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Conceptualizing and Testing a Social Cognitive Model of the Digital Divide

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The digital divide has loomed as a public policy issue for over a decade. Yet, a theoretical account for the effects of the digital divide is currently lacking. This study examines three levels of the digital divide. The digital access divide (the first-level digital divide) is the inequality of access to information technology (IT) in homes and schools. The digital capability divide (the second-level digital divide) is the inequality of the capability to exploit IT arising from the first-level digital divide and other contextual factors. The digital outcome divide (the third-level digital divide) is the inequality of outcomes (e.g., learning and productivity) of exploiting IT arising from the second-level digital divide and other contextual factors. Drawing on social cognitive theory and computer self-efficacy literature, we developed a model to show how the digital access divide affects the digital capability divide and the digital outcome divide among students. The digital access divide focuses on computer ownership and usage in homes and schools. The digital capability divide and the digital outcome divide focus on computer self-efficacy and learning outcomes, respectively. This model was tested using data collected from over 4,000 students in Singapore. The results generate insights into the relationships among the three levels of the digital divide and provide a theoretical account for the effects of the digital divide. While school computing environments help to increase computer self-efficacy for all students, these factors do not eliminate knowledge the gap between students with and without home computers. Implications for theory and practice are discussed.

Key words: digital divide; social cognitive theory; computer ownership; school IT environment; computer self-efficacy; learning outcomes; adoption and impact of IT
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1. Introduction

The ubiquity of computer use in our everyday world grows exponentially (Cooper 2006). As information technology (IT) becomes increasingly pervasive, there is an alarming concern that those without access to IT may be highly disadvantaged (Becker 2000, Dewan and Riggins 2005, Jaeger 2004, Kvasny and Keil 2002). Of particular concern to governments is the lack of access to IT by young people, which can exacerbate social stratifications (Ching et al. 2005, Warschauer 2003a) in a world dominated by IT.[1] Using data from the U.S. Department of Education, DeBell and Chapman (2006) highlight the presence of a digital divide among students, based on demographic and socioeconomic factors. Others have noted that the lack of access to IT is likely to deprive young people of opportunities to develop computer self-efficacy (CSE) (e.g., Attewell and Battle 1999), which is important for learning outcomes (Marakas et al. 1998).

Many countries have adopted policies to reduce the digital divide. For example, the United States and Singapore have increased public access to computers through schools, libraries, and other public places. In spite of the prevalence of such policies, there is an insufficient understanding of whether and how such policies have reduced the digital divide between those who have computers at home and those who do not (Attewell 2001, Warschauer 2003b). Since increasing public access to computers has often been deemed the holy grail of reducing the digital divide, this study seeks to develop a sound theoretical understanding of the effects of this key policy.

Toward this end, we need a fine-grained understanding of the digital divide, which may be considered at three levels (Dewan and Riggins 2005). The

[1] The 2008–2009 *Occupational Outlook Handbook* from the U.S. Bureau of Labor Statistics shows that, at the bachelor degree level, two of the top five fastest growing occupations are IT-related (see http://www.bls.gov/oco/reprints/ocor001.pdf).

first level is an access divide, which may lead to a capability divide, which in turn may lead to an outcome divide (as described in detail later). Home and school access to computers belongs to the first level. The effects of home and school access on the capability divide help us assess the outcomes of policies on providing home and school access. Beyond this, it is important to understand the effects of the capability divide on learning outcomes for students, which is the outcome divide. Past research that examined the effects of the digital divide on learning outcomes has not offered a clear theoretical explanation of the underlying mechanisms. Going beyond past research, this study uses social cognitive theory (Bandura 1997, 2001) to explain the chain of effects from the digital access divide through the digital capability divide to the digital outcome divide. This study explicates the mechanisms by which access to and use of IT (for study and leisure) in homes and schools, school IT environments, and individual characteristics (e.g., gender) influence CSE and, through CSE, learning outcomes. Such a rigorous understanding of the digital divide phenomenon is valuable in an increasingly knowledge-intensive and IT-laden world where IT-based learning is critical.

2. A Digital Divide Framework

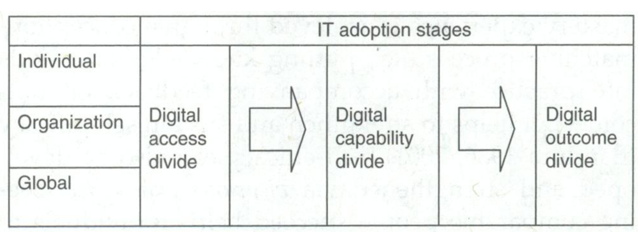
The digital divide issue has attracted much attention from researchers as well as the popular press. There are two levels of the digital divide in the extant literature, based on a framework by Dewan and Riggins (2005). This framework uses the adoption process to explain the stages of having access to IT, developing usage capability, and achieving outcomes. The first level refers to the inequality of access to IT, such as access to computers in homes and schools (Dewan and Riggins 2005), typically described as the "narrow sense" of the digital divide (Friedman 2001). For example, the report by OECD (2001, p. 5) describes the digital divide as "the gap between individuals, households, businesses, and geographic areas at different socioeconomic levels with regard to both their opportunities to access information and communication technologies and their use of the Internet for a wide variety of activities." Thus, the first level of the digital divide covers both hardware access as well as use of software.

The second level refers to the inequality of IT capability or "the ability to use the technology" (Dewan and Riggins 2005, p. 301). It arises due to the first-level digital divide and other contextual factors. "One of the most important aspects of inequality of use has to do with differences in computer skill levels" (Dewan and Riggins 2005, p. 310). A narrower definition of the second level focuses on abilities to find information online (OECD 2007). Besides computer skills, CSE is an important alternative for assessing the ability to exploit IT (Bandura 1977, Friedman 2001, Thatcher and Perrewe 2002). In this study, we use the "digital access divide" to refer to the first level and the "digital capability divide" to refer to the second level.

Extending the framework by Dewan and Riggins (2005), we add a third-level digital divide, the "digital outcome divide," which arises due to the second-level digital divide and other contextual factors. The existence of the third level has been alluded to in Dewan and Riggins (2005). They have raised research questions about the impact of the second-level digital divide with implicit goals of closing outcome differences. We explicitly articulate the third level to align with the wide interest in studying outcomes from IT use and investment (Shu and Strassmann 2005). Does the capability divide lead to the outcome divide? Examples of digital outcome divide include differences in learning outcomes and productivity. Such a focus on outcomes has also been done by studies examining broadband access (e.g., OECD 2007), IT adoption in organizations (e.g., Ramamurthy and Premkumar 1995), and IT productivity paradox (e.g., Brynjolfsson 1993, Ross and Ernstberger 2006). The extended three-level digital divide framework is shown in Figure 1. Each level of the digital divide can be studied at the individual, the organizational, or the country levels (Dewan and Riggins 2005). For example, the digital access divide can be measured by home computer ownership by individuals, IT investment by organizations, and national IT expenditure by countries. This study focuses on individuals.

Most digital divide studies have focused on the first-level digital divide as the dependent variable (Kauffman and Techatassanasoontorn 2005) with individual, socioeconomic, or geographical factors as determinants (e.g., Agarwal et al. 2008, DeBell and Chapman 2006, Ching et al. 2005, Hsieh et al. 2008). Van Dijk and Hacker (2003) suggest that skill and usage gaps are likely to increase with the first-level digital divide. To date, there has been little research on the effects of a lack of a home computing environment (Attewell and Battle 1999, Subrahmanyam et al. 2000) on the digital capability divide and the digital outcome divide. It is especially unclear how access to and use of IT at home may interact with

Figure 1 **Three-Level Digital Divide Framework**



school IT environment (the digital access divide) to impact CSE (the digital capability divide) and learning outcomes (the digital outcome divide). Dewan and Riggins (2005, p. 312) opined that "it is still not clear how providing public access (e.g., in schools) is effective in bridging the divide." To shed light on this issue, this study investigates the combined effects of the digital access divide in homes and schools on the subsequent two levels of the digital divide.

