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Measuring Sustainable Broadband Adoption: An Innovative Approach to Understanding Broadband Adoption and Use

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Measuring Sustainable Broadband Adoption:
An Innovative Approach to Understanding Broadband Adoption and Use

Efforts to promote sustainable broadband Internet adoption urge new attention to the classic diffusion of innovations paradigm. For this study, innovation attributes were reconceptualized following Social Cognitive Theory (SCT). In a sample of inner-city residents, the model accounted for 36% of the variance in intentions to adopt broadband technology and services, primarily from the SCT variables of expected outcomes and self-efficacy. Prior habitual use of the Internet was also a predictor. Price sensitivity was unrelated to adoption. Among demographic variables, only age had a significant (negative) relationship to broadband adoption after accounting for the SCT variables. Recommendations for the design and monitoring of sustainable broadband adoption interventions are made based on these findings.

Introduction

Ongoing efforts to improve the broadband Internet infrastructure in the United States afford an opportunity to revisit the digital divide, or the gap in Internet access and utilization between groups (Hoffman & Novak, 1998). Significant public investments are being made in broadband infrastructure and public computing facilities with the goal of reducing the disparities in Internet access between urban and rural, majority and minority, high-income and low-income, young and old, and highly educated and less educated citizens. Now attention turns to achieving sustainable broadband adoption through interventions aimed at leveling the utilization and skill gaps that constitute further facets of the digital divide (van Dijk, 2005). The problem can be reframed as one of digital inclusion (National Telecommunications and Information Administration [NTIA], 2010) and extended to include the adoption and utilization of life-enhancing broadband applications as well as basic broadband network access.

The evolution of the digital-divide issue urges new attention to the classic diffusion of innovations (DoI) paradigm (Rogers, 2003). Here, the classic diffusion paradigm was reconceptualized through sociocognitive theories of diffusion (Bandura, 1994; LaRose, Gregg, Strover, Straubhaar, & Carpenter, 2007) and Internet use (LaRose & Eastin, 2004). These pose an alternative to research related to consumer technology adoption and utilization found in the management information systems literature (e.g., Brown & Venkatesh, 2005; Venkatesh, Thong, & Xu, 2012). A sociocognitive model of broadband adoption was developed and tested through a survey study of inner-city residents in the United States, with the goal of contributing to scientific knowledge of the adoption process and, in so doing, guiding the further development of sustainable broadband adoption interventions. The present article extends previous research conducted among rural populations (LaRose et al., 2007) to an urban population and examines new explanatory variables in light of recent developments in theories of technology adoption.

Closing the Broadband Gap

Ongoing public policy initiatives enacted in the United States aim to improve its lagging broadband infrastructure standing relative to other developed nations (OECD, 2011) and to catalyze economic and community development at home (e.g., Gillett, Lehr, Osorio, & Sirbu, 2006; Katz & Suter, 2009). Congress directed the Federal Communications Commission (FCC) to develop a comprehensive National Broadband Plan

> for use of broadband infrastructure and services in advancing consumer welfare, civic participation, public safety and homeland security, community development, healthcare delivery, energy independence and efficiency, education, worker training, private sector investment, entrepreneurial activity, job creation and economic growth, and other national purposes. (FCC, 2010)

The American Recovery and Reinvestment Act (ARRA) of 2009 (Pub. L. No. 111-5, Sec. 6001, 2009) included $7.2 billion to improve broadband access in communities that are unserved (defined as less than 10% broadband penetration) or underserved (less than 40%) by broadband (defined as 768 kbps or faster). The U.S. Department of Agriculture (USDA) awarded $3 billion of the ARRA broadband appropriation through a program administered by the Rural Utilities Service called the Broadband Investment Program. The NTIA awarded the balance of the funds through its Broadband Telecommunication Opportunities Program (BTOP), which specifically targeted minority and low-income communities that have been a consistent theme of public policy discussions (e.g., Cherry, Wildman, & Hammond, 1999). In addition to infrastructure construction, the BTOP funds community computing centers and sustainable adoption projects intended to facilitate the use of broadband technology for the benefit of health care, education, children, employment, and public safety. The present research was conducted as part of one of the latter projects, known more formally as the Sustainable Broadband Adoption program.

These efforts dovetail with other ongoing developments. The FCC's National Broadband Plan (FCC, 2010) aims to extend 100 Mbps broadband service to 100 million homes by 2020. In 2011, the FCC ordered an expansion of universal service to include broadband access in order to bring broadband access to an additional seven million rural Americans (FCC, 2011). Earlier in 2011, the Obama administration had announced a Wireless Broadband Initiative aimed at expanding 4G wireless coverage to 98% of the population by 2014. Also, as a condition for approval of its acquisition of NBC Universal, Comcast agreed to provide, for at least three years, a low-cost ($9.99 per month) broadband Internet service to families with children participating in the National School Lunch Program, a model that other cable companies are emulating. The Gig.U initiative proposes to provide gigabit Internet service in communities surrounding major U.S. universities (Markoff, 2011). Meanwhile, a public-private initiative by electronics retailer Best Buy and the National Science Foundation is addressing the human dimension of Internet adoption by organizing "geek squads" in major urban areas.

Broadband Adoption Demography

Although promoting broadband adoption is a matter of continuing importance, our current understanding of what drives it remains somewhat limited. Previous efforts focused on demographic differences between adopters and nonadopters (e.g., Hoffman & Novak, 1998; NTIA, 1995, 2010, 2011). The latest national study put the U.S. broadband adoption rate at 68% of households as of October 2010 and reported that the "wave of broadband Internet adoption cuts across all demographic groups" (NTIA, 2011, p. 2).

Nonetheless, significant demographic disparities have persisted in the most recent data reported by the NTIA: Adults with college degrees adopted broadband at home at almost triple the rate of those with some high school education (84% versus 30%). The adoption rates for White (68%) and Asian non-Hispanics (69%) exceeded those for Black non-Hispanics (50 %) and Hispanics (45%). By income levels, adoption ranged from 32% among those with $15,000 or less in annual family income, to 90% among those with family incomes in excess of $150,000. Across age groups, persons aged 18 to 24 had the highest rate of broadband use at home, while the lowest rate was among those aged 55 or older. These findings are consistent with classic DoI research (Rogers, 2003) in that younger, higher income, better educated, majority persons are more likely to be earlier adopters of any innovation than older, lower income, less educated, minority ones.

