Communications of the Association for Information Systems

Volume 26 Article 12

3-2010

Understanding the Formation of General Computer Self-Efficacy

Jun He
University of Michigan - Dearborn, junhe@umd.umich.edu

Lee A. Freeman
University of Michigan—Dearborn

Recommended Citation
He, Jun and Freeman, Lee A. (2010) "Understanding the Formation of General Computer Self-Efficacy," *Communications of the Association for Information Systems*: Vol. 26 , Article 12.
DOI: 10.17705/1CAIS.02612
Available at: https://aisel.aisnet.org/cais/vol26/iss1/12

Communications of the Association for Information Systems
CAIS

Understanding the Formation of General Computer Self-Efficacy

Jun He
College of Business, The University of Michigan—Dearborn
junhe@umd.umich.edu

Lee A. Freeman
College of Business, The University of Michigan—Dearborn

Abstract:

This study investigates the information sources of general computer self-efficacy suggested by its origin in Social Cognitive Theory. These antecedents are rarely explored in the literature, and much of the focus has been on personal experiences or environmental factors. A re-examination of the theoretical foundation of self-efficacy suggests a broader set of antecedents. Selecting business students as the research subject, we propose and test a comprehensive nomological network of computer self-efficacy with seven antecedents and two consequences—computer attitudes and MIS intention (defined as one's intention to select MIS for his/her future study and career). The results support that computer knowledge, current computing experiences, computer anxiety, and age affected the formation and development of computer self-efficacy among the sampled students; computer self-efficacy and social norms had strong effects on computer attitudes and MIS intention. Implications for both research and MIS education are discussed.

Keywords: General computer self-efficacy, self-efficacy, computer anxiety, MIS education

Volume 26, Article 12, pp. 225-244, March 2010

The manuscript was received 5/28/2009 and was with the authors 3 months for 2 revisions.

I. INTRODUCTION

As information technology increasingly saturates our daily life, assessing one's ability to use information technologies to cope with business problems has received increasing attention in IS research, career training, and business education. However, there is no commonly accepted list of which computer applications are deemed relevant to certain careers, and to what extent the mastery of these applications is considered adequate [Lee et al., 2002]. With the fast pace of technology development, producing a detailed list of concrete computing skills may be an impossible task. Perception-based measures, therefore, become a realistic solution for the assessment of computer knowledge and skills in most situations.

Several perception-based measures of one's computer knowledge and skills, such as perceived ease of use [Davis et al., 1989; Venkatesh, 2000; Venkatesh et al., 2003], computer anxiety [Harrison and Rainer, 1992; Compeau et al., 1999], and personal innovativeness in IT [Thatcher and Perrewe, 2002] have been proposed in the IS literature. Among the existing measures, computer self-efficacy (CSE), defined as an individual's belief about his or her capabilities to use computers [Compeau and Higgins, 1995b], is a commonly used proxy for assessing one's capability of using computers. In the IS literature, the construct of CSE has been applied to the study of technology usage behavior [Venkatesh, 2000; Lewis et al., 2003; Venkatesh et al., 2003], IT training [Compeau and Higgins, 1995a], and job performance and status [Compeau et al., 1999]. In the business education literature, CSE has been used to investigate software training [Havelka, 2003] and computer learning behavior [Vincent et al., 2002].

Given the increasing research attention placed on this construct, however, our understanding of CSE is still imperfect with its sources and special makeup. The aforementioned studies test CSE as a key factor regulating individual's computer behaviors; the information sources upon which CSE is formed, however, are rarely explored in the literature. Also, the measurement of the construct needs to be re-examined with regard to its conceptualization [Marakas et al., 1998] and operationalization [Marakas et al., 2007]. The recent debate of formative approach vs. reflective approach of measurement has used CSE as an exemplar construct to bring important implications to empirical research in IS in general [Hardin et al., 2008a; Marakas et al., 2008].

This study aims to investigate (1) the information sources (antecedents) of CSE suggested by its theoretical foundation in Social Cognitive Theory and (2) the validity of a formative measure of CSE newly developed by Marakas et al. (2007). To this end, we propose a comprehensive model of CSE with seven antecedents and two consequences—computer attitudes and MIS intention (defined as one's intention to select MIS for his or her future study and/or career).

We believe that a more thorough understanding of the development of CSE will provide CSE researchers a grounded starting line for studying the formation and consequences of CSE in different technology-usage-related contexts. Such an understanding will also provide career trainers and MIS educators with a framework to build or increase CSE in light of the known effects of CSE on behavior and computer use. The results will also provide implications on how CSE affects people's decisions on selecting their education (e.g., academic majors) and future careers. In addition, the testing of the formative measure of CSE will enrich the current dialogue on formative measurement with another empirical examination that may be of interest to many researchers.

The remainder of the paper is organized as follows: The next section introduces the theoretical foundations of CSE, describes the research model, and presents the hypotheses. Section III discusses the research methodology and instruments, including the construct validation techniques. The paper ends with a discussion of the results and the implications for future research.

II. THEORETICAL FOUNDATIONS AND HYPOTHESES

In a study of end-user satisfaction with medical information systems, Henry and Stone [1994] found that CSE has the largest impact among the tested predictors including management support, ease of system use, and outcome expectancy. Compeau and Higgins [1995b] further clarified the concept of CSE and its importance to the IS research. Since then, CSE has been widely studied in the IS literature as a key factor guiding one's reactions to computers. Much of the research focuses on the consequences of CSE; its antecedents have been explored only sporadically in the literature. Table 1 summarizes previous studies that have investigated the antecedents of CSE.

Studies	Hypothesized Antecedents	Hypothesized Effects	Results
Henry and Stone, 1994	Management support Ease of use Previous experience with computer systems	+ + +	Supported: $p < 0.01$ Supported: $p < 0.01$ Supported: $p < 0.01$
Compeau and Higgins, 1995a	Training methods (behavioral modeling vs. lecture-based training) Prior performance	+ +	Mixed results: $\beta = 0.398$ and 0.161 ($p< 0.05$) for Lotus training; $\beta = –0.017$ ($p > 0.05$) and –0.173 ($p < 0.05$) for WordPerfect training. Partially supported: $\beta=0.482$ ($p < 0.05$) for Lotus training; $\beta = 0.092$ ($p > 0.05$) for WordPerfect training.
Compeau and Higgins, 1995b	Encouragement by others Others' use Organizational support	+ + +	Supported: $\beta = 0.18$ ($p < 0.01$) Supported: $\beta = 0.11$ ($p < 0.01$) Unsupported: $\beta =-0.16$, ($p < 0.01$)
Agarwal et al., 2000	Prior experience Personal innovativeness in IT	+ +	Supported: $\beta = 0.284$ ($p < 0.05$) Supported: $\beta = 0.467$ ($p < 0.05$)
Bolt et al., 2001	Training methods (behavioral modeling vs. Lecture-based training) Prior performance	+ +	Unsupported: $\beta = –0.17$ ($p=0.31$) Supported: $\beta = 0.22$ ($p < 0.01$)
Sheng et al., 2003	Organizational culture Teamwork Climate & morale Information flow Involvement Supervision Occurrence of meetings	 + + + + + +	 Supported: $\beta = 0.214$ ($p < 0.01$) Unsupported: $\beta = 0.05$ ($p = 0.50$) Supported: $\beta = 0.18$ ($p = 0.02$) Unsupported: $\beta = –0.18$ ($p = 0.01$) Unsupported: $\beta = –0.09$ ($p = 0.20$) Unsupported: $\beta = 0.05$ ($p = 0.43$)
Srite et al., 2008	Masculinity/femininity Individualism/collectivism	+ +	Supported: $\beta = 0.28$ ($p< 0.01$) Unsupported: $\beta = 0.03$ ($p > 0.10$)
Beyer, 2008	Gender (female vs. male)	–	Supported[1]

Table 1: Antecedents of CSE Being Studied in the Literature

Note
[1] Beyer [2008] performed correlation analysis between gender and each item of self-developed CSE measures. No overall correlation was reported.

One may note that much of the research places emphasis on prior experiences and environmental factors as the main sources of CSE. Additionally, some of the above results are contradictory or inconclusive—prior performance, training methods, and some aspects of organizational support and culture. The theoretical foundation of CSE—Social Cognitive Theory—suggests a broader range of information sources upon which one may form and develop the perception of his/her computing capabilities. In the current study, we propose a comprehensive model to study the formation of CSE based on the original theoretical propositions of the self-efficacy concept. To rule out possible confounding effects caused by the complexity of external environment (e.g., management support, organizational culture), we selected business students as our research subject.

