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Refining the scope in computer self-efficacy relationships: an empirical comparison of three instruments in predicting competence and attitudes

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REFINING THE SCOPE IN COMPUTER SELF-EFFICACY RELATIONSHIPS: AN EMPIRICAL COMPARISON OF THREE INSTRUMENTS IN PREDICTING COMPETENCE AND ATTITUDES

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Abstract

Computer self-efficacy (CSE) has been successfully used in many studies as a significant predictor of individual performance and attitudes. However there have been ongoing criticisms concerning self-efficacy's conceptual foundations as well as its measurement. In the IS field, there have been a number of studies in which the relationship between CSE and consequent behaviors or attitudes was weak or non-existent. Reasons given for such results include problems associated with the construct of general self-efficacy, and more recently the mismatching of scope (general or specific) between self-efficacy and its predicted outcomes. Little research exists in the IS field to ascertain which instrument is appropriate given the circumstances of the study or to determine if scope plays a significant role in predictability. This study examines three CSE instruments, one general, one global, and one specific (in six domains) in their ability to predict specific and general outcomes (competence and attitudes). The CSE instruments are empirically compared using a sample of 310 ROTC Midshipmen from fourteen universities, using six common computing domains. Results suggest that instrument choice makes a significant difference in predictability and that the alignment in scope of CSE with outcomes is moderated by task mastery in that domain.

Keywords: self-efficacy, social cognitive theory, self-efficacy outcomes, self-efficacy instruments

1 INTRODUCTION AND BACKGROUND

There has been an increasing research effort in the area of self-efficacy and in particular computer self-efficacy (Downey 2004). Computer self-efficacy (CSE) has been shown to play a role in a variety of computer dispositions and activities, including positive attitudes toward computers (Compeau, Higgins, & Huff 1999), computer systems ability or performance (Gist, Schwoerer, & Rosen 1989), and computer skills development (Martocchio & Webster 1992). However self-efficacy, and in particular computer self-efficacy has been criticized and not always yielded consistent results, confounding and blurring its value as a predictor of interest to the IS profession.

CSE is defined as an individual judgment of one's capability to use a computer and computer applications (Compeau & Higgins 1995). It has been measured using task- or application-specific indices (called specific CSE or AS-CSE and including, for example spreadsheet CSE), global measures (one or two item instruments), and more generally with task-independent approaches (general CSE, or GCSE). Yet little research exists in the IS field that establishes which measure(s) of computer self-efficacy have the greatest predictive power, or under what conditions one instrument may be more appropriate than another. Recently cognitive researchers outside the IS field have recommended that the scope of self-efficacy measures (general or specific) match the scope of the predicted outcomes. While this makes intuitive sense, is scope-matching applicable in the IS field? Using a sample of 310 participants from fourteen different universities, this study compares three common self-efficacy instruments in six computer domains to establish which instrument is best in predicting the outcomes of computer competency and two attitudes (anxiety and liking). Additionally it examines whether scope-matching is an important consideration in the self-efficacy-outcome relationship.

1.1 General and Specific Computer Self-efficacy

Self-efficacy as a construct of interest is based primarily on Bandura's (1986) Social Cognitive Theory (SCT). SCT explains human behavior in terms of a continuous reciprocal interaction between cognitive, behavioral, and environmental determinants. This "triadic reciprocality" suggests that behavior, environment and cognition influence each other, resulting in a continual assessment and reassessment of actions (Bandura 1986, p. 397). According to Bandura (1986, 1997), cognition primarily influences behavior in two ways, through outcome expectations and through self-efficacy. Self-efficacy is a conviction that one can successfully execute a given task or behavior. It is a self-perception of ability to accomplish an activity. Bandura (1986) contends that self-efficacy is not merely a belief in one's ability level; it also helps generate motivation. Self-efficacy helps determine what activities an individual engages in, the effort in pursuing that activity, and the persistence in the face of adversity. It stimulates a motivational component in individuals that mobilizes the effort and cognitive skills necessary in task accomplishment (Marakas, Yi & Johnson 1998). In the field of computer behavior, studies show that self-efficacy is a significant influence in choice of technology behavior (Burkhardt & Brass 1990), attitudes toward technology (Gist et al. 1989) and performance in a wide variety of computing technologies (Rainer & Harrison 1993).

