

UNDERSTANDING DIGITAL INEQUALITY: COMPARING CONTINUED USE BEHAVIORAL MODELS OF THE SOCIO-ECONOMICALLY ADVANTAGED AND DISADVANTAGED¹

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Abstract

Digital inequality is one of the most critical issues in the knowledge economy. The private and public sectors have devoted tremendous resources to address such inequality, yet the results are inconclusive. Theoretically grounded empirical research is needed both to expand our understanding of digital inequality and to inform effective policy making and intervention. The context of our investigation is a city government project, known as the LaGrange Internet TV initiative, which allowed all city residents to access the Internet via their cable televisions at no additional cost. We examine the residents' post-implementation continued use intentions through a decomposed theory of planned behavior perspective, which is elaborated to include personal network exposure. Differences in the behavioral models between socio-economically advantaged and disadvantaged users who have direct usage experience are theorized and empirically tested. The results reveal distinct behavioral models and isolate the key factors that differentially impact the two groups. The advantaged group has a higher tendency to respond to personal network exposure. Enjoyment and confidence in using information and communication technologies, availability, and perceived behavioral control are more powerful in shaping continued ICT use intention for the disadvantaged. Implications for research and practice are discussed.

Keywords: Digital divide, digital inequality, IT policy, technology acceptance, socio-economic inequality

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Introduction

The Internet represents tremendous opportunities for advancing social, economic, educational, and governmental development (U.S. Advisory Council on the National Information Infrastructure 1996). However, digital inequality between individuals with different backgrounds prevents the socio-economically disadvantaged from exploring digital opportunities (Lenhart 2002; OECD 2001). Digital inequality, in this research, refers to inequality in the access and use of information and communication technologies (DiMaggio et al. 2004). Survey studies have indicated that digital inequality exists across a variety of demographic, ethnic, and geographic dimensions (Katz and Aspden 1997; Lenhart 2002; NTIA 1998, 1999, 2000, 2002; OECD 2001). Among these dimensions, income and education—which suggest one's socio-economic status—have exhibited the most significant power in distinguishing use or nonuse of information and communication technologies (ICT) (Jung et al. 2001; Lenhart 2002). Other factors also tend to correlate with these two. Thus, in this study, we use income and education to differentiate between the socio-economically advantaged and disadvantaged and focus on their behavioral differences in using ICT.

Digital inequality is a substantial global problem, even in developed countries such as the United States. Quite ironically, the United States (birthplace of the Internet) has fallen behind in the household adoption of high-speed Internet. One reason for this is digital inequality. Ranked fourth worldwide by OECD in 2001, U.S. high-speed Internet penetration slipped to twelfth in 2006. In a similar ranking by International Telecommunication Union, the United States slipped from thirteenth in 2004 to sixteenth in 2005. This relative slowdown in high-speed Internet penetration signals a problem that may threaten future U.S. economic development, governmental efficiency, social structure, and ultimately the ability to compete in the global market.

Digital inequality is a complex, multifaceted, problem and there is growing recognition that material, cognitive, and social resources are required to address it effectively (De Haan 2004; Payton 2003; Van Dijk and Hacker 2003). Much of the previous research on digital inequality has focused on descriptively profiling adoption rates, or the extent of ICT access, among advantaged versus disadvantaged groups (De Haan 2004; DiMaggio et al. 2001).² While examining trends in digital inequality is useful, these studies have been cri-

²Adoption in most digital inequality literature refers to having ICT access (e.g., NTIA 2000, 2002); similarly, adopters, or "the haves," usually refers to individuals who have ICT access.

ticized as atheoretical (DiMaggio et al. 2001; Kvasny 2002). To confront the problem substantively and to guide future policy initiatives, digital inequality researchers have emphasized the importance of developing a *theoretical* understanding of the *how* and *why* questions related to the phenomenon (DiMaggio et al. 2001). In this research, we draw on both sociology literature and the theory of planned behavior to explore differences in continued use behavior between socio-economically advantaged and disadvantaged groups in response to a government sponsored initiative to address digital inequality.

Many people stubbornly cling to the belief that digital inequality can be solved by addressing a single factor: technology access (e.g., Kvasny 2002; Van Dijk and Hacker 2003). As a result, most governmental digital inequality initiatives have emphasized technology access. One problem with these technology-centered initiatives is that they assume that technology access is the key hurdle to overcome (DiMaggio et al. 2001; Kvasny 2002). However, we know from prior literature, which has examined a variety of ICT (e.g., e-mail, Windows, e-banking, text editor, Web, etc.), that providing technology access and creating conditions for its initial usage is only the first step and does not guarantee continued intention to use ICT (e.g., Agarwal and Prasad 1997; Bhattacharjee 2001; Davis 1993; Karahanna et al. 1999; Szajna 1996). This line of research has indicated that understanding post-implementation acceptance is essential as benefits from ICT occur through sustained use. Consistent with the research in this literature stream, we use the general term *user acceptance* to represent individuals' continuance usage intention of the sponsored technology (e.g., Agarwal and Prasad 1997; Szajna 1996). To recap, government initiatives to implement ICT will not alter the state of digital inequality unless there is continued use.

Unfortunately, limited theoretical understanding exists on what it takes to sustain continued use intention among the socio-economically disadvantaged. Government policy makers often make the implicit assumption that the advantaged and disadvantaged will respond to the same technology in similar ways (Hoffman et al. 2001). But, is this assumption valid? Will the drivers of continued use intention be the same and exert similar influence for the advantaged and the disadvantaged when they are provided access to the same technology? The purpose of this study is to gain a better understanding of user acceptance of ICT provided to citizens through a governmental digital inequality initiative. Toward this end, we investigate differences in the underlying factors affecting continued use intention for socio-economically advantaged and disadvantaged groups by comparing their behavioral intention models. The above discussion leads to our major research question:

In the context of governmental digital inequality initiatives that provide ICT access, how do the overall behavioral models for continued use compare for the socio-economically advantaged and disadvantaged?

Theory, Research Model, and Hypotheses

Digital Inequality

Norris (2001) argued that digital inequality relates to deeper patterns of social inequality. While there exist various forms of social inequality, DiMaggio et al. (2004) specifically indicated the need to investigate socio-economic inequality among those who have ICT access. They urged scholars to examine whether people with different socio-economic backgrounds have different behavioral patterns and whether these behavioral differences may diminish once everyone has easy access to ICT. When it comes to understanding digital inequality, the focus on socio-economic inequality is quite reasonable, especially given that income and education exert the most power in explaining use and nonuse (Jung et al. 2001; Lenhart 2002).

Socio-economic inequality has been associated with differential behavioral patterns in such fields as sociology, marketing, education, health psychology, and child development. Socio-economic status essentially brings about a synergy of social and economic forces that derive from assets internal to individuals and resources contained in their surrounding environments (Bornstein and Bradley 2003). Life factors such as income, education attainment, health status, unemployment rate, mortality rate, and so on tend to correlate and be distributed unequally across the socio-economic continuum in a gradational pattern that is unfavorable to the socio-economically disadvantaged (Bornstein and Bradley 2003; Williams 1990). Consequently, these distinctions have been construed as internal and external resources, or constraints, that, together, shape experiences and opportunities, living and working conditions, place in society, and even ways in which the world is viewed (Mayer and Buckley 1970; Williams 1990). What is especially challenging for the disadvantaged is that when encountering constraints in these resources, factors related to behavioral control can have more serious behavioral consequences than would be experienced by the socio-economically advantaged, leading to an unequal impact that further marginalizes the disadvantaged (e.g. Fan and Eaton 2001; Kessler 1979; Krause and Stryker 1984, Wheaton 1985; Williams 1990).

In this research, we view digital inequality from a socio-economic perspective; and the behavior of interest to us relates to the continued use of ICT after the technology has been made available. Surprisingly, the phenomenon of digital inequality has seldom been studied from the theoretically rich perspective of ICT acceptance. Consistent with calls for more theory-based research into the psychological factors affecting digital inequality (DiMaggio et al. 2001; Jackson et al. 2001), we use a theory of planned behavior (TPB) perspective to identify and compare post-implementation behavioral intention models for the socio-economically advantaged and disadvantaged. The basic TPB model was elaborated to tap into the complex social and behavioral aspects associated with the digital inequality phenomenon.

Theory of Planned Behavior as the Theoretical Framework

Psychological theories, such as the technology acceptance model (TAM), the theory of reasoned action (TRA), and the theory of planned behavior (TPB), have been applied to study ICT acceptance, including post-implementation ICT acceptance by individuals who have interaction experience with the technology (i.e., Davis 1993; Hong et al. 2006; Szajna 1996; Taylor and Todd 1995a). Since digital inequality concerns disproportionate ICT innovation behavior, psychological theories for ICT acceptance provide an excellent base to advance theoretical development of this phenomenon. Specifically, TPB is suggested as an ideal framework for understanding ICT acceptance in homes (Venkatesh and Brown 2001), as well as acceptance by individuals who have had some usage experience (Taylor and Todd 1995a). TPB suggests that attitudes (A), subjective norms (SN), and perceived behavioral control (PBC) will influence the individual's behavioral intention, which will in turn determine the individual's behavior (B). Unlike other theories that have been applied to examine ICT acceptance (e.g., TRA and TAM), TPB captures information about social and behavioral control factors (Mathieson 1991; Taylor and Todd 1995b). As these factors are crucial to understand digital inequality (Kvasny 2002), TPB serves as an ideal theoretical foundation for this study.

In this study, we are concerned with causal mechanisms that shape continued use intention in a volitional use context. Specifically, the context is one where, through the implementation of an initiative designed to address digital inequality, individuals have not only received the technology and information about it but also have direct experience with the use of the technology. These conditions, then, enable individuals to form stable behavioral intentions for continued use in the

future. While behavioral intention is the best predictor for future behavior when the behavior is volitional and the individual has the information to form stable behavioral intentions (Ajzen 1991; Karahanna et al. 1999; Sheppard et al. 1988), some researchers have recommended investigating actual behavior (e.g., Kim and Molhotra 2005). This may be especially useful when investigations are concerned with the causal mechanisms other than behavioral intention that influence behavior in non-volitional or quasi-volitional contexts or when the focus is on the consequences of ICT use. Figure 1 presents the research model with continued use intention specified as the dependent variable of interest. TPB is displayed in Block 1. Table 1 lists construct definitions and sources.

Consistent with TPB, attitude should affect continued use intention for both the advantaged and the disadvantaged. However, it is also important to consider Triandis's (1971) argument that the impact of social norms decreases once behavior takes place. After gaining direct experience, individuals turn to their own experience to evaluate behavioral consequences, and rely less on referents' opinions. In the context of ICT, evidence has shown that the influence of SN on behavioral intention attenuates after individuals have used the technology, as their attention shifts more toward outcome expectations (Karahanna et al. 1999). Thus prior research would suggest that for individuals who have usage experience, attitude should have a stronger impact on continuance intention than SN (i.e., $\beta_1 > \beta_2$ as in Figure 1).