A broadband gap has also been noted between urban and rural areas (Grubesic, 2006). This discrepancy has been addressed by the Broadband Investment Program (see above) and earlier USDA initiatives (e.g., the Community Connect program), as well as in the FCC's plan to reallocate universal service fund revenues to rural broadband. However, core inner-city residents also have lower levels of broadband adoption (45%) compared to suburbanites (51%, NTIA, 2007) and the majority of ARRA infrastructure grants through the NTIA's BTOP program were targeted, at least in part, to urban populations (LaRose et al., 2011).

Demographic variables have been used to explain—or, one might even say, "explain away"—geographic differences. The gap between urban and rural broadband penetration was found to be a function of the low levels of income and education in rural areas compared to urban ones (Government Accountability Office [GAO], 2006). Likewise, the demographic profile of core inner-city residents matches up with the demographics of nonadopters of broadband.

However, observing that less well-to-do, less educated, minority and older Americans adopt broadband at lower rates than others does not offer actionable solutions to overcoming the digital divide. Framing the issue in terms of demographic categories addresses neither the consumer perceptions and knowledge barriers that impede access, nor the marketing practices of broadband providers that may contribute to the disparity in the first place. For example, perceptions of the value of broadband service and the relevance of broadband content (Pew Research Center, 2010) and perceptions of the importance of broadband in modern life (Dailey, Bryne, Powell, Karaganis, & Chung, 2010) may affect its adoption. Broadband education and government service applications are of particular interest to inner-city populations (ACPLI, 2009).

A focus on demography can also lead to unhelpful prescriptions for implementing the National Broadband Plan (see Compaine, 2001; GAO, 2006). Either there is nothing to be done because the real problem is relatively intractable income (or racial or educational or age) inequality, or nothing needs to be done because eventually the laggard demographic groups will catch up as they always tend to do with any new technology. At best, demographic analyses of the digital divide lead to calls to action but provide no specifics about the actions to be taken.

A more theoretically robust and heuristic approach should uncover the psychological dynamics that are shared by groups of people as a function of their common experiences and that mediate the effects of demographic variables on broadband adoption. The present research seeks to uncover underlying processes explaining broadband adoption that transcend demography and frame actionable interventions that will sustain digital inclusion for all citizens.

Theoretical Models of Technology Adoption and Utilization

The present analysis begins by examining two contemporary models of technology adoption and utilization that originated in the management information systems literature, the unified theory of the adoption and utilization of technology (UTAUT, Venkatesh et al., 2012) and the model of adoption of technology in households (MATH, Brown & Venkatesh, 2005). These will be examined in relationship to the classic DoI paradigm (Rogers, 2003),[1] and a sociocognitive theory of adoption and utilization will be developed thereafter.

UTAUT and UTAUT2

UTAUT (Venkatesh, Morris, Davis, & Davis, 2003) is an extension of the earlier Technology Acceptance Model (Davis, 1989), itself an adaptation of the theory of reasoned action (TRA, Fishbein & Ajzen, 1972). Performance expectancy, effort expectancy, social influence, and facilitating conditions determine people's behavioral intention to use a technology in organizational settings. The model was extended, as UTAUT2, to explain consumer technology adoption. Hedonic motivation, price–value perceptions, and habit strength were added to the basic model. After adding interaction terms for gender, age, and the amount of prior experience, the model explained 73% of the variance in mobile Internet adoption intentions in a Hong Kong sample (Venkatesh et al., 2012).

However, superior empirical results have been obtained at the expense of parsimony and elegance (Bagozzi, 2007). UTAUT is not notably superior to other models until the demographic moderators are added, an inelegant solution that does not embrace or develop an overarching, integrated theory of human behavior (Dulle & Minishi-Majanja, 2011). Also, UTAUT2 uses generic measures of performance expectancy and hedonic motivation (e.g., "I find [technology] useful in my daily life," "Using [technology] is fun") so that the same operational measures can be used across studies. While enhancing

[1] The reason the 2003 edition of Rogers' work is cited rather than later versions will become more apparent shortly; namely, its reference to social cognitive theory as the basis for understanding adoption processes.

the generalizability of the model, this approach offers little in the way of actionable information. For example, UTAUT2 might indicate that broadband is adopted because it is "fun" but would not provide information about exactly which applications produce that outcome. This also departs from the recommended practice in TRA, from which the model originates, of assessing specific expectancies about the behavior in question.

MATH

Based on the theory of planned behavior (TPB, Ajzen, 1985), Brown and Venkatesh (2005) proposed the MATH model, which is closely related to UTAUT2, to explain technology adoption in households. This model includes attitudinal, normative, and control beliefs. Attitudinal beliefs pertain to applications for personal use, utility for children, utility for work-related use, applications for fun, and status gains. Normative beliefs relate to the influence of friends and family, secondary sources (e.g., television and newspapers), and workplace referents. Control beliefs pertain to the fear of technological advances, declining cost, present cost, perceived ease of use, and possession of requisite knowledge. However, like UTAUT, the theory proposes generic measures of beliefs about the outcomes of adoption rather than beliefs specific to a particular technology in question. It also relies on a myriad of moderating demographic relationships that interact with the key explanatory variables to explain variance at satisfactory levels. These demographic relationships are not recognized in the TPB model from which MATH is drawn.

Diffusion of Innovations (DoI)

The DoI paradigm, a widely used approach to understanding technology adoption, was originally developed in the field of communication. Diffusion is "the process by which an innovation is communicated through certain channels over time among the members of a social system" (Rogers, 2003, p. 35). DoI was among the paradigms evaluated in the development of UTAUT; however, aside from that there has been little cross-fertilization across disciplinary boundaries.

Five characteristics of an innovation that affect its rate of adoption have received considerable empirical attention: (1) Relative advantage—the degree to which an innovation is perceived as better than the existing alternatives. (2) Compatibility—the degree to which an innovation is consistent with one's values, beliefs, and needs, and with previously adopted innovations. (3) Complexity—the perceived difficulty of adopting and using the innovation. (4) Trialability—the degree to which the innovation can be experimented with on a limited basis. (5) Observability—the degree to which the benefits of the innovation are visible (Rogers, 2003).