Bandura characterized self-efficacy as primarily a situation-specific belief (Bandura 1986). This is a person's judgment of ability regarding specific tasks. It is an assessment linked to a specific activity in a particular time frame. In the computing domain, specific computer self-efficacy is a judgment of ability in specific computing tasks, which are frequently organized in application domains such as word processing, spreadsheets, databases, etc. In this study, this will be labeled AS-CSE (application-specific CSE).

Bandura, however, recognized that past experiences may be generalized across domains, that is, to domains outside the specific area of interest. An individual that experiences multiple successes in many different fields may have a higher belief in his/her ability (or self-efficacy) when encountering other situations. Likewise, one who has limited success or repeated failures in a variety of fields should have lower expectations. This gives rise to a conceptual distinction between general and specific self-efficacy. Eden and Kinnar (1991) maintain that general self-efficacy measures capture those activities that transfer among domains. They describe it as a "product of a lifetime of experience, ... not amenable to change under short-lived conditions" (p. 772). In a computing context, Agarwal, Sambaburthy, and Stair (2000) call the generalized form of computer self-efficacy as a stable trait. It is a judgment of ability across multiple computer application domains (Marakas et al. 1998). General computing self-efficacy (labeled GCSE in this study) is a relatively stable attribute or characteristic of an individual that forms over time from a range of computing activities.

1.2 Issues and Problems with GCSE

Despite some impressive results, self-efficacy (and GCSE in particular) has faced a variety of important conceptual and empirical criticisms. It has been suggested, for example, that self-efficacy cannot be extricated from outcome expectations, making it multi-dimensional and confounding its measurement (Eastman & Marzillier 1984). Recently, much of the criticism concerns the construct of general self-efficacy, which some contend has little value as a predictor (Bandura 1986, 1997, Mischel & Shoda 1995). In the IT field, for example, there have been several studies in which the relationship between GCSE and performance or behavior was weak or nonexistent. Martocchio (1994) found that the relationship between training and the acquisition of declarative knowledge was not moderated as expected by computer self-efficacy (using a GCSE instrument from Hollenbeck & Brief 1987). Agarwal et al. (2000) found that GCSE (using Compeau & Higgins 1995) significantly influenced Windows 95 self-efficacy, but did not influence spreadsheet self-efficacy. Another study which used Compeau and Higgins GCSE found that it was significant *but in the opposite direction* to the perceived usefulness of a technology application (Chau 2001).

A growing number of researchers claim that the primary problem in such studies is the misuse of self-efficacy instruments; they suggest that the scope of the self-efficacy measure should match the scope of the predicted behavior (Ajzen 1991, Chen, Gully & Eden 2001). Labeled specificity matching (Chen et al. 2001), in practice this means that when the predicted behavior is performance at specific tasks, a specific SE instrument should be employed. If the behavior is general in nature, such as computing anxiety, a general SE instrument should be employed. In one recent study in an academic setting (non-IT), matching the level of specificity in measuring self-efficacy with specificity of performance affected relationship significance (Bong, 2002). The study also found that specific measures were superior to the more general measures when predicting outcomes, and there were high correlations between three levels of self-efficacy measurements (subject-, task-, and problem-specific), but concluded these were independent factors.

It has long been held (particularly in the IS field) that specific measures are superior to general measures in predicting outcomes (Bandura 1986, Gist 1987, Marakas et al. 1998). In fact there has been criticism of the most used general CSE instrument, Compeau and Higgins (1995), suggesting that it does not satisfactorily isolate the general CSE construct (Marakas et al. 1998) or that it may really measure a person's self-efficacy in learning to use computers (this from the authors themselves, Compeau & Higgins 1995). Yet little research exists that studies which CSE instrument (specific or general) is most appropriate, and almost no research compares the specificity of CSE to the specificity of outcomes. Does specificity matching apply to IT? Or do specific CSE instruments predict general outcomes (and vice versa)? This study examines the effectiveness of three CSE instruments, one specific and two general, in predicting common outcomes of self-efficacy, both specific (competence) and general (attitudes).