Our first hypothesis relates to the differential effect of PBC on continued use intention for the advantaged and disadvantaged. Prior work has suggested that socio-economic status can moderate the relationship between behavioral control and its consequences (Hoffman 2003; Kessler 1979). For example, comparably stressful events can have more serious influence on the socio-economically disadvantaged (SED) than their advantaged peers (Kessler 1979). Stressors, such as divorce, lack of parental supervision, or chronic illness, have a stronger negative impact on children from disadvantaged than advantaged socio-economic backgrounds (Fan and Eaton 2001; Hoffman 2003). It is also the case that the socio-economically disadvantaged (SED) with poor health habits have worse health than the socio-economically advantaged (SEA) who exhibit the same health behaviors (Pratt 1971). The core argument is that equivalent levels of sense of control differentially impact the socio-economically advantaged and disadvantaged groups, and constrain the disadvantaged more (Krause and Stryker 1984; Wheaton 1985; Williams 1990). While sense of control describes one's expectancy about control over life behavior in general, perceived behavioral control in TPB refers to control over a specific behavior of

interest (Ajzen 1991). Although the target behavior may differ in scope, both concepts concern individuals' belief in their ability to control behavior. Accordingly, we expect PBC to have a greater influence on continued use intention for the socio-economically disadvantaged than for the socio-economically advantaged.

H1: Socio-economic status will moderate the positive relationship between perceived behavioral control and continued use intention such that the relationship is stronger for the SED group than for the SEA group.

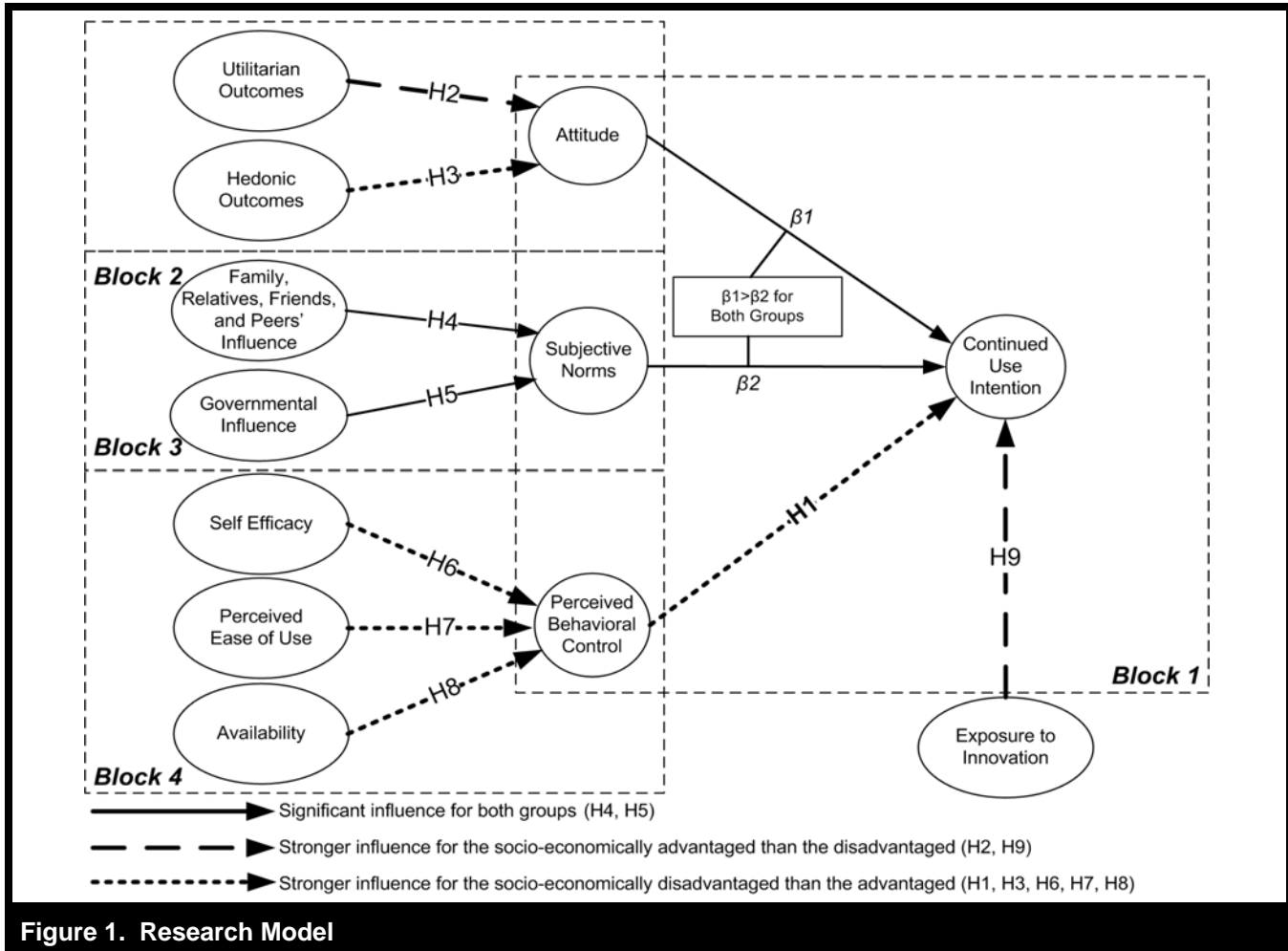
Decomposing TPB

Following Taylor and Todd (1995b) and Venkatesh and Brown (2001), we decomposed the three TPB belief constructs. This decomposition can generate managerial information about specific factors that influence continuance intention. With the aim of providing guidance to policy makers in the formulation of initiatives to address digital inequality, we decomposed the TPB belief constructs to reflect specific underlying factors based on a detailed literature review.

The Attitudinal Belief Structure (Block 2)

Drawing on motivation theory, Davis et al. (1992) differentiate between extrinsic motivation and intrinsic motivation for ICT usage. In their study of the determinants of ICT acceptance at home, Venkatesh and Brown (2001) identified two key attitudinal beliefs: utilitarian outcomes (UO) and hedonic outcomes (HO) (see Table 1 for construct definitions).³ Utilitarian outcomes refers to the expected utility gained by using the technology. Individuals' attitudes toward using an ICT will change as their evaluation of the behavioral outcomes changes (Davis 1989; Davis et al. 1989). Hedonic outcomes refers to the enjoyment derived from the process of using an ICT (Venkatesh and Brown 2001). IS researchers have pointed to the importance of the hedonic aspect of ICT usage as a determinant of household ICT innovation behavior (e.g., Van der Heijden 2004; Venkatesh and Brown 2001). For decades, researchers in consumer behavior have acknowledged that people have differential dispositions toward utilitarian or hedonic behaviors (e.g., Holbrook 1986; Venkatraman and MacInnis 1985). Recent digital inequality studies have also found that the socio-economically disadvantaged, particularly

³UO approximates the concept of perceived usefulness.



those with lower education attainment, tend to use ICT more for entertainment purposes, while the advantaged tend to use ICT in an instrumental way (Bonfadelli 2002; Shah et al. 2001).

A theoretical explanation for the differential nature of ICT usage by the socio-economically advantaged and the socio-economically disadvantaged is that the pleasure and satisfaction derived from using a technology is more important for the disadvantaged, whereas the utility obtained from using a technology is more critical for the advantaged. As the SEA are better educated and tend to have more access to and experience with ICT (Norris 2001; NTIA 1999), they are in a better position than the SED to appreciate utilitarian ICT usage. Moreover, the SED exhibit greater tendencies than the SEA for hedonic activities, such as gambling and substance abuse, to avoid life difficulties that they believe to be out of their control (Parker and Endler 1996). As the hedonic use of ICT

permits people to immerse in a virtual world and escape from reality (Venkatesh and Brown 2001), we suggest the SED will place more importance on the hedonic impact of ICT use than the SEA. Thus, in determining ICT innovation behavior, utilitarian outcomes may have a higher impact for the socio-economically advantaged, while hedonic outcomes may have a higher impact for the socio-economically disadvantaged.

H2: Socio-economic status will moderate the positive relationship between utilitarian outcomes and attitude such that the relationship is stronger for the SEA group than for the SED group.

H3: Socio-economic status will moderate the positive relationship between hedonic outcomes and attitude such that the relationship is stronger for the SED group than for the SEA group.

Table 1. Construct Definitions and Sources		
Construct	Definition	Sources that Inform Construct
Attitude	Individual's evaluation of the behavior of interest	Ajzen 1991; Ajzen and Madden 1986
<i>Utilitarian Outcomes (UO)</i>	The extent to which performing the behavior enhances the effectiveness of personal related activity	Davis 1989; Rogers 2003; Venkatesh and Brown 2001
<i>Hedonic Outcomes (HO)</i>	The pleasure and inherent satisfaction derived from performing the behavior of interest	Davis 1989; Venkatesh 1999; Venkatesh and Brown 2001
Subjective Norms (SN)	The perceived expectation from an individual's key referents to perform the behavior of interest	Ajzen 1991; Ajzen and Madden 1986
<i>Family, Relatives, Friends, and Peers' Influence</i>	The perceived expectation from family, relatives, friends and peers for an individual to perform the behavior of interest	Karahanna et al. 1999; Venkatesh and Brown 2001; Taylor and Todd 1995b
<i>Governmental Influence</i>	The perceived expectation from the government institutions for individuals to perform the behavior of interest	Lynn et al. 1995; Keil et al. 2003; Kvasny 2002
Perceived Behavioral Control (PBC)	An individual's perception of existence or nonexistence of required resources and opportunities to perform the behavior of interest	Ajzen 1991; Ajzen and Madden 1986
<i>Self-Efficacy (SE)</i>	The belief in one's capabilities to organize and to execute the course of action required to attain a goal	Bandura 1977; Compeau and Higgins 1995
<i>Perceived Ease of Use (PEOU)</i>	The degree to which an individual believes that performing the behavior of interest would be free of effort	Davis 1989; Davis et al. 1989
<i>Availability</i>	The availability of the technology to perform the behavior of interest	Kvasny and Keil 2002; Meader et al. 2002; Taylor and Todd 1995b
Personal Network Exposure (PNE)	The proportion of adopters in an individual's personal network	Fligstein 1985; Palmer et al. 1993; Valente 1995
Continued Use Intention	The intention to continue using the technology	Ajzen 1991

The Normative Belief Structure (Block 3)

Evidence suggests that key members from one's social network may exert normative influence upon one's innovation behavior (Valente 1995), since they have more chances to exchange important information (Childers and Rao 1992; Cocanougher and Bruce 1971). Such members may include family, relatives, friends, and peers (Childers and Rao 1992). The subjective norms that shape an individual's behavior will be influenced by expectations from these salient referents (Taylor and Todd 1995b).

H4: Family, relatives, friends, and peers' influence will be positively related to subjective norms for both the SEA and the SED groups.

Government institutions are important in facilitating the diffusion of ICT innovation (King et al. 1994) and reducing digital inequality (DiMaggio et al. 2001). While researchers have suggested the need to study such effects (DiMaggio et al. 2001; Kvasny 2002), few digital inequality studies have examined governmental influence on individual ICT innovation behavior.

Governments that devise initiatives to address digital inequality generally expect these interventions to help citizens, particularly the disadvantaged, access and use ICT, develop digital skills for work opportunities, and eventually attain improvements in quality of life (see Crump and McIlroy 2003; Kvasny 2002; Van Winden 2001). Studies have found that governments may use systematic approaches to raise

awareness and interest among citizens about these initiatives. They can use different media channels, including communicating directly with citizens, to explain the benefits of using ICT and to offer training and technical support (e.g., Kvasny 2002; Van der Meer and Van Winden 2003). From the citizen's perspective, these institutional efforts to encourage and facilitate ICT use convey the message that the government is committed to their interests and has taken their needs and requirements into consideration (Kvasny 2002). In fact, prior research has revealed that government agencies may serve as important referents whose expectation affects individual innovation acceptance (Lynne et al. 1995). Thus, governmental expectation may influence individuals' ICT innovation behavior. In this research, the governmental influence construct captures this perceived governmental expectation.