Social Cognitive Theory and Self-Efficacy

CSE is a special application of the more general construct of self-efficacy, which is a key element of social cognitive theory developed in the field of learning and individual behavior [Bandura, 1977]. Social cognitive theory emphasizes the role of self-referent thinking in guiding human motivation and behavior. The concept of self-efficacy, defined as beliefs about one's ability to perform a specific behavior, forms the core of an intervening mechanism that explains the transition from information achieved through various learning modes to future action.

As a perception, self-efficacy is induced from psychological procedures of deliberating information from various sources. These sources can be summarized into four categories [Bandura, 1977; 1982]. From most to least influential, they are:

1. Performance accomplishments, or one's previous mastery experience with a target behavior
2. Vicarious experience, or observations of others' performance of the target behavior
3. Verbal persuasion, or suggestions and comments from others on one's ability to perform the target behavior
4. Emotional arousal, or physiological states caused by stressful and taxing situations

The various information sources—whether enactive, vicarious, persuasive, or physiological—provide clues relevant to one's mastery of a target behavior. These clues are not inherently enlightening. Rather, they are cognitively appraised to become instructive. People deliberately process, weigh, and integrate diverse sources of information concerning their capability to determine the level and strength of self-efficacy that subsequently affect individual behavior [Bandura 1977, 1982].

Social cognitive theory posits that self-efficacy regulates one's behavior and choice of activities based on forethought of the balance between behavior costs (or the required effort) and motivations (e.g., the expected benefits of performing the behavior). "Expectations of personal efficacy determine whether coping behavior will be initiated, how much effort will be expended, and how long it will be sustained in the face of obstacles and aversive experiences" [Bandura, 1977, p. 191]. A large body of evidence in the social and behavior research supports that self-efficacy exerts strong impact on thought, affect, motivation, and action, leading to the claim that "among the mechanisms of human agency, none is more central or pervasive than beliefs of personal efficacy" [Bandura and Locke, 2003, p. 87].

Computer Self-Efficacy at the General Level

Social cognitive theory emphasizes that behavior must be measured precisely in an analysis of efficacy and that measures should be tailored to the domain being studied [Bandura and Adams,1977; Bandura, 2001]. CSE is a special application of the self-efficacy concept in the field of MIS. CSE is commonly defined as one's judgment of his/her capability to use a computer [e.g., Compeau and Higgins, 1995b]. But this definition has been criticized as vague in specifying the particular domain to which the concept is most relevant. For example, a CSE measure designed for Excel computing performance should be distinct from one designed for studying Internet surfing performance because the two target applications require different sets of computing skills. The lack of acknowledgement of the complex nature of CSE could lead to inappropriate operationalization of the construct and result in equivocal or contradictory findings [Marakas et al., 1998].

Marakas et al. [1998] theorized that CSE exists at both the general computing behavior level and the specific computer task or application level. General CSE refers to an individual's judgment of his or her ability to perform across multiple computer application domains; specific CSE refers to an individual's perception of efficacy in performing specific computer-related tasks within the domain of general computing. General CSE largely influences other specific CSEs [Agarwal et al., 2000; Hasan, 2006], while the development of specific CSEs further enhances general CSE [Downey et al., 2008].

In the current study, we select general CSE as the focal construct for three reasons: (1) general CSE is especially relevant for the study of people's general reactions to computers [Marakas et al., 1998; Agarwal et al., 2000]; (2) although not tailored to a special analysis context, the strong generalizability of general CSE allows the construct to be used as an effective predictor of individual performance in a specific technology domain [Downey et al., 2008]; and (3) at the point of mastery, the strong predictive power of general CSE may surpass that of a tailored specific CSE as "over time and multiple experiences within the general computing domain, a measure of GCSE will become an equally effective, or possibly superior, predictor of future performance with the domain as any appropriately designed task-specific measure of CSE" [Marakas et al., 2007, p. 17].

Antecedents of General Computer Self-Efficacy

In line with the social cognitive theory that self-efficacy is formed based on the deliberation of different information sources, this study proposes that various factors such as computer knowledge, current computing experience, computer anxiety, social norms, gender, age, and job status may serve as information sources for an individual to judge his or her level of general CSE. The development of general CSE, in turn, affects one's academic and career interests and choices. These factors are graphically presented in the research model of Figure 1.

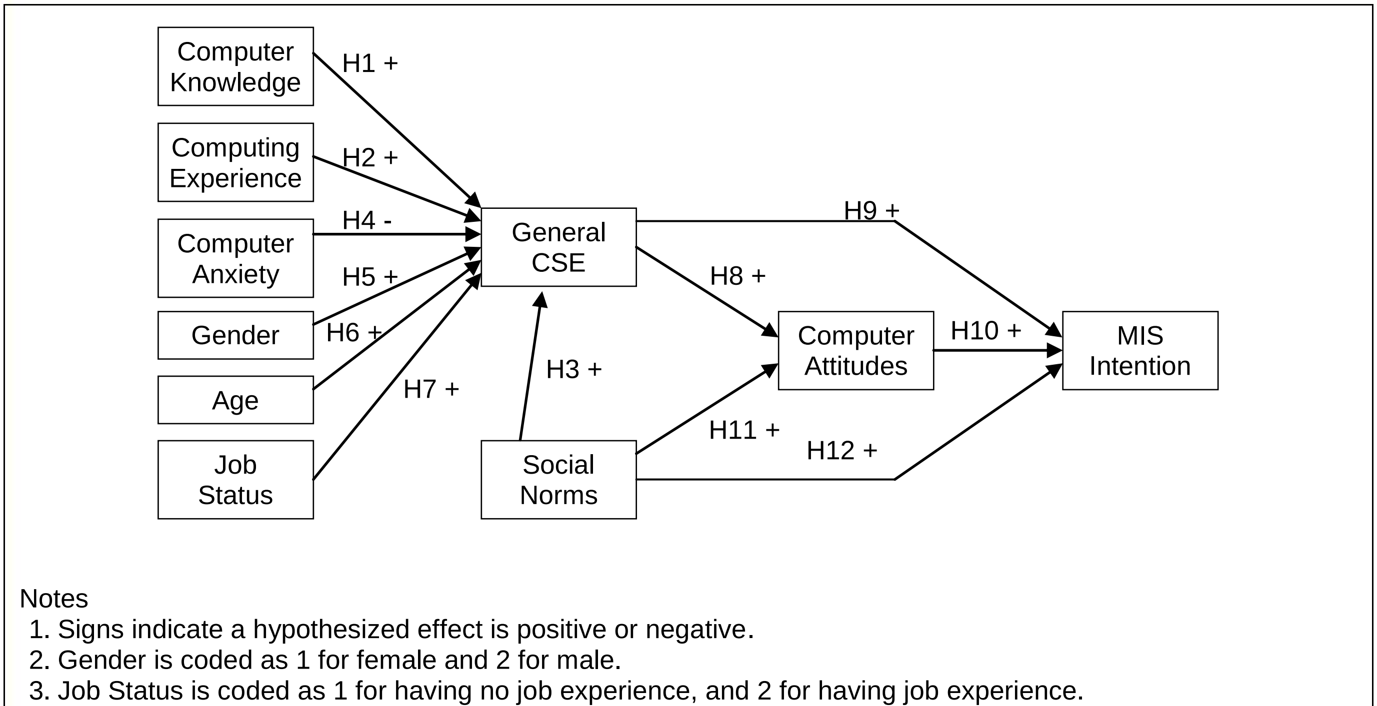


Figure 1. Research Model

Computer Knowledge and Current Computing Experience: Computer knowledge is defined as a self-perception of the extent of knowledge regarding the use of computers across different application domains. *Current computing experience* is defined as the frequency of using computers for different tasks and purposes in one's current situations. Both factors reflect one's direct experience with computers from the past and the present. Following the social cognitive theory, knowledge from one's own experience provides the most important source of information for the formation and development of one's self-efficacy [Bandura, 1977].

Hypothesis 1: The level of computer knowledge is positively associated with the level of general computer self-efficacy.

Hypothesis 2: The frequency of current computing usage is positively associated with the level of general computer self-efficacy.

Social Norms: Social cognitive theory suggests verbal persuasion as an important information source for one to judge his/her ability of performing a target behavior. In the MIS literature, social influence on one's use of technology is captured by the construct of social norms (also labeled as subjective norms in Fishbein and Ajzen [1975] and Davis et al. [1989]), defined as "the person's perception that most people who are important to him think he should or should not perform the behavior in question" [Fishbein and Ajzen, 1975, p. 302].