1.3 Measuring Computer Self-efficacy

Specific Measures: According to Bandura (1986, 1997), specific measures of self-efficacy are necessary to provide explanatory and predictive power. This guidance has been followed by many leading researchers in the IS field (e.g., Johnson & Marakas 2000, Murphy, Coover & Owen 1989). Specific CSE instruments target an individual's perception of ability to perform specific tasks within a specific computer domain, such as the familiar word processing, spreadsheet, or database domains. These examples comes from the Johnson and Marakas (2000) instrument for measuring spreadsheet self-efficacy: "I believe I have the ability to enter numbers in a spreadsheet" and "I believe I have the ability to use a spreadsheet to assist me in making decisions".

General Measures: General CSE has been operationalized in studies using two different types of instruments, general and global. Both are general instruments; the primary difference between the two is that general instruments include a dimension of difficulty (in the task or computing domain), while global instruments do not. The most common non-global approach asks the responder to assess ability given differing levels of assistance (e.g., Compeau & Higgins 1995, Gist et al. 1989). These assistance levels correspond to different levels of task difficulty. In the GCSE instrument of Compeau and Higgins (1995), for example, the respondent is asked if he/she could "complete the job" using an "unfamiliar software package", under a variety of assistance levels, including this: "If there was no one around to tell me what to do as I go".

Global Measures (GL): Global measures of self-efficacy are not task- or domain-specific (similar to GCSE) but unlike GCSE have no levels which distinguish difficulty. They are abbreviated general measures that typically include one or two items. The global instrument of Hill, Smith, and Mann (1987) has two items, one which asks respondents to rate their confidence in their computer skills. Global measures, however, have had some success in the computing field (Hill, et al. 1987, Igbaria & Iivari 1995). Global instruments are what Bandura (1986) describes as omnibus measures, which he believed had little explanatory nor predictive power.

1.4 Outcomes of CSE and Hypotheses

In previous studies, CSE has been a significant predictor of both computer performance (ability) and beliefs or attitudes. These outcomes or consequences of CSE are used in this study to compare three different CSE instruments, one task- or application-specific (AS-CSE), and two general measures (GCSE and global). The dependent variables or outcomes include competence or ability and two attitudes—computer anxiety and computer liking. Because AS-CSE is domain specific, this study included six common computing domains, word processing, spreadsheets, graphic programs (e.g., PowerPoint), databases, email programs, and web design. The outcomes of self-efficacy and hypotheses are summarized below:

Performance/Ability: One of the most fruitful influences of CSE is on ability or competence. According to Bandura (1986, 1997), self-efficacy exerts a strong and positive influence on performance and the acquisition of skills. In the computing environment, studies show that CSE is a strong predictor of computing ability (Rainer & Harrison 1993) and subsequent performance on related tasks (Marakas et al. 1998). But Bandura and others (Marakas et al. 1998, Mone 1994) contend that specific measures of self-efficacy are the strongest predictors of domain specific tasks. Spreadsheet CSE, for example, should be a stronger predictor of spreadsheet ability than a general or global measure of CSE. And the global measure should be the weakest given concerns noted by Bandura (1986). Overall computing competence can be thought of as the sum of an individual's ability level in all computing domains. It is not domain specific, but rather a generalized computing proficiency. Unlike domain-specific competence, Marakas et al. (1998) suggest that the primary value of a general instrument is in its capacity to predict overall computing performance. This leads to the first two hypotheses:

H1: Domain specific measures of CSE (AS-CSE) will have the strongest influence on domain specific competence (domains of word processing, spreadsheets, graphic programs, databases, email, and web design), followed by GCSE and then the global measure.

H2: GCSE will have the strongest influence on overall computing competence, followed by the global and application-specific measures of CSE (AS-CSE).