3. A Social Cognitive Model of the Digital Divide

While the digital divide framework is used to analyze the effects of the digital divide on students, these effects can be explicated with social cognitive theory (Bandura 1997, 2001). Using social cognitive theory as the theoretical foundation, we develop the research model and hypotheses within the digital divide framework.

3.1. Social Cognitive Theory

The social cognitive theory advances the view that individuals possess a self-belief system that allows them to exercise control over their cognitive processes, feelings, motivation, and behavior. At the core of the self-belief system is self-efficacy—"the belief in one's capability to organize and execute the courses of action required to manage prospective situations" (Bandura 1997, p. 2). Strong self-efficacy facilitates human accomplishments (Bandura 1997). The theory operates within a causal model of triadic reciprocity, where (a) *personal factors* in the form of cognition, affect, and biological events, (b) *behavior*, and (c) *environmental factors* interact and influence one another (Bandura 1986).

The environmental and the personal conditions in which an individual is situated afford four sources of influence that can shape self-efficacy: mastery experience, vicarious experience, social persuasions, and physiological states (Bandura 1977). *Mastery experience*, the interpreted result of one's performance, can create and strengthen self-efficacy. Outcomes interpreted as success raise self-efficacy while outcomes interpreted as failure lower it. There are two forms of mastery experience: guided and enactive. Guided mastery experience is achieved by instructional modeling or training. It helps to cultivate self-efficacy through knowledge and skills development. Enactive mastery experience is achieved through a conception-matching process (i.e., putting knowledge and skills into practice with accompanying feedback on outcomes). It helps to strengthen and sustain self-efficacy (Bandura 1986, 2001). Self-efficacy can also be developed and strengthened via *vicarious experience*. Seeing comparable people succeed helps individuals to increase self-efficacy. Vicarious experience influences self-efficacy by transmitting knowledge, skills, and strategies to observers about the effective management of environmental demands.

Individuals also develop self-efficacy as a result of the *social persuasions* they receive from others. Bandura (1997, p. 101) argues that "to the extent persuasive boosts in perceived efficacy lead people to try hard enough to succeed, self-affirming beliefs promote the development of skills and a sense of personal efficacy." Self-efficacy can also be influenced by *psychological states* (e.g., anxiety) that individuals experience when contemplating a behavior. Compared to mastery experience and vicarious experience, social persuasions, and physiological states have lesser influence on self-efficacy (Bandura 1997).

3.2. Social Cognitive Theory and the Digital Divide

In the triadic reciprocal causation model of social cognitive theory, personal factors, behavioral patterns, and environmental factors influence one another (Bandura 1986). Contextualized in this study, personal factors include gender, academic ability, and CSE. Behavioral patterns include computer usage patterns at home and at school. Environmental factors include availability of computer resources at home and at school as well as various sources of social cognitive influence (e.g., mastery experience, vicarious experience, social persuasions, and physiological states) exercised through family, school, and training.

Our central thesis is that the access to and use of IT at homes and at schools, personal factors such as gender and academic ability, and environmental conditions of homes and schools (i.e., factors pertaining to the digital access divide) afford various sources of social cognitive influence to impact CSE, the central factor pertaining to the digital capability divide for individuals (Dewan and Riggins 2005). CSE, in turn, affects learning outcomes of individuals (i.e., factors pertaining to the digital outcome divide). In using social cognitive theory to explicate the relationships between these factors, we are not attempting to be comprehensive in studying all sources of influence in the environment.[2] Rather, we are focusing on sources of influence that are important in the study of the digital divide.

In the context of this study, home computer access (ownership) can be taken as a key indicator of the digital access divide in the home environment. For those

[2] Prior studies on CSE have examined individual factors such as computer ownership, training, enrollment in computer courses, computer usage, experience, cognitive playfulness, motivation, gender, and age as well as environmental factors such as organizational support, management support, external support, and encouragement from others (Marakas et al. 1998).

having access to a home computer, their usage patterns (for study and leisure) would become potential factors influencing CSE. We have also included the gender factor because this is a key factor in research on CSE and the digital divide (Cooper 2006, Dewan and Riggins 2005, Marakas et al. 1998). CSE is generally higher for males than for females (Cassidy and Eachus 2002, Cooper 2006). In two surveys done ten years apart (in 1996 and 2006), Karsten and Schmidt (2007) found that males had significantly higher CSE than females. In the school environment, the interactive social system comprising resources, computer usage, teaching quality, and culture of the school, can provide a positive environment that promotes CSE and, through CSE, learning outcomes. Hence, we include factors such as availability of school IT resources, computer usage in school, school IT culture, and IT training quality.

3.3. From Capability Divide to Outcome Divide

CSE has been identified as the most important factor representing the digital capability divide for individuals (Dewan and Riggins 2005). This is particularly true in our context of school students. Thus, CSE is the focal construct through which personal, behavioral, and environmental factors influence outcomes. CSE reflects the judgment of people about how good they are at using computers (Compeau and Higgins 1995b; Marakas et al. 1998, 2007). To perform well with IT, CSE is important (Venkatesh and Davis 1996, Thatcher and Perrewe 2002). Marakas et al. (1998) distinguish general from task-specific CSE. There is a strong correlation between both types of CSE (Agarwal et al. 2000, Downey 2006, Wang et al. 2008). In this study, since learning outcomes require a repertoire of task-specific skills (e.g., document retrieval, file organization, and electronic mail), we focus on general CSE. Other studies have taken a similar focus (e.g., Thatcher and Perrewe 2002). Indeed, general CSE has been found to be influential in affecting learning outcomes in educational (e.g., Greenberg 2001) and organizational settings (Compeau and Higgins 1995b, Webster and Martocchio 1995).

To examine the digital outcome divide, we focus on learning outcomes. In particular, we are interested in the effects of CSE on learning outcomes. Learning outcomes can be generic (e.g., have a wide vocabulary) or specific (e.g., know the periodic table of chemical elements). Given that our focus is not on any specific course (where specific learning outcomes would be relevant), we focus on generic learning outcomes. Hooper-Greenhill (2004, p. 154) identifies a comprehensive set of five generic learning outcomes, which are "an increase in knowledge and understanding; an increase in skills; a change in attitude or values; enjoyment, inspiration, creativity; [and] action, behavior, progression." Within the context of our study (i.e., the Singapore secondary school system), the Ministry of Education has also identified general learning outcomes. For example, for a general project module, the outcomes would comprise knowledge application, communication skills, collaboration skills, and independent learning.[3] These outcomes map onto the knowledge, skills, and attitude outcomes identified by Hooper-Greenhill (2004).

Knowledge and skills are key learning outcomes in education and information systems studies. For example, in the field of information systems, Carswell and Venkatesh (2002) studied learning outcomes based on expected grades and Alavi et al. (2002) studied perceived subject matter learning (a knowledge outcome) and perceived skills development (a skills outcome). In the field of education, Multon et al. (1991) did a meta-analysis of 36 studies and identified knowledge and skills as two major learning outcomes. Waxman et al. (2003) conducted a meta-analysis of 42 studies and identified knowledge (which they labeled cognitive outcome, comprising of tests and assessments) as the main outcome. Consistent with prior literature, we measure knowledge outcome in terms of subject matter gained and academic results attained and skills outcome in terms of communications with peers and teachers.