H5: Governmental influence will be positively related to subjective norms for both the SEA and the SED groups.

The Behavioral Control Belief Structure (Block 4)

Based on the literature review, PBC is decomposed into three important behavioral control factors: self-efficacy (SE) (Taylor and Todd 1995b), perceived ease of use (PEOU) (Ajzen 1991; Mathieson 1991), and availability (Lenhart 2002).

Self-efficacy has long been suggested as the key determinant for behavioral control (Bandura 1977) and for ICT implementation (Compeau and Higgins 1995). Moreover, Eastin and LaRose (2000) have argued that self-efficacy is critical in understanding digital inequality. Empirically, studies have revealed that self-efficacy affects ICT usage (Eastin and LaRose 2000) and that a lack of confidence, or self-efficacy, is one of the most important factors deterring the disadvantaged from accessing and using ICT (see Bishop et al. 2001; Crump and McIlroy 2003). Researchers have also suggested that psychological factors associated with an individual's sense of control may affect the socio-economically disadvantaged to a greater degree than the socio-economically advantaged (e.g., Kessler 1979; Krause and Stryker 1984; William 1990). For example, studies have shown that self-efficacy plays a more important role in affecting perceived health and depression for those in difficult socio-economic conditions than those who are better off (Schwarzer and Jerusalem 1995). Following this logic, SE should have a stronger influence on PBC for the disadvantaged.

H6: Socio-economic status will moderate the positive relationship between self-efficacy and per-

ceived behavioral control such that the relationship is stronger for the SED group than for the SEA group.

Ajzen and his colleagues (Ajzen 1991; Ajzen and Madden 1986) claimed that PBC is related to the perceived ease or difficulty in conducting a behavior. Specifically, Ajzen (1991) noted that PBC "refers to people's perception of the ease or difficulty of performing the behavior of interest" (p. 183). Most IS studies in the past have positioned PEOU as an attitudinal determinant (e.g., Davis 1989). Some have alternatively suggested that PEOU is associated with behavioral control (e.g., Mathieson 1991; Venkatesh 2000). The logic for this association is that the ease or difficulty of ICT use affects individuals' beliefs about the control they have on the use of the technology. Recent empirical evidence also supports this view of PEOU being associated with behavioral control in the contexts of home PC acceptance (Brown and Venkatesh 2005; Venkatesh and Brown 2001) and of electronic commerce (Pavlou and Fygenson 2005). Consistent with this stream of research, we treat PEOU as a behavioral control belief.

Technological complexity is one major barrier that causes ICT nonuse (Lenhart 2002), and people strongly desire easy-to-use technologies (Katz and Aspden 1997). When facing a difficult challenge, the advantaged, relative to the disadvantaged, can more flexibly and effectively cope with issues to neutralize downside effects (Fan and Eaton 2001; Kessler 1979; Pearlin and Schooler 1978). In this vein, when interacting with an ICT, the relatively higher educational attainment of the advantaged should enable them to more flexibly cope with the complexity embedded in the technology, thus minimizing the impact of the difficulty or ease in operating the technology on their perceived control. Therefore, PEOU should have a stronger impact for the socio-economically disadvantaged than the advantaged.

H7: Socio-economic status will moderate the positive relationship between perceived ease-of-use and perceived behavioral control such that the relationship is stronger for the SED group than for the SEA group.

Prior digital inequality studies have indicated that cost and availability are barriers that prevent people, especially the disadvantaged, from successfully using ICT (Lenhart 2002). Given that government digital inequality initiatives tend to subsidize the financial expenditure of ICT access, this study focuses on the availability issue.

Availability, or the accessibility of the technology when needed, represents another behavioral barrier, especially for

the socio-economically disadvantaged. In many situations, technological access is provided in theory; but in practice, the technology may not be available when people want to use it. In a study about the use of a computer resource center, Taylor and Todd (1995b) suggested that if there were not enough computers available for all the students who wanted to use the center concurrently, this might represent a barrier for ICT use. Therefore, when there are more users than units of technologies, or the competition for access is high, availability can surface as a behavioral barrier. If such availability constraints emerge for ICT implemented through a governmental digital inequality intervention, the disadvantaged's lower disposable economic and material resources, in comparison to the advantaged's, puts them in a weaker position to address it. Such a constraint is, therefore, expected to have a greater influence on PBC for them.

H8: Socio-economic status will moderate the positive relationship between availability and perceived behavioral control such that the relationship is stronger for the SED group than for the SEA group.

Personal Network Exposure

Since innovations often involve uncertainty and many innovations have low visibility, an individual's innovative behavior can be influenced strongly by how other members in that individual's personal network respond to the innovation (Valente 1995, p. 70). Valente (1995) proposed the construct *personal network exposure* (PNE) which represents the cumulative proportion of adopters in one's personal network. While subjective norms in TPB captures one aspect of social influence, it does not capture the aggregate personal network exposure. Further, subjective norms focus solely on the "expectation" from "important others," while PNE accounts for the "observed" aggregate behaviors in one's overall personal network. Therefore, PNE is conceptually distinct from subjective norms.

Valente contended that the larger the proportion of individuals in one's personal network that are engaged in an innovation behavior, the more likely it is that the individual will take on the same behavior. The direct effect from personal network exposure to continued use intention represents this causal mechanism. The concept of *perceived critical mass* introduced by Lou et al. (2000) and Li et al. (2005) represents a related construct, which refers to the degree to which a person believes that most of his or her peers are using a particular innovation (Lou et al. 2000). As in the case of PNE, individ-

uals with a higher perceived critical mass will have a greater intention to continue using the technology (Li et al. 2005; Lou et al. 2000).

We offer two reasons—one relates to prior experience and the other relates to education—on why personal network exposure should have a stronger effect on the socio-economically advantaged than the disadvantaged.

First, individuals have a tendency to interpret information in a way that is more congruent with their prior experience and preexisting knowledge structure (Bobrow and Norman 1975; Klapper 1960). Studies have found the SEA in general have greater ICT access and use (Lenhart 2002; NTIA 1998, 1999, 2000); and the SED tend not to view ICT as a priority of daily living, especially those for whom life is a day-to-day struggle (Crump and McIlroy 2003). Arguably, as the SEA are generally more familiar with ICT relative to the SED, information about ICT innovation, such as from personal networks, should be more consistent with their experience and knowledge structures.

Second, the higher education of the SEA relative to the SED allows them to more readily access and comprehend information signals related to ICT innovations (De Haan 2004). Their education facilitates the absorption and comprehension of information (Hilgard and Bower 1975), such as from personal networks, and makes them more responsive to innovation triggers that require thought stimulation and cognitive effort (Venkatraman and Price 1990).

The above arguments on prior experience and resource conditions suggest that the SEA may be more susceptible to the influence of *personal network exposure* than the socio-economically disadvantaged.

H9: Socio-economic status will moderate the positive relationship between personal network exposure and continued use intention such that the relationship is stronger for the SEA group than for the SED group.

Control Variable

The existence of an alternate mode of Internet access in the household may reduce an individual's need to use whatever Internet access is offered through public policy interventions aimed at addressing digital inequality. Since a PC is the dominant mode of household Internet access, the ownership of an Internet PC was measured and used as a control variable for continued use intention.

Research Method

The Free Internet TV Initiative in LaGrange, Georgia

LaGrange, with a population of 27,000, is located 60 miles southwest of Atlanta, Georgia. The LaGrange city government, unlike most municipal governments in the United States, finances their operation by collecting sales tax and generating revenue by providing services without charging property tax (Keil et al. 2003; Meader et al. 2002). The services offered include electricity, natural gas, sanitation, and telecommunications to both commercial and residential customers. In the 1990s, the city government created a two-way 750 MHz hybrid coaxial and fiber-based system with 18 fiber optic nodes around the city. Each node further connects between 500 and 900 households via coaxial cable. In addition to cable TV and broadband services offered via this infrastructure, in April 2000, city officials devised a three-way contract with the cable company (Charter Communications) and an Internet service provider (Worldgate Communications) to use the excess bandwidth to provide an Internet TV service to every household at no additional cost. Thus, residents were able to receive household Internet service without paying anything beyond the basic cable fee of \$8.70 per month.⁴ One of the chief aims of this city-wide initiative was to address digital inequality.

The Internet TV used a television-based Internet access device. Subscribers received a free wireless keyboard and digital set-top-box, which connected the cable and TV. Users could use the wireless keyboard to browse the Internet via their TV. At the rate of 158 Kbits per second, the connection speed was nearly three times higher than the typical dial-up service (56 Kbits/sec). Subscribers also enjoyed unlimited access, a free e-mail service, 5 MB of web space, and a technical support hotline that was available seven days a week (Keil et al. 2003). Training was available in the community center, over cable TV, as well as through the technical support hotline. The Internet TV was user-friendly in that users did not have to install or maintain an operating system or application programs. However, the Internet TV did not allow printing, storing files, or browsing websites that required software plug-ins (e.g., Adobe Acrobat and Apple QuickTime). Users also could not use the Internet TV and watch TV simultaneously.

⁴Because of poor reception of broadcast TV signals in LaGrange, the majority of the population has the cable connection. In those few cases where a household wanted to use LITV but could not afford the cable fee, the city was willing to provide free cable connection.

The LaGrange Internet TV (LITV) initiative is believed to be the first project in the world in which a city government offered free high-speed Internet access and service to every household (National Public Radio 2000). Compared to a typical Internet PC, the Internet TV was easier to use, yet more limited in its capability. Still, the Internet TV represented a chance to connect for those who might not otherwise explore high-speed household Internet access and all that it has to offer. The LITV initiative provided a unique opportunity to study post-implementation ICT acceptance across socio-economically advantaged and disadvantaged groups in response to a government initiative designed to eliminate economic barriers and provide universal access. Our interest here was to evaluate how the behavioral intention models for continued use differed across the two groups.

Data Collection

A survey instrument was developed to collect the quantitative data needed for model and hypothesis testing. For most constructs in the research model, Likert-type scale items were adapted from existing measures (see Appendix C). Following prior research measuring the proportion of adopters in a social system (Fligstein 1985; Palmer et al. 1993), a single item using a 10-level interval scale ranging from 0 to 100 percent was used for personal network exposure. The survey instrument was pretested with 20 subjects from LaGrange and minor modifications were made prior to its full-scale administration.

In summer 2003, the survey instrument was administered to all LaGrange households of record who had implemented the digital set-top boxes needed to use the Internet TV. According to the city's records, this included approximately 3,500 households, or 38.9 percent of the 9,000 eligible households. The survey was mailed to each household where the LITV had been implemented, with two waves of reminder postcards mailed one week and three weeks after the initial survey. The adult member of the household who had used LITV the most was requested to respond to the survey.

In all, 526 residents responded to the mail survey, indicating that the government had implemented the technology within their homes and that they had used it, yielding a raw response rate of 15.03 percent.⁵ Adjusting for the number of non-

⁵As indicated by some researchers, the general response rate for mail survey of the general public has been decreasing to lower than 20%, 15%, and even 10% in the past few decades due to the increasing use of this method (Harbaugh 2002; Steeh 1981). This decline has also been seen in some IS research (Pinsonneault and Kraemer 1993; Ravichandran and Rai 2000).

deliverable surveys, the overall adjusted response rate was 19.5 percent. Finally, after excluding cases with missing or incomplete responses, 451 complete and usable surveys were retained for quantitative analysis. A total of 96 percent of the respondents reported first using LITV at least one year prior to the data collection, and the remaining 4 percent first used it between two and six months prior to the data collection. Thus, all respondents had direct experience with the technology for a sufficient time to formulate stable intentions of their future LITV usage.