Beliefs/Attitudes: Previous studies show that CSE influences a variety of beliefs or attitudes. For example, CSE has been shown to exhibit an influence on outcome expectations or perceived usefulness and perceived ease of use (Agarwal et al. 2000). Computer anxiety, or fear of computers (Loyd & Gressard 1984), is one well-researched belief. Empirically different than computer attitudes (Kernan & Howard 1990), studies show that persons with high CSE have less anxiety, while those with low CSE exhibit higher anxiety (Johnson & Marakas 2000, Martocchio 1994). Computer affect has also been studied as a consequence of self-efficacy. Positive affect, or computer liking, is the enjoyment a person gets from using computers (Compeau et al. 1999) and in studies, CSE has exerted an influence on an individual's positive affect toward technology (Compeau et al. 1999, Rainer & Harrison 1993). Both computer anxiety and affect (computer liking) are general attitudes towards computing, and if specificity matching applies, GCSE should be the best predictor. Because the global measure is general, it is predicted to be better than domain-specific measures. This leads to these hypotheses:

H3: GCSE will have the strongest influence on computer anxiety, followed by the global measure then the domain-specific measure.

H4: GCSE will have the strongest influence on computer liking, followed by the global measure then the domain-specific measure.

2. METHODOLOGY

Data were gathered in early 2004 at fourteen US universities. The population of interest was Midshipmen in the U.S. Navy's commissioning program. The selection of this population was part of an ongoing study to determine the effectiveness of technology training for newly commissioned officers. The universities were selected at random from among 57 nationwide that have a Naval ROTC program. All ROTC universities received 24 surveys; the US Naval Academy received 61. Table 1 lists the participating universities with their associated response rate.

University	Recvd	% Returned	% of Total	University	Recvd	% Returned	% of Total
Naval Academy	61	100%	19.7%	Penn State	19	79%	6.1%
South Florida	24	100%	7.7%	Idaho	18	75%	5.8%
Florida	23	96%	7.4%	Ohio State	18	75%	5.8%
South Carolina	23	96%	7.4%	Washington	17	71%	5.5%
Missouri	22	92%	7.1%	Purdue	16	67%	5.2%
Minnesota	22	92%	7.1%	Oregon State	15	62%	4.8%
Kansas	20	83%	6.5%	Vanderbilt	12	50%	3.9%

Table 1. Participating universities

Of the 373 surveys sent, 310 completed responses were received for an overall response rate of 83%. Participant demographics are presented in Table 2.

Variable	M	SD	College Year		
Age	21.1	2.91	Freshmen	66	21.3%
	Number	% of Total	Sophomore	105	33.9%
Gender	267 male	86.1%	Junior	91	29.3%
	43 female	13.9%	Senior	48	15.5%
	2 unmarked				

Table 2 Sample Demographics

2.1 Measures

With few exceptions, research constructs were operationalized using scales previously developed and validated. All CSE scales followed the recommendations of Bandura (1986), including a yes/no (does the individual believe he/she can accomplish the task or item) and level of their confidence in that belief (on a 1-10 scale). CSE scores were obtained by averaging the level of confidence only for those items where a "yes" was marked, following the recommendation of Lee and Bobko (1994).

Competence: Computer competence was measured for the six computing domains of word processing, spreadsheets, graphic programs, databases, email programs, and web design, plus overall ability. The measure was adapted from a user competence instrument developed by Munro et al. (1997). For each of the applications, the respondent included the number of specific domain packages used, number of courses taken in that domain, and thoroughness of current knowledge of the domain (on a scale of 0 = "No Knowledge", 1 = "Very Limited Knowledge" to 7 = "Complete Knowledge"). Ability for that domain was calculated by summing the items. Overall competence was calculated by summing the six domain scores above, plus reported expertise in two other domains, "other" software (programming languages, financial and statistical software) and hardware (PCs, mainframes, networks, PDAs).

Global Self-efficacy: Adapted from an instrument by Hill et al. (1987), this two-item construct asks respondents to rate their confidence in "computer ability" and ability to "learn computer applications".