A review of social cognitive theory and the CSE literature by Marakas et al. (1998) indicates that CSE has positive effects on performance outcomes (e.g., knowledge and skills outcomes), especially in a knowledge-intensive and IT-driven environment. Other studies have reported that CSE plays an influential role in shaping learning outcomes by affording individuals with capabilities to explore Internet content and use communication technologies with ease (e.g., Greenberg 2001, Joo et al. 2000, Mann et al. 1999, Papasratorn and Wangpipatwong 2006). In line with this stream of literature, we hypothesize:

Hypothesis 1A (H1A). *CSE is positively related to knowledge outcome.*

Hypothesis 1B (H1B). *CSE is positively related to skills outcome.*

3.4. From Access Divide (Home) to Capability Divide

There is a sizeable difference in home computer ownership across and within countries. For example, the percentage of households with at least a computer varies from 12% to 85% among OECD countries (OECD 2008). In the United States, 70% of households owned a computer (OECD 2008). In Singapore,

[3] Ministry of Education, Singapore, http://www.moe.gov.sg/projectwork/#Learning_Outcomes.

77% of households had at least one computer (IDA 2007); about one in four households did not have a computer.

As computers become an integral part of school curricula and learning, the digital divide poses not only learning problems but also social and economic challenges (Papert 1996). The importance of the home computing environment to student learning is growing as societies become more knowledge intensive and IT-driven. However, "access to PCs...by income...not only shows a significant gap between the top and the bottom groups (expressed in penetration rates in percentages) but in most countries except Sweden and Finland, this gap has increased" (OECD 2007, p. 31).

3.4.1. Home Computer Ownership. Home computer ownership provides several sources of influence that cultivates CSE. Sibling or parental use of a home computer can provide vicarious learning experiences that increase CSE. A survey of the digital divide on African-American students revealed that more than half of the respondents look to their family for role models (Payton 2003). Having siblings and parents who are knowledgeable in IT can also enable students to make better use of home computers (Becker 2000). Social persuasion from family members has a positive impact on CSE. Students are more likely to exert persistent effort when they are verbally persuaded that they have the ability to succeed in using home computers to solve problems. Positive encouragement and situational support help to build CSE (Compeau and Higgins 1995a, Marakas et al. 1998). Students owning a home computer have higher perceived computing skills than those who do not (Selwyn 1998). While vicarious learning and social persuasion may help to boost CSE, the enactive mastery experience (obtained via repeated home computer usage) is likely to produce the greatest effect on CSE. Hence, we hypothesize:

Hypothesis 2 (H2). *Home computer ownership is positively related to CSE.*

3.4.2. Home Computer Usage. Based on social cognitive theory, usage is a central event with which self-efficacy is produced. Thus, beyond home computer ownership, the amount and pattern of home computer usage are important factors (Attewell 2001). Home computer usage can have utilitarian and hedonic outcomes (Venkatesh and Brown 2001). For students, utilitarian outcome may come from home computer use for study activities, such as word processing, programming, presentation, and information gathering (Selwyn 1998). Computers for Youth, a nonprofit organization based in New York City, found that 90% of school-age children in the United States used home computers for activities such as homework, word processing, and finding information on the Internet. Hedonic outcome may come from home computer use for leisure activities, such as exchanging electronic mails with friends, music playing, online chatting, and computer gaming (Selwyn 1998, Sutherland et al. 2000).

The use of home computers for utilitarian and hedonic purposes is important for developing CSE. Frequent usage allows students to acquire enactive mastery experience, leading to higher CSE (Eastin and LaRose 2000). Previous research suggests that home computer usage can give individuals confidence in handling computers, which in turn affects learning outcomes (Mumtaz 2001). While there is consensus on the impact of study usage of home computers on CSE, little is known about the impact of leisure usage of home computers.

Although many parents consider game playing on home computers a waste of time (Sutherland et al. 2000), recent studies have shown some positive effects of game playing. For example, video game playing was found to have a positive effect on visual attention: "Although video game playing may seem to be rather mindless, it is capable of radically altering visual attention processing" (Green and Bavalier 2003, p. 536). While the benefits gaming has on academic skills have not been thoroughly studied, some researchers have recognized the learning efforts involved in game playing (e.g., Kafai et al. 2002). Unlike study-related applications, gaming applications typically do not have training courses. Students have to learn the skills on their own and this helps them to build up CSE. In light of these findings, we hypothesize:

Hypothesis 2A (H2A). *Home computer usage for studies is positively related to CSE.*

Hypothesis 2A (H2B). *Home computer usage for leisure is positively related to CSE.*

Both study-related and leisure-related applications require common skills, such as Internet access, software installation, and even typing and mouse use. However, some researchers argue that leisure usage may be a better predictor of CSE than study usage because the former is based on intrinsic motivation, where usage itself bring pleasure and satisfaction, even without external rewards (e.g., Vallerand 1997). In particular, game playing affords immediate pleasure, induces a strong sense of involvement, and attracts strong concentration. Game-based training has fostered favorable perceptions of new technology (Venkatesh 1999). In contrast, study usage is usually linked with external rewards to motivate students to use home computers for this purpose. Therefore, we hypothesize:

Hypothesis 2C (H2C). *Home computer usage for leisure is more strongly related to CSE compared to home computer usage for studies.*

3.5. From Access Divide (School) to Capability Divide

The school computing environment (in the form of availability of IT resources, quality of IT training, and IT culture) has the potential to significantly influence students' CSE. As in the case of the home computing environment, the mechanisms of social cognitive theory undergird the foundation on which CSE is cultivated. Availability and usage of IT resources provide the bases through which students acquire enactive mastery experience. The presence of peers provides rich vicarious experience for students as they observe and model one another in using computers. Guided and enactive mastery experience should come from receiving high quality IT training from teachers. Schools with a culture that promotes usage of IT for academic attainment are also more socially persuasive in helping students to attain CSE. Given that students typically spend a large proportion of their time in school, the school computing environment is clearly important for developing CSE.[4] In schools, CSE can be constructed through a complex constellation of efficacy information conveyed through guided mastery (education and training), enactive mastery (putting into practice what is learned and receiving feedback), vicarious learning (observing and modeling), and social persuasion (exhortation and encouragement).

Schools play a significant role in providing more equal opportunities for students to use IT resources. The school computing environment can significantly impact the effectiveness of IT-based learning initiatives through improving the IT proficiency of students (Mann et al. 1999). The U.S. Census Bureau report in 2000, on computer and Internet access, claims that school IT access helps to close the digital divide between children from high income and low income families (Wilhelm et al. 2002). A thorough review of the empirical literature on education identifies four important school characteristics that may affect students' CSE: school IT resource availability, school IT resource usage[5] (Barry and Wise 1996), school IT culture (Olson and Eaton 1996), and school IT training quality (Krissoff and Konrad 1998).

[4] In this study, student participants spent at least 33 hours in school each week. Many students without home computers have opted to remain in school after classes to make use of school IT facilities.

[5] School IT resource availability refers to the sharing of computers for classroom activities whereas school IT resource usage refers to the use of school computers outside of classroom activities (after regular school hours).

3.5.1. School IT Resource Availability and Usage. School IT resource availability (measured as the student-to-computer ratio for IT-based lessons) and school IT resource usage are especially important for development of CSE among students. These resources enable students to gain enactive mastery experience, which comes with using IT tools to perform learning tasks, and vicarious learning experience, which comes from observing their classmates. In the United States, students without home computers are more likely to access and use IT resources from their schools to enhance their learning experience compared to students with home computers (Mineta 2000, Wilhelm et al. 2002). For students without home computers, school IT resources are their only means of gaining enactive mastery experience. Thus, school IT resource availability and usage should be particularly important for these students. We hypothesize:

Hypothesis 3A (H3A). *School IT resource availability is positively related to CSE, particularly for students without home computers.*

Hypothesis 3B (H3B). *School IT resource usage is positively related to CSE, particularly for students without home computers.*

3.5.2. School IT Culture. School IT culture is defined as the importance and influence of IT usage in the school environment (Akker et al. 1992). A strong IT culture espouses the use of computers to solve problems. Students' CSE can be enhanced through exposure to successful IT applications, especially by teachers (Oliver and Shapiro 1993). Schools with a strong IT culture inculcate positive attitudes toward using IT. Teachers tend to be very proactive in embracing IT innovations, which in turn influence students' CSE. In such schools, teachers would also be more likely to provide good support to students in the form of guidance, encouragement, and inducement for using computers. These factors are important for developing CSE among students (Marakas et al. 1998). In contrast, isolated and infrequent exposure to IT-based teaching in schools with weak IT culture is unlikely to motivate students to raise their CSE (Mumtaz 2001).