Social cognitive theory contends that people can be socially persuaded, through suggestions, into believing that they possess the capabilities to cope with even difficult situations [Bandura, 1977]. With encouraging words from people one trusts, an individual will be more confident of his/her ability and will tend to exert more effort into using computers. Thus, social norms are expected to positively affect one's perception of general CSE.

Hypothesis 3: The level of social norms is positively associated with the level of general computer self-efficacy.

Computer Anxiety: According to social cognitive theory, anxiety is an emotional arousal that is caused partly by fear of aversive physiological reactions (i.e., nausea, dizziness, high blood pressure) to a stressful and taxing situation. "Fear reactions generate further fear of impending stressful situations through anticipatory self-arousal" [Bandura, 1977, pp. 198–199]. Such fear-provoking thoughts will lead to elevated levels of anxiety and lend doubts about one's ability to perform the target behavior successfully, therefore, reduce the levels of perceived self-efficacy. Compared to other sources of information, social cognitive theory suggests anxiety as less important in affecting self-efficacy.

Computer anxiety refers to a feeling of apprehension or anxiety toward using computers [Compeau et al., 1999]. Computer anxiety is less likely caused by clinical physiological reactions (e.g., the so-called “computer phobia” observed among a minority of computer users [Weinberg and Fuerst, 1984]). Rather, computer anxiety is more affective in nature and reflects “fear and apprehension, intimidation, hostility, and worries that one will be embarrassed, look stupid, or even damage the equipment” [Heinssen et al., 1987, p. 50]. Such a psychological state of affect is expected to have a strong impact on one’s perception of self-efficacy. Previous empirical studies have repeatedly observed the relationship between computer anxiety and CSE as negative and strong [e.g., Harrison and Rainer, 1992; Staples et al., 1999; Thatcher and Perrewe, 2002].

Hypothesis 4: The level of computer anxiety is negatively associated with the level of general computer self-efficacy.

Gender, Age, and Job Status: Social cognitive theory emphasizes cognitive factors, i.e., the four types of information sources, in the formation and development of self-efficacy. However, we should not ignore personal factors for their profound psychological and social significance. The influence of personal factors on self-efficacy “derives not from their physical presence per se, but rather from the characteristic reactions they may evoke from the social/cultural environment” [Lent et al., 1994, p. 104]. In this study, we selected three personal factors—gender, age, and job status—to study their effects on the development of general CSE.

Generally speaking, males tend to feel more at ease with computers than females. This may be partially caused by men and women using different cognitive structures to encode and process information that determine an individual’s perceptions [Bem, 1981] as well as by gender role standards and expectations that the society has developed over time [Srite and Karahanna, 2006]. Because computing has developed a masculine image on par with the traditionally masculinized subjects such as mathematics, physics, and engineering [Gilbert et al., 2003], females tend to feel less comfortable with computers than males [Lowe and Krahn, 1989; Frankel, 1990]. Several studies have observed gender differences on the confidence or perceived ease of use of using computers in general [e.g., Harrison and Rainer, 1992; Venkatesh and Morris, 2000; Beyer, 2008].

Hypothesis 5: Gender has an effect on computer self-efficacy such that males tend to have higher levels of general computer self-efficacy than females.

Age has long been studied as an important antecedent for the formation of IT attitudes. Common perception holds that younger users tend to be more comfortable with information technology than do older people due to different interest levels [Igbaria et al., 1989; Igbaria and Nachman, 1990]. This study aims to investigate the formation of computer self-efficacy in business students. As a demographically-homogeneous group, it can be argued that students, both young and old, are equally interested in learning new skills that are important to their future careers. Other factors being equal, older students may have had more chances to use various computing technologies and accumulate computing experiences. Following the social cognitive theory that the development of self-efficacy is largely induced by experience [Bandura, 1977], it is expected that older students may feel more confident with computers than do younger students.

Hypothesis 6: Age is positively associated with levels of general computer self-efficacy.

Job status also reflects students’ experiences. Students with job experiences are expected to have more chances to expose themselves to and use a new technology, observe other people using the technology, and receive comments and suggestions from others regarding the technology. In contrast, students without job experiences may have limited chances to learn how different information technologies are applied in real situations. Therefore, students with jobs are expected to have higher levels of general CSE than students without jobs.

Hypothesis 7: People with job experience tend to have higher levels of general computer self-efficacy than people with no job experience.

Effects of General Computer Self-Efficacy

Social cognitive theory assumes that people decide on their behavior and activities in a cognitive fashion. In addition to the expected outcomes of performing certain behaviors, one’s perceived self-efficacy will significantly influence his/her choice of behavioral settings. Especially when motivation of performing a behavior is adequate, high levels of perceived self-efficacy will encourage the performance of certain activities in pursuit of desired outcomes, even in the face of obstacles and aversive experiences. “The stronger the perceived self-efficacy, the more active the efforts” [Bandura, 1977, p. 194].

Lent and colleagues [1994, 1996] applied social cognitive theory to the field of career development. The derivative Social Cognitive Career Theory elaborates on a few intervening mechanisms to explain paths through which a variety of personal, contextual, and behavioral variables affect career developmental outcomes such as career interest, choice, and performance. Self-efficacy plays a central role in these mechanisms. Taking interest development as an example, self-efficacy in terms of perceived capabilities on a subject matter induces the formation of interests, both academic and career, in the subject-related domains. “People form enduring interests in activities in which they view themselves to be efficacious and in which they anticipate positive outcomes … it may be difficult for robust interests to blossom where self-efficacy is weak or where neutral or negative outcomes are foreseen” [Lent et al., 1994, p. 89]. Similarly, self-efficacy strongly influences the development of career choices and affects career-related performances in concert with other factors. Even in taxing situations where people do not achieve desired outcomes (e.g., a physics major finds that he/she could not finish the coursework), one revisits and corrects one’s inaccurate judgment of self-efficacy to form a new cognitive basis for guiding future career behaviors (e.g., changing to another major) [Lent and Brown, 1996].

Social cognitive career theory has received wide support in the literature of career development, education, and human resources management [Lent and Brown, 1996; Bandura and Locke, 2003; Rasdi et al., 2009]. In MIS, researchers have long recognized the importance of computer self-efficacy in IT-related education, training, and workplace [Compeau and Higgins, 1995a; Hasan, 2006]. For example, Hill and colleagues (1987) found that confidence in ability to use a computer predicts one’s future involvement with information technologies. Employing the social cognitive career theory, researchers find evidence that computer self-efficacy strongly affects one’s interest of majoring in IT [Akbulut et al., 2008; Heinze and Hu, 2009] as well as academic performance [Smith, 2002].

This study selects computer attitudes and MIS intention as the dependent variables partially because the two affective variables have been well-studied in MIS. Computer attitudes is defined as one’s positive feelings toward using computers, and MIS intention is defined as the intention of selecting MIS for one’s future study and/or career. The two variables assess one’s interest in exposing oneself to computing activities and MIS. Given the pervasiveness of IT in today’s world, few people doubt the importance of mastering computers to their career success. With adequate motivation, general CSE is expected to serve as a key determinant of one’s computer attitudes and intentions of selecting MIS for his or her future study and/or career.

The discussed effects of general computer self-efficacy can also find support from the theory of reasoned action (TRA). TRA argues that one’s intention of performing a behavior is the single most important factor in determining the execution of the behavior [Fishbein and Ajzen 1975]. Intention is largely determined by social norms and attitudes, and attitudes are formed based on a set of beliefs toward performing the behavior. General CSE is in fact a set of beliefs about one’s ability of using computers in various situations. Following the frameworks of TRA, social cognitive theory, and its derivative of social cognitive career theory, we propose that general CSE has effects on both computer attitudes and MIS intention; as a partial intervening mechanism, computer attitudes also helps to shape MIS intention in addition to the effects of general CSE.

Hypothesis 8: The level of general computer self-efficacy is positively associated with computer attitudes.

Hypothesis 9: The level of general computer self-efficacy is positively associated with the intention of selecting MIS for one’s future study and/or career.

Hypothesis 10: The level of computer attitudes is positively associated with the intention of selecting MIS for one’s future study and/or career.

In addition, social norms may have strong effects on computer attitudes and MIS intention. The significance of social norms as a predictor for one’s computing behavior has been well established, especially in the technology acceptance literature [e.g., Lucas and Spitler, 1999; Venkatesh and Davis, 2000; Venkatesh et al., 2003]. Social cognitive theory also acknowledges that social norms as an information source may be weak in affecting self-efficacy but strong in regulating behaviors [Bandura, 1977]. Thus, we propose that general CSE only partially mediates the effects of social norms on one’s computer attitudes and MIS intention.

