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A Meta-Analytic Review of More than a Decade of Research on General Computer Self-Efficacy: Research in Progress

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ABSTRACT

In their seminal work, Compeau and Higgins (1995) provided the IS research community with a measure of computer self-efficacy (CSE) based on Bandura's (1986) Social Cognitive Theory. The use of this CSE measure has since flourished within various academic literatures. Recent research interest (Marakas, Johnson, & Clay, 2007; Thatcher, Zimmer, Gundlach et al., 2008), however, challenges the continued application and analysis of Compeau and Higgins' (1995) measure despite its widespread adoption. This paper presents the results of a meta-analysis of general CSE provided through the foundation of technology adoption research. The results should create future dialogue regarding general CSE and its application. We show evidence of moderate associations (r = |0.32| to |0.59|) of general CSE with several technology adoption research constructs. Guidance is offered for future moderator analyses, which may likely provide empirical evidence for either the support or refutation of current research claims in regard to general CSE.

Keywords

General Computer Self-Efficacy, Meta-analysis, Compeau and Higgins 1995, CSE.

INTRODUCTION

Since Compeau and Higgins' (1995) development and initial test of a measure of general computer self-efficacy (hereafter referred to as the C&H95), many authors have cited this work and/or utilized the C&H95 to help provide support for their individual research models. Compeau and Higgins (1995), however, was not the first attempt of a systematic review of computer self-efficacy. Many authors have also studied and/or developed measures of computer self-efficacy (Cassidy & Eachus, 2002; Gist, Schwoerer, & Rosen, 1989; Torkzadeh & Koufteros, 1994; Webster & Martocchio, 1992).

Despite this fact, none of the above measures has received more interest (both positive and negative attention) than the C&H95. Agarwal, Sambamurthy, and Stair (2000), for example, successfully utilized the general CSE measure to show how such cognitive beliefs influence the perceived ease of use of new technologies. Others have successfully shown CSE's significant relationship with individuals' perceptions of computer anxiety (Compeau, Higgins, & Huff, 1999). For as much benefit as the measure has rendered in the past, though, it seems that struggles are ahead. Recent interests in the IS discipline have challenged authors' continued use of the C&H95 in application-specific domains. More specifically, researchers believe an overall general measure of CSE like the C&H95 may explain less variance in the dependent variable(s) of interest than would a CSE measure tailored specifically to the application or technological domain of interest (Marakas, Yi, & Johnson, 1998; Marakas et al., 2007). Furthermore, authors suggest that organizational computing environments have changed quite dramatically from the development period of the C&H95 and other measures of CSE thus making them less appropriate for much of the current research in today's more advanced organizational computing settings (Marakas et al., 2007). And, while the authors that question the C&H95's ability to capture the needed explanatory variance across different studies believe that it is no doubt of high quality (Marakas et al., 2007), other researchers call into question the C&H95's unidimensionality (Thatcher et al., 2008).

The purpose of the current study is twofold. First, we conduct meta-analytic techniques to determine the strengths of the C&H95's associations with five variables of interest to technology adoption researchers (i.e., perceived usefulness, perceived ease of use, behavioral intention to use, actual usage, and technology anxiety). Such a study would help to determine the overall predictive validity of the C&H95 (at least in regard to technology adoption research). From our analysis, we conclude that the C&H95 maintains moderate correlations with these five variables at the population level. Second, from our additional omnibus tests, we show that moderators are likely to be present among these associations. Guidance is offered as to which moderators may be present and whose analysis would benefit the current debate regarding general CSE.

Why the C&H95?

At first glance, some might wonder why a meta-analytic review of the C&H95 is needed. Several reasons should interest readers in such a study. First, with the exception of Davis' (1989) measures regarding perceived usefulness and perceived ease of use of technologies, researchers of many disciplines have utilized the C&H95 perhaps more than any other measure created within the IS literature. In fact, our efforts show that over 700 articles cite the Compeau and Higgins (1995) paper and/or utilize the C&H95 for empirical analysis in research models across academic disciplines. This finding lends evidence that Compeau and Higgins (1995) has provided a background that appeals to IS and non-IS authors alike who study various technological domains.