To investigate possible nonresponse bias, a wave analysis was conducted to compare the indicators of key constructs as well as demographic profiles between the early and late respondents. Since the second wave postcard reminder was mailed three weeks after the initial mail, subjects responding within three weeks were classified as early respondents, while those responding later than three weeks were classified as late respondents. A t-test of the key variables collectively showed that the late respondents were quite similar to the early ones, suggesting that if there is any nonresponse bias, it would be minimal.

To further examine the issue of nonresponse bias, we adopted the general procedure used by Ravichandran and Rai (2000). Telephone interviews were conducted with 140 randomly sampled nonrespondents. Interviewees were asked about reasons for nonresponse. The top three reasons for nonresponse were (1) did not like to fill out any survey or threw it away (28 percent), (2) did not receive survey (27 percent), and (3) too busy and did not have time to complete the survey (14 percent). The main reasons given for nonresponse were general issues that would be expected in any survey research and were not topic relevant. However, a small portion of nonrespondents' reasons might be specific to the survey theme, such as "did not know anything about computers" (2 percent), and/or "did not like LITV" (5 percent). While caution should always be exercised when generalizing from survey data, there appears to be little or no evidence of a threat from nonresponse bias.

As discussed earlier, income and education, which suggest one's socio-economic status, have proven to be strong predictors for ICT use (Jung et al. 2001; Lenhart 2002). These two variables⁶ were therefore used to classify subjects as socio-economically advantaged or disadvantaged using Ward's method of hierarchical cluster analysis (Hair et al. 1998). The analysis yielded two clusters with 307 socio-economically advantaged subjects in one and 144 disad-

vantaged subjects in the other. As expected, a comparison of the two groups' profiles reveals considerable difference (see Tables 2 and 3). The socio-economically disadvantaged relative to the advantaged were more likely to have lower income and education level and consist of more elder and younger, African American, and female individuals. Such a profile is consistent with the findings in most national surveys (NTIA 1998, 1999, 2000, 2002).

Next, to verify the representativeness of the respondents, in terms of income and education, and that of the classified advantaged and disadvantaged, two additional analyses were performed. Public data containing the median household income and average education level for each census block in the city of LaGrange were acquired from the U.S. Census Bureau. The correlations of household income, as well as education level, between the survey and census data across all census blocks were calculated. The high correlation values obtained (Table 4) support the representativeness of the survey respondents relative to the LaGrange population.

To further evaluate the representativeness of the extracted clusters, a ratio of the number of advantaged respondents to the number of the disadvantaged for each block group was computed. In effect, this ratio characterizes the socio-economic status of a block group. As can be seen in Table 5, the ratio demonstrated high correlation with both the census median household income and average education level across all block groups, indicating that the extracted clusters are representative of the advantaged and disadvantaged groups in the city of LaGrange.

Data Analysis and Results

Measurement Model

Partial least squares (PLS), which uses component-based estimation, maximizes the variance explained in the dependent variable, does not require multivariate normality of the data, and is less demanding on sample size (Chin 1998). For these reasons, PLS-Graph 3.0 was used for the data analysis. The measurement and structural models were first evaluated separately for the socio-economically advantaged and disadvantaged groups, before cross-group comparisons were conducted.

For the measurement model, each construct was modeled to be reflective, with one exception: FRPF is modeled as formative. Its items, which tap into influence from friends, family, relatives, and peers, do not necessarily have to covary, are not interchangeable, and the direction of causality is from the items to the latent construct (Jarvis et al. 2003).

⁶Both income and education level were operationalized as ordinal scales. No indication of nonresponse bias was observed on these two variables.

Table 2. Descriptive Statistics of Respondents		
	Disadvantaged	Advantaged
Household Income		
< 10,000	28.8%	0.0%
10,000 – 14,999	23.7%	0.0%
15,000 – 24,999	38.1%	4.3%
25,000 – 34,999	8.5%	14.5%
35,000 – 49,999	0.9%	22.7%
50,000 – 74,999	0.0%	22.7%
75,000 – 99,999	0.0%	14.2%
> = 100,000	0.0%	21.6%
Education Level		
Some Elementary/High School	20.9%	0.0%
High School Diploma	64.4%	26.2%
College Degree	14.7%	42.4%
Post Graduate	0.0%	31.4%
Age		
18 – 30	11.4%	5.7%
31 – 40	15.0%	12.2%
41 – 50	19.3%	26.1%
51 – 60	14.3%	22.7%
> 60	40.0%	33.3%
Gender		
Male	18.6%	44.3%
Female	81.4%	55.7%
Ethnic Group		
White American	15.9%	40.3%
African American	81.8%	53.5%
Other	2.3%	6.2%

Table 3. Comparison of Demographics between Disadvantaged and Advantaged				
Test	Mann-Whitney Test		Chi-Square Test	
	Z-Score	Sig.	Chi-Square	Sig.
Income	-15.22	0	Not Applicable	
Education	-10.97	0	Not Applicable	
Age	-0.22	0.824	Not Applicable	
Gender	Not Applicable		48.01	0
Ethnic	Not Applicable		55.14	0

Table 4. Correlation Between Survey and Census Data Across All Block Groups

Dimension	Correlation
Median Household Income (Survey Data versus Census Data)	0.83
Average Education Attainment (Survey Data versus Census Data)	0.85

Table 5. Correlation between Advantaged Versus Disadvantaged Ratio and Census Data

Dimension	Correlation
Ratio (# of advantaged / # of disadvantaged) versus Median Household Income (Across 30 block groups)	0.81
Ratio (# of advantaged / # of disadvantaged) versus Average Education Attainment (Across 30 block groups)	0.84

For all constructs, the internal consistency and convergent validity were evaluated by examining the item–construct–loading, composite reliability, and average variance extracted (AVE).⁷ For individual item reliability, item loadings are higher than 0.707 (Chin 1998) (see Appendix A). As shown in Table 6, the values of composite reliabilities are all higher than 0.707 (Nunnally and Bernstein 1994), and values of AVE are all above 0.50 (Fornell and Larcker 1981). Next, discriminant validity was assessed by examining if the squared correlation between a pair of latent variables was less than the AVE associated with each construct (Appendix B1 and B2). Furthermore, we calculated item cross-loadings based on the procedure recommended for PLS (Gefen and Straub 2005). Each item loaded higher on its principal construct than on other constructs (Appendix A). While cross-loadings derived from this procedure will be inevitably higher than from typical exploratory factor analysis (Gefen and Straub 2005), the cross-loading differences were much higher than the suggested threshold of 0.1 (Gefen and Straub 2005). These results collectively suggest good measurement properties for both groups. Table 6 also lists the means and standard deviations for constructs.

⁷When formative constructs exhibit high internal consistency, retaining multiple indicators is problematic due to multicollinearity problems (Jarvis et al. 2003). In these situations, such as with FRPF in our case (average correlation equals 0.92 for the SED, 0.95 for the SEA), a linear composite based on unit means of indicator scores can be used. Given the high correlation among the indicators, this unit mean-based index score is naturally highly correlated with index scores derived using alternate weighting schemes (Rozeboom, 1979). Moreover, the use of unit means, as opposed to factor scores, is recommended when new measures are used and transferability is desired (Hair et al, 1998). Accordingly, we use a unit mean-based index score for FRPF in subsequent analysis.

Structural Model

With an adequate measurement model in place, the structural model was independently tested for socio-economically advantaged and disadvantaged groups. A bootstrap analysis was performed with 500 subsamples, with sample size set equal to the SEA and SED sample sizes (n = 307 and n = 144, respectively). The resulting models for both groups explained a significant amount of variance in the dependent and mediating variables. Figure 2 presents the standardized path coefficients and the explained construct variances.

As noted earlier in the theory section, the proffered knowledge from the technology acceptance literature is that attitudes play a greater role than social norms in shaping the behavioral intention for individuals who have had direct experience in using the technology. While we requested respondents who had used LITV the most in the household to participate in the survey, the collected data enabled us to evaluate the relative influence of attitudes and subjective norms on continued use intention. As can be seen in Figure 2, for both groups, the path from attitude to BI is significant, whereas the path from SN is not. In addition, the association between attitude and BI is indeed significantly higher than the association between SN and BI (t = 1.97 for the SED; t =2.5 for the SEA).⁸ This finding is consistent with past studies on the relative importance of attitude and SN for BI for experienced users, suggesting that the respondents indeed had first-hand LITV usage experience.

⁸ We used the following equation $[T = (r_{xy} - r_{vy}) \cdot \text{sqr}((n-3)(1+rxv)) / \text{sqr}(2 \cdot (1 - r_{2xy} - r_{2vy} - r_{2xv} + 2 \cdot r_{xy} \cdot rxv \cdot r_{vy}))]$, where x = UO, v = HO, y = ATT, n = sample size], as per Cohen and Cohen (1983), to compare the relative strengths of the associations between constructs.

Table 6. Descriptive Statistics and Reliability of Constructs

Construct [†]	Disadvantaged Group			Advantaged Group		
	Mean (S.D.)	Composite Reliability	AVE [‡]	Mean (S.D.)	Composite Reliability	AVE [‡]
Attitude (3)	5.76 (1.74)	0.99	0.98	4.86 (1.87)	0.99	0.96
Utilitarian Outcomes (4)	5.37 (1.83)	0.99	0.95	4.09 (2.18)	0.99	0.97
Hedonic Outcomes (3)	5.69 (1.85)	0.99	0.98	4.27 (2.26)	0.98	0.97
Subjective Norms (2)	3.83 (2.16)	0.98	0.96	2.74 (2.02)	0.98	0.96
Fam., Rel., Fri., & Peers (1)*	4.01 (2.18)	NA	NA	2.84 (2.02)	NA	NA
Governmental Influence (2)	4.23 (2.27)	0.96	0.93	3.81 (2.12)	0.97	0.94
PBC (3)	5.77 (1.59)	0.95	0.85	6.05 (1.49)	0.95	0.87
Self-Efficacy (3)	5.89 (1.68)	0.97	0.92	5.76 (1.73)	0.97	0.92
Perceived Ease of Use(4)	5.49 (1.80)	0.95	0.82	4.96 (1.87)	0.93	0.78
Availability(2)	2.57 (1.73)	0.90	0.82	2.52 (1.55)	0.88	0.79
Continued Use Intention (3)	4.91 (2.37)	0.98	0.95	3.31 (2.55)	0.99	0.96
Personal Network Exposure(1)	0.42 (0.29)	NA	NA	0.31 (0.26)	NA	NA
Internet PC Ownership (1)	0.20 (0.40)	NA	NA	0.66 (0.47)	NA	NA

*Influence of family, relatives, friends, and peers is a formative construct whose score is computed as a unit mean of four items.

[†]The number in parentheses indicates the items in the scale. [‡]Average Variance Extracted.

Multi-Group Analysis for Differences Across Advantaged and Disadvantaged Groups

To test our hypotheses associated with differential behavioral impact, we compared the coefficients of individual paths between the two structural models. This analysis is similar to a test of the moderation effect of socio-economic status on the path strength across groups. To do so, it was necessary to first assess whether the latent constructs were perceived in a similar fashion between the advantaged and disadvantaged (Carte and Russell 2003). An examination of Appendix A suggests that the loading patterns are the same and factor loadings are very similar, thus permitting between-group path comparison.⁹ Chin (2004) notes that, when variances are not too different across groups, a t-test can be applied to assess statistical differences in path coefficients for each pair of paths. Alternatively, the Smith-Satterthwait (S-S) test with a pooled error term should be used if the variance varies profoundly across groups. Only 2 of the 12 factors exhibit different variance across groups. Given that the variances are not too different, we first examined the path differences using t-tests. To evaluate the stability of these results when an assumption of unequal variance is made, we also applied the S-S test. The results from the application of the t-test and the

S-S test identify the same set of paths to differ across groups.¹⁰ The direction of the differences (> or <) can be evaluated by comparing the estimated coefficients from the two groups. Six pairs of paths were found to be different between the groups (Table 7). Thus, the results of the PLS analysis provide evidence of the moderation effect of socio-economic status on the behavioral models for continued ICT use.