Hypothesis 11: The level of social norms is positively associated with attitudes toward selecting MIS for one’s future study and/or career.

Hypothesis 12: The level of social norms is positively associated with intention of selecting MIS for one’s future study and/or career.

III. METHODS

Participants

Participants in this study were 281 undergraduate business students of a Midwestern public university. The students enrolled in two MIS courses: one course was about basic computing skills designed for freshmen, the other course was an MIS survey course designed for students with sophomore status and beyond. Students were instructed to take two online surveys during the first month of their MIS study.

Although students were encouraged by the course instructor, their participation in the study was voluntary. Students were told that survey responses would not affect their course grades in any way. Some students failed to take the two surveys on time, and some submitted incomplete answers. This resulted in 243 usable sets of individual data for analysis, or an 86.5 percent effective response rate. Demographics of participants are reported in Table 2.

Table 2: Demographics of Participants

		Counts	Percentage
Gender	Female	127	52.26%
	Male	116	47.74%
	Total	243	100.00%
Age	17	21	8.64%
	18	81	33.33%
	19	32	13.17%
	20	40	16.46%
	21–25	43	17.70%
	26–30	13	5.35%
	31–40	7	2.88%
	41–52	6	2.47%
	Total	243	100.00%
Status	Freshmen	111	45.68%
	Sophomore	52	21.40%
	Junior	65	26.75%
	Senior	15	6.17%
	Total	243	100.00%
Job Status	Having Job	187	76.95%
	No Job	56	23.05%
	Total	243	100.00%

Procedures

Data were collected at two points in time. Participants were instructed to take the first survey during the first week of their MIS course; two weeks later, the participants were instructed to take the second survey. The purpose of designing two surveys was to reduce possible common-source bias by separating the measurement of predictors and dependent variables [Podsakoff et al., 2003]. More specifically, the dependent variables [computer attitudes and MIS intention] and antecedents of general CSE such as computer knowledge, current computing experiences, computer anxiety, and participants' demographic information were asked in the first survey, and general CSE was asked in the second survey.

Measures

This study investigates the formation and effects of general CSE among MIS students. The measurements of involved factors are explained below (with specific items included in Appendix 1).

Computer Knowledge was measured by six questions using a 5-point Likert scale (from strongly disagree to strongly agree) asking students whether they have good knowledge and skills about computers, operating systems, Excel, HTML, Access, and PowerPoint. Current computing experience was measured by six questions asking students to rate the frequency on a five-point scale (from once a month to several times a day) regarding the use of computers for different purposes. The way of operationalization suggests the two constructs being modeled as formative indicators in the test of the research model.

Job status was measured by one item asking respondents whether he or she had a job (either full-time or part-time) with binary answers of yes or no.

Computer Anxiety was measured by a four-item instrument adopted from Compeau et al. [1999]. This instrument was based on the Computer Anxiety Rating Scale development by Heinssen and colleagues [1987], and the four items were found to best capture the feeling of anxiety associated with computer use [Compeau and Higgins, 1995a].

Social norms were measured by a two-item instrument adapted from Venkatesh and Davis [2000]. This instrument has been widely used and validated particularly in technology acceptance studies [Venkatesh et al., 2003].

General CSE was measured by a six-item instrument recently developed by Marakas and colleagues [2007]. Marakas and colleagues [2007] critically reviewed previous instruments of CSE, and argued that they were outdated and should be redesigned with articulated alignment to the situation under study. The six-item instrument of general CSE was developed with special attention on general computing skills across various situations, and was validated using data collected from business students. Marakas and colleagues [2007] also suggested that general CSE should be modeled as a formative indicator based on its theoretical conceptualization (i.e., the perceived ability of performing a certain set of activities).

Computer attitudes were measured by four items asking respondents to rate on a 1–5 point scale that knowing how to use computers is important to the success of his or her future career. MIS intention was measured by two items asking respondents whether he or she will consider selecting MIS for his or her future study and/or career with binary answers of yes or no.

Formative Constructs

This study makes use of three formative constructs—Computer Knowledge, Computing Experience, and General Computer Self-Efficacy. Unlike reflective constructs, where the latent variable causes the observed variables, formative constructs exist where the observed variables cause (or are the "causal formative of" [Marakas et al., 2007, p. 18]) the latent variable. Without retelling the public debate between Marakas and colleagues [2007, 2008] and Hardin and colleagues [2008a, 2008b] regarding the appropriate measurement of Computer Self-Efficacy as a reflective or a formative construct in particular, we offer the following explanation for our use of these three constructs as formative constructs.

Formative constructs are those where the direction of causality is from the items to the construct. As a result, changes in the indicators (items) should cause changes in the construct, while changes in the construct do not cause changes in the indicators. More than just the direction of causality, the indicators (items) in a formative construct need not be interchangeable or share a common theme. In fact, the conceptual domain of the construct may be altered when an indicator is dropped from the construct [Diamantopoulos and Winklhofer, 2001; Marakas et al., 2007]. A close look at our three formative constructs (see Appendix 1) demonstrates that the indicators conform to the above properties of construct causality and non-interchangeability of indicators. For example, with any of the three constructs, a change in the indicators will cause a change in the measurement of the latent variable, but a change in the latent variable will not cause a change in the indicators. Additionally, a respondent may rate one indicator (item) highly while rating another quite low. While the items within these three constructs may be correlated, they need not co-vary and may be mutually exclusive [Hardin et al., 2008a].

Construct Validity

The test of construct validity was conducted with Partial Least Squares (PLS)—a structural equation modeling (SEM) technique that has been commonly used in IS research. Similar to other SEM techniques (e.g., LISREL), PLS tests the validity of constructs and the structural model at the same time, and is, therefore, considered methodologically rigorous when compared with regression-based techniques that separate the test of construct validity (e.g., factor analysis) from the test of the research model [Gefen et al., 2000]. Two other distinctive features of PLS made the technique a particularly suitable testing tool for this study:

1. PLS has the flexibility of accepting single-item constructs (e.g., gender, age, and job status in this study);
2. The algorithm of PLS, which is component-based rather than covariance-based, allows the modeling of formative indicators [Chin, 1998]. In this study, the constructs of computer knowledge, current computing experiences, and general CSE were modeled as formative indicators based on their conceptualizations and operationalizations.

Validity of Formative Indicators

Conventional procedures used to assess the validity of reflective constructs (e.g., factor analysis) may not be appropriate for assessing the validity of formative constructs [Diamantopoulos and Winklhofer, 2001]. A multitrait–multimethod (MTMM) approach [Campbell and Fiske, 1959] with some modification designed for assessing the validity of formative constructs [Loch et al., 2003] was used here to examine the convergent and discriminant validity of the three formative indicators. This method is also practiced in Marakas et al. [2007] for the development of different types of CSEs.

In this method, a composite score of each formative indicator was calculated based on the sum of products between its formative items and their associated weights. The weight represents the extent to which an item contributes to the overall value of a latent variable. A correlation matrix is then calculated between items of formative constructs and all constructs under study. To establish convergent validity, items should correlate high with items measuring the same construct, and low with items measuring other constructs. To establish discriminant validity, items should correlate highly with the assigned constructs and less with unassigned ones. If the number of items being tested is large, some violations may be observed due to chance. Thus, the validity test of formative indicators is both a science and an art [Marakas et al., 2007].

The matrix calculated for assessing the validity of formative indicators is reported in Table 3a and Table 3b.

There are 333 correlations calculated in Table 3a and Table 3b. Among them, fourteen correlations violated the rules discussed above. Upon close examination of these fourteen violations, it is noted that most general CSE items correlated highly with two items of computer knowledge measuring one's perceived knowledge about computers and operating systems. The two items were retained to preserve the integrity of the construct for two reasons: (1) the two items were closely aligned with the conceptualization of the computer knowledge construct; (2) the features of a formative indicator (e.g., indicators are exogenously determined by items; therefore, within-construct item correlations need not necessarily be high, and cross-construct item correlations need not necessarily be low [Diamantopoulos and Winklhofer, 2001]) allows violations to the rules of convergence and discriminance among valid measures.

In addition, the percentage of violations was low (the number of violations of the comparison parameters was fourteen out of the 333 correlations, or a 4 percent violation rate, which is below the 5 percent rule suggested in Campbell and Fiske [1959]) and, therefore, we could not reject chance as an alternative explanation. Because the overall pattern of correlations was not much different from the expectation, validity of these formative indicators could be concluded.