Second, as stated above, the evaluation of CSE measures has recently become a point of heightened interest to IS researchers. The recent publications in *Information Systems Research* and the *Journal of the Association for Information Systems* by Marakas and colleagues challenge the notion that the C&H95 should hold equally useful across all technological evaluations and time frames. Though this notion was not specifically proposed by Compeau and Higgins (1995), many authors who utilize the C&H95 reinforce this impression by applying the general measure in a multitude of application-specific situations.

Third, and perhaps most important from an IS research methods standpoint, few meta-analytic reviews of research in the IS discipline exist. A search of three well-respected IS journals (i.e. *MISQ, ISR,* and *JMIS*) reveals only five meta-analytic works since 2000 (i.e., Dennis & Wixom, 2001; Dennis, Wixom, & Vandenberg, 2001; Kohli & Devaraj, 2003; Sharma & Yetton, 2003; Sharma & Yetton, 2007). We believe that meta-analyses present a much needed complement to single empirical studies by providing population parameter estimates within the nomological network of constructs. Granted that the IS discipline is more immature (i.e., less aged) than other disciplines and therefore may not provide an abundance of opportunities for such reviews, we believe the meta-analytic technique should be given increased attention as it represents a powerful method to synthesize previous empirical research. For all of the above reasons, we feel that this research is quite timely and desired.

In the sections that follow, we briefly describe the theoretical foundation upon which much of the general CSE research has been based as well as an introduction to some of the empirical works it has been integrated in. Following this discussion, we detail our methodology for obtaining articles for inclusion in our meta-analysis as well as our initial tests. Finally, we provide evidence of the presence of moderators within the examined relationships from our omnibus tests and provide guidance for the selection of plausible moderators to expand this work.

LITERATURE REVIEW

The theoretical foundation for much of the research in computer self-efficacy is Social Cognitive Theory (SCT) (Bandura, 1986). As proposed by Bandura (1986), SCT provides a basis for understanding how an individual's characteristics, an individual's environment, and an individual's behavior reciprocally reinforce each other. Also within the SCT framework, Bandura (1986) suggests that an individual's self-efficacy is an important cognitive element in the actual achievement of individual goals or the demonstration of particular behaviors. Self-efficacy is defined as "people's judgments of their capabilities to organize and execute courses of action required to attain designated types of performances" (Bandura, 1986, p. 391). This definition suggests that self-efficacy represents the perception of an individual's ability to engage in a course of action rather than a measure of actual capability. Thus, individuals who are self-efficacious judge themselves as having the capability of successfully taking on a course of action whether the individual can in reality do so.

In application of the self-efficacy concept to IS research, Compeau and Higgins (1995) define computer self-efficacy as "an individual's perceptions of his or her ability to use computers in the accomplishment of a task…rather than reflecting simple component skills" (p.191). Further, this measure of general CSE is based on three interrelated dimensions of self-efficacy (i.e., magnitude, strength, and generalizability). In regard to computing environments, magnitude reflects the degree of task difficulty one believes s/he is capable of attaining. Strength refers to the level of conviction or confidence in one's judgment of CSE. And finally, generalizability represents the degree to which one's CSE judgments are limited to a particular situation (Compeau & Higgins, 1995).

The initial test of the C&H95 helped provide evidence of the strength of Bandura's (1986) SCT as a theoretical framework in understanding the influence of one's environment on perceptions of CSE. In further support of SCT as the foundation for the development of the C&H95, the authors found that CSE perceptions significantly influence one's affect toward computing technology, one's anxiety in using computing technology, and ultimately one's use of computing technology (Compeau &

Higgins, 1995). Subsequent longitudinal research also supports the above findings relative to general CSE's consequences (Compeau et al., 1999).