Students without home computers can improve their CSE in schools with a strong IT culture because they have access to IT resources that they lack at home. But for students with home computers, a strong school IT culture may merely reinforce their usage of computers by influencing them to engage in additional activities to enhance their CSE (Fishman 1999, Kafai et al. 2002). Overall, the CSE of students with home computers should be higher. Thus, the additional effect arising from school IT culture is likely to be smaller for these students. Hence, we hypothesize:

Hypothesis 3C (H3C). *School IT culture is positively related to CSE, particularly for students without home computers.*

3.5.3. School IT Training Quality. The quality of school IT training reflects student perceptions of their IT training in terms of usefulness, relevance, and adequacy (Krissoff and Konrad 1998). Few studies have examined the role of school IT training in fostering CSE among students. Such training provides students with guided mastery experience that can significantly raise their self-perception of capability. Guided mastery is one of the most effective ways to cultivate competency. High-quality training enables students to internalize IT skills, which leads to higher CSE.

Students without home computers should improve their CSE significantly if provided with high-quality school IT training because such training gives them a major avenue to acquire IT skills. But students with home computers should also be able to benefit from such training, although to a lesser extent, because they have alternative means to receive some training at home. Overall, the CSE of students with home computers should be higher. Thus, the additional effect from school IT training quality is likely to be smaller for these students. Hence, we hypothesize:

Hypothesis 3D (H3D). *School IT training quality is positively related to CSE, particularly for students without home computers.*

3.6. Individual Characteristics and the Access and the Capability Divides

There is growing recognition of a digital divide between genders (Ching et al. 2005, Kennedy et al. 2003, Soker 2005). According to the social cognitive theory, "gender conceptions and roles are the product of a broad network of social influences operating interdependently in a variety of societal subsystems" (Bussey and Bandura 1999, p. 676). In essence, the theory emphasizes gender role learning. Gender-based behavior is developed through repeated modeling of prototypical behavior associated with same-gender models at homes and at schools (Bandura 1986). When children observe the behavior of their same-gender models diverging from those of opposite-gender models, they tend to pattern their behavior after that of same-gender models.

Female role models tend to have lower computer aptitude (Felter 1985), lower computer usage, higher computer anxiety, and hence lower CSE (Hunt and Bohlin 1993). These factors are likely to be salient in influencing behavior of female students. Thus, the CSE of female students is likely to be lower than that of male students. The IT culture is generally seen as less attractive for females (Frankel 1990). Family and cultural biases may result in girls having less access to home computers than boys[6] (Kafai et al. 2002). Male students are likely to spend more time using home computers for study-related and leisure-related activities than female students. Indeed, previous research has found male students to have higher CSE than female students (e.g., Gefen and Straub 1997, Karsten and Schmidt 2007, Marakas et al. 1998, Miura 1987, Venkatesh and Morris 2000). Thus, we hypothesize:

Hypothesis 4A (H4A). *Female students will have lower CSE compared to male students.*

Hypothesis 4B (H4B). *Female students will have lower home computer usage for studies compared to male students.*

Hypothesis 4C (H4C). *Female students will have lower home computer usage for leisure compared to male students.*

3.7. Control Variables

Among other factors, academic performance has been found to be a key antecedent factor affecting the completion of learning tasks (Attewell and Battle 1999), including acquisition of CSE. In view of its importance, academic performance is measured and included as a control variable in the regression models on CSE and learning outcomes. The hypotheses are summarized in Figure 2.

4. Research Method

4.1. The Survey

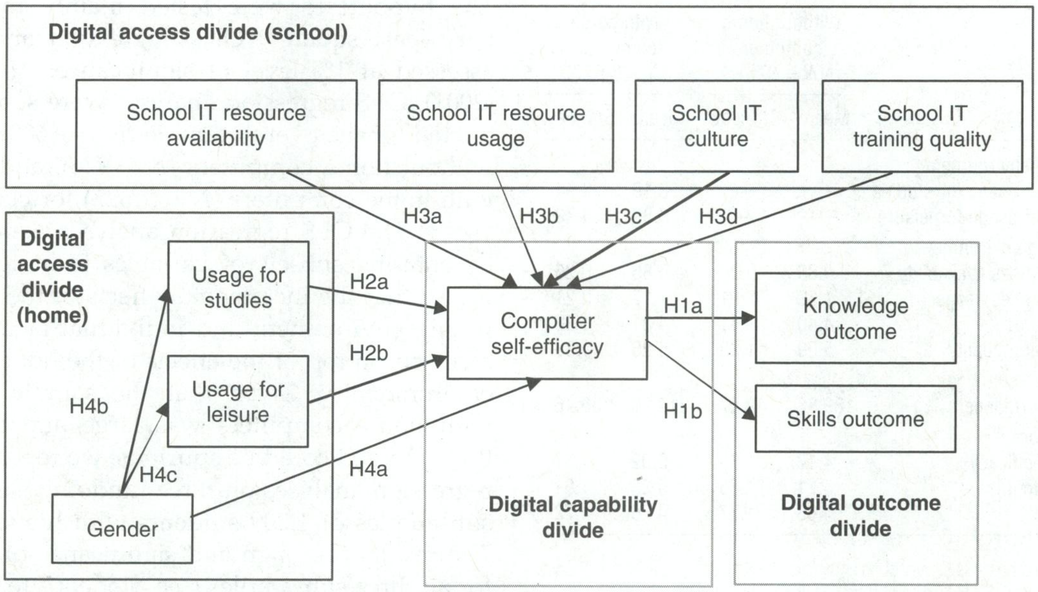
The data were gathered through a survey employing a purposive sampling strategy because it was necessary to identify eligible secondary schools that had integrated IT into their curricula. The first author and his research assistant contacted the principals of 98 eligible secondary schools in Singapore to solicit participation in the research project.[7] Twenty-six schools with about 6,000 students agreed to participate. To ensure that there was no response bias at the school level, the 26 schools were compared to the population of 98 eligible schools based on their national school ranking.[8] School ranking was chosen as the criterion for comparison for three reasons. First, it is a good surrogate measure for school innovativeness,

[6] Kafai et al. (2002) report that if a brother and a sister both want to use the home computer, the parents are likely to give the boy priority over the girl.

[7] In our cover letter, we assured the schools of anonymity, confidentiality, and the use of aggregate statistics only.

[8] School ranking is a categorical variable derived from achievements in academic, cocurricular activities, and a host of other criteria (e.g., offering of value-added programs). It is public information made available by the Singapore Ministry of Education.

Figure 2 Summary of Hypotheses



Notes. H2C: H2B will be stronger than H2A. H3A–H3D: Effects will be stronger for students without home computers compared to students with home computers.

which has the potential to influence school willingness and ability to integrate IT into their curricula. Second, it reflects the socio-economic status of students because students from higher income families tend to be associated with higher ranked schools. Third, data on school ranking is available from an authoritative and reliable source. A chi-square test based on school ranking categories showed no response bias (chi-square = 2.28, $p =$ n.s.).