General Computer Self-efficacy: The ten-item measure by Compeau and Higgins (1995) was used for GCSE. This instrument asks respondents if they have the ability to carry out unspecified tasks, using an "unfamiliar" software package, with ten levels of assistance.

Specific Computer Self-efficacy: AS-CSE measures for the six computing domains were task-oriented and developed in part by Johnson and Marakas (2000), who developed the spreadsheet instrument. The other five AS-CSEs were self-developed, but were similar in scope and design to the spreadsheet measure.

Anxiety/Affect: Anxiety and affect were measured using the anxiety and computer liking subscales of the Computer Attitude Scale developed by Loyd and Gressard (1984). This instrument was validated by Al-Jabri and Al-Khaldi (1997). The anxiety subscale included eight items; the liking subscale included ten items. Both used a seven-point scale, where 1 is "completely disagree" and 7 is "completely agree".

3. RESULTS

3.1 Demographics and Variables of Interest

Demographics: Demographic variables demonstrated some statistically significant influence on the dependent variables, although it was slight (less than 1.3% of the variance explained for all variables, except one). There was an age effect for both word processing and email program competencies (younger recipients had more competence). There was a class effect on web design competence (seniors, juniors had more competence). Finally there was a gender effect for computer liking (accounting for 2.3% of the variance); males had more liking than females. There were no other significant effects for age, gender or class, nor was there a significant effect on any variable due to college attended or major. Because of the very small influence, the effect of demographics was not considered in the rest of the study.

Domain	M	SD	Domain	M	SD
Email	7.81	2.3	Web Design	2.84	3.3
Word Processing	7.39	1.9	Database	2.06	2.4
Graphic Programs	5.49	2.2	Overall Ability	53.9	22.1
Spreadsheet	5.11	2.1			

Table 3 Descriptive Statistics for Computer Competence

Competence: Competence was computed for all six computing domains plus overall computing competence. Means and standard deviations are presented in Table 3. Respondents had the highest competence in email and word processing, followed by graphic programs and spreadsheets, and then web design and database. Correlations were significant between all domains, which suggest some similarities, including keyboarding skills and Windows environment.
Attitudes: The means and standard deviations for anxiety was 1.83 (sd = 1.01) and for computer liking was 4.62 (sd = 1.26). This suggests that this population of respondents was not particularly anxious about computing and their liking for computers was relatively high. Reliabilities were .918 and .901, respectfully. The correlation between anxiety and liking was -.556. This indicated the constructs, though similar, are distinguishable and concur with previous findings (Kernan & Howard 1990).
Specific Computer Self-efficacy (AS-CSE): Descriptive statistics and intercorrelations are presented in Table 4. Respondents judged their email and word processing abilities highly, and their database and web design abilities the lowest.

Construct	**Alpha**	**M**	**SD**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1. Word processing	.949	9.06	1.43	1.0							
2. Email	.911	8.72	2.05	.589	1.0						
3. Graphic programs	.951	8.70	1.89	.635	.523	1.0					
4. Spreadsheets	.968	7.61	2.49	.498	.371	.582	1.0				
5. Web design	.976	5.30	3.60	.325	.367	.268	.392	1.0			
6. Database	.989	3.59	3.23	.143*	.225	.223	.391	.491	1.0		
7. GCSE	.930	6.87	1.83	.452	.348	.421	.484	.392	.385	1.0	
8. Global CSE	.842	7.70	1.97	.525	.401	.501	.499	.359	.334	.690	1.0

*Table 4. Descriptive statistics and correlations for self-efficacy measures. All correlations significant at $p < .01$ except that marked by * (significant at $p < .05$)*

General and Global Computer Self-efficacy: Descriptive statistics for the GCSE and global measures are also presented in Table 4. Means (out of a possible 10), indicated that the respondents had relatively high judgments of their computing ability, for both measures.

3.2 Hypotheses Testing

In order to test which self-efficacy measure is the better predictor of competence and attitudes, regression analyses were used. For each of the six computing domains, the relationship between all three self-efficacy measures (application-specific, general, and global) and each domain's competence was tested. Overall competence and the two attitudes were examined similarly. To assess which measure was a better predictor, a comparison was made of standardized regression coefficients and the amount of variance explained on the dependent variable by each form of self-efficacy.