In addition to a SCT foundation, much of the work on general CSE has been integrated with Davis' (1989) Technology Acceptance Model (TAM). These studies help explain how cognitions regarding personal capabilities influence the adoption of new technologies. One of the first works to integrate these two streams was Venkatesh and Davis (1996). This study found that general CSE had a significant positive effect on perceived ease of use (PEOU) (Venkatesh & Davis, 1996). Practical reasoning for this relationship suggests that individuals will base their perceptions regarding the PEOU of a technology on their perceptions of their abilities in utilizing computing technology in general, regardless if the individual has any experience with the new technology under assessment. Other studies have subsequently linked CSE with other TAM variables such as the perceived usefulness (PU) of a technology (Agarwal & Karahanna, 2000; Ong, Lai, & Wang, 2004; Thompson, Compeau, & Higgins, 2006) and the similar construct of outcome expectancies (Agarwal & Karahanna, 2000; Compeau & Higgins, 1995; Compeau et al., 1999). CSE's direct relationship with behavioral intention (BI) to adopt a technology and ultimately technology usage, though less often investigated, have also been cited (Compeau et al., 1999; Hasan, 2006; Mathieu, Ahearne, & Taylor, 2007; Mellarkod, Appan, Jones, et al., 2007). These studies combine to show the important role that CSE has played in technology adoption research.

In addition to integration with TAM variables, the literature has also reviewed the empirical link between CSE and technology anxiety (Compeau et al., 1999; Thatcher et al., 2008; Venkatesh, 2000). The literature supports the notion that when cognitions regarding one's efficacy in utilizing a computer to accomplish tasks are high, the individual should be less likely to experience anxiety towards actual utilization of that technology. One longitudinal study already mentioned showed that general CSE and anxiety exhibited a strong and negative correlation with each other (i.e., $r = -0.54$; Compeau et al., 1999).

Agarwal, Sambamurthy, and Stair (2000) have already noted the research utilizing the general CSE measure is not limited to its predictive focus in the technology adoption literature. For instance, research in learner effectiveness has shown that virtual learning environments can produce higher levels of CSE in participants beyond that produced by traditional classroom methods (Piccoli, Ahmad, & Ives, 2001). Others have attempted to show that prior experience builds CSE and that CSE ultimately leads to increased performance following computer training (Bolt, Killough, & Koh, 2001). Notwithstanding the advancements proffered by these and other studies outside of the technology adoption arena, most of them do not empirically examine relationships involving the same constructs, a necessary condition for meta-analytic techniques. Due to the IS community's vast interest in technology adoption research, the adoption literature provides an adequate number of studies desired for our meta-analytic purposes of general CSE. Therefore, we rely heavily on studies integrating general CSE with TAM.

In the following sections, we briefly describe the meta-analytic technique as well as our data collection method. We then provide evidence from our initial meta-analysis results of the overall level of influence that general CSE (i.e., C&H95) exhibits among five variables researched in the adoption literature (i.e., perceived usefulness, perceived ease of use, behavioral intention to adopt, usage, and technology anxiety). Following this report, we discuss future directions that should be taken in order to more fully examine potential moderators of these relationships.

METHODOLOGY

Meta-analyses are appropriate when determining the strength of correlations between variables at the population level by integrating findings across a myriad of studies. These techniques allow the researcher (1) to correct for sampling error and (2) to correct for measurement attenuation of both constructs in a correlation (Hunter & Schmidt, 2004). Because multiple studies are integrated in meta-analyses that show correlations of any magnitude, researchers utilizing this technique do not need to worry about Type I error. In other words, empirical evidence already supports the existence of a relationship within the population. Thus, the null hypothesis of no relationship between two variables can be automatically rejected.

To obtain articles relevant to our study, we searched three electronic databases: Google Scholar, Web of Science, and Business Source Premier. We identified over 700 unique articles from these sources that cite Compeau and Higgins (1995) after removing duplicates. Only 49 studies actually utilized the C&H95 **and** provided the necessary statistics for conducting a meta-analysis (a list of these articles is available upon request). This grouping included studies examining the adoption of various technologies (e.g., MS Excel, text editors, sales technology, Internet banking, Oracle Developer 2000) in various countries (e.g., Belgium, Canada, Hong Kong, Taiwan, United States) since 1995 thus providing a good "proving ground" for the general applicability of the C&H95. Studies that did not report correlations but provided a covariance structure among constructs along with standard deviations and construct means were converted to correlational statistics. Studies that recorded only the inter-item correlations among items in a research model were included by averaging the inter-item