The questionnaires were hand-delivered to each school. An administrator in each school then distributed the questionnaires to the students. The students,[9] aged about 13, were in their first year of secondary school in the Singapore education system (similar to seventh grade in the United States education system). A telephone line was set up to answer queries from students. The questionnaires were collated by the administrator and collected by the first author and his research assistant two weeks later. A total of 5,829 questionnaires were collected, yielding a response rate of 97.1%. The returned questionnaires were subjected to scrutiny for data reliability. Returns that contained conflicting answers (e.g., responses reporting nonzero computer usage at home for students without home computers) or inconsistent answers (e.g., responses reporting computer-to-student ratios that are significantly different from most other responses from the same school) were removed. This yielded 4,603 usable questionnaires (of which 3,627 were from students with home computers).

4.2. Instrument Development

Instrument development was carried out based on procedures prescribed in Churchill (1979), DeVellis (1991), and Moore and Benbasat (1991). The education and information systems literature were thoroughly reviewed to identify validated questions or to generate new questions for constructs for which no validated questions existed. Objective measures were used for study usage, leisure usage, school IT resource availability (student-computer ratio), and school IT resource usage. Questions for learning outcomes, school IT culture, and school IT training quality were developed based on definitions and statements in the literature. Questions for CSE were adapted. All perceptual questions were anchored on appropriately labeled seven-point interval scales (see the appendix).

Discussions with three information systems faculty members and 20 students[10] from different schools were held to assess content validity. Based on the feedback obtained, minor adjustments were made to some questions. A process of conceptual validation involving sorting of questions into categories and labeling the categories (i.e., constructs) was then performed (DeVellis 1991, Moore and Benbasat 1991).

[9] The students have no problems understanding the questionnaire because English is the medium of instruction for all schools in Singapore.

[10] Our research assistant randomly approached students within the school premises to obtain their views and feedback about the questionnaire. Care was taken to ensure that the students did not belong to the secondary one cohort that we were targeting.

Table 1 Descriptive Statistics

	Without home computer ($N = 976$)		With home computer ($N = 3,627$)	
	Mean	Std. dev.	Mean	Std. dev.
Home computing environment				
Home computer usage for studies	—	—	3.19	2.94
Home computer usage for leisure	—	—	6.89	4.78
School computing environment				
School IT resources availability	0.80	0.28	0.85	0.26
School IT resources usage	1.59	1.91	1.17	2.21
School IT culture	4.40	1.41	4.31	1.38
School IT training quality	5.09	1.38	5.26	1.33
Individual factor				
Academic performance	189.38	42.57	214.29	35.46
Endogenous factors				
Computer self-efficacy	4.17	1.33	5.02	1.31
Knowledge outcome	5.11	1.65	5.23	1.61
Skills outcome	4.63	1.77	4.76	1.72

Conceptual validity was assessed based on the percentage of questions correctly placed on the intended constructs (this ranged from 95% to 100%). The revised questionnaire was subjected to a pilot test involving 100 students.[11] Cronbach's alpha and factor analyses (Kerlinger 1986) supported the stability and validity of these constructs. Table 1 summarizes the descriptive statistics and Table 2 presents the correlation matrix for all the constructs.

5. Data Analysis and Results

5.1. Discriminant and Convergent Validity

Perceptual questions used to measure constructs were assessed for discriminant and convergent validity (Campbell and Fiske 1959). To assess discriminant validity, a principal components analysis was conducted and factors with eigenvalue greater than one were extracted (Johnson and Wichern 2002). The factors extracted corresponded to the constructs. All questions load onto the intended constructs (see Table 3). Convergent validity, the extent to which multiple questions measuring the same construct agree (Cook and Campbell 1979), was assessed using Cronbach's alpha (Nunnally 1978). All constructs had Cronbach's alpha exceeding 0.70 (see Table 3). These results indicated that the constructs in this study had adequate discriminant and convergent validity.

[11] Of these 100 students: 49 were in secondary two (14 years old), 35 were in secondary three (15 years old), and 16 were in secondary four (16 years old); 44 were females and 56 were males; 39 had no home computers and 61 had home computers.

5.2. Tests of Hypotheses

The hypotheses were tested mainly through ordinary least squares (OLS) regression analyses[12] and assessed at 1% level of significance. As in Mumtaz (2001), OLS regression analyses were separately conducted for the overall sample ($N = 4,603$), the sample without home computers ($N = 976$), and the sample with home computers ($N = 3,627$) for clarity of analyses.[13] The OLS regression analyses were conducted by entering subsets of variables in a stepwise manner so that the incremental effects of the school computing environment and individual factors could be assessed on top of the effects of the home computing environment.[14] Given that the sample of students with home computers was large and some effects that emerged could be spurious, we repeated the OLS regression analyses on three randomly selected equal subsamples of 1,209 students with home computers. The results (i.e., sign and significance of coefficients) for all three subsamples (see Models 7 to 9 in Table 4) were consistent with the results for the overall sample (see Model 6 in Table 4). Hence, the findings were robust.

H1A and H1B predicted the effects of CSE on the two learning outcomes, controlling for gender and academic performance. The results showed that CSE had a significant impact on learning outcomes for all the data sets, explaining 14% to 20% of the variance of knowledge outcome and 12% to 17% of the variance of skills outcome (see Models 3 and 6 to 9 in Table 4). Hence, H1A and H1B were supported.

H2 assessed the effects of home computer ownership on CSE. Home computer ownership had a significant effect on CSE (see Model 1 in Table 4) so H2 was supported. In addition, a comparison of means revealed that students with home computers had significantly higher CSE than students without home computers ($t = 13.37$, $p < 0.01$). Also, home computer usage for studies and leisure had significant effects

[12] The data met the assumptions of normality and homogeneity, required for OLS regression analyses. There is a low likelihood of error in estimations due to collinearity problems because none of the correlation coefficients exceeded 0.80 (see Table 2).

[13] The general effects of home computer ownership with all other predictor variables were assessed by Model 1 in Table 4. As home computer usage for studies and leisure would not be applicable for students without a home computer, it would be incorrect to impute zero usage for them as this would make them indistinguishable from students who had but did not use a home computer. Hence, we split the overall sample based on home computer ownership for subsequent analyses. Such an approach allowed us to see the intersection effects of home and school computing environments.

[14] To assess the robustness of the results, we also varied the order in which the subsets of variables were entered. For example, we conducted another analysis by entering school computing environment factors first. The change in R-square was very small and there were no changes in the significance of coefficients.

Table 2 Correlation Matrix ($N = 4,603$)

Construct	1	2	3	4	5	6	7	8	9	10	11	12
1 Home computer ownership	1.00											
2 Home computer usage for studies	0.45	1.00										
3 Home computer usage for leisure	0.55	0.45	1.00									
4 School IT resource availability	0.08	0.03	0.06	1.00								
5 School IT resource usage	0.08	0.34	0.14	0.02	1.00							
6 School IT culture	−0.03	0.06	−0.05	0.10	0.12	1.00						
7 School IT training quality	0.05	0.10	0.02	0.08	0.07	0.38	1.00					
8 Gender	−0.02	−0.04	−0.12	−0.03	−0.05	−0.06	−0.06	1.00				
9 Academic performance	0.27	0.14	0.25	0.08	0.02	−0.05	−0.03	−0.11	1.00			
10 Computer self-efficacy	0.25	0.28	0.01	0.10	0.13	0.25	0.46	−0.07	0.01	1.00		
11 Knowledge outcome	0.04	0.13	0.02	0.06	0.11	0.36	0.47	−0.04	0.04	0.40	1.00	
12 Skills outcome	0.01	0.08	0.02	0.09	0.08	0.38	0.42	−0.11	0.03	0.36	0.52	1.00

on CSE (see Model 4 in Table 4) and accounted for 8.5% of the variance in CSE. H2A and H2B were supported. Home computer usage for leisure had a stronger impact on CSE than home computer usage for studies for all samples (see Models 4 to 9 in Table 4). A dominance analysis[15] (Budescu 1993) confirmed this result because adding home computer usage for leisure to all OLS regression models yielded a greater increase in R-square compared to adding home computer usage for studies. Hence, H2C was supported.