Table 3a: Validity Test of Formative Indicators												
	Computer Knowledge (CK) Items						Current Computing Experiences (CEXP) Items					
	CK1	CK2	CK3	CK4	CK5	CK6	CEXP1	CEXP2	CEXP3	CEXP4	CEXP5	CEXP6
CK1												
CK2	**0.75**											
CK3	**0.50**	**0.50**										
CK4	**0.41**	**0.32**	**0.55**									
CK5	**0.42**	**0.39**	**0.35**	**0.46**								
CK6	**0.49**	**0.50**	**0.58**	**0.33**	**0.33**							
CEXP1	0.24	0.28	0.22	0.09	0.12	0.21						
CEXP2	0.32	0.35	0.19	0.18	0.13	0.15	**0.32**					
CEXP3	0.20	0.26	0.19	0.09	0.12	0.23	**0.62**	**0.16**				
CEXP5	0.24	0.27	0.20	0.11	0.20	0.15	**0.68**	**0.21**	**0.65**			
CEXP6	0.30	0.29	0.19	0.08	0.12	0.16	**0.54**	**0.41**	**0.48**	**0.62**		
CEXP7	0.17	0.17	0.14	0.04	0.08	0.10	**0.52**	**0.32**	**0.30**	**0.49**	**0.50**	
GCSE1	0.36	0.35	0.15	0.2	0.35	0.13	0.19	0.19	0.05	0.19	0.25	0.16
GCSE2	0.46	0.55	0.29	0.27	0.39	0.27	0.28	0.25	0.22	0.28	0.32	0.19
GCSE3	0.49	0.51	0.31	0.19	0.31	0.34	0.17	0.26	0.14	0.16	0.17	0.16
GCSE4	0.39	0.42	0.22	0.24	0.31	0.19	0.20	0.31	0.24	0.21	0.30	0.15
GCSE5	0.41	0.5	0.24	0.17	0.26	0.22	0.23	0.19	0.20	0.20	0.23	0.14
GCSE6	0.45	0.46	0.29	0.23	0.27	0.29	0.21	0.25	0.13	0.19	0.18	0.19
CK	**0.83**	**0.9**	**0.48**	**0.47**	**0.71**	**0.44**	0.25	0.33	0.23	0.28	0.28	0.16
CEXP	0.38	0.4	0.25	0.17	0.17	0.20	**0.65**	**0.81**	**0.48**	**0.64**	**0.83**	0.52
SN	0.12	0.08	0.15	0.03	0.08	0.13	0.11	–0.05	0.10	0.12	0.07	0.01
CA	–0.39	–0.34	–0.24	–0.19	–0.24	–0.22	–0.14	–0.20	–0.11	–0.14	–0.17	–0.10
Gender	0.19	0.19	0.07	0.11	0.15	0.01	0.23	–0.03	0.20	0.20	0.15	0.00
Age	0.01	–0.05	–0.09	0.01	–0.02	–0.28	0.01	0.21	–0.20	0.06	0.16	0.16
Job Status	–0.12	–0.15	–0.12	–0.10	–0.04	–0.14	–0.15	–0.18	–0.10	–0.20	–0.08	–0.10
GCSE	0.54	0.59	0.31	0.29	0.43	0.29	0.28	0.32	0.21	0.28	0.34	0.22
Computer Attitude	0.23	0.23	0.15	0.12	0.05	0.09	0.10	0.13	0.01	0.17	0.23	0.16
MIS Intention	0.21	0.12	0.08	0.13	0.16	0.04	0.03	–0.03	0.01	0.13	0.11	0.04

Table 3b: Validity Test of Formative Indicators						
	General Computer Self-Efficacy (GCSE) Items					
	GCSE1	GCSE2	GCSE3	GCSE4	GCSE5	GCSE6
GCSE1						
GCSE2	**0.50**					
GCSE3	**0.52**	**0.51**				
GCSE4	**0.38**	**0.60**	**0.46**			
GCSE5	**0.39**	**0.62**	**0.53**	**0.57**		
GCSE6	**0.37**	**0.53**	**0.46**	**0.44**	**0.51**	
CK	0.44	0.58	0.52	0.46	0.49	0.47
CEXP	0.28	0.36	0.27	0.36	0.27	0.27
SN	0.10	0.13	0.06	0.03	0.07	0.10
CA	–0.37	–0.35	–0.34	–0.34	–0.31	–0.27
Gender	0.23	0.21	0.21	0.26	0.21	0.09
Age	0.17	0.11	0.06	0.12	0.06	0.02
Job Status	–0.14	–0.14	–0.11	–0.18	–0.11	–0.05
GCSE	**0.75**	**0.86**	**0.72**	**0.78**	**0.73**	**0.65**
Computer Attitude	0.20	0.23	0.11	0.18	0.15	0.17
MIS Intention	0.19	0.19	0.12	0.18	0.21	0.16

Notes
1. Expected high correlations are presented in bold. More specifically, item-item correlations are expected to be high at within-construct level and low at cross-construct level; item-construct correlations are expected to be high with assigned constructs and low with unassigned constructs.
2. Cells in shade indicate violations of Note 1.
3. N=243

Validity of Reflective Indicators

Assessing the validity of reflective items follows the conventional practice based on the examination of construct reliability, convergent validity, and discriminant validity. Construct validity can be assessed by composite reliability calculated in PLS (should be larger than 0.70). Convergent validity can be assessed by the average variance extracted (AVE) among measures (should be larger than 0.50). Discriminant validity can be assessed by comparing the square root of AVEs and inter-construct correlations—the former should be larger than the latter to support disciminant validity. Close examination of Table 4 suggested that all the conditions were satisfied. Thus, validity of the reflective indicators under study was ready to be concluded.

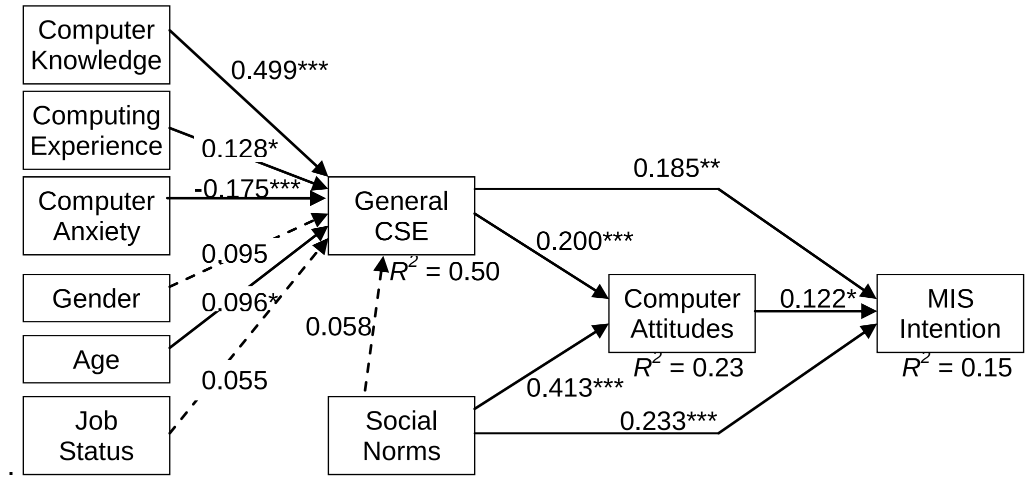
Table 4: Inter-Construct Correlations

	Reliability	1	2	3	4	5	6	7	8	9	10
1. General Computer Self-Efficacy†	-	-									
2. Computer Knowledge†	-	0.65	**-**								
3. Current Computing Experience†	-	0.42	0.46	**-**							
4. Computer Anxiety	0.90	–0.44	–0.39	–0.24	**0.83**						
5. Gender	1	0.28	0.22	0.13	–0.23	**1**					
6. Age	1	0.14	–0.03	0.08	–0.16	–0.06	**1**				
7. Job Status	1	–0.17	–0.13	–0.16	0.12	–0.07	–0.07	**1**			
8. Social Norms	0.84	0.11	0.09	0.12	–0.01	0.19	–0.08	0.07	**0.85**		
9. Computer Attitude	0.89	0.25	0.22	0.28	–0.16	0.03	0.17	0.04	0.44	**0.81**	
10. MIS Intention	0.85	–0.24	–0.19	–0.14	0.16	–0.21	–0.10	–0.02	–0.31	–0.27	**0.86**

Notes
1. Reliability: composite reliability calculated in PLS
2. Numbers in bold on the diagonal are the square root of the average variance extracted (AVE).
3. † These constructs are modeled as formative indicators. Calculations of construct reliability and shared variance are not relevant for them.
4. Off diagonal elements are correlations among constructs.
5. For discriminant validity of reflective constructs, diagonal elements should be larger than off-diagonal elements.