Initial Tests of Overall CSE Influence						
Variable	N	k	r_{bar}	r_{corr}	95% Conf.	Fail Safe N
PU	4849	21	0.25	0.32	(0.26 0.38)	494
PEOU	6195	24	0.36	0.47	(0.42 0.52)	832
BI	3153	14	0.27	0.35	(0.26 0.43)	360
USAGE	3822	9	0.28	0.38	(0.27 0.49)	246
ANXIETY	2742	9	-0.46	-0.59	(-0.64 -0.53)	404

Table 1. Results of Initial Tests

N = sample size, k = number of studies, r_{bar} = uncorrected population correlation estimate, r_{corr} = corrected population correlation estimate, 95% Conf. = 95% confidence interval for r_{corr}

correlations to form a single correlation. Correlations from studies with a longitudinal approach were averaged across measurements as were correlations from a single sample on multiple technologies within the same study.

Along with correction for sample sizes, meta-analyses also allow researchers to correct for measurement attenuation. These corrections utilize the internal consistency measures provided by researchers, most often in terms of Cronbach alphas. Due to an increased focus on partial least squares (PLS) analysis, however, composite reliabilities were sometimes reported rather than Cronbach alphas, while some studies reported both. The use of composite reliabilities should not pose a threat to our corrections for measurement attenuation as Cronbach alphas represent a lower limit of internal consistency than other measures of consistency (Hair, Black, Babin, et al., 2006). Therefore, by using composite reliabilities rather than Cronbach alphas when possible, we decrease our chance of over-correcting for measurement attenuation when reporting our corrected correlation statistics. In instances where no internal consistency measure was reported, we substituted the average of the internal consistency measures within the respective grouping of studies as suggested by Hunter and Schmidt (2004).

INITIAL FINDINGS

As shown in Table 1, we were able to obtain studies for all five of our relationships of interest (i.e., PU, PEOU, BI, Technology Usage, and Anxiety). The r_{bar} indicates the association strength at the population level before any correction is applied, whereas the r_{corr} indicates the population effect following the application of both sample size and measurement attenuation corrections. Fail safe N represents the reliability of sample selection, and it indicates the number of nonsignificant studies that would be necessary to reduce the effect size to a nonsignificant value. According to the initial findings, the C&H95 exhibits moderate associations with the other variables at the population level. For example, the C&H95 (in a bivariate relationship) would help explain 10% (i.e., r_{corr} = 0.32) of the variance in PU and 35% (i.e., r_{corr} = -0.59) of the variance in anxiety.

DISCUSSION

Before expounding upon our initial findings, we should note that the meta-analysis performed herein is based on a small to a moderate number of studies. Hence, our inability to find more studies reporting statistics necessary for meta-analytic techniques may pose a limitation on any derived meanings. Further, we did not readily seek unpublished studies to include in the analysis; thus, the introduction of publication bias in the study is possible.

Given the recent debate regarding the continued usefulness of a general measure of CSE across a myriad of applications and time frames, our findings indicate that the use of general CSE in research modeling the adoption of technology provides relatively important levels of predictive validity. In particular, the general CSE measure exhibits its strongest influence on anxiety and perceived ease of use perceptions. Lower population effects were found for relationships with perceived usefulness as well as behavioral intention to use and actual usage of the technology. Thus, while the strength of the relationships between CSE and the other variables examined ranges from |0.32| to |0.59|, we are comfortable in making the assessment that, to date and in general, the C&H95's applicability across various technological domains and time frames within the technology adoption literature has thus been warranted, at least from a predictive standpoint. This claim must not be construed, however, to indicate that improvements cannot be made to increase the predictive validity of the measure or that other measures of CSE are incapable of producing similar or better results. As our omnibus tests for potential moderators show below, variations do exist among the studies collected, which are an indication that the C&H95 is likely to have varying influences in different situations.