Note that these are characteristics of the innovation and center on technology rather than the adopter. The relevant characteristics of individuals are thought to be their demography (e.g., age, education) and their inherent innovativeness. Lacking is an underlying theory of behavior that might describe the dynamic thought processes that lead to adoption. For this reason, DoI is often referred to as a paradigm rather than a theory. As in UTAUT and MATH, its strength is in the empirical results rather than its theoretical elegance. Recent diffusion studies have proposed adopter-related variables such as values, attitudes, and social learning (Johan, 2011; LaRose et al., 2007; Peng, Fan, & Dey, 2011). The classic description of innovation attributes does not explicitly mention cost. However, relative advantage might be understood as a ratio of expected benefits to costs of adopting an innovation. Thus, the rate of innovation adoption might be expected to increase if the cost of adoption is relatively low vis-à-vis the expected benefits.

A Social Cognitive Theory of Innovation Adoption

The lack of an overarching theory of human behavior has emerged as a shortcoming of current approaches to understanding technology adoption. One such theory of human behavior, social cognitive theory (SCT), was adopted at one point in the development of the DoI paradigm (Rogers, 1995). At about the same time, SCT was extended to explain innovation diffusion (Bandura, 1994). Both SCT and diffusion paradigms regard communication—learning from observing other people—as the basis for an individual's behavior change. LaRose et al. (2007) further developed and tested a sociocognitive model of innovation diffusion in the context of broadband Internet adoption in a rural U.S. population.

An important SCT process is observational learning. Through symbols, people can reflect and describe what they have experienced and evaluate the benefits of an innovation. People can also self-evaluate their behaviors through their own experience, that is, enactive learning. Both observational and enactive learning provide information about the likely outcomes of future behavior. According to SCT, the eventual performance of a behavior is contingent on its expected outcomes. In the technology adoption literature, perceived usefulness and performance expectancy are parallel concepts. However, the underlying learning processes have received little attention.

Another determinant of behavior is that individuals perceive that they have self-efficacy, or the capability to perform the behavior in pursuit of important attainments (Bandura, 1997). This concept has perhaps been misconstrued in both TPB and recent technology adoption research, where it has been confounded with facilitating conditions, operationally defined (e.g., Venkatesh et al., 2012) in terms of the availability of help or necessary knowledge rather than the potential adopters' belief in their own capabilities. This is an important distinction because individuals with self-efficacy for a particular behavior are likely to persist, even to the point of engaging in experimentation and knowledge acquisition and overcoming barriers, while those lacking it may yield to frustration (Bandura, 1997). Hargittai and Hinnant (2008) found that perceived online skill (an indicator of self-efficacy) is an important factor mediating the types of activities people pursue online. However, skill is not the essence of self-efficacy. Rather, it is individuals' confidence that they can succeed in performing a behavior, even in instances (such as the adoption of a new technology) where they have not yet acquired specific skills involved in executing the behavior in question.

LaRose et al. (2007) equated the diffusion concept of relative advantage with the sociocognitive concepts of expected outcomes, trialability with enactive learning, observability with observational learning, complexity with self-efficacy, and compatibility with prior experience with related technologies. In doing so, the researchers argued that the approach allows innovation adoption to be examined from the perspective of user-centered perceptions of the technology rather than the characteristics of the technology. This sociocognitive model of broadband adoption is reproduced in Figure 1. In further analyses (not shown) demographic variables including age, income, education, and Hispanic ethnicity were added as antecedent variables, but their impacts on the dependent variable of broadband adoption intentions were mediated by the explanatory SCT variables in the model.

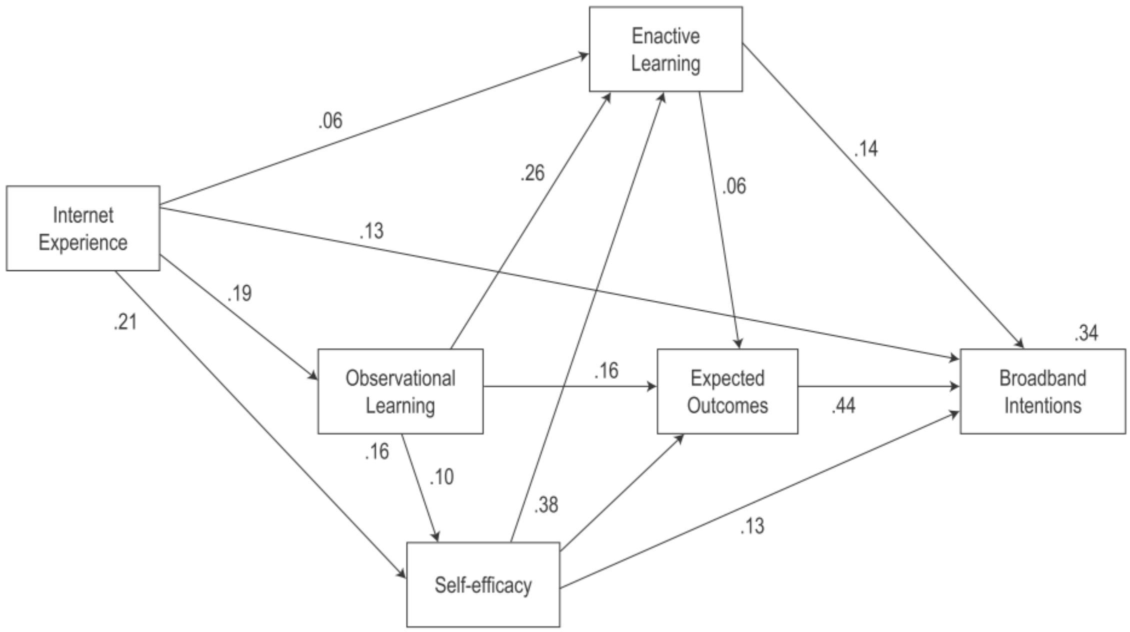

Figure 1. Sociocognitive model of rural broadband adoption (LaRose et al., 2007, p. 367). Standardized path coefficients are shown.