To further investigate the type of moderation effect of SES, to ensure that the detected moderation was not an artifact of unequal measurement error across subsamples, and to evaluate if the conclusion regarding the type of moderation is sensitive to nonlinear effects of the predictors on the criterion, we applied the moderated regression analysis (MRA) procedure proposed by Sharma et al. (1981). The results of these analyses provide additional evidence in support of SES moderating the strength of relationship between identified criterion and predictor variables (see Appendix F).

In addition to applying moderated regression analysis to validate the moderation effect of socio-economic status, we evaluated if the detected moderation was an artifact of the measurement model, which in PLS is idiosyncratic to the sample. While there is *prima facie* supporting evidence of identical

⁹A supplementary measurement invariance analysis was performed to further validate the similarity of measurement models between the two groups. The results in Appendix D provide additional support for measurement invariance.

¹⁰Our findings are consistent with Chin's (2004) assertion that with sufficient sample size, such as in our scenario, results obtained from the two tests should be similar.

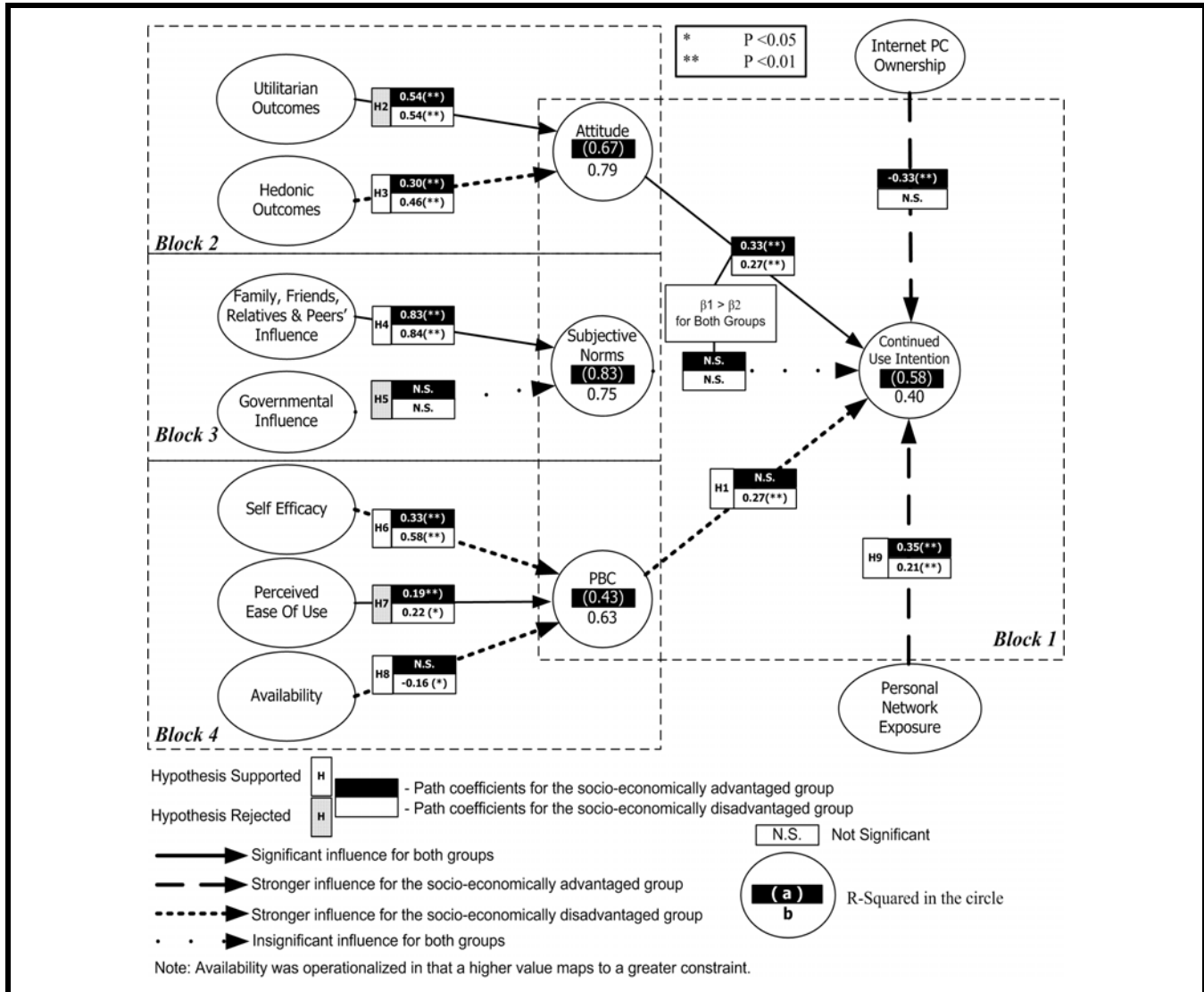


Figure 2. Structural Model

Table 7. Path Comparison

Path	SE Disadvantaged		SE Advantaged
H1: PBC → BI	0.27 (0.084)**	>	0.05 (0.039) N.S.
H3: Hedonic Outcome → Attitude	0.46 (0.076)**	>	0.30 (0.053)**
H6: Self-Efficacy → PBC	0.58 (0.085)**	>	0.33 (0.078)**
H8: Availability → PBC	-0.16 (0.078)**	>	0.07 (0.069) N.S.
H9: Personal Network Exposure → BI	0.21 (0.022)**	<	0.35 (0.047)**
Control Internet PC Ownership → BI	-0.09 (0.067) N.S.	<	-0.33 (0.057)**

Path coefficient is significant at: **p < 0.01, *p < 0.05; N.S.: Path coefficient is not significant.

- a. One-tailed tests were performed as the direction of differences was hypothesized.
- b. Availability was operationalized such that a higher value connotes a greater constraint.
- c. Numbers in parentheses are the standard errors.

loading patterns and similar item loadings across the samples for the SEA and SED, we used the measurement model results from the other group to compute the latent scores and then reevaluated the structural models. In other words, we computed the latent construct scores for the SEA using the estimated measurement model (item loadings) of the SED and then compared the structural models across the two groups. We repeated this procedure, where we computed the latent scores for the SED using the measurement model (item loadings) of the SEA and, again, compared the structural models across groups. The results are similar to those reported earlier, ruling out the threat that the observed moderating effect is due to idiosyncrasy of loadings associated with the samples.

Finally, given the high proportion of females in the SED sample, we wanted to rule out the possibility that the moderation results detected earlier were because of gender rather than socio-economic status. Prior IS studies have indicated that the influence of some factors on use intention may vary according to gender (e.g., Venkatesh and Morris 2000). To evaluate the moderation role of gender, we split the sample and compared the behavioral models of males and females. Based on these results, there are no common differences between the behavioral models for females and males and between the behavioral models for the advantaged and disadvantaged, with one exception: the path from self-efficacy to PBC is stronger for females than males and for the disadvantaged than the advantaged. Additionally, we compared the behavioral models of SED and SEA female groups. The results reveal similar differences between the behavioral models for SEA and SED females and those between the advantaged and disadvantaged with one exception: there is no difference in the relationship from self-efficacy to PBC between the SEA and SED female groups. Thus, regardless of socio-economic status, gender moderates the relationship between self-efficacy and perceived behavioral control.

We took several actions to address the potential threat of *common method bias* (CMB). First, the instrument contains different scale formats to reduce scale commonality (Podsakoff et al. 2003). After data collection, we performed the Harmon one-factor test recommended by Podsakoff and Organ (1986). A factor analysis combining independent and dependent variables revealed no sign of a single-factor accounting for the majority of covariance. Next, following the recommendation of Podsakoff et al. (2003) and the analytical procedure used by Liang et al. (2007), we added a common method factor to the PLS model. The indicators of all constructs were associated reflectively with the method factor. Then, each indicator variance explained by the principle construct and by the method factor was computed. The results in Appendix E show that (1) only 3 out of the 31

method loadings are significant, and (2) while the average substantively explained variance for an indicator is 0.906, the common method-based variance is only 0.003. In addition, results of the structural models demonstrated different levels of significance for path coefficients. The above evidence collectively suggests that common method bias is not a significant issue in this study.

Discussion

In total, the results support six of the nine hypotheses (Table 8) and reveal six paths with differential impact between the advantaged and disadvantaged groups (Table 7). Contrary to our expectations, utilitarian outcomes and PEOU had no differential impact, and governmental influence did not influence subjective norms for either group.

Attitudinal Influence and Antecedents

In line with prior studies, attitude had a stronger influence than SN on continuance intention for our subjects (Figure 2). In determining attitude, hedonic outcomes, as predicted, was marginally more influential for the disadvantaged than the advantaged. However, utilitarian outcomes had no differential impact on attitude across groups, and thus H2 was not supported. Utilitarian outcomes of ICT can possibly be classified into different levels of sophistication. Given the nature of the technology offered by the government to citizens in our context, the measurement items of UO focused on simple ICT functions like communication and information search. The results revealed no differential motivational influence based on socio-economic status toward using ICT for these basic purposes. Nevertheless, the hypothesized differential motivational impact may be more salient for advanced functions like investment analyses or other complex analytical tasks, since the SEA are more likely to have greater exposure to utilitarian applications and to better understand their potential benefits, thus appreciating these functions more strongly. Future research should further examine this conjecture.

Social Influence: Subjective Norms and Personal Network Exposure

Subjective norms was primarily shaped by expectation from important referents in one's social network. In contrast, governmental influence was not significant for either group, and thus H6 was not supported. A *post hoc* analysis revealed that when the path from FRPF to SN was removed, govern-

Table 8. Hypotheses Testing Results

Type of Hypothesis	Supported	Not Supported
Differential Impact Across Groups	Stronger Influence for the Disadvantaged	
	H1: PBC → BI H3: Hedonic Outcomes → Attitude H6: Self-Efficacy → PBC H8: Availability → PBC	H7: PEOU → PBC
	Stronger Influence for the Advantaged	
	H9: Personal Network Exposure → BI	H2: Utilitarian Outcomes → BI
Same Impact Across Groups	H4: Family, Relatives, Peers, and Friends' Influences → SN	H5: Governmental Influence → SN

mental influence significantly affected SN. Thus, in the presence of normative influence from one’s key referents, government influence does not play a key role in shaping subjective norms. Importantly and consistent with past research, once users have directly experienced using the system, subjective norms is not influential for continued use.

While subjective norms per se was not found to be important, our results suggest that the social network still affects post-implementation ICT acceptance through personal network exposure. As we hypothesized, the effect of PNE was stronger for the advantaged than for the disadvantaged. As delineated earlier, while SN concerns the expectation from “important” referents, PNE focuses on “observing” the aggregate manifest behavior across one’s personal network. The advantaged did indeed appear to be more sensitive in responding to such a signal.