Hypothesis Testing

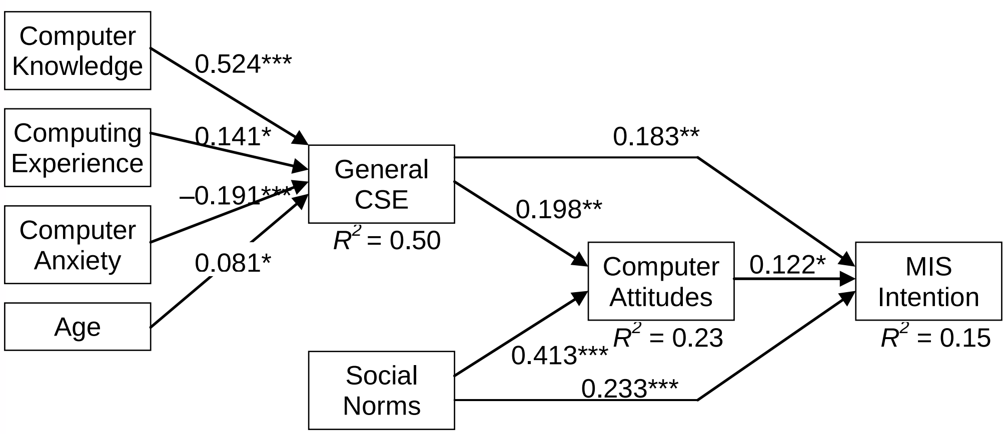
The test of the research model and the results are presented in Figure 2. Examination of the resulting path significances suggested the rejection of several hypothesized relationships. More specifically, the effects of gender, job, and social norms on general CSE, although in their expected directions, were found to be insignificant.



Note
Dashed lines indicate insignificance with $p > 0.05$ (two-tailed).
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (two-tailed)

Figure 2. Testing Results

The research model was then revised by dropping the insignificant paths from the original model. The testing results of the revised model are presented in Figure 3.



Note
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (two-tailed)

Figure 3. Revised Model

The revised model well interpreted the sample data with significant path coefficients (all with p < 0.05), acceptable R^2, and good construct reliability with high levels of internal consistency [Gefen et al., 2000]. In addition, the predictive power on general CSE was satisfactory, with 50 percent of the variance being explained by the four investigated predictors. In contrast, the explained variances of computer attitudes and MIS intention were moderate, with 23 percent and 15 percent respectively.

IV. DISCUSSION

As a main factor that influences people's reactions to computers, CSE has received much research attention [Compeau and Higgins, 1995; Marakas et al., 1997, 2007; Agarwal et al., 2000]. A profound understanding of the nature of CSE in terms of its formation (antecedents), effects (consequences), and special make-up (measurement) will bring important implications to IS research and practices in areas such as education, training, implementation, and technology acceptance [Marakas et al., 1997]. This study was designed to investigate the information sources of CSE suggested by its theoretical origin in Social Cognitive Theory, and test the validity of a formative measure of CSE that was recently developed in the literature. The effects of CSE on two dependent variables—computer attitudes and MIS intentions—were also included in the research model. Much of the propositions received support from the sampled data. Main findings and the implications for research and MIS education are discussed in this section.

Implications for Research

Computer knowledge, computing experience, computer anxiety, and age were all found to be important antecedents of general CSE. These findings support and extend previous work in this area regarding the formation of CSE. Researchers who study the development of CSE should not ignore these factors as important information sources. Knowing the supported antecedents of general CSE provides the research community with additional opportunities to flesh out these constructs, expand them to broader subject pools, and study them in conjunction with other previously studied (and yet to be studied) antecedents tailored to the special research context.

In our sample, computer knowledge is found to be the most influential determinant of the level of general CSE. Although these two variables are highly correlated, one should not equate computer knowledge with general CSE. Social cognitive theory highlights the role of self-efficacy on transitioning one's knowledge and experience into behavior and motivation. Career development literature further articulates the mediation role of self-efficacy as "the effects of ability on interests … will be largely mediated by self-efficacy beliefs, since people may rely more on perceived than tested abilities in formulating their interests" [Lent et al., 1994; p. 90].

We tested the mediating role of general CSE by adding direct paths from computer knowledge to computer attitudes and MIS intention in the revised model. The resulted path coefficients were insignificant with $\beta = 0.102$ ($p = 0.19$) and –0.075 ($p = 0.41$) respectively; the rest of the model remained mostly unaffected. Combining the results with that from the correlation matrix (Table 4) and the revised model (Figure 3), we can safely conclude that general CSE fully mediates the influence of computer knowledge on computer attitudes and MIS intension.

The results also suggest that one's formation of favorable attitudes and intentions toward using computers and selecting MIS for future study and career is a more complicated phenomenon than can be explained by self-efficacy. This is consistent with observations from the career development literature that other variables such as social and economic factors often intervene the transition of interests and skills developed during the school years into career selection outcomes [Lent et al., 1994; Lent and Brown, 1996]. Nonetheless, computer self-efficacy, with acceptable predictive power, provides a solid ground upon which we can continue our investigation and enrich our understanding of the complex and important phenomenon.

The results did not support the effects of gender, job status, and social norms on the formation of general CSE. Inter-construct correlations (Table 4) indicated that gender correlated significantly with general CSE ($r = 0.28$, $p < 0.001$). But in the test of the overall research model, the effect was largely diluted. Thus, other factors, such as computer knowledge and experiences, could capture the difference between females and males regarding their perceptions of general CSE.

Gender effects on general CSE have received mixed support from the literature. There are studies arguing that the ubiquitous nature of computing technologies tends to ease the perception gaps between females and males. For example, using computers frequently for communication helps females to view computers as less of a threat [King et al., 2002]. Havelka [2003] also found that gender did not lead to different perceptions of software self-efficacy between female and male students. This study found a significant correlation between gender and general CSE and an insignificant path in the proposed research model. Future research is needed to clarify this issue.

Students' job status was found to be an insignificant predictor of general CSE. This is not surprising. The comparatively homogeneous background among the sampled students might not produce enough variance in the experiences of computer usage. Thus, perception of general CSE could barely be affected. Rejecting the hypothesized effect of job status in the current study should not preclude the construct from being tested in the future study of CSE, especially with research subjects having more varied work experiences and/or job status. In addition, the type of job, which may reflect different levels of exposure to computing activities, also warrants further investigation.

Social norms did not have a significant impact on general CSE. Although social cognitive theory suggests social norms as an information source for self-efficacy, the theory also acknowledges that social norms may weakly affect self-efficacy but strongly affect behaviors [Bandura, 1977]. Results of the study provide evidence to support this argument. The effects of social norms on computer attitudes and MIS intention were found to be positive and significant. The magnitudes were comparable to, if not larger than, that of general CSE.

Implications for MIS Education

Attracting more students to major in MIS is a big challenge faced by today's MIS educators. Many MIS scholars have expressed concerns regarding the declining enrollment of MIS over the past five years, and much research has been done to study solutions and strategies to encourage more students to select MIS as their major and ultimately as their career [George et al., 2005; Akbulut and Looney, 2007; Firth et al., 2008]. This study takes another approach and investigates how personal perception of computing capability will affect one's interest in MIS.

The results show that general CSE and social norms have significant impacts on students' computer attitudes and intention of selecting MIS. One should note that the prediction power of the concluded model on Computer Attitudes and MIS Intention is not large, with modest R^2 of 23 percent and 15 percent respectively. This finding suggests that computer self-efficacy alone does not fully predict students' perceptions of the relevance of computers to their career success. Other factors, such as job market and economic situations, may play important roles in affecting students' willingness to select MIS for their future study and careers.

Although the effects of general CSE and social norms on students' computer attitudes and MIS intention are modest in magnitude, their statistical significances have important implications for MIS educators. Given that many business schools require their students to take one or more MIS courses for IT knowledge and computing skills, MIS educators are in a good position to levy legitimate influence on students' perceptions of MIS. The teaching of computing skills can help increase the perceived level of general CSE among students and, therefore, enhance the chance for students to major and work in MIS. In addition, social norms, over which MIS educators may carry out strong control, also affect students' attitudes and intention toward MIS.