Research Model

The present research employs the model in Figure 1 as a basis for further theorizing mechanisms of broadband adoption. The present research adds habits and price sensitivity as potential explanatory variables. Refinements to previously examined variables that may have limited the reliability and predictive power of the model are also proposed. Here, the model of broadband adoption is tested in an urban, inner-city context, providing evidence of its generalizability to a population that is quite different from the rural populations in which it was developed.

Media habits, defined as automaticity in media consumption, have lately received new attention as determinants of media behavior (LaRose, 2010; LaRose & Eastin, 2004) and have also emerged as predictors of technology adoption (Allouch, van Dijk, & Peters, 2009; Venkatesh et al., 2012). In SCT terms, habits are conceptualized as deficiencies in the self-regulatory mechanism through which individuals control their own behavior. Habits are conceived of as a failure to monitor behavior consciously, sometimes to the point of losing conscious control (LaRose, 2010). In the context of broadband adoption it is expected that prior habitual use of the Internet (including dial-up connections in the home and broadband use outside the home) will be a significant determinant of broadband adoption intentions as individuals yield to urges to further pursue existing online habits through broadband connections. In DoI terms, this prior habitual use can be viewed as an aspect of compatibility; in this case, compatibility with existing online habits. In the model depicted in Figure 1, habit strength would be expected to precede observational and enactive learning as well as self-efficacy, since habitual Internet use can be expected to provide additional opportunities to observe and directly experience the outcomes of broadband adoption while bolstering beliefs about individual abilities to use the Internet effectively. Habit strength would itself be preceded by prior Internet experience, as media habits are believed to form initially through repeated behavior (LaRose, 2010).

As mentioned above, technology adoption models have largely ignored the issue of cost of service as a factor in technology adoption. In the DoI paradigm, cost is only one component of relative advantage and is not necessarily limited to monetary expenditures. UTAUT properly ignores the issue, since in organizational settings the cost of the technology is absorbed by the organization rather than the individual adopter-employee. UTAUT2 includes price value. MATH (Brown & Venkatesh, 2005) considers the cost of service and changing costs. However, none of the above studies include willingness to pay or price sensitivity, though the latter is possibly important when discussing low-income populations of the inner city.

Savage and Waldman (2009) used a consumer survey to explore current and prospective broadband users' willingness to pay for an increase in the speed of a broadband service and found that consumers without access to broadband valued an increase in bandwidth at less than one third the amount consumers with broadband access were willing to pay. They also found that the amount consumers were willing to pay for additional bandwidth increased with their ability to exploit the technology, as did Rosston, Savage, and Waldman (2010) in a related study. Thus, if broadband's value to a user increases with experience, and if consumers' appreciation of the contribution experience makes to the value derived from broadband is itself substantially dependent on experience, then new and prospective broadband customers will value broadband service less than will otherwise identical customers who have been using the service for a while. This unanticipated contribution of experience to the use value of broadband will make experienced users' demands for the service less sensitive to small variations in price than new users' and potential new users' demands, at least at price levels currently observed in the marketplace. In SCT terms, this suggests that the expected outcomes of broadband technology gained through prior experience, alongside the ability to observe the experiences of others as market penetration increases, attenuates the impact of cost. Thus price sensitivity may not be a significant factor in broadband adoption once observational and enactive learning are considered, a possibility that the present study will explore.

LaRose et al. (2007) pointed out that relationships between prior experience and both observational learning and expected outcomes suggest a mechanism for understanding the operation of innovation clusters previously uncovered in diffusion research (LaRose & Mettler, 1989; Rogers, 2003). Prior relevant experience may cue individuals to observe others' experiences with further innovations.

Such experience can also provide direct information about the expected outcomes of related innovations. However, the link between prior experience and enactive learning was nonsignificant—possibly, the researchers suggested, because of the use of a single-item, generalized operational measure for enactive learning. To improve on this model, the current study uses multi-item indices for both enactive and observational learning.

Finally, SCT does not recognize demographic variables as either direct predictors of behavior or as moderators of the primary mechanisms of observational learning, enactive learning, self-efficacy, or self-regulation. Rather, differences between demographic groups are thought to be the result of consistent differences in the reinforcement histories of different social groups. For example, compared to suburbanites, inner-city residents may have less opportunity to directly experience the benefits of the Internet for themselves. Those differences, rather than the urban-rural location per se, are thought to predict behavior.

Thus, demographic variables will be modeled as prior causes of differences in the main explanatory variables of SCT shown in Figure 1. Habit strength is added to the model as previously described (Figure 2). Price sensitivity is evaluated as a potential explanatory variable as well.

Research Methods

Data Collection

A mail survey was conducted following the tailored design method (Dillman, Smyth, & Christian, 2009). This involved five contacts, including a prenotification, initial questionnaire mailing (with $1 cash incentive), a reminder postcard, a duplicate questionnaire, and finally a certified mail contact with replacement questionnaire. An online version of the survey was also made available. Two thousand households were randomly sampled through a commercial mailing list vendor that supplied residential addresses in the inner-city areas of a Midwestern state. A response rate of 42% was derived from the 538 completed surveys out of 1,294 valid addresses. About 10% of the completed surveys were completed online.

Respondents

Based on the latest U.S. Census Bureau's Current Population Survey data, Internet adoption at home for core inner-city areas of the state in question was 62% (Blank & Strickling, 2010). Fifty-seven percent of the survey respondents had Internet access at home. The sample comprised 53% females and 47% males with a median age of 52. Forty-five percent of the respondents were White, 51% were African American and 5% were Hispanic. The median household income of the sample was between $25,000 and $49,999 compared to the median household income of $28,000 in the population. The mean age of the sample was 53.5 years compared to the median age of 52 in the population (persons under the age of 18 were not included in the study). Based on census data (U.S. Census Bureau, 2011) the demographics of the sample were within the limits of sampling error at the 95% confidence level.

