, this study relied on the CFI, TLI, and RMSEA values. We report completely standardized coefficients and their p values. When examining our hypotheses and research questions, we controlled for the following variables: age, gender, race/ethnicity, marital status, employment status, TV watching hours per day, newspaper reading days, and radio listening days.

Figure 1 Modeling the Influences of SES and Community Participation on Internet Engagement



H4: mediation of community participation

Notes: ** $p < .01$, *** $p < .001$. The solutions are completely standardized. Age, gender, race/ethnicity, marital status, employment status, TV watching hours per day, newspaper reading days, and radio listening days were included as potential confounding factors (CFI = 1.00, RMSEA = .00 (95% confidence interval: .000-.004), TLI = 1.02). However, the influences of control variables are not presented to maintain the visual simplicity.

We found that community participation was positively related to Internet engagement ($\beta = .07, p < .01$), which supports H1. Also, as expected in H2, people with high levels of household income were more likely than those with low levels of income to engage in community participation (β = .09, p < .001). In addition, formal education years was positively associated with community participation (β = .23, p < .001), supporting H3. Notably, there was a positive correlation between household income and formal education years (r = .41, p < .001).

Next, we explored whether community participation serves as a mediator between Internet engagement and two indicators of SES (i.e. household income and formal education years). The indirect effect of household income on Internet engagement through community participation is .006 and the asymmetric 95% CIs showed that community participation was a significant mediator between household income and Internet engagement (95% CI = .001, .011). Likewise, community participation was a significant mediator between formal education years and Internet engagement (β = .018; 95% CI = .005, .028). The direct effects of household income and formal education years are .13 (p < .001) and .20 (p < .001) each.

Discussion

One can gain an in-depth understanding of socioeconomic disparities in the adoption and use of ICTs, such as the Internet, by looking beyond having or not having access to the Internet and by studying how individuals develop relationship with the Internet in their social environment. The present study thus focused on new ways of envisioning the multiple, more subtle, varied manners in which people are using the Internet, such as Internet engagement. More importantly, we examined the effects of community participation and SES on Internet engagement. Our findings first demonstrated that inequalities in the adoption and use of the Internet are multilayered. That is, in addition to the frequency of use, education and income both predicted the number of activities using computers and the Internet, psychological comfort using these technologies, places of using the Internet, Internet adoption period, and Internet-connection speed. Moreover, individuals with high levels of community participation were more likely than those with low levels of community participation to exhibit high levels of Internet engagement. Based on these findings, we contend that the adoption and use of the Internet should be studied in the context of audience's social contexts, such as community participation.

Limitations

Before discussing the implications of our findings, we should highlight a few limitations of this paper. First, we used a cross-sectional dataset. Thus, the causal order between community participation and Internet engagement cannot be confirmed in this study. The reverse causal order could be the case considering that a group of studies have shown that Internet use for public-affairs information acquisition may promote the extent to which people are involved in their community groups (see Boulianne, 2009). Also, it may be that the causal paths may go both ways between community participation and Internet engagement. By focusing on the potential importance of social networks formed and maintained within a community in technology diffusion and use, however, this paper emphasizes the influences that community participation may have on whether and how people build relationships with the Internet. More in-depth, nuanced understanding of the nature of the relationship between community participation and Internet engagement awaits future, time-series data collection efforts.

Second, our measure of Internet engagement should be constantly updated and refined. The ways in which people are accessing and using the Internet have been rapidly changing. Also, as technology advances, people may come up with new ways of employing the Internet in their daily lives. For example, future research should investigate relatively new platforms for Internet connection, such as smartphone, tablet computer, digital television, and personal digital assistants (PDAs). In addition, our Internet engagement measure includes only one aspect of psychological states related to Internet use (i.e. comfort level in using computers and the Internet). Other important psychological variables, such as attitude toward computers or the Internet and perceived importance of these technologies, should be considered in future research.

Third, our scale of community participation is not ideal either. Community participation scale reported here consists of dichotomous indicators; therefore, we were not able to compare respondents on the basis of their frequency of participating in a variety of community group activities. Future studies should employ a continuous version of these measures and tap community participation in greater detail.

Fourth, our response rate is rather low (10.1%). Thus, our claim for national representativeness is somewhat limited. However, this limitation is not critically problematic because weighting the original sample to the U.S. population distribution on crucial variables (e.g. gender, education, race/ethnicity, region, etc.) did not materially affect the distribution of this paper's key variables.

Finally, although the data that this study used is from a nationally representative sample, the data could not reflect the current circumstance, since it was collected in 2010. The ICT technologies are changing constantly, therefore, there are possibilities the data could not show the complete picture of digital inequality. However, given the fact that new ICT technologies emerging these days follow a similar track of Internet in terms of user engagement, the research questions we raised are still valid and the results of the study still could provide insightful interpretations to explain other forms of digital inequality.