H3 assessed the effects of school computing environments on CSE. Specifically, school IT resource availability, school IT resource usage, school IT culture, and school IT training quality were expected to enhance CSE, particularly for students without home computers. To test H3, coefficients of school computing environment factors for students without home computers (see Model 3 in Table 4) were compared with the corresponding coefficients for students with home computers (see Model 6 in Table 4) (Chin 2000).[16] School IT resource availability ($t = 54.14$, $p < 0.01$), school IT resource usage ($t = 279.21$, $p < 0.01$), and school IT culture ($t = 72.99$, $p < 0.01$) had a significantly stronger impact on CSE for students without home computers than students with home computers. However, the reverse was true for school IT training quality ($t = -13.26$, $p < 0.01$). Hence, H3A, H3B, and H3C were supported but H3D was not supported. The school computing environment accounted for an additional 28.1% and 20.2% of the variance in CSE for students without and with home computers, respectively (see Models 2 and 5 in Table 4).

H4A predicted that female students would have lower CSE than male students. This prediction was confirmed by the negative significant relationship between gender and CSE for all samples (see Models 1, 3, and 6 to 9 in Table 4). A comparison of means confirmed that male students had significantly higher CSE than female students ($t = -12.15$,

[15] A dominance analysis can assess whether one predictor variable is more important than another predictor variable. Dominance analysis states that X_1 dominates X_2 if adding X_1 to any possible model always results in a greater increase in R-square than adding X_2 (Budescu 1993).

[16] Comparison of coefficients across the two samples (Models 3 and 6 in Table 4) was done using the t-statistic $= (C_1 - C_2)/[S_{\text{pooled}} \times v(1/N_1 + 1/N_2)]$, where

$$S_{\text{pooled}} = v\{[(N_1-1)/(N_1+N_2-2)] \times SE_1^2 + [(N_2-1)/(N_1+N_2-2)] \times SE_2^2\}.$$

C_i = coefficient of Model i; N_i = sample size of Model i; SE_i = standard error of Model i.

Table 3 Discriminant and Convergent Validity Tests

Question	Cronbach's Alpha	Component 1	2	3	4	5
School IT culture 1	0.70	0.16	0.05	0.13	0.16	**0.74**
School IT culture 2		0.18	0.17	0.10	0.01	**0.68**
School IT culture 3		0.14	0.09	0.06	0.20	**0.79**
School IT training quality 1	0.88	**0.81**	0.10	0.19	0.08	0.18
School IT training quality 2		**0.81**	0.13	0.17	0.10	0.22
School IT training quality 3		**0.81**	0.14	0.17	0.12	0.14
School IT training quality 4		**0.80**	0.12	0.21	0.05	0.18
School IT training quality 5		**0.76**	0.26	0.08	0.18	0.06
School IT training quality 6		**0.69**	0.24	0.04	0.23	0.01
Computer self-efficacy 1	0.90	0.18	**0.81**	0.10	0.10	0.12
Computer self-efficacy 2		0.19	**0.76**	0.10	0.12	0.12
Computer self-efficacy 3		0.12	**0.78**	0.01	0.08	0.08
Computer self-efficacy 4		0.22	**0.74**	0.26	0.03	0.08
Computer self-efficacy 5		0.19	**0.79**	0.21	0.07	0.08
Computer self-efficacy 6		0.04	**0.75**	0.03	0.16	0.01
Knowledge outcome 1	0.80	0.21	0.20	**0.75**	0.19	0.15
Knowledge outcome 2		0.21	0.18	**0.80**	0.19	0.12
Knowledge outcome 3		0.19	0.12	**0.72**	0.24	0.08
Skills outcome 1	0.74	0.21	0.09	0.20	**0.73**	0.14
Skills outcome 2		0.17	0.10	0.23	**0.78**	0.13
Skills outcome 3		0.12	0.22	0.14	**0.69**	0.12
Eigenvalue		**4.12**	**3.96**	**2.15**	**2.00**	**1.90**
Variance explained (%)		**19.60**	**18.84**	**10.22**	**9.50**	**9.06**
Cumulative variance explained (%)		**19.60**	**38.44**	**48.66**	**58.16**	**67.22**

Table 4 Results of OLS Regression Analyses

	Sample								
	All ($N = 4{,}603$)	Without home computer ($N = 976$)		With home computer ($N = 3{,}627$)			With home computer ($N = 1{,}209$)		
Model	1	2	3	4	5	6	7	8	9
Dependent variable: Computer self-efficacy									
Home computing factors									
Home computer ownership	0.197**								
Home computer usage for studies				0.161**	0.109**	0.112**	0.100**	0.081**	0.114**
Home computer usage for leisure				0.202**	0.227**	0.195**	0.206**	0.205**	0.193**
School Computing Factors									
School IT resource availability	0.025**	0.072**	0.072**		0.022	0.006	0.028	0.014	0.005
School IT resource usage	0.068**	0.131**	0.125**		0.006	0.006	0.022	0.026	0.037
School IT culture	0.089**	0.136**	0.136**		0.093**	0.089**	0.097**	0.085**	0.151**
School IT training quality	0.402**	0.411**	0.403**		0.408**	0.412**	0.409**	0.432**	0.402**
Individual factors									
Gender (0-male; 1-female)	−0.122**		−0.122**			−0.097**	−0.065**	−0.108**	−0.082**
Academic performance	0.108**		0.006			0.121**	0.133**	0.121**	0.135**
R-square	0.305	0.281	0.296	0.085	0.287	0.313	0.316	0.332	0.327
Change in *R*-square		0.281**	0.015**	0.085**	0.202**	0.026**			
Adjusted *R*-square	0.304	0.278	0.292	0.085	0.285	0.311	0.312	0.328	0.322
Dependent variable: Knowledge outcome									
Computer self-efficacy			0.391**			0.416**	0.433**	0.423**	0.452**
Individual factors									
Gender (0-male; 1-female)			0.065			0.013	0.033	0.017	0.022
Academic performance			0.042			0.096**	0.069**	0.065**	0.094**
R-square			0.148			0.174	0.185	0.180	0.203
Adjusted *R*-square			0.144			0.173	0.183	0.177	0.201
Dependent variable: Skills outcome									
Computer self-efficacy			0.347**			0.365**	0.353**	0.404**	0.354**
Individual factors									
Gender (0-male; 1-female)			−0.007			−0.064*	−0.075**	−0.063*	−0.059*
Academic performance			0.016			0.076**	0.041*	0.074**	0.081**
R-square			0.120			0.145	0.138	0.172	0.138
Adjusted *R*-square			0.116			0.145	0.136	0.170	0.136

Notes. Figures in the table (except *R*-square values) are standardized coefficients. The test of significance for change in *R*-square was based on *F*-values.
$^*p < 0.05$; $^{**}p < 0.01$.

$p < 0.01$). Hence, H4A was supported. H4B and H4C predicted that female students would have less home computer usage for studies and leisure compared to male students. Indeed, female students had lower home computer usage for studies (standardized mean $= -0.06$) than male students (standardized mean $= 0.03$) ($t = 1.60$, $p < 0.01$). Also, female students had lower home computer usage for leisure (standardized mean $= -0.13$) than male students (standardized mean $= 0.11$) ($t = 2.87$, $p < 0.01$). Therefore, H4B and H4C were supported.