Limitations of the Study

Although the results are encouraging, the study has several limitations. One is the operationalization of the constructs of computer knowledge and current computing experiences. The operationalization was based on a set of newly developed, rather than existing, measures. This practice is highly advocated, especially for modeling formative indicators [Marakas et al., 2007]. However, the lack of validity support from the existing literature could question the validity and generalizability of the two constructs.

Validity tests of the three formative indicators may be another concern for this study. The literature falls short on a commonly accepted procedure to test the validity of formative indicators [Diamantopoulos and Winklhofer, 2001]. The method used here was also employed in Marakas et al. [2007] as the best practice so far in the literature. However, several measurement issues, such as the calculation of reliability and situations in which violations of comparison parameters may be accepted or unaccepted, remain unsolved. Given the increasing acceptance of formative indicators among IS researchers, these measurement issues should call for future research.

This study selected business students as the research subject. Thus, special caution is needed when applying the findings to business professionals. Future research with real business settings is desired to test the generalizability of the findings in various contexts.

All constructs were self-reported by sampled students. Thus, common-source bias could be another concern for the study. A measurement strategy of separating the survey of predictors from that of dependent variables was carefully executed to alleviate such a concern. To assess the extent of common source variance, we performed Harman's single factor test by loading all the self-reported items (except personal factors of gender, age, and job status) into an exploratory factor analysis [Podsakoff et. al., 2003]. The maximum variance accounted for by one single factor is 26 percent. Although the method does not explain the exact source of the extracted variance, which may be caused by the use of a common method, the lack of discriminant validity, and/or the existence of causal relationships among the investigated constructs, the limited amount of variance suggests that there is no strong common-source bias present.

V. CONCLUSION

The aim of this study was to investigate the formation of CSE suggested by the concept's theoretical origin in Social Cognitive Theory. Various factors were investigated as the antecedents of general CSE, and computer attitudes and MIS intention were selected to be the dependent variables. About 50 percent of the variance of general CSE was explained by the research model. Of the twelve hypothesized relationships, three failed to conclude significance at the $p < 0.05$ level. Thus, most of the propositions received support from the sampled students, demonstrating evidence that the formation of general CSE is comparable to the formation of the more general concept of self-efficacy.

REFERENCES

Agarwal, R., V. Sambamurthy, and R.M. Stair (2000) “Research Report: The Evolving Relationship Between General and Specific Computer Self-Efficacy—An Empirical Assessment”, *Information Systems Research* (11)4, pp. 418–430.

Akbulut, A.Y., and C.A. Looney (2007) “Their Aspirations Are Our Possibilities: Inspiring Students to Pursue Computing Degrees”, *Communications of the ACM* (50)10, pp. 67–71.

Akbulut, A.Y., C.A. Looney, and J. Motwani (2008) “Combating the Decline in Information Systems Majors: The Role of Instrumental Assistance”, *The Journal of Computer Information Systems* (48)3, pp. 84–93.

Bandura, A. (1977) “Self-Efficacy: Toward a Unifying Theory of Behavioral Change”, *Psychological Review* (84)2, pp. 191–215.

Bandura, A. (1982) “Self-Efficacy Mechanism in Human Agency”, *American Psychologist* (37)2, pp. 122–147.

Bandura, A. (2001) Guide for Constructing Self-Efficacy Scales (Revised). Available from Frank Pajares, Emory University, Atlanta, GA, 30322.

Bandura, A., and N.E. Adams (1977) “Analysis of Self-Efficacy Theory of Behavioral Change”, *Cognitive Therapy and Research* (1)4, pp. 287–310.

Bandura, A., and E.A. Locke (2003) “Negative Self-Efficacy and Goal Effects Revisited”, *Journal of Applied Psychology* (88)1, pp. 87–99.

Bem, S.L. (1981) “The BSRI and Gender Schema Theory: A Reply to Spence and Helmreich”, *Psychological Review* (88), pp. 369–371.

Beyer, S. (2008) “Gender Differences and Intra-Gender Differences amongst Management Information Systems Students”, *Journal of Information Systems Education* (19)3, pp. 301–310.

Bolt, M.A., L.N. Killough, and H.C. Koh (2001) “Testing the Interaction Effects of Task Complexity in Computer Training Using the Social Cognitive Model”, *Decision Sciences* (32)1, pp. 1–20.

Campbell, D.T., and D.W. Fiske (1959) “Convergent and Discriminant Validation of the Multitrait-Multimethod Matrix”, *Psychological Bulletin* (56)2, pp. 81–105.

Chin, W.W. (1998) “Issues and Opinion on Structural Equation Modeling”, *MIS Quarterly* (22)1, pp. vii–xvi.

Compeau, D.R., and C.A. Higgins (1995a) “Application of Social Cognitive Theory to Training for Computer Skills”, *Information Systems Research* (6)2, pp. 118–143.

Compeau, D.R., and C.A. Higgins (1995b) “Computer Self-Efficacy: Development of a Measure and Initial Test”, *MIS Quarterly* (19)2, pp. 189–211.

Compeau, D.R., C.A. Higgins, and S. Huff (1999) “Social Cognitive Theory and Individual Reactions to Computing Technology: A Longitudinal Study”, *MIS Quarterly* (23)2, pp. 145–158.

Davis, F.D., R.P. Bagozzi, and P.R. Warshwa (1989) “User Acceptance of Computer Technology: A Comparison of Two Theoretical Models”, *Management Science* (35)8, pp. 982–1003.

Diamantopoulos, A., and H.M. Winklhofer (2001) “Index Construction with Formative Indicators: An Alternative to Scale Development”, *Journal of Marketing Research* (38)2, pp. 269–277.

Downey, J.P., R.K. Rainer Jr., and S.E. Bartczak (2008) “Explicating Computer Self-Efficacy Relationships: Generality and the Overstated Case of Specificity Matching”, *Journal of Organizational and End User Computing* (20)3, pp. 22–40.

Firth, D., C. Lawrence, and C.A. Looney (2008) “Addressing the IS Enrollment Crisis: A 12-Step Program to Bring About Change Through the Introductory IS Course”, *Communications of the Association for Information Systems* (23), pp. 17–36.

Fishbein, M., and I. Ajzen (1975) *Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research*, Reading, MA: Addison-Wesley.

Frankel, K.A. (1990) "Women and Computing”, *Communications of the ACM* (33)11, pp. 34–45.

Gefen, D., D.W. Straub, and M. Boudreau (2000) “Structural Equation Modeling Techniques and Regression: Guidelines for Research Practice”, *Communications of the Association for Information Systems* (4)7, pp. 1–78.

George, J.F., J.S. Valacich, and J. Valor (2005) “Does Information Systems Still Matter? Lessons for a Maturing Discipline”, *Communications of the Association for Information Systems* (16), pp. 219–232.

Gilbert, D., L. Lee-Kelley, and M. Barton (2003) "Technophobia, Gender Influences and Consumer Decision-Making for Technology-Related Products", *European Journal of Innovation Management* (6)4, pp. 253–263.

Hardin, A.M., J.C. Chang, and M.A. Fuller (2008a) "Formative vs. Reflective Measurement: Comment on Marakas, Johnson, and Clay (2007)", *Journal of the Association for Information Systems* (9)9, pp. 519–534.

Hardin, A.M., J.C. Chang, and M.A. Fuller (2008b) "Clarifying the Use of Formative Measurement in the IS Discipline: The Case of Computer Self-Efficacy", *Journal of the Association for Information Systems* (9)9, pp. 544–546.

Harrison, A.W., and R.K.Jr. Rainer (1992) "The Influence of Individual Differences on Skill in End-User Computing", *Journal of Management Information Systems* (9)1, pp. 93–111.

Hasan, B. (2006) "Delineating the Effects of General and System-Specific Computer Self-Efficacy Beliefs on IS Acceptance", *Information & Management* (43)5, pp. 565–571.

Havelka, D. (2003) "Predicting Software Self-Efficacy Among Business Students: A Preliminary Assessment", *Journal of Information Systems Education* (14)2, pp. 145–152.

Heinssen, R.K., C.R. Glass, and L.A. Knight (1987) "Assessing Computer Anxiety: Development and Validation of the Computer Anxiety Rating Scale", *Computer and Human Behavior* (3), pp. 49–59.

Heinze, N., and Q. Hu (2009) "Why College Undergraduates Choose IT: A Multi-Theoretical Perspective", *European Journal of Information Systems* (18)5, pp. 462–479.