Operational Measures

Table 1 presents the means and standard deviations of the composite scales and demographic data used in the data analysis. The exact wording of survey questions and the Cronbach alpha internal consistency coefficients for the multi-item additive indices constructed can be found in the appendix. The dependent variable, broadband intentions, was based on a four-item additive scale of future plans regarding the usage of broadband Internet in the home (α = .86). The validity of behavioral intentions as predictors of future behavior has been established by Ajzen (1985). Intentions were rated on a 7-point scale ranging from very likely (scored as 7) to very unlikely (scored as 1).

The SCT variables were operationalized after LaRose et al. (2007). The SCT concepts were rated on 7-point scales ranging from strongly agree (scored 7) to strongly disagree (scored 1), and negatively worded items were reflected. The responses to multi-item indices were averaged across the number of items. Missing data were replaced by mean values. Expected outcomes of broadband usage were a 12-item index (α = .96). Internet self-efficacy comprised five items (α = .95). Observational learning (α = .93) and enactive learning (α = .94) comprised three items each and were also assessed on Likert-type agree–disagree scales. Habit strength was assessed with eight items (α = .91).

The amount of Internet experience was the base 10 logarithm of time, in months plus 1,[2] since the respondent first used the Internet. Nonusers, who comprised 31% of the sample, were assigned a value of 0. The mean for Internet experience before the logarithmic transformation was 82.7 months. Respondents were also asked to indicate the year of their birth, and that date was subtracted from the year of the survey to assess age. The years of education completed by each respondent, excluding kindergarten, were recorded. Household income was broken down into mutually exclusive categories: under $10,000 (scored as 1), $10,000–$19,999, $20,000–$34,999, $35,000–$49,999, $50,000–$74,999, $75,000–$99,999, and $100,000 or more (scored as 7). Gender was entered as 0 for male and 1 for female. Race was also included in a larger correlation matrix as three variables: White, African American, and Hispanic. Each variable was entered as 0 for no and 1 for yes. The race variables of White and Hispanic did not correlate with broadband intentions and were excluded from the reported correlation matrix and regression analyses.

Price sensitivity was operationalized as the most the respondents were willing to pay monthly for a high-speed broadband connection (reflected). This could also be measured as a proxy of price sensitivity in that the more respondents were willing to pay for high-speed Internet, the less price-sensitive they were. The measure was broken down into these categories: nothing (scored as 1), less than $10, $10 but less than $30, $30 but less than $45, $45 but less than $75, $75 but less than $100, $100 or more (scored as 7).

[2] Since the log of zero is undefined, Internet experience = log 10 (time in months + 1).

Results

Pearson product–moment correlations were calculated using IBM SPSS Statistics version 19 (IBM Corporation, 2010). Table 1 shows the Pearson product–moment correlations among the dependent and independent variables.

Table 1.Means, Standard Deviations, and Pearson Product-Moment Correlations Among Dependent and Independent Variables.

Variable	1	2	3	4	5	6	7	8	9	10	11	12	*M*	*S.D.*
1. Broadband intentions	α=.86												4.30	1.77
2. Expected outcomes	.538**	α=.96											3.99	1.96
3. Internet experience	.363**	.481**	-										1.36	.96
4. Observational learning	.454**	.846**	.406**	α=.93									4.20	2.17
5. Enactive learning	.511**	.867**	.472**	.895**	α=.94								4.24	2.21
6. Self-efficacy	.428**	.440**	.527**	.321**	.400**	α=.95							4.61	1.95
7. Habit strength	.271**	.258**	.157**	.170**	.219**	.289**	α=.91						2.96	1.25
8. Price sensitivity	.011	.023	.020	.017	.022	.004	.004	-					4.95	1.12
9. Age	-.327**	-.328**	-.359**	-.237**	-.305**	-.294**	-.179**	.005	-				52.33	14.56
10. Income	.162**	.219**	.310**	.190**	.232**	.135**	-.043	-.020	-.015	-			3.37	1.71
11. Education	.102*	.203**	.284**	.156**	.152**	.189**	-.047	.016	.012	.361**	-		13.24	2.94
12. Gender	.033	-.014	-.020	-.022	-.063	-.009	-.005	.101*	-.056	-.196**	.010	-	.53	.50
13. African American	-.217**	-.139**	-.085	-.112*	-.135**	-.180**	-.069	.073	.207**	.029	-.042	-.035	1.34	.59

Note: * Correlation is significant at the 0.05 level (two-tailed)
** Correlation is significant at the 0.01 level (two-tailed)
Cronbach alphas are entered in the diagonal

Three hierarchical regressions were conducted, first with expected outcomes as the dependent variable and then with broadband intentions as the dependent variable. The results of the regressions are presented in Tables 2 and 3 respectively.

Table 2. Regression of Demographic, SCT and Price Sensitivity Variables on Expected Outcomes.

		Standardized Coefficients	t	Sig.
Model 1	(Constant)		9.652	.000
	Gender	.012	.298	.766
	Age	-.314	-7.616	.000
	Income	.193	4.368	.000
	Education	.113	2.605	.009
	African American	-.075	-1.817	.070
Model 2	(Constant)		-.213	.832
	Gender	.026	1.226	.221
	Age	-.054	-2.349	.019
	Income	.019	.802	.423
	Education	.047	2.114	.035
	African American	-.003	-.155	.877
	Internet experience	.026	.956	.340
	Observational learning	.386	8.472	.000
	Enactive learning	.426	8.739	.000
	Self-efficacy	.090	3.542	.000
	Habit strength	.063	2.924	.004
	Price sensitivity	.009	.439	.661

Note: F (11, 496) = 175.938, p < .001; Adjusted R^2 = .79; R^2 change for additional variables in model 2 = .61.

The independent variables in model 2 predicted 79% of the variability in expected outcomes. The four demographic variables accounted for 19% of the variance, and the SCT variables accounted for an additional 61% of the variance. Controlling for other variables, gender, income, Internet experience, and price sensitivity were not significant predictors of expected outcomes. With this combination of factors, observational learning, enactive learning, self-efficacy, and habit strength were significant predictors of expected outcomes.

In terms of the expected outcomes of broadband adoption, the SCT variables accounted for more than 3 times the variance compared to the demographic variables. These results suggest that demographic variables such as age, income, and education play a relatively small role in forming perceptions of the expected outcomes of broadband adoption. SCT variables that are more pliable to interventions play a relatively larger role. In other words, expected outcomes can be enhanced by creating opportunities for observing and learning about the benefits of broadband adoption. This finding underscores the argument that demography is not destiny.