Omnibus Tests for the Presence of Moderators			
Variable	**Obs. Var**	**95% Cred.**	**% of Variance**
PU	0.020275	(-0.00 0.63)	22%
PEOU	0.014764	(0.21 0.74)	30%
BI	0.027824	(-0.04 0.73)	17%
USAGE	0.028520	(-0.04 0.80)	9%
ANXIETY	0.007552	(-0.71 -0.47)	68%

Table 2. Results of Omnibus Tests for Moderators

Obs. Var = observed variance, 95% Cred. = 95% credibility interval for r_{corr},% of Variance = percentage of variance accounted for by research artifacts

FUTURE MODERATOR ANALYSES

Each of the groupings from Table 1 was further subjected to omnibus tests to help gauge whether moderators were likely to exist among the studies. Specifically, two techniques were provided to assist in this determination: the calculation of credibility intervals (not to be confused with confidence intervals) and the calculation of the percentage of variance accounted for by research artifacts. Briefly, if the credibility interval for any grouping includes zero and/or is large, then moderators are likely to be present (Whitener, 1990). Also, if the percentage accounted for by research artifacts is less than 75%, then moderators may be present within the relationships (Hunter & Schmidt, 2004). The results shown in Table 2 indicate that moderators are likely to be present in all five of our groupings. (We note that the omnibus test for the CSE-Anxiety relationships is near the suggested cutoff of 75% variance accounted for by artifacts while also exhibiting a relatively narrow credibility interval in comparison with the other groupings.)

With substantial evidence of moderators present, we believe that the examination of several possible moderators should assist in expanding our work. We propose that a review of the source of data (both respondent type and culture) as possible moderators would prove beneficial as they have in previous meta-analytic works (Schepers & Wetzels, 2007) to further assist in determining how generalizable the initial findings described here are. We also believe that current CSE issues in the academic literature provide the guidance in our selection of three more possible moderators: (1) the use of an adapted (i.e., tailored) measure; (2) the use of a shortened measure; and, (3) the time period in which studies were conducted. Researchers have indicated (Johnson & Marakas, 2000) that a CSE measure might be a stronger predictor if the stem were adapted or tailored to the particular software or technology under examination. Perhaps this suggestion would help answer one of Compeau and Higgins' (1995) original closing questions: "Is it reasonable to use general self-efficacy measures, or is it necessary to tailor the items to these specific hardware and/or software domains?" (p. 206). Current research has also proposed that the C&H95 is formative rather than reflective in nature (Marakas et al., 2007), which should suffer from researchers using shortened versions in lieu of the complete 10-item C&H95 measure (Diamantopoulos & Winklhofer, 2001). Finally, major changes in the adoption of technology have occurred since the C&H95 was released. Such changes (e.g., increased utilization of both the Internet and PCs) may lead to significant increases in respondents' scores on an overall general measure such as the C&H95, thereby reducing the C&H95's ability to capture variance in the dependent variables of interest. Thus, we suggest that a final potential moderator of interest would likely be the time period in which the individual studies took place. We are currently in the process of coding our studies in hopes of presenting the results of such moderator analyses at conference.

CONCLUSION

The academic literature is becoming infused with work critical of authors' application and analysis of the general CSE construct. We present a meta-analysis regarding scholarly work utilizing the general CSE construct (more specifically, Compeau and Higgins' (1995) measure). Our initial findings indicate moderate associations at the population level between general CSE and variables in technology adoption research (i.e., PU, PEOU, BI, Usage, and Anxiety) with the largest influences evident in relationships with PEOU ($r_{corr} = 0.47$) and anxiety ($r_{corr} = -0.59$) across a myriad of studies. Thus, this study shows the extent of predictive validity of general CSE with these variables under a wide range of different technological investigations (e.g., MS Excel, text editors, sales technology, Internet banking, Oracle Developer 2000) in various international settings (e.g. Belgium, Canada, Hong Kong, Taiwan, United States), thereby showing support for the general applicability of the C&H95. We close by providing a discussion to guide future moderator analyses, which should provide important empirical evidence to help researchers make decisions regarding the current debate on the general CSE measure.

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