Henry, J.W., and R.W. Stone (1994) "A Structural Equation Model of End-User Satisfaction with a Computer-Based Medical Information System", *Information Resources Management* (7)3, pp. 21–33.

Igbaria, M., and S. Nachman (1990) "Correlates of User Satisfaction with End User Computing: An Exploratory Study", *Information & Management* (19)2, pp. 73–82.

Igbaria, M., F.N. Pavti, and S.L. Huff (1989) "Microcomputer Applications: An Empirical Look at Usage", *Information & Management* (16)4, pp. 187–196.

King, J., T. Bond, and S. Blandford (2002) "An Investigation of Computer Anxiety by Gender and Grade", *Computers in Human Behavior* (18)1, pp. 69–84.

Lee, S., S. Koh, D. Yen, and H.L. Tang (2002) "Perception Gaps between IS Academics and IS Practitioners: An Exploratory Study", *Information & Management* (40)1, pp. 51–61.

Lent, R.W., S.D. Brown, and G. Hackett (1994) "Toward a Unifying Social Cognitive Theory of Career and Academic Interest, Choice, and Performance", *Journal of Vocational Behavior* (45)1, pp. 79–122.

Lent, R.W,, and S.D. Brown (1996) "Social Cognitive Approach to Career Development: An Overview", *The Career Development Quarterly* (44) 4, pp. 310–321.

Lewis, W., R. Agarwal, and V. Sambamurthy (2003) "Sources of Influence on Beliefs about Information Technology Use: An Empirical Study of Knowledge Workers", *MIS Quarterly* (27)4, pp. 657–678.

Loch, K.D., D.W. Straub, and K. Sherif (2003) "Diffusing the Internet in the Arab World: The Role of Social Norms and Technological Culturation", *IEEE Transactions on Engineering Management* (50)1, pp. 45–63.

Lowe, G.S., and H. Krahn (1989) "Computer Skills and Use Among High School and University Graduates", *Canadian Public Policy* (15)2, pp.175–188.

Lucas, H.C., Jr., and V.K. Spitler (1999) "Technology Use and Performance: A Field Study of Broker Workstations", *Decision Sciences* (30)2, pp. 291–311.

Marakas, G.M., M.Y. Yi, and R.D. Johnson (1998) "The Multilevel and Multifaceted Character of Computer Self-Efficacy: Toward Clarification of the Construct and an Integrative Framework for Research", *Information Systems Research* (9)2, pp. 126–163.

Marakas, G.M., R.D. Johnson, and P.F. Clay (2007) "The Evolving Nature of the Computer Self-Efficacy Construct: An Empirical Investigation of Measurement Construction, Validity, Reliability and Stability Over Time", *Journal of the Association for Information Systems* (8)1, pp. 15–46.

Marakas, G.M., R.D. Johnson, and P.F. Clay (2008) "Formative vs. Reflective Measurement: A Reply to Hardin, Chang, and Fuller", *Journal of the Association for Information Systems* (9)9, pp. 535–543.

Podsakoff, P.M., et al. (2003) "Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies", *Journal of Applied Psychology* (88)5, pp. 879–903.

Rasdi, R.M., I. Maimunah, and U. Jegak (2009) “Towards Developing a Theoretical Framework for Measuring Public Sector Managers’ Career Success”, *Journal of European Industrial Training* (33)3, pp. 232–254.

Sheng, Y.P., J.M. Pearson, and L. Crosby (2003) “Organizational Culture and Employees' Computer Self-Efficacy: An Empirical Study”, *Information Resources Management Journal* (16)3, pp. 42–58.

Smith, S.M. (2002) “The Role of Social Cognitive Career Theory in Information Technology Based Academic Performance”, *Information Technology, Learning, and Performance Journal* (20)2, pp. 1–10.

Srite, M., and E. Karahanna (2006) “The Role of Espoused National Cultural Values in Technology Acceptance”, *MIS Quarterly* (30)3, pp. 679–704.

Srite, M., J.B. Thatcher, and E. Galy (2008) “Does Within-Culture Variation Matter? An Empirical Study of Computer Usage”, *Journal of Global Information Management*, (16)1, pp. 1–25.

Staples, D.S., J.S. Hulland, and C.A. Higgins (1999) “A Self-Efficacy Theory Explanation for the Management of Remote Workers in Virtual Organizations”, *Organization Science* (10)6, pp. 758–776.

Thatcher, J.B., and P.L. Perrese (2002) “An Empirical Examination of Individual Traits as Antecedents to Computer Anxiety and Computer Self-Efficacy”, *MIS Quarterly* (26)4, pp. 381–396.

Venkatesh, V. (2000) “Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model”, *Information Systems Research* (11)4, pp. 342–365.

Venkatesh, V., and F.D. Davis (2000) “A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies”, *Management Science* (45)2, pp. 186–204.

Venkatesh, V., and M.G. Morris (2000) “Why Don't Men Ever Stop to Ask For Directions? Gender, Social Influence, and Their Role in Technology Acceptance and Usage Behavior”, *MIS Quarterly* (24)1, pp.115–139.

Venkatesh, V., et al. (2003) “User Acceptance of Information Technology: Toward a Unified View”, *MIS Quarterly* (27)3, pp. 425–478.

Vincent, A., M.A. Meche, and D.R. Ross (2002) “Computer Learning Behavior: Strategies for Learning and Behavior Improvement”, *Journal of Information Systems Education* (13)4, pp. 331–341.

Weinberg, S.B., and M. Fuerst (1984) *Computer Phobia*, Effingham, IL: Banbury.

APPENDIX 1. INSTRUMENTS USED IN THE STUDY

Computer Knowledge

I have good knowledge and skills of … (on a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5))

1. Computers and information systems in general
2. Windows or another operation system
3. Excel
4. Access
5. HTML/Website Development
6. PowerPoint

Computing Experience

Before taking the course, how often did you use a computer for the following purposes? (On a 7-point scale ranging from never (1) to a few times a day (7))

1. Using computer for job and academic work
2. Using computer for entertainment
3. Using Office software (e.g., Word, Excel)
4. Surfing online for information (news, weather, etc)
5. Writing/checking email
6. Online chatting and other virtual communication

Social Norm (Adapted from Venkatesh and Davis [2000])

Do you agree with the following statements? (on a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5))

1. People important to me believe I should develop great expertise on computing.
2. Instructors from my previous courses encouraged me to learn more about computing.

Computer Anxiety (Adopted from Compeau et al. [1999])

Regarding my anxiety toward a NEW computer application, in fact ... (on a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5))

1. I feel apprehensive about using a new application.
2. It scares me to think that I could lose a lot of information using a new application by hitting the wrong key.
3. I hesitate to use a new application for fear of making mistakes I cannot correct.
4. A new application is somewhat intimidating to me.

General Computer Self-Efficacy (Adopted from Marakas et al. [2007])

Do you agree with the following statements about your capability of using computers? (on a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5))

1. I believe I have the ability to describe how a computer works.
2. I believe I have the ability to install new software applications on a computer.
3. I believe I have the ability to identify and correct common operational problems with a computer.
4. I believe I have the ability to unpack and set up a new computer.
5. I believe I have the ability to remove information from a computer that I no longer need.
6. I believe I have the ability to use a computer to display or present information in a desired manner.

Computer Attitudes

Do you agree with the following statements? (on a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5))

1. Knowledge and skills of computers help me on my current study.
2. Knowledge and skills of computers are critical to my academic performance.
3. Knowledge and skills of computers are critical to getting a good job.
4. Knowledge and skills of computers are critical to my future career success.

MIS Intention

(with binary answers of Yes or No)

1. Will you consider taking MIS as your major or minor?
2. Will you consider selecting MIS-related jobs for your future career?

ABOUT THE AUTHORS

Jun He is an Assistant Professor of MIS in the College of Business at the University of Michigan-Dearborn. He received his M.B.A. from Tsinghua University (China) and his Ph.D. from the University of Pittsburgh. Besides computer self-efficacy, his other research interests include systems design and development, knowledge management, and methodological issues. He has published articles in journals such as Communications of the Association for Information Systems, Information and Management, and Journal of Management Information Systems.

Lee A. Freeman is the Associate Dean of Administration and an Associate Professor of MIS in the College of Business at the University of Michigan-Dearborn. Besides computer self-efficacy, his other research interests include the pedagogy of online learning, mental modeling, information ethics, and information security. He received his B.A. from the University of Chicago and M.B.A. and Ph.D. from Indiana University.

Communications of the Association for Information Systems

ISSN: 1529-3181