To examine how the impact of home and school computing environments on CSE might vary by gender, we split the samples of students with and without home computers by gender (see Table 5). Although female students used home computers significantly less than male students, the impact of home computer usage on CSE was higher for female students (see Models 3 and 4 in Table 5) than for male students (see Models 1 and 2 in Table 5). Home computing environments accounted for 10.1% of the variance in CSE for female students (see Model 3 in Table 5) but only 6.0% of the variance in CSE for male students (see Model 1 in Table 5). For students with home computers, the school computing environment could explain 23.0% of the variance in CSE for male students (see Model 2 in Table 5) but only 16.9% of the variance in CSE for female students (see Model 4 in Table 5). A Chow test confirmed that the coefficients for Model 2 (male students) and Model 4 (female students) in Table 5 were significantly different ($F = 14.10$, $p < 0.01$). For students without home computers, the school computing environment accounted for 29.5% of the variance in CSE for male students (see Model 5 in Table 5)

Table 5 Results of OLS Regression Analyses by Gender

	Sample					
	With home computer ($N = 3{,}627$)				Without home computer ($N = 976$)	
	Male ($N = 1{,}980$)		Female ($N = 1{,}647$)		Male ($N = 511$)	Female ($N = 465$)
Model	1	2	3	4	5	6
Dependent variable: Computer self-efficacy						
Home computing environment						
Home computer usage for studies	0.148**	0.106**	0.186**	0.125**		
Home computer usage for leisure	0.162**	0.193**	0.205**	0.235**		
School computing environment						
School IT resource availability		0.033		0.012	0.120**	0.049
School IT resource usage		0.025		0.021	0.095**	0.131**
School IT culture		0.090**		0.085**	0.129**	0.149**
School IT training quality		0.442**		0.372**	0.428**	0.383**
R-square	0.060	0.290	0.101	0.270	0.295	0.258
Change in R-square		0.230**		0.169**		
Adjusted R-square	0.059	0.287	0.100	0.267	0.290	0.252

Notes. Figures in the table (except R-square values) are standardized coefficients. The test of significance for change in R-square was based on F-values.
$^{*}p < 0.05$; $^{**}p < 0.01$.

but only 25.8% of the variance in CSE for female students (see Model 6 in Table 5). Again, a Chow test confirmed that the coefficients for Model 5 (male students) and Model 6 (female students) in Table 5 were significantly different ($F = 5.52$, $p < 0.01$).

6. Discussion and Implications

6.1. Theoretical Contribution and Implications

This study is a pioneering attempt to advance a theoretical account of the digital divide and systematically test it with empirical data. Going beyond earlier studies on the digital divide (Dewan and Riggins 2005), this study comprehensively demonstrates how the digital access divide can profoundly influence the digital capability divide, which in turn impacts the digital outcome divide. Using social cognitive theory as a foundation, the results shed light on the nomological relationships among home computing environments, school computing environments, CSE, and learning outcomes. This theoretical account is an alternative to socio-economic explanations of the impact of the digital access divide, which has become less convincing in light of falling computer prices and the emergence of no-frills computers.

Overall, this study makes three key theoretical contributions. First, the model of digital divide from Dewan and Riggins (2005) is extended into a three-stage digital divide framework and empirically tested in the context of student learning. Beyond this context, the three-stage digital divide framework can be applied to individuals in other contexts, organizations, and even countries (Dewan and Riggins 2005). Testing this framework in a wide variety of contexts would help to establish the boundaries of its applicability.

Second, the use of social cognitive theory gives us a better understanding of how and why learning outcomes can be impacted by IT access. The results provide a finer explanation about how home and school computing environments may intersect to impact CSE of students, which in turn affects their learning outcomes. The results also illuminate the three-stage digital divide framework by showing the precise relationship between the digital access divide and the digital capability divide (e.g., students without home computers had lower CSE even when they had IT access in schools) as well as the precise relationship between the digital capability divide and the digital outcome divide (e.g., students with lower CSE had poorer learning outcomes). This study also yields some intriguing results, showing that some factors may increase the CSE gap among students. For example, school IT training quality has a stronger effect on CSE for students with home computers than on students without home computers. This suggests that it has helped to increase rather than reduce the digital capability divide. One plausible explanation is that students with home computers may be nearer to the center of the S-learning curve (Thurstone 1919, Zangwill and Kantor 2000) where they are in a better position to gain from high-quality school IT training (Wiedenbeck et al. 1999). Another example is that the home computing environment has a stronger impact on CSE of female students compared to male students but the school computing environment produces the opposite result. Based on these results, it would appear that a policy aimed at using the school computing environment to equalize CSE for students with and without home computers may instead induce a CSE gap between male and female students. These observations need further theoretical elaboration and testing to generate more insights about the effectiveness of various commonly used interventions for the digital divide. Taken together, these relationships contribute to the education and information systems literature by highlighting the critical role of CSE as a mediator[17] in translating home and school computing environments to learning outcomes.

Third, contrary to past beliefs, the results reveal that students using home computers for hedonic purposes may gain much in CSE compared to students using home computers for utilitarian purposes. This is because students using home computers for hedonic purposes tend to be driven by intrinsic motivation whereas students using home computers for utilitarian purposes tend to rely on extrinsic motivation (Walker et al. 2006). These results appear to be consistent with the findings of studies which show that game-based training leads to more favorable perceptions of IT compared to traditional training (e.g., Starbuck and Webster 1991; Venkatesh 1999, 2000).

6.2. Implications for Practice

The results of this study have important practical implications. These results underscore the importance of CSE for achieving good learning outcomes. In knowledge economies where educational and career tasks are increasingly IT driven, cultivation of CSE among students has taken on added significance. Promoting CSE at the individual level may yield national-level effects. For instance, it has been argued that the high level of CSE in India has made it possible for India to become the global call center and software development center. At the school level, as curricula become increasingly IT-based (as is happening in Singapore), the digital access divide among students is likely to exacerbate the learning outcome gap between students with and without home computers, through impacting the CSE of students. Beyond students, education service providers can use our results (i.e., the importance of CSE) to promote IT training services to the populace at large. For instance, the Singapore Government has collaborated with private IT training institutes to introduce a heavily subsidized National IT Literacy program targeted at the populace who did not have an opportunity to learn IT skills in schools or in workplaces.

This study shows that in the absence of home computing access, school computing access can help to raise the CSE of students. However, having school computing access is not sufficient to close the digital capability divide among students arising from differences in home computing access. Students without home computers continue to have lower CSE than students with home computers even when all students have school computing access. It is important to have both home and school computing access.

The overall results suggest a two-pronged approach for alleviating the digital divide among students: governments should provide computers at school and households should get computers. Government policy makers should be cognizant that every school needs to have adequate computing resources to effectively support IT-based curricula. The Education Trust (a research group that endorses the "No Child Left Behind" law) report that in New York state, schools in poorer districts received US$2,040 less per student than those in wealthier districts (Winter 2004). Such a situation can aggravate the digital divide problem. Recognizing the importance of enhancing CSE among students, the Singapore Government launched a SGD$2 billion master plan for IT in education to help schools achieve a 2:1 student-to-computer ratio and a 30% IT-based curriculum (MOE 2003).

Home computer ownership (which leads to home computer usage for studies and leisure) may be addressed on several fronts. Government policy makers can work with schools to reduce the burden for low income households to purchase home computers. For example, the Singapore Ministry of Education has pooled the demand for home computers from students in all schools and asked vendors to give bulk purchasing discounts for home computers. More recently, the Singapore Government launched a US$3.2 billion IT master plan that, among other objectives, aimed to equip every household with a school-going child with a computer (IDA 2006). Despite lower prices, some households may still be reluctant to purchase home computers for fear of obsolescence (Venkatesh and Brown 2001). Hence, it is imperative that government policy makers highlight the importance of CSE on learning outcomes of students through public education programs. The goal is to help households see home computers as an absolutely essential educational tool. Another alternative is for government policy makers to encourage private organizations to donate their old but workable computers to

[17] We performed mediating analyses (Baron and Kenny 1986) for each independent variable. Except for academic performance, the effects of all other variables on learning outcomes were either completely or partially mediated by CSE.

low income households, perhaps through tax incentives. Moreover, vendors can offer no-frills home computers that are affordable to low income households. Charity organizations (e.g., "One Laptop per Child"[18] association) can also help to increase home computer ownership. A concerted effort by the government, schools, vendors, private organizations, and charity organizations should be effective in helping to alleviate the digital access divide among students.