Table 3. Regression of Demographic, SCT, and Price Sensitivity Variables on Broadband Intentions.

		Standardized Coefficients	t	Sig.
Model 1	(Constant)		13.296	.000
	Gender	.047	1.117	.265
	Age	-.301	-7.206	.000
	Income	.178	3.981	.000
	Education	.005	.113	.910
	African American	-.157	-3.764	.000
Model 2	(Constant)		5.168	.000
	Gender	.052	1.422	.156
	Age	-.115	-2.866	.004
	Income	.085	2.071	.039
	Education	-.048	-1.221	.223
	African American	-.104	-2.824	.005
	Expected outcomes	.259	3.310	.001
	Internet experience	.000	-.006	.995
	Observational learning	-.024	-.277	.782
	Enactive learning	.163	1.785	.075
	Self-efficacy	.165	3.666	.000
	Habit strength	.097	2.538	.011
	Price sensitivity	.012	.332	.740

Note: F (12, 495) = 25.497, $p < .001$; Adjusted R^2 = .36; R^2 change for additional variables in model 2 = .24.

In the regression of demographics, SCT, and price-sensitivity variables on broadband intentions, the independent variables in model 2 accounted for 37% of the variability; age, income, and race accounted for 16% of the variability; and an additional 21% of the variance was predicted by expected outcomes, enactive learning, self-efficacy, and habit strength. With this combination of factors, age, income, race, expected outcomes, self-efficacy, and habit strength were significant predictors of broadband intentions.

In terms of the intentions to adopt broadband, the SCT variables accounted for twice the variance compared to the demographic variables. As was the case with expected outcomes, these results suggest that demographic variables such as age, income, and race play a relatively smaller role in intentions to adopt broadband, whereas SCT variables such as self-efficacy and habit strength play a relatively larger role. Like expected outcomes, the intentions to adopt broadband can be enhanced by increasing the self-efficacy and habit strength of Internet users.

Table 4. Regression of Demographic, SCT, and Price Sensitivity Variables on Broadband Intentions for Subset of Nonusers of Broadband.

		Standardized Coefficients	t	Sig.
Step 1	(Constant)		8.274	.000
	Gender	-.104	-1.521	.130
	Age	-.241	-3.423	.001
	Income	-.044	-.609	.543
	Education	-.025	-.357	.721
	African American	-.165	-2.357	.019
Step 2	(Constant)		3.807	.000
	Gender	-.062	-.971	.333
	Age	-.060	-.844	.400
	Income	-.063	-.939	.349
	Education	-.109	-1.574	.117
	African American	-.120	-1.864	.064
	Expected outcomes	.257	1.795	.074
	Internet experience	-.001	-.009	.993
	Observational learning	.066	.359	.720
	Enactive learning	-.011	-.060	.952
	Self-efficacy	.251	3.341	.001
	Habit strength	.085	1.301	.195
	Price sensitivity	.022	.349	.728

Note: F (12, 185) = 7.273, p < .001; Adjusted R^2 = .28; R^2 change for additional variables in model 2 = .18.

Table 4 presents the results of a third regression conducted for the subset of 197 respondents who reported that they did not use broadband Internet at home. The demographic variables of age and race predicted about 11% of the variability in broadband intentions. An additional 18% of the variability was predicted by self-efficacy. With this combination of factors, only self-efficacy was a significant predictor of broadband intentions. Compared to the full sample of respondents, broadband intentions were not predicted by expected outcomes, enactive learning, or habit strength. Thus, nonusers of broadband who feel most confident about their ability to perform tasks on the Internet are also more likely to adopt broadband than less confident nonusers are. Conversely, the finding suggests that the main deterrent to broadband adoption could be a perceived deficiency in personal abilities to use broadband Internet.

To better understand the interrelationships among the independent variables, structural equation modeling was used to analyze the model of the posited causal links presented in Figure 2. For this analysis, enactive learning and observational learning were combined into a single latent variable called "learning." Gender and price sensitivity were excluded from this analysis since preliminary bivariate and multivariate analyses indicated they were unrelated to broadband intentions.