Behavioral Control Influence and Antecedents

Consistent with our conjectures, perceived behavioral control (PBC), self-efficacy, and availability were more critical in determining continuance intention for the disadvantaged than the advantaged. Note that because gender also had a moderating effect on the path from self-efficacy to PBC, this relationship needs to be probed further in future research. Interestingly, the salient negative impact of availability for the disadvantaged suggests that potential conflict between household members who wanted to watch TV and those who wanted to use the Internet TV may have created accessibility issues. Our probing of this issue through open-ended face-to-face discussions with a few respondents from the socio-economically disadvantaged cluster confirmed that such conflicts were commonplace among household members, with

each member wanting to use the same device for different purposes. The functionality of the TV, once a mass media appliance, was expanded to serve as a multi-purpose home device. The elaborated functionality induced competition for this resource, which is an issue that has not surfaced in prior research on ICT acceptance. Such access-related considerations suggest that even when certain services are free, the necessity of sharing the ICT in the case of the SED dampens their perceived behavioral control.

Contrary to our expectation, perceived ease of use had no differential influence across groups, thus H8 was not supported. One possible reason for this insignificant result may be the user-friendly design of the Internet TV, which appears to have addressed the coping challenges that the SED are likely to face when interacting with ICT that is less user-friendly.

Regardless of the impact of SE, PEOU, and availability on PBC, PBC only affected behavioral intention for the disadvantaged. This finding reinforces a key point: even when the technology is made available, disadvantaged individuals still need to deal with psychological and material barriers that are not addressed directly by technology-centered interventions.

Internet PC Ownership

On average, the advantaged, relative to the disadvantaged, had a higher level of ownership of Internet PCs (66 percent versus 20 percent). This ownership understandably exerted a damping effect on the advantaged’s intention to continue using the Internet TV. Interestingly, the disadvantaged’s Internet PC ownership had little influence on their continuance intention. Our face-to-face interviews on this issue

suggest two possible explanations for the insignificant relationship. Some of the disadvantaged, who already had Internet PCs, wanted to use the Internet TV rather than buying another computer, so that other family members could use the existing Internet PC. In this scenario, the Internet TV served as an alternative device to meet the high demand for Internet access within these households. Some disadvantaged, however, participated in the LITV initiative because it allowed them to discontinue their paid Internet service and save the monthly subscription fee. Both explanations, to a certain degree, reflect how the socio-economic status of the disadvantaged may have resulted in Internet PC ownership not having a negative effect on their behavioral intention of continued use.

Summary

The results suggest very different post-implementation behavioral models, between socio-economically advantaged and disadvantaged groups, in response to LITV, a government sponsored digital inequality intervention that emphasized technology access. Factors that influenced individuals' intention to continue using the technology were different between the two groups. Taken as a whole, 58 percent and 40 percent of the variance in a user's continuance intention were explained by the behavioral models for advantaged and disadvantaged groups, respectively. The discrepancy in the explained variance suggests that there may be additional factors that are relevant to the disadvantaged that deserve further consideration. Such factors may include physical conditions, emotional variables (e.g., fear and anxiety), employment status, family structure (e.g., single parent family), and so forth.

Limitations and Implications

Digital inequality exists across not only individuals but also nations. The nature of the inequality may vary tremendously across countries with different economic development status (Checchi et al. 2003). While developed countries like the United States are eager to stimulate sustained ICT usage, many underdeveloped nations are still struggling with basic infrastructure. People from different countries may also hold different cultural assumptions toward modern technologies. Thus, while the findings from this study may be extended to other similar technology-centered initiatives, the generalizability to other nations may be limited to a certain degree.

While digital inequality exists across different socio-demographic dimensions, we focused on socio-economic status as the key distinction between advantaged and disadvantaged

groups. Although it is logical and reasonable to use socio-economic status for classification since it represents a deep-rooted inequality in modern society, there may be other dimensions that are worthy of study. Future research, for example, may also look into other groups, such as the disabled, to investigate unique barriers and facilitators of ICT acceptance.

Today, Internet access is becoming available through a broader range of devices, including computers, cell phones, personal data assistants (PDA), Internet TV, and other emerging technologies. Although availability of multiple access mechanisms may influence one's usage of a specific innovation, this research, given its focus on ICT innovation behavior at home, controlled only for the most common form of Internet access, namely household Internet PC ownership. Future research could shed more light on the impact of all of these alternative access mechanisms on patterns of home ICT usage.

Finally, this research represents a snapshot of the digital inequality phenomenon. A longitudinal study tracing individuals' pre- and post-implementation behavior may yield a richer understanding of behavioral patterns, critical factors, and how these are shaped over time.

Implications for Theory

For digital inequality researchers, this study represents an important step toward understanding the problem of digital inequality using a theoretically grounded approach based on the theory of planned behavior. This model addresses the often-cited need to understand the intricacies of user acceptance of ICT in the context of digital inequality (Bonfadelli 2002; Van Dijk and Hacker 2003). It demonstrates that a TPB-based model can explain a significant amount of variance in continued use intention both for advantaged and disadvantaged groups of a government-sponsored technology innovation aimed at providing household Internet access. Most importantly, key between-group differences were theoretically deduced and empirically tested. Thus, from the standpoint of digital inequality, this study constitutes an important theoretical contribution to explain the phenomenon. The observed between-group differences warrant elaboration and further examination as they represent promising avenues for insight into differential behavioral patterns and their causes.

Personal network exposure appears to be a noteworthy factor that is relevant in the context of digital inequality, suggesting that researchers should explore other social influence mechanisms in addition to subjective norms as well as their collec-

tive effect. For instance, information on high aggregate innovation behavior in the social system provides a cue that reinforces the social desirability of continued use. Similarly, information about the innovation relayed through the mass media (e.g., TV, radio, and newspapers) exerts another type of social influence (Rogers 2003; Venkatesh and Brown 2001). In the early stages of innovation diffusion, since very few people have or know about the innovation, mass media serves as an important information source for early adopters (Rogers 2003; Valente 1995).

This study also responds to the call for increased attention in investigating governmental influence on digital inequality (DiMaggio et al. 2004). Apparently, the technology-centered LITV initiative partially achieved its objective by successfully removing access barriers for citizens. Meanwhile, expectations from key referents overshadowed the effect of governmental expectation in shaping subjective norms, even though these norms had no effect on continued use. Nonetheless, besides financial subsidy, technology supply, and normative expectation, the impact of governmental influence on behavioral intention may operate in other forms such as people's trust in the government (e.g., Meader et al. 2002) and training and support programs (e.g., Kvasny 2002). These different forms of influence suggest additional mechanisms that the government can employ to stimulate user acceptance. A more comprehensive conceptualization of possible mechanisms of governmental influence should further enhance theoretical development and facilitate effective policy formulation. For instance, partnerships between the government and the private sector, in which the former provides training programs and the latter provides appropriate applications and infrastructure, are emerging as potentially powerful mechanisms for addressing digital inequality. Illustratively, Project Shiksha, a Microsoft-sponsored initiative in India, establishes a partnership between state governments, school systems, and Microsoft to promote IT literacy and skills among 80,000 teachers and 3.5 million students in government and government-aided schools (Microsoft 2006).

Finally, prior digital inequality research has ignored alternative benefits from ICT usage. Traditionally, digital inequality researchers have focused on improving one's life chances from technology use. Thus, when the disadvantaged embrace technology for "recreational" purposes, it has been viewed as noncapital-enhancing. Nevertheless, some researchers have indicated that recreational use of various kinds of technologies can have educational value (Prensky 2003), and that hedonic uses of ICT may result in *learning* that eventually contributes to utilitarian outcomes (e.g., Belanger and Van Slyke 2000). Thus, given our findings that entertainment represents a key factor motivating the disadvantaged to use

ICT, and past findings that recreational use represents a majority of their ICT usage (e.g., Bonfadelli 2002), the value of entertainment in ICT use deserves careful investigation. Researchers in digital inequality should tap into the educational aspect of ICT entertainment and seek to connect the recreational use to skills and/or opportunities that can make the disadvantaged better off.

For the field of technology acceptance, our findings suggest several important theoretical contributions and implications. First, as Legris et al. (2003) noted, although current ICT acceptance theories are useful, incorporating additional critical factors is necessary to improve their explanatory power. This study illustrates that TPB can be meaningfully extended through the addition of personal network exposure, which captures the behavioral consequences of aggregate social informational influence. The addition of the personal network exposure construct explained 10 percent more of the variance in the dependent variable. This strong influence suggests that aggregate signals about the states and trends of ICT usage can be used to shape post-implementation intention to continue use.

Second, the differences in the behavioral models of the SEA and SED groups, particularly in the continued use context, shed light on the importance of developing nuanced theories that can be applied to shape the post-implementation behavior of specific groups. Thus, researchers should not only continue to examine distinctions across diffusion stages but also evaluate how differences among individuals with different backgrounds or characteristics impact ICT acceptance.

As the importance of digital technologies range beyond the scope of organizations, some IS researchers have called for investigating problems relevant to everyone (Lytras 2005). Our study is of particular interest and importance in this respect, as it represents one of the few efforts to investigate ICT innovation behavior in households and beyond typical workplace settings. Specifically, the results identify many key factors that may not be salient in the context of ICT use in organizational settings, yet exert significant influence on individuals' ICT innovation behavior in the context of digital inequality. Behavioral control, for instance, is a critical issue when cognitive and material resources are of concern. This research also identifies a specific form of the social informational mechanism (i.e., personal network exposure) that can powerfully affect individuals' post-implementation behavior. This result, in particular, extends our understanding from prior IS research that individuals will rely less on social information in shaping ICT behavior after direct interaction with the technology (e.g., Karahanna et al. 1999, Venkatesh and Davis 2000). These findings, as a whole, illustrate the com-

plexity and dynamics involved in ICT acceptance in non-workplace settings for the socio-economically advantaged and disadvantaged.

Implications for Practice

For practitioners, particularly public policy makers and Internet service providers, understanding what variables affect post-implementation ICT innovation behavior across groups is critical to effectively planning and implementing interventions like the free Internet TV initiative in LaGrange. This type of project involves considerable resources from many stakeholders. Unsuccessful projects result in a waste of valuable resources, which could discourage the government, residents, and other stakeholders from orchestrating similar initiatives in the future. The integrated set of findings from this research explains why digital inequality interventions (e.g., the LITV initiative) often fail to achieve high levels of success. A policy that focuses not just on reducing or eliminating barriers to technology access but also on complementary aspects that shape behavioral motivations of members within targeted groups to continue to use ICT innovations is essential.

To address digital inequality effectively and economically, we propose a group alignment strategy to replace the typical generic policy that treats everyone as the same and offers a single invariant solution to all populations. This strategy, instead, incorporates the behavioral models of different groups, and configures resources that align with their distinctive needs. This approach might inevitably incur higher administration cost for investigating and understanding the distinctions in behavioral patterns between groups. Nevertheless, with such knowledge, it entails potentially less implementation cost since particular resources would be distributed only to those who need them most. Such a segmentation and alignment strategy, we believe, will lead to a more effective outcome while requiring less total resources.

Based on our analysis of the LaGrange initiative, we believe that providing access to easy-to-use ICT alone—even at no cost—is only part of the solution. The analysis pinpoints other key factors that affect continued ICT use intention (see Figure 2). Understanding these factors and the ones particularly important for the disadvantaged provide points of leverage for policymakers and service providers who wish to address digital inequality and accelerate high-speed Internet usage in the household.