Providing home and school computing access can only lay the foundation for cultivating CSE among students. Our results show that a strong IT culture and a high-quality IT training program in schools are also crucial for enhancing CSE. These results are consistent with those of Kvasny and Keil (2002, p. 827), who found that "providing access to IT—even access that is delivered for free at public institutions or in the home—is insufficient to adequately address the digital divide." They elaborate that social capital, as in group participation (or in our context, school computing environment), is particularly important for enhancing the ability of people to use IT (Kvasny and Keil 2002). Hence, schools should equip teachers with necessary IT skills and foster IT mindsets so that these teachers can offer high-quality IT training to students and can design stimulating IT-based curricula. Schools can strengthen their IT culture by promoting visibility of IT through the use of IT in administrative and educational activities (e.g., taking quizzes through touch-screen computers and informing students and parents of test results through automated messages). Such activities help imbue students with the confidence in using IT through the processes of mastery experience, vicarious experience, and social persuasions.

6.3. Limitations and Future Research

The study may be seen as a field experiment, evaluating the differences between students with and without home computers, in a context where the interaction among home and school computing environments could be observed. In advancing a three-level digital divide framework that potentially has wide applicability, this study enhances our understanding of the digital divide phenomenon. As with any piece of research, this study has limitations.

One limitation is that the causality arguments can only be inferred from our theoretical exposition because this study used a cross-sectional data set. Future research can take a longitudinal approach in which the endogenous variables are measured before and after the introduction of interventions to confirm the direction of causality. For example, if we had known the CSE of students over time, we would be able to examine whether the S-learning curve explanation (Wiedenbeck et al. 1999, Zangwill and Kantor 2000) can account for the results showing that school IT training quality has increased rather than reduced the digital capability divide. Given that our objective is to assess the relationships among many constructs pertaining to the three levels of digital divide, the data collection effort is already a massive exercise. Doing it multiple times would be hardly feasible.

Another limitation arises due to the age of our student respondents. Because of their relatively young age, we deliberately kept our questions simple, close-ended, and short to be able to obtain valid and reliable responses. This constraint prevents us from asking probing questions (e.g., listing activities they had performed using home and school computers, listing educational software or game software they had used at home and at school, and providing sensitive information such as socio-economic status, family income, and degree of parental supervision). Answers to such probing questions can potentially contribute to a richer understanding of the digital divide phenomenon. In the future, researchers can incorporate these factors by building on our three-stage digital divide framework and work with census authorities to collect pertinent data.

Caution must be exercised when attempting to generalize the results of this study to educational institutions and students in other countries with different institutional, cultural, and political environments. Cross-country studies have focused on the identification of the digital access divide as well as socio-economic and other factors causing it (e.g., Chinn and Fairlie 2007, Dewan et al. 2005, Kauffman and Techatassanasoontorn 2005, Ono 2005). To date, there has been no cross-country studies linking the digital access divide through the digital capability divide to the digital outcome divide. In a study on digital access involving 161 countries, Singapore was ranked sixth (with 51 computers per 100 population), comparable to Canada, Norway, Korea, and Australia (Chinn and Fairlie 2007). In countries where digital access is very low (e.g., less than one computer per 100 population, as in Cambodia and Ethiopia), these findings may not apply. The context of this study is in a small country with a population of 4.5 million and a land space of about 680 square kilometers.[19] Hence, these findings may be more applicable to cities with a comparable urban population density.

Social cognitive influence at home operates through family members and should be contingent upon family size. In Singapore, family units are relatively small.[20] In countries where family units are large,

[18] See http://www.laptop.org/.

[19] See https://www.cia.gov/library/publications/the-world-factbook/.

[20] Birth rate is 1.8 for never-married females, aged 30–39 (http://www.singstat.gov.sg/papers/snippets/family.html).

students are likely to have less access time on home computers and this lowers their CSE. However, these students may also benefit from social persuasions if more family members are proficient computer users. The net effect of family size is hard to gauge. In Singapore, there is little discrimination between male and female students at home or at school. In countries with strong gender discrimination, there may be little access to computers at home or at school for female students. Hence, the results of this study should be more applicable in countries with characteristics comparable to those of Singapore. Despite these limitations, the practical implications arising from the results offer valuable advice for the government, schools, vendors, private organizations, and charity organizations in other countries.

7. Concluding Remarks

Although the digital divide has been deemed a public policy issue for over a decade, a theoretical account of the effects of the digital divide has been lacking. Extending past relevant research (e.g., Dewan and Riggins 2005), this study proposes and empirically tests a three-level digital divide framework. Building on social cognitive theory, this study advances a theoretical account on the digital divide. Specifically, it demonstrates how the digital access divide (e.g., home and school computing environments) can influence the digital capability divide (e.g., CSE) which in turn can affect the digital outcome divide (e.g., learning outcomes). Such a theoretical account helps to shed light on key issues (that are previously not well understood), such as the intersection effects of home and school computing environments and the differential effects of various interventions on male and female students.

Moving forward, countries and societies would become increasingly knowledge intensive and IT-laden. IT-based learning can emerge as a critical factor impacting the digital divide among people, thereby affecting the well-being of the populace in countries and societies. As a pioneering effort to advance a theoretical account of the digital divide, this study offers a platform upon which subsequent studies on the digital divide can be built. More research on this topic is warranted because understanding the precise effects of the digital divide and knowing how to use appropriate interventions to alleviate problems arising from it can contribute to the vision of many governments that "No Child [be] Left Behind" (Winter 2004).

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Appendix

Measurement of constructs

Home computer ownership:
Do you have a computer at home? Yes/No
If YES: please answer the following questions:

Home computer usage for studies:
On average, I spend__hours in a week using the computer at home to do my school work.

Home computer usage for leisure:
On average, I spend__hours in a week using the computer at home for leisure activities (e.g., emailing friends, chatting online, and playing computer games etc.).

School IT resources availability:
Student-to-computer ratio in computer classrooms:__

School IT resources usage:
On average, I spend__hours in a day using the computer at school to do my school work outside of classroom lessons.

School IT culture: (seven-point interval scale from strongly disagree to strongly agree)
1. My school always tells me the importance of computers in education.
2. My school uses computers to handle administrative work.
3. My school encourages me to use the computers in school.

School IT training quality: (seven-point interval scale from strongly disagree to strongly agree)
1. Computer training in my school helps me to be more confident in using computers.
2. Computer training in my school helps me to handle computer software.
3. Computer training in my school helps me to make fewer mistakes when handling computer software.
4. Computer training in my school helps me to improve my computer skills.
5. Computer training in my school helps me to be able to guide my friends in using computer software.
6. Computer training in my school helps me to solve computer software problems for my friends.

Gender: Please indicate your sex: Male/Female

Academic performance:
Your primary school leaving examination aggregate score is:__

Appendix (cont'd.)

Measurement of constructs

Computer self-efficacy: (seven-point interval scale from strongly disagree to strongly agree)
1. I am confident in working with computers.
2. I have no difficulties following instructions in using software to finish exercises.
3. I feel comfortable working with computers.
4. I am sure I can work with computers.
5. I can work on the computers even if no one tells me how to do it.
6. I can handle computers better than most people do.

Knowledge outcome: (seven-point interval scale from strongly disagree to strongly agree)
1. IT-based learning enlarged my scope of learning beyond the textbook.
2. IT-based learning helped me to become more knowledgeable in the subjects.
3. IT-based learning helped me to achieve better academic results

Skills outcome: (seven-point interval scale from strongly disagree to strongly agree)
IT-based learning developed my ability to do group discussions with my classmates
IT-based learning developed my ability to work with my teacher any time.
IT-based learning developed my ability to ask critical questions openly.

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