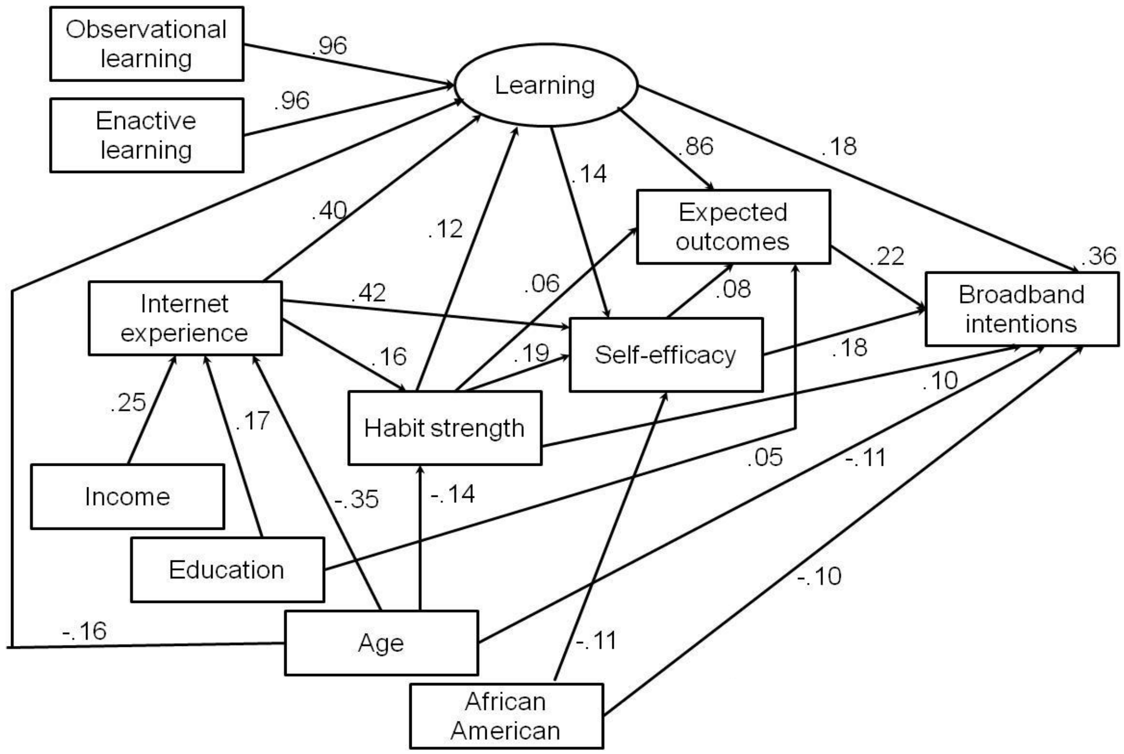

Figure 2. Path model of broadband intentions: Sociocognitive and demographic variables.
$X^2(29)$ = 63.97, *p* < .001, CFI = .987, RMSEA = 0.047.

The model was an acceptable fit for the data following the criteria proposed by Hu and Bentler (1999): $\chi^2(29)$= 63.97, *p* < .0001, CMIN = 2.206, CFI = 0.987, RMSEA = 0.047. All of the path coefficients shown were significant, *p* < .05. In this model, the proximal causes of broadband intentions were learning (ρ = .18), expected outcomes (ρ = .22), self-efficacy (ρ = .18), and habit strength (ρ = .10). Among demographic variables, age (ρ = -.11) and race (African American, ρ = -.10) had direct relationships to the primary dependent variable of broadband intentions. The effects of the other demographic variables on broadband intentions were mediated by the SCT variables in the model. As expected, habit strength also predicted learning (ρ = .12) and self-efficacy (ρ = .19) and was itself predicted by prior Internet experience (ρ = .16). Habit strength also had a direct relationship to expected outcomes (ρ = .06). In the present model, experience was related to learning (ρ = .40), as previously hypothesized by LaRose et al. (2007). Expected outcomes were predicted by education (ρ = .05), learning (ρ = .86), self-efficacy (ρ = .08), and habit strength. Self-efficacy was predicted by learning (ρ = .14), habit strength, and Internet experience (ρ = .42). Age had negative relationships with Internet experience (ρ = -.35), habit strength (ρ = -.14) and learning (ρ = -.16). Income had a direct relationship with Internet experience (ρ = .25), and education also predicted Internet experience (ρ = .17).

Discussion

The present research revisited and extended a sociocognitive model of diffusion of innovation to explain broadband Internet adoption among inner-city residents. Reinterpreting classic DoI concepts as sociocognitive variables made it possible to establish causal ordering among those variables and to arrive at a relatively parsimonious model that predicted broadband adoption intentions from prior learning, expected outcomes, self-efficacy, and the strength of Internet habits.

An important implication of the present model is that demography is not destiny. With the exception of age and race, the effects of demographic variables were entirely mediated by the explanatory variables of SCT. Still, demography does matter to some extent: income and education determined the amount of individuals' prior experience with the Internet, and education also had a direct effect on expected outcomes. In line with the long tradition of digital divide research, it is likely that poverty restricts access to computing resources, both in the home and in inner-city neighborhoods. The impact of education may arise from access to educational opportunities that expose individuals to computing resources and enable them to discover online applications that improve their lives. Age had a direct, inverse effect on broadband intentions, suggesting that expected broadband outcomes of particular interest to young adults (e.g., social networking experiences enhanced by video applications) may have been overlooked. However, age had linkages to other variables in the model including learning, self-efficacy, and habit strength. It is possible that a generational difference was at work. The survey was limited to individuals age 18 and over, so it did not include "digital natives" born after the dawn of the Internet era. However, the younger respondents presumably came in contact with Internet technology during their years in school, unlike older generations.

Race also had a direct effect on broadband adoption intentions: African-Americans were less likely to intend to adopt broadband than other groups. As was the case with age, this relationship was partially mediated by self-efficacy, suggesting that interventions aimed at increasing African Americans' confidence about using the Internet to attain important goals could stimulate adoption.

Juxtaposing the regression of the full dataset with that of the subset of nonusers of broadband suggested that nonusers' intentions to adopt broadband may have been attenuated by relatively low levels of self-efficacy. Self-efficacy interventions thus emerge as a highly promising avenue for stimulating sustainable broadband adoption in the inner city. SCT proposes four strategies for increasing self-efficacy that should be the focus of further research. These are observational learning, enactive mastery (i.e., progressive learning of a task), persuasion, and anxiety control.

Price sensitivity played a surprisingly minor role in broadband adoption among the inner-city residents surveyed. The more individuals were willing to pay for broadband, the greater were their adoption intentions. This finding was in the expected direction, but was nonsignificant and virtually zero (r = .01). This result raises the interesting possibility that broadband adoption is not a purely economic decision in which the value of broadband service is carefully calibrated against its dollar cost. However, because a single-item measure was used to assess price sensitivity, it is possible that the present research design did not reliably assess this variable. Moreover, willingness to pay is not the same as the ability to pay, which may be the crucial distinction in high-poverty areas. Price sensitivity was captured with a measure intended to indicate the willingness to pay for broadband; however, responses that reflect the true willingness to pay are notoriously difficult to obtain. For example, price effects could be subsumed in other independent variables (e.g., relative advantage, expected outcomes). Nevertheless, the correlation analysis also revealed a negative relation between income and price sensitivity (r = -.02), which was in the expected direction. The greater their income, the less price sensitive respondents were. Specifically, a scatter plot of price sensitivity and income showed that the price range of "$10 but less than $30" is the most common choice among all income groups. Respondents reporting incomes of $50,000 to $74,999 were more willing to pay more for broadband service.

Comparing the present results with those obtained from rural populations (Figure 1), it is evident that the same basic model held in both cases. However, it appears that expected outcomes had a stronger relationship to broadband adoption in rural communities than in urban ones, while self-efficacy was the stronger predictor in the urban sample. Tracing the causal chains, the amount of prior Internet experience was more strongly related to self-efficacy among inner-city residents than among rural ones. These results further suggest that confidence-building online experiences are especially critical in promoting broadband adoption in the inner-city context.