To devise effective interventions, policy-makers need to consider personal network exposure, self-efficacy, hedonic

outcome, utilitarian outcomes, PEOU, and availability, as these offer substantial leverage for the socio-economically disadvantaged group (Figure 2). For personal network exposure, one possible avenue to exploit this lever is to establish mechanisms that enable high exposure to aggregate patterns of ICT innovative behavior. It is especially important to create such signaling mechanisms for the disadvantaged, as their social networks are characterized by fewer contacts who are innovative (Putnam 2000). Opinion leaders, community centers, and other sources considered to be credible by the disadvantaged should be effective in relaying information about aggregate patterns of deployment of the innovation.

Furthermore, to boost the disadvantaged's confidence in using ICT, consistent with the self-efficacy literature, interventions can enable them to repeat successful experiences and learn vicariously through others' successful usage, while providing verbal persuasion when appropriate. Admittedly, these approaches may require significant social support. For example, verbal persuasion implies human resources that can provide appropriate oral support and guidance, and vicarious learning implies circumstances or environments in which group learning or social exchange can occur.

Moreover, besides the utilitarian advantages of ICT usage, digital inequality interventions can incorporate services with special emphasis on the entertainment or hedonic aspect of usage to attract the disadvantaged. It is perhaps equally important to infuse an educational element into such services so that the disadvantaged can develop useful skills, rather than just enjoying the technology. In that way, they may apply the skills learned for better life opportunities.

Finally, to address the issue of availability will require significant financial resources. Consequently, partnerships among private and public institutions (e.g., federal and state governments, foundations and philanthropists, and private corporations) with shared interests in addressing digital inequality may be effective to deal with this thorny issue. Of course, it is imperative that initiatives provide ICT that is easy to use for members of the targeted group.

Conclusion

Drawing upon the perspective of the theory of planned behavior, the present research approaches the digital inequality phenomenon by comparing the post-implementation continued use behavioral models between the socio-economically advantaged and disadvantaged. This study empirically examined the two groups' models of continued use intention in response to a government initiative that

offered free high-speed Internet access to every household in a city. The findings reveal significant differences in the behavioral models and identify pivotal factors that shape continued use of ICT by members of each group. This study represents an important step toward developing our theoretical understanding of the digital inequality phenomenon. The results thus provide insights for policymakers to devise effective interventions to achieve planned outcomes.

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Appendix A

Item-Factor Loadings and Sample Cross-Loadings

SED Group Item Loading	ATT	UO	HO	SN	FRPF	GII	PBC	SE	PEOU	Avail	PNE	U_Int	SEA Group Item Loading
ATT1	0.99	0.72	0.76	0.46	0.51	0.35	0.27	0.39	0.49	-0.15	0.31	0.47	0.98
ATT2	0.99	0.73	0.78	0.46	0.51	0.33	0.28	0.39	0.51	-0.15	0.32	0.46	0.99
ATT3	0.99	0.78	0.78	0.42	0.48	0.30	0.32	0.44	0.54	-0.12	0.33	0.46	0.97
UO1	0.72	0.98	0.67	0.53	0.56	0.36	0.22	0.37	0.49	-0.09	0.31	0.49	0.99
UO2	0.71	0.98	0.68	0.55	0.58	0.39	0.22	0.34	0.46	-0.06	0.31	0.51	0.99
UO3	0.74	0.96	0.70	0.55	0.59	0.40	0.24	0.37	0.48	-0.06	0.32	0.52	0.98
UO4	0.78	0.98	0.65	0.51	0.55	0.36	0.27	0.40	0.52	-0.06	0.30	0.49	0.98
HO1	0.75	0.69	0.99	0.51	0.56	0.40	0.24	0.39	0.50	-0.03	0.38	0.51	0.99
HO2	0.73	0.70	0.99	0.52	0.57	0.41	0.25	0.41	0.52	-0.02	0.36	0.51	0.99
HO3	0.73	0.70	0.99	0.51	0.56	0.43	0.27	0.42	0.51	-0.02	0.36	0.50	0.99
SN1	0.44	0.55	0.51	0.98	0.78	0.57	0.08	0.16	0.23	0.07	0.37	0.36	0.98
SN2	0.44	0.52	0.50	0.98	0.77	0.57	0.00	0.11	0.20	0.11	0.35	0.30	0.98
FRPF*	0.49	0.57	0.55	0.72	1.00	0.63	0.03	0.17	0.23	0.15	0.37	0.33	1
Gov1	0.31	0.38	0.40	0.59	0.65	0.97	0.07	0.10	0.10	0.21	0.21	0.18	0.97
Gov2	0.33	0.37	0.40	0.54	0.61	0.96	0.10	0.14	0.18	0.17	0.18	0.20	0.97
PBC1	0.27	0.24	0.25	0.06	0.02	0.07	0.94	0.71	0.64	-0.11	0.18	0.36	0.94
PBC2	0.32	0.26	0.27	0.05	0.04	0.07	0.97	0.74	0.69	-0.13	0.17	0.39	0.95
PBC3	0.21	0.18	0.18	-0.01	0.03	0.11	0.86	0.65	0.53	-0.03	0.04	0.30	0.91
SE1	0.37	0.35	0.34	0.13	0.14	0.12	0.71	0.97	0.69	-0.05	0.18	0.51	0.96
SE2	0.41	0.38	0.44	0.15	0.19	0.10	0.71	0.96	0.70	-0.02	0.18	0.53	0.95
SE3	0.40	0.36	0.38	0.13	0.18	0.12	0.70	0.95	0.69	-0.02	0.17	0.50	0.96
PEOU_1	0.42	0.37	0.41	0.11	0.15	0.07	0.73	0.73	0.93	-0.03	0.18	0.41	0.93
PEOU_2	0.39	0.39	0.37	0.14	0.16	0.09	0.61	0.64	0.92	-0.05	0.25	0.33	0.91
PEOU_3	0.58	0.55	0.58	0.25	0.28	0.18	0.57	0.69	0.93	-0.08	0.28	0.41	0.88
PEOU_4	0.52	0.54	0.52	0.35	0.30	0.19	0.53	0.57	0.84	-0.05	0.25	0.40	0.81
Avail_1	-0.21	-0.14	-0.12	-0.02	0.04	0.15	-0.10	-0.05	-0.09	0.91	-0.11	-0.13	0.95
Avail_2	0.02	0.08	0.15	0.23	0.26	0.20	-0.06	0.02	0.02	0.86	0.11	0.12	0.82
PNE	0.32	0.32	0.37	0.37	0.38	0.20	0.14	0.19	0.26	-0.03	1.00	0.40	1
U_Int_1	0.47	0.50	0.51	0.35	0.34	0.20	0.37	0.52	0.40	-0.05	0.40	0.99	0.98
U_Int_2	0.45	0.50	0.47	0.33	0.32	0.17	0.39	0.55	0.45	-0.07	0.38	0.97	0.99
U_Int_3	0.45	0.51	0.51	0.32	0.35	0.20	0.34	0.50	0.39	0.01	0.38	0.97	0.97

PLS item cross-loadings were calculated according to the procedure suggested by Gefen and Straub (2005). While the cross-loadings for ATT, UO, and HO are relatively high, the differences between loadings on principal factors and on other constructs are higher than the threshold suggested by Gefen and Straub. In fact, only 6 out of the 372 cross-loading differences are between 0.1 and 0.2; all other cross-loading differences are higher than 0.2.

*FRPF is a formative construct, whose index score is computed as a unit mean of four items.

Appendix B

Squared Pairwise Correlations and Assessment of Discriminant Validity

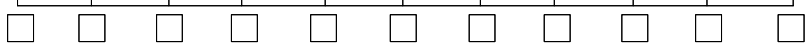
B1. Disadvantaged Group												
	ATT	UO	HO	SN	FPRF	Gov. Inf.	PBC	Self-Efficacy	PEOU	Availability	PNE	Intention
ATT	0.98											
UO	0.73	0.95										
HO	0.69	0.64	0.98									
SN	0.20	0.30	0.26	0.96								
FPRF	0.26	0.34	0.32	0.75	N/A							
Gov. Inf.	0.11	0.15	0.17	0.34	0.43	0.93						
PBC	0.09	0.06	0.06	0.00	0.00	0.01	0.85					
Self-efficacy	0.17	0.14	0.17	0.02	0.03	0.01	0.60	0.92				
PEOU	0.27	0.25	0.26	0.05	0.05	0.02	0.44	0.54	0.82			
Availability	0.02	0.00	0.00	0.01	0.03	0.04	0.13	0.00	0.00	0.82		
PNE	0.11	0.10	0.14	0.14	0.15	0.04	0.02	0.03	0.07	0.00	N/A	
Intention	0.22	0.26	0.26	0.10	0.12	0.04	0.14	0.29	0.18	0.00	0.16	0.95

B2. Advantaged Group												
	ATT	UO	HO	SN	FPRF	Gov. Inf.	PBC	Self-Efficacy	PEOU	Availability	PNE	Intention
ATT	0.96											
UO	0.64	0.97										
HO	0.60	0.76	0.97									
SN	0.29	0.34	0.31	0.96								
FPRF	0.33	0.39	0.33	0.79	N/A							
Gov. Inf.	0.12	0.13	0.12	0.27	0.29	0.94						
PBC	0.04	0.02	0.02	0.00	0.00	0.02	0.87					
Self-Efficacy	0.09	0.06	0.08	0.00	0.01	0.01	0.40	0.92				
PEOU	0.19	0.18	0.20	0.03	0.05	0.03	0.28	0.52	0.78			
Availability	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.79		
PNE	0.27	0.28	0.29	0.25	0.31	0.08	0.03	0.07	0.15	0.01	N/A	
Intention	0.38	0.43	0.43	0.26	0.30	0.08	0.02	0.08	0.17	0.01	0.35	0.96

Note: AVE of every multi-item construct is shown on the main diagonal. (Personal Network Exposure (PNE) is a single-item construct.) Squared correlations are off the diagonal.

Appendix C

Measurement Items for Key Constructs

Construct	Items	Sources That Inform the Construct
Attitude	All things considered, using the Internet TV is (1-7 scale) 1. extremely negative ...extremely positive 2. extremely bad...extremely good 3. extremely harmful ...extremely helpful	Ajzen 1991 Ajzen and Madden 1986
Utilitarian Outcomes	Using the Internet TV (Strongly Disagree/Agree) (1-7 scale) 1. improves my performance for communication & information search. 2. improves my productivity for communication & information search. 3. enhances my effectiveness for communication & information search. 4. is useful for my communication & information search.	Davis 1989 Rogers 2003 Venkatesh and Brown 2001
Hedonic Outcomes	Using the Internet TV (Strongly Disagree/Agree) (1-7 scale) 1. is enjoyable. 2. is pleasant. 3. is fun.	Davis 1989 Venkatesh 1999 Venkatesh and Brown 2001
Subjective Norms (SN)	(Strongly Disagree/Agree) (1-7 scale) 1. People who influence me think that I should use the Internet TV. 2. People who are important to me think that I should use the Internet TV.	Ajzen 1991 Ajzen and Madden 1986
Family, Relatives, Friends, and Peers' Influence	(Strongly Disagree/Agree) (1-7 scale) 1. My family thinks that I should use the Internet TV. 1. My relatives think that I should use the Internet TV. 3. My friends think that I should use the Internet TV. 4. People I work with think that I should use the Internet TV	Karahanna et al. 1999 Taylor and Todd 1995b Venkatesh and Brown 2001
Government Institutions' Expectation	(Strongly Disagree/Agree) (1-7 scale) 1. The city government expects me to use the Internet TV. 2. The city government thinks that I should use the Internet TV	Karahanna et al. 1999 Lynne et al. 1995
Perceived Behavioral Control (PBC)	(Strongly Disagree/Agree) (1-7 scale) 1. I have the resources, knowledge, and ability to use the Internet TV. 2. I can use the Internet TV. 3. Using the Internet TV is entirely within my control.	Ajzen 1991 Ajzen and Madden 1986
Self-Efficacy	(Strongly Disagree/Agree) (1-7 scale) 1. I feel comfortable using the Internet TV on my own. 2. I can easily operate the Internet TV on my own. 3. I feel comfortable using the Internet TV even if there is no one around me to tell me how to use it.	Bandura 1977 Compeau and Higgins 1995
Perceived Ease of Use	(Strongly Disagree/Agree) (1-7 scale) 1. My interaction with the Internet TV is clear and understandable. 2. Interacting with the Internet TV does not require a lot of my mental effort. 3. I find the Internet TV easy to use. 4. I find it easy to get the Internet TV to do what I want it to do.	Davis 1989 Davis et al. 1989
Availability	(Strongly Disagree/Agree) (1-7 scale) 1. It is difficult for me to use the Internet TV when other members in my household want to watch TV. 2. Many people in my household want to use Internet TV, and I don't always get to use it.	Kvasny and Keil 2002 Meader et al. 2002 Taylor and Todd 1995b
Personal Network Exposure	What percent of the people you know in LaGrange has adopted the Internet TV? 0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100% 	Fligstein 1985 Palmer et al. 1993 Valente 1995
Behavioral Intention for Continued Use	(Strongly Disagree/Agree) (1-7 scale) I intend to continue using the Internet TV 1. during the next three months. 2. for email, browsing, or searching during the next three months. 3. frequently during the next three months.	Ajzen 1991 Ajzen and Madden 1986