Relationship of CSE and Competence: The relationship between all self-efficacies and each competence measure was strong and positive. To some extent this serves as construct validation of both the competence and CSE measures. Given the literature supporting this relationship, the fact that these relationships were strong lends validity to the way the constructs were measured. Simple linear regression was used to assess the strength of the relationship between each form of self-efficacy and each application-specific competence. Results are presented in Table 5, where self-efficacy measures are ordered by strength; the first one listed in the table is strongest. Results show that in five of the six domain competencies, the application-specific measures of CSE were strongest predictor. The only exception was email competence, where the global measure was strongest, although there was little difference between the top two (global and AS-CSE). For most domains, particularly the three in which respondents had less competence and usage (spreadsheets, databases, and web design), the task-specific measure explained considerably more variance in competence than did the GCSE or global instrument (between 25 and 30% more).

Competence	#1	R^2	β	#2	R^2	β	#3	R^2	β
WP	AS	.235	.487	GL	.225	.477	GCSE	.177	.424
SS	AS	.458	.678	GL	.199	.449	GCSE	.174	.420
GP	AS	.237	.489	GL	.166	.411	GCSE	.107	.332
DB	AS	.370	.610	GCSE	.108	.333	GL	.096	.315
EM	GL	.167	.412	AS	.155	.397	GCSE	.130	.365
Web	AS	.418	.648	GCSE	.127	.361	GL	.091	.307

Table 5 Best predictors of domain specific competence. AS: application specific CSE; GL: global CSE; R^2 is adjusted R^2; β is standardized beta

The domains of word processing and email were different, as was graphic programs, though to a lesser extent. For these relationships, there was not a sizeable difference between the best and second-best predictor (or between any of the three). The difference in adjusted R^2 between the best and worst predictors for email competence was only 3.7%; for word processing the difference was less than 6% (and only 1% difference between the top two). The amount of variance explained was much lower than that explained in the domains of spreadsheet, web design, and databases. For these rather ubiquitous domains (Greenlaw & Hepp 2002), the instrument used to measure self-efficacy did not make as much difference.

Hypothesis 1 predicted that the GCSE instrument would be stronger than the global measure. This was not supported. The global measure was a better predictor in four of the domains; in the other two domains both the global and general measures had similar predictive powers. The global measure was the best predictor for email competence. Overall, the global measure was a better predictor than the general measure. This was perhaps the most surprising result in the study, particularly since a similar effect was also observed in the relationship of self-efficacy and attitudes.

All CSEs (specific, general and global) significantly predicted overall computer competence. Hypothesis 2 predicted that the general measure of CSE would be the strongest predictor of overall competence. This was not supported. In fact, the global measure was the strongest predictor (accounting for 32.9% of the variance), followed by AS-CSEs of web design (30.5%) and spreadsheet (29.9%). Fourth best was GCSE (29.3%). The weakest, email, still explained 16% of the variance in overall competence. The difference between the best and fourth best predictor was only 3.5% difference in explained variance.

Relationship of CSE and Attitudes: The relationship between self-efficacy and the attitudes of anxiety and computer liking was relatively strong and in the assumed direction. Self-efficacy was positively related to liking and negatively related to anxiety. The global and general measures were the strongest predictors, in that order, followed by different AS-CSE measures. In predicting anxiety, the global measure accounted for 14% more variance than GCSE; for liking, the difference was 5%. Every specific measure (AS-CSE) significantly predicted both anxiety and liking, but these relationships were weaker than the two general measures. Regression results are presented in Table 6, ordered vertically by relationship strength.

Hypotheses 3 and 4 predicted that GCSE would be the best predictor of computer attitudes (anxiety and liking). While the general measure was better than specific measures, it was not better than the global measure. Again, the global instrument displayed some unexpected strength. Also, it is important to note that every application-specific CSE significantly predicted each general attitude, some with rather strong relationships. In this study, specific CSEs significantly predicted general outcomes and general CSEs significantly predicted specific outcomes. This suggests that specificity matching, or using the same instrument scope for both predictor and outcome, cannot be the only basis for significant relationships.