Observational learning, aka observability, and enactive learning, aka trialability, once again appeared to be causal antecedents of expected outcomes. However, learning also had a direct effect on adoption intentions. It can be argued from SCT that outcome expectations arise solely from what has been previously learned through either personal experience or the observation of others. The reason for the discrepancy may be that important expected outcomes of broadband adoption were not assessed in the present research. However, observational and enactive learning may also operate on behavior through yet another SCT mechanism, self-regulation, in a way that was not represented here. For example, individuals might learn about norms for the utilization of online applications that affect adoption, which would suggest a need for variables that have been advanced in UTAUT, MATH, and DoI research.

The present model was also successful compared to the MATH and UTAUT2 models of consumer adoption found in the management information systems literature. The variance explained in adoption intentions was comparable to that accounted for by those two models when only the variables justified by the overarching theories on which they were based (TPB and TRA, respectively) were considered. Future research might productively add perceived social norms to the model to make the variance explained by the social cognitive approach fully equal to that found in the information systems research. Within SCT, social norms can be understood as a component of the self-regulatory mechanism through which individuals monitor, judge, and modify their behavior (Bandura, 1997). As in previous research (LaRose et al., 2007), self-efficacy was once again identified as a significant predictor of adoption. This lends credence to the argument made previously that self-efficacy is an important omission from two other contemporary models of technology adoption, UTAUT2 and MATH. This in turn raises the question whether it is the ease of use of the technology or the capabilities of the adopter that matter most in adoption decisions.

Limitations

The generalizability of the current findings is limited in that they were obtained from inner-city communities in a single state that were the targets of a sustainable broadband adoption grant from an ARRA program. Cross-sectional survey data can be used to test causal relationships, but cannot definitively establish the direction of those relationships or rule out third-variable explanations. The dependent variable in the present study was behavioral intentions, which are not always valid indicators of actual future behavior.

Implications for Policy and Research

Time series analysis is needed to further explore causal antecedents of technology adoption by consumers. Competing variables explaining consumer technology adoption, for example, ease of use and self-efficacy, should be pitted against one another as they have been previously in organizational settings (Venkatesh et al., 2003), and their effects on adoption over time should be assessed.

Educating the public about the benefits of broadband adoption and their effective use emerges as an important public policy objective in pursuit of the goal of extending broadband access to all citizens. NTIA's BTOP initiative is a step in that direction, providing funding for public computing centers and the promotion of sustainable adoption. However, much needs to be learned about which approaches to public computer education are most effective and how to sustain these efforts after ARRA funding ends in 2012. NTIA is funding an evaluation of the ARRA initiatives (Department of Commerce, 2010) by a private contractor to identify "best practices." However, the evaluation emphasizes the ARRA goals of promoting employment and economic development and is subject to government review. Independent, peer-reviewed research is needed to assess the impacts of these initiatives and identify the best ways to bring the potential benefits of broadband Internet to inner-city residents.

The present research provides evidence of the conceptual validity of the social cognitive model of innovation adoption and its practical utility. As previously discussed, the need for self-efficacy interventions targeted to inner-city residents is one important implication. Further analysis of expected outcomes can provide insight into the nature of the public education efforts that might also be effective. Decomposing the expected outcomes measure into its components, the highest positive correlations with broadband intentions were observed for the expectations that broadband Internet could be used to download music more efficiently ($r = .52$, $p < .001$) and to complete online courses ($r = .52$, $p < .001$). Beliefs that broadband could be used to start a home business ($r = .49$, $p < .001$) or to place phone calls ($r = .49$, $p < .001$) were also powerful. These might be the most effective attributes to promote to inner-city residents in hopes of encouraging sustained broadband adoption, especially since, aside from improvements in music downloads, they are not benefits of broadband that commercial providers strongly emphasize in marketing efforts. Although price sensitivity played a surprisingly minor role in broadband adoption, future research can look into alternative measurements such as whether broadband service is worth the cost and how much the broadband bill has to rise before the user drops the service.

Finally, the present model could be used to monitor the effectiveness of public education efforts to achieve the goals of the National Broadband Plan. The model has been validated in an urban population in the present study and previously among rural populations (LaRose et al., 2007), so it appears to have broad applicability in projects to achieve sustainable broadband adoption. Tracking changes in expected outcomes, Internet habits, Internet self-efficacy, and opportunities to engage in enactive and observational learning of the benefits of broadband allows for evaluation of the effectiveness of public education campaigns and pinpointing of their strengths and weaknesses, resulting in more effective sustainable broadband interventions.

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Appendix 1. List of measures.

Broadband intentions (In the next year, I will. . .)

1. Place phone calls over the Internet from my home.
2. Have high-speed Internet at home.
3. Use a high-speed Internet connection outside my home.
4. Use a wireless computer network at home.

Expected outcomes

1. It's not worth the cost (reflected).
2. I can share pictures with my family and friends.
3. I can download music and movies more quickly.
4. I can listen to near-CD quality radio stations.
5. It would improve my life.
6. There is nothing I need it for (reflected).
7. I could take online courses more easily.
8. I could start a home business.
9. I could use it to get health problems treated and diagnosed remotely without a hospital visit.
10. I could work in another state while still living here.
11. I could play multi-user games over the Internet.
12. I could use it to make phone calls.

Observational learning (High-speed Internet perceptions)

1. I have seen others benefit from having it.
2. I have heard good things about it through the media.
3. I have heard good things about it from people I know.

Enactive learning

1. It is easy to install.
2. I liked it when I tried it.
3. I have tried it enough to know what it can do.

Self-efficacy

1. I feel confident using the Internet to gather data.
2. I feel confident I know how to learn advanced skills related to the Internet.
3. I feel confident understanding terms/words relating to Internet software.
4. If I had problems relating to the Internet I know I could work them out

Habit strength

1. I use the Internet so much it interferes with other activities.
2. Going online is part of my daily activity.
3. I get strong urges to be on the Internet.
4. I have a hard time keeping my Internet use under control.
5. I feel out of touch when I can't get on the Internet.
6. I feel I am part of the online community.
7. I have to struggle with myself to limit my time online.
8. I spend much longer on line than I intend.