Appendix D

Supplemental Measurement Invariance Analysis for Group Comparison ██████████

To further evaluate the appropriateness to compare path coefficients between the two groups, we applied multigroup measurement invariance analysis (Doll et al. 1998; Steenkamp and Baumgartner 1998). Using AMOS 5.0, we performed configural and metric invariance analyses to evaluate if the measurement models are invariant across the advantaged and disadvantaged groups. Configural invariance denotes that the patterns of item loadings are congeneric across groups (Doll et al. 1998; Steenkamp and Baumgartner 1998). No restrictions are imposed on metrics across groups when modeling configural invariance (Doll et al. 1998). Next, metric invariance checks whether items have equal loadings between groups. Item loadings are constrained to be equivalent across groups when modeling metric invariance. If the change in CFI between these two nested (configural and metric) models is smaller than the suggested threshold 0.01 (Cheung and Rensvold 2002), then metric invariance is supported, permitting path coefficient comparison between groups.

We applied the analytical procedure described above to assess measurement invariance across the advantaged and disadvantaged groups. Due to sample size and model complexity constraints, we performed this analysis separately for each block of the research model. Configural invariance analysis revealed the pattern of item loadings to be congeneric across the two groups. In terms of metric invariance, the changes in CFI for block 1, 2, 3, and 4 were 0.002, 0.001, 0.001, and 0.002 respectively for each of their nested models. Given that these values were all lower than the recommended 0.01 level (Cheung and Rensvold 2002), metric invariance is established, providing additional support for meaningful path coefficient comparison across groups.

Appendix E

Common Method Bias Analysis

Item	Substantive Factor Loading (R1)	R1 ²	Common Method Factor Loading (R2)	R2 ²
Attitude (item_1)	0.981 **	0.962	0.062	0.004
Attitude (item_2)	0.978 **	0.956	-0.012	0.000
Attitude (item_3)	0.985 **	0.970	-0.051	0.003
SN (item_1)	0.999 **	0.998	0.018	0.000
SN (item_2)	0.972 **	0.945	-0.019	0.000
PBC (item_1)	0.946 **	0.895	-0.031	0.001
PBC (item_2)	0.953 **	0.908	0.002	0.000
PBC (item_3)	0.885 **	0.783	0.034	0.001
Utilitarian Outcomes (item_1)	0.992 **	0.984	-0.008	0.000
Utilitarian Outcomes (item_2)	0.991 **	0.982	-0.035	0.001
Utilitarian Outcomes (item_3)	0.880 **	0.774	0.000	0.000
Utilitarian Outcomes (item_4)	0.976 **	0.953	0.044	0.002
Hedonic Outcomes (item_1)	0.993 **	0.986	0.000	0.000
Hedonic Outcomes (item_2)	0.976 **	0.953	0.018	0.000
Hedonic Outcomes (item_3)	0.991 **	0.982	-0.018	0.000
FRPF (item_1)	0.973 **	0.947	0.016	0.000
Gov. Institutions' Influence (item_1)	0.973 **	0.947	-0.003	0.000
Gov. Institutions' Influence (item_2)	0.969 **	0.939	0.003	0.000
Self-Efficacy (Item_1)	0.952 **	0.906	0.013	0.000
Self-Efficacy (item_2)	0.952 **	0.906	0.010	0.000
Self-Efficacy (item_3)	0.968 **	0.937	-0.023	0.001
PEOU (item_1)	0.939 **	0.882	-0.016	0.000
PEOU (item_2)	0.925 **	0.856	0.081	0.007
PEOU (item_3)	0.913 **	0.834	0.086	0.007
PEOU (item_4)	0.854 **	0.729	0.160 **	0.026
Availability (item_1)	0.811 **	0.658	0.170 **	0.026
Availability (item_2)	0.788 **	0.621	-0.182 **	0.029
Personal Network Exposure (item_1)	1.000 **	1.000	0.000	0.000
Intention for Continued Use (item_1)	0.993 **	0.986	-0.006	0.000
Intention for Continued Use (item_2)	0.989 **	0.978	-0.011	0.000
Intention for Continued Use (item_3)	0.961 **	0.924	0.017	0.000
Average	0.950	0.906	0.010	0.003

Appendix F

Supplementary Analysis on Type of Moderation of Socio-Economic Status

Results of the PLS analysis support the moderation effect of socio-economic status (SES) on some of the hypothesized relationships. To further investigate the type of moderation of SES (i.e., pure moderator, quasi-moderator, or homologizer) and to examine if the detected moderation was not an artifact of unequal measurement error across the subsample (i.e., homologizer), we followed the MRA procedure recommended by Sharma et al. (1981). Additionally, we examined if the conclusion regarding the type of moderation is sensitive to nonlinear effects of the predictors on the criterion. These additional analyses validate our conceptualization of SES as moderating the strength of the relationships between the identified criterion and predictor variables.

Description of Moderated Regression Analysis

Sharma et al. (1981) suggest that the Chow test can be used to detect differences across groups in the vector of coefficients of the predictor variables. Importantly, they note that, additionally, a distinction should be made among pure moderators and quasi-moderators, and homologizers, based on the direct and/or moderating effect of the moderator on the predictor and criterion variables. The moderated regression analysis (MRA) procedure suggested by them and summarized in Table F1 can be applied to make this assessment.

Based on the MRA guidelines, we can conclude that the moderator variable is

- a pure moderator, if there is an interaction effect and no direct effect with criterion or predictor variables
- a quasi-moderator, if there is an interaction effect and a direct relationship with the predictor, the criterion variable, or both
- a homologizer, if there is neither a direct effect nor a moderation effect but the *detected* interaction derives from unequal measurement errors across subsamples.

Application of MRA Procedure and Findings

Each block in our model contains a criterion variable, a set of predictors, and SES as the moderator. Accordingly, for each of the four blocks, we estimated the three MRA equations and applied the Chow test (Chow 1960) to examine for differences across groups in the vector of coefficients of the predictor variables.

Type of SES Moderation in TPB BLOCK (Block 1)

Behavioral intention (BI) is the criterion variable; attitude (ATT), subjective norm (SN), perceived behavioral control (PBC), personal network exposure (PNE), and the control variable, Internet PC ownership (IPC), are the five predictors. Based on the MRA procedure, we find

- For direct effects of the predictors on the criterion (BI), all of them, with the exception of SN, are significant.
- For direct effects of the moderator (SES) on the criterion (BI), a significant relationship is not detected.
- For the interaction effects of SES and the predictors, the Chow test indicates that the *vector* of coefficients for ATT, SN, PBC, PNE, and IPC are different across SES groups.

The above results suggest pure moderation of the relationship between the predictors and the criterion variable in this block.

Type of SES Moderation in ATTITUDE BLOCK (Block 2)

Attitude (ATT) is the criterion variable; utilitarian outcomes (UO) and hedonic outcomes (HO) are the predictors. Based on the MRA procedure, we find

- For direct effects of the predictors on the criterion (ATT), both UO and HO are significant.
- For direct effects of the moderator (SES) on the criterion (ATT), a significant relationship is not detected.
- For the interaction effects of SES and the predictors, the Chow test indicates that the vector of coefficients for UO and HO are different across SES.

The results suggest pure moderation of the relationship between the predictors and the criterion variable in this block.

Type of Effect	Equations	Decision Rules
Direct Effect of Predictor	$Y = a + b1 \cdot X$	<ul style="list-style-type: none"> • Z is not a moderator if $b3 = 0$ and $b2 \neq 0$. (i.e., Eq2 and Eq3 are not different.) • Z is a pure moderator, if $b2 = 0$ but $b3 \neq 0$. (i.e., Eq1 and Eq2 are not different from each other but are different from Eq3). • Z is a quasi-moderator, if $b2 \neq b3 \neq 0$. (i.e., All three equations are different from each other.)
Direct Effect of Predictor & Moderator	$Y = a + b1 \cdot X + b2 \cdot Z$	
Interaction	$Y = a + b1 \cdot X + b2 \cdot Z + b3 \cdot X \cdot Z$	

Type of SES Moderation in SUBJECTIVE NORM BLOCK

SN is the criterion variable; FRPF and governmental influence (GovInf) are the predictors. Based on the MRA procedure, we find

- For direct effects of the predictors on the criterion (SN), FRPF has a significant effect while GovInf does not.
- For direct effects of the moderator (SES) on the criterion (SN), a significant relationship is not detected.
- For the interaction effects of SES and the predictors, the Chow test does not detect significance.

The above results suggest no moderation of the relationship between the predictors and the criterion variable in this block.

Type of SES Moderation in PERCEIVED BEHAVIORAL CONTROL BLOCK

PBC is the criterion variable; self-efficacy (SE), perceived ease of use (PEOU), and availability are the predictors. Based on the MRA procedure, we find

- For direct effects of the predictors on the criterion (PBC), SE and PEOU have a significant relationship while availability does not.
- For direct effects of the moderator (SES) on the criterion (PBC), a weak significant relationship is detected.
- For the interaction effects of SES and the predictors, the Chow test indicates that the vector of coefficients for SE, PEOU, and availability are different across SES.

The results suggest quasi-moderation of the relationship between the predictors and the criterion variable in this block.

For quasi-moderation, the interaction effect is ambiguous and can be interpreted as (1) SES moderates the relationship between a predictor and PBC, or (2) the predictor moderates the relationship between SES and PBC. To deal with such situations, Sharma et al. (1981) suggest that the interpretation should be “guided by theory rather than empiricism.” Given the established body of literature that has theorized and found evidence of the direct effect of internal control and external control on PBC and our own theoretical reasoning for SES to moderate these relationships, we conclude that SES is the moderator.

Evaluation of Moderation Confounds from Multicollinearity and Nonlinear Effects

High multicollinearity between the moderator and predictor can induce nonlinear effects that confound interaction (Carte and Russell 2003; Cortina 1993). While the correlations between SES and the predictors are low, we did evaluate for the stability of the above moderation results in the presence of nonlinear effects of the predictors. When the squared effect of the predictors is controlled for, the moderation effect remains significant.