	Anxiety				Liking		
	R^2	β	t		R^2	β	t
Global	.373	-.613	-13.6	Global	.358	.600	13.2
GCSE	.232	-.484	-9.71	GCSE	.306	.555	11.7
AS-Email	.214	-.465	-9.20	AS-SS	.178	.422	8.17
AS-WP	.208	-.459	-9.06	AS-WP	.139	.376	7.12
AS-GP	.197	-.447	-8.76	AS-Web	.125	.357	6.70
AS-SS	.153	-.395	-7.55	AS-GP	.118	.347	6.50
AS-Web	.075	-.280	-5.11	AS-DB	.078	.285	5.22
AS-DB	.032	-.189	-3.37	AS-Email	.078	.284	5.20

Table 6 Regression Analyses of CSE and Attitudes. Note: all results are significant at $p < .001$

4. DISCUSSION

Computer self-efficacy has been an established predictor of computing performance and attitudes. This study was no exception. The relationship between an individual's computer self-efficacy and the computing behaviors in this study was relatively strong in all cases. There were, however, some important differences in the predictive ability of different self-efficacy measures. These results clearly suggest that some self-efficacy measures are more appropriate than others, depending on the outcome that is to be predicted and the ability level of the participants. The choice of CSE instrument, therefore, is a controllable factor in optimizing the strength of the CSE-outcome relationship. Major findings and limitations are discussed below.

The results of this study suggest that there are different levels or scopes of self-efficacy, specific to general, and each provides discrete explanatory power in the relationship between the individual and behavior. This empirically confirms the conviction of Marakas et al. (1998) that general and specific self-efficacies are distinct constructs and supports similar findings in a non-IT area (e.g., Bong 2002). General self-efficacy appears to capture that which transfers among computing domains, a trait characteristic that is described as a "stable personality disposition" (Mischel & Shoda 1995, p. 257). It also challenges the notion of some leading researchers (Bandura 1986, Gist 1987, Marakas et al. 1998) that specific instruments are best and provide the most predictive and explanatory powers for self-efficacy outcomes. In this study, general instruments were better than specific instruments for some outcomes.

One of the most surprising results in this study was the predictive strength of the global instrument. It clearly outperformed Compeau and Higgins' (1995) GCSE in predicting domain specific competencies, attitudes, and overall ability. Because of the inherent weaknesses in any two-item instrument (Netemeyer, Bearden & Sharma 2003), these results, though remarkable, may reveal more about the shortcomings of the GCSE instrument than the strength of the global (see Marakas et al. 1998 for a review of potential problems in the GCSE instrument). Although the GCSE instrument has demonstrated weaknesses, it remains the only general measure of computer self-efficacy (other than global instruments). Still, this should not obscure the results that the global instrument used in this study demonstrated impressive predictive capability in a variety of outcome relationships.

There is some indication that specificity matching applies in the IT field. In predicting domain-specific computing competence, such as database competence, application-specific measures of self-efficacy were the superior instruments. In almost all cases, AS-CSE instruments were better predictors than general or global measures of self-efficacy. As Bandura (1986) and others suggest (Gist 1987, Marakas et al. 1998), specific measures are most appropriate for specific applications. For the general attitudes of anxiety and liking, the general measures were stronger in predictive power. Both of these findings suggest that specificity matching is important. However, both the general and global measures were also significant for all domain specific abilities, and all AS-CSEs significantly predicted both attitudes. Results suggest, therefore, that matching the scope (specific or general) of the self-efficacy instrument to the scope of the predicted outcome provides some basis with which to choose an appropriate self-efficacy instrument.