Theoretical Implications for ICT Diffusion Research

Despite the aforementioned limitations, there is an important contribution of this paper. This study focuses on the role of social environments in the extent to which individuals have close connections with the Internet, which has been relatively ignored by previous studies. To be more specific, this paper focuses on the role of social networks formed and maintained within a community (i.e. community participation) in Internet engagement. This is because 'we know very little about social-network processes that culminate in adoption' (DiMaggio et al., 2004: 22). Although social networks or social contextual factors have long been regarded as being crucial in the diffusion-of-innovation process (Rogers, 2003; Valente, 1995), most Internet diffusion studies have examined how individuals perceive of the Internet and Internet use, and focused on a few proximate, contextual factors, such as primary social ties (i.e. family and friends). This relative ignorance of ecological or contextual factors may reflect the general trends of some major disciplines of social science (e.g. sociology and psychology; see Oishi and Graham, 2010) and communication in particular since the Second World War (see Viswanath and Emmons, 2006). By demonstrating the effect of community participation on Internet engagement, this study leads researchers and policy makers to consider a much larger social system (i.e. community) as an important factor that may play a key role in diffusing relatively new ICTs.

It should be noted that the focus of this paper is somewhat different from that of previous studies considering that most prior research on social networks or social support in the spread or use of new ICTs has paid attention to *technology-specific* networks or support (Hargittai, 2003; Selwyn, 2004). We tried to broaden the scope of social networks that are important to technology use and thereby situated the relationship between individuals and the Internet in the context of a community. Because our social networks reach far beyond the narrow boundary of family and friends (Hampton et al., 2011; McPherson et al., 2006; Putnam, 2000) and because individuals' adoption and continued use of ICTs depends not only on their family members, friends, and relatives, but also on neighbors, technical experts in their community, and other local material resources (Agarwal et al., 2009; Hampton et al., 2011; Selwyn, 2004; Zhong, 2011), examining the extent to which one engages in community activities and interacts with other community residents (i.e. community participation) is important in investigating the effects of social networks on technology adoption and use.

The aforementioned expansion of the boundary of social networks in studying Internet use is also theoretically meaningful in light of the true meaning of *social systems* in diffusion of innovation in general. As Rogers (2003: 67) stated, 'Social system is a kind of collective learning system in which the experiences of the earlier adopters of an innovation, transmitted through interpersonal networks, determine the rate of adoption of their followers…Thus the social system in which an innovation diffusion acts like a participatory democracy in which the aggregated individual adoption decisions of its members represent a consensus vote on the new idea.' In fact, the importance of community participation in the adoption and use of the Internet demonstrated in this study is consistent with the findings of the pioneering study of the diffusion of innovation, i.e. Ryan and Gross' (1943) hybrid seed corn study. Ryan and Gross showed that farmers' participation in community organizations or attendance at community meetings as well as individual farmers' characteristics was among the strongest predictor of farmers' relative earliness in adopting hybrid corn seed. In this vein, we argue that this study reaffirmed the importance of community in the diffusion of innovations, which was originally emphasized and then got lost in the Internet diffusion studies (i.e., Hilbert, 2011; Selwyn, 2004; Tsatsou, 2011; Wei, 2012), by highlighting the positive association between community participation and Internet engagement. Future studies should move one step further by adopting a refined classification of community participation, such as bonding/bridging social capital and Olson- versus Putnam type of groups (see Ellaway and Macintyre, 2007), and examine which specific community activities are beneficial to the adoption and use of the Internet.

Practical Implication for Digital Inequalities

This study shows the value of using comprehensive indices such as Internet engagement that captures the relationship that individuals have built with the Internet. These days, scholars and policy makers came to agree that the exclusive focus on owing or having access to the Internet is not sufficient to capture and examine more contextual, subtle dimensions of use and consequences of the Internet (Selwyn, 2004; Talukdar and Gauri, 2011; van Deursen and van Dijk, 2010; Wei, 2012). Thus, recent studies have carefully analyzed how and why people from different SES groups are accessing and using the Internet in different ways by adopting comprehensive indices such as Internet engagement and Internet connectedness. These indices tap *contexts* of Internet use, such as location of use, adoption period, Internet connection speed, as well as such *qualitative* aspects of Internet use as kinds of online activities and psychological comfort using the Internet or perceived importance of the Internet in one's daily life. By demonstrating that income, education, and community participation are positively associated with Internet engagement, this study provides additional evidence that we should pay attention to postaccess disparities even after solving the digital divide.

Moreover, community participation was found to have beneficial effects on the effective use of and active engagement with the Internet. Community participation seems to serve as a very useful source of *informational* and *normative* influences for individuals who are about to make a decision about whether to employ a certain information technology and how to use that technology. Prior studies have consistently shown that two indicators of SES, i.e. household income and education, are the primary predictors of the effective use of and active engagement with the Internet. This study contributes to this line of research by showing that social networks formed and maintained within a community in a form of community participation matter in technology diffusion and use above and beyond income and education. Media educators and policy makers should thus try to promote community participation as one potential way of reducing the persistent, worrisome gaps between high- and low-SES groups in the extent to which people incorporate the Internet in their daily lives.

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