There were some relationships, however, in which specificity matching did not play a prominent role in the relationship between self-efficacy and outcome. These were the relationships involving word processing and email. In these domains individuals reported the highest usage, competence, and self-efficacy. The difference between the top two predictors was small (1%) for both word processing and email. The choice of instrument, general or specific, made no difference in predictive power for application-specific competence in these two ubiquitous domains. In this study, results suggest that it wasn't that general measures had increased predictive powers in these two domains; the predictive power of GCSE/global was similar to other domains. Actually it was the specific measures that had less predictive power in email/word processing, particularly when compared to the more difficult domains (such as web design or databases). This suggests that as an individual masters a computing domain, their judgment of ability (self-efficacy) is not based on careful cognitive processing but on other things, such as experience. This supports the findings of Mone (1994), where the relationship between self-efficacy (specific in that study) and performance deteriorated over time as mastery occurred. It supports the conjecture of Marakas et al. (1998), that general measures become more useful as mastery occurs.

There are several limitations in this study. The measure of competence used in this study lacks validation. Self-reported ability measures are inherently biased (Hufnagel & Conca 1994). This measure attempts to limit this bias by including items of non-judgment-based information, such as number of courses taken in this domain and number of different domain packages used. Though still self-reported, these additional inputs mitigate to some extent the bias of a purely judgmental rendering of ability. In addition, an optional objective ability test was given in the domains of word processing or spreadsheet. These fifteen-item multiple choice tests were given to provide some convergent validity between self-reported competence measures and actual performance, in the two domains of word processing and spreadsheets. Of the 310 participants, 204 tests were received (66%). The correlation between the word processing ability measure and performance test was .367; for spreadsheets the correlation was .605. Using the tests as dependent variables, regressions were run to compare the results to previous regressions using the self-reported competence. Table 7 presents the results; for comparative purposes, the results using the self-reported competence measure as the dependent variable is also provided in parentheses.

	Word Processing		**Spreadsheet**	
	R^2	β	R^2	β
Global	.157 (.225)	.407 (.477)	.148 (.199)	.396 (.449)
GCSE	.071 (.177)	.283 (.424)	.190 (.174)	.445 (.420)
AS-CSE	.156 (.235)	.406 (.487)	.324 (.458)	.575 (.678)

Table 7 Comparison of general CSEs in predicting performance tests. Note: all results significant at p < .001. Results in parenthesis use word processing or spreadsheet competence measures.

The results suggest that there are similarities between the self-reported competence measures and actual performance. Particularly in the spreadsheet domain, correlations and regression results were strong. For both domains, all three CSEs significantly predicted performance (as measured by test), although the amount of variance explained was somewhat less. Notable also is that essentially the same self-efficacy order of strength is preserved, whether the outcome variable is the actual performance (test) or self-reported domain competence. By strength, the order remains AS-CSE, global, and GCSE.

Another limitation involves the cross-sectional nature of the study. Because data were gathered at one time, causation cannot be determined and other factors cannot be ruled out. It cannot be established that self-efficacy caused the variability in outcomes; it could be that competence or attitudes caused the variation in self-efficacy. Indeed, Bandura (1986) notes the reciprocal nature of self-efficacy and ability; he also notes that either relationship direction can be examined at any particular point in time. Finally, generalizability to a general population must be approached with caution. This population is one in a commissioning program and may be different than the American population at large or even a university student population. Particularly vulnerable was the gender ratio (86% male). However there is some indication that this population is no different than other student groups (c.f., Carlson & Grabowski 1992).

This study establishes that self-efficacy instruments should be tailored to the individual study. When the interest is in predicting domain specific abilities, task-or application-oriented (AS-CSE) measures are best. However, general measures have an important role and best predict general attitudes and overall computing ability. The global instrument was surprisingly robust in this study and outperformed Compeau and Higgins' GCSE instrument. This clearly indicates a need in the IS community to develop an effective general CSE instrument that does not have the shortcomings of GCSE or a two-item global instrument. Future studies should continue to explore the role of specificity in the relationship between self-efficacy and its outcomes, particularly with respect to the effect of domain ability. In this study, matching the scope of self-efficacy with outcome was not important in domains with high ability. An examination of the moderating effects of ability on the CSE-performance relationship would further refine the construct. Self-efficacy remains one of the important constructs of interest in IS to both practitioners and researchers, and studies should continue to explore its relationship with outside variables of interest.

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