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Computer Self-Efficacy: A Meta-Analytic Review

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Abstract

After more than 30 years of research into computer self-efficacy (CSE), the time has come to assess the progress made on this construct and whether we need to reconsider its conceptualization and nomological network. To do so, we used meta-analytic techniques to review 683 papers and aggregated results across 749 independent samples. Our results suggest that out of 30 variables suggested by Marakas et al. (1998) in their narrative review, only 7 were sufficiently examined to warrant inclusion in an empirical meta-analysis. At the same time, our analysis identifies 18 variables that had not been examined as part of CSE's nomological network. Our research also indicates that relationships are robust and consistent across 11 potential categorical and continuous moderators, suggesting few moderators in a relationship with CSE. Evidence suggests that national culture and the setting where a study is conducted can moderate the relationship between CSE and such variables. Although these findings are consistent with current theory, much work remains if we wish to systematically test a theoretical understanding of how CSE is formed and influences performance. Our work confirms CSE's continuing relevance in managing contemporary work environments and offers directions for future research.

Keywords: Computer Self-Efficacy, Meta-Analysis, Training, National Culture, Sampling, Personality, Social Cognitive Theory, Measurement

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1 Introduction

In 1998, Marakas and colleagues published a synthesis of computer self-efficacy (CSE) research that succeeded in tying the fragmented literature together. Drawing insight from disciplines such as education, information systems (IS), management, and psychology, the synthesis articulated a nomological network of 30 variables that were either antecedents to CSE or mediated the relationship between CSE and performance. By linking the disparate fragments of CSE research, the authors established a foundation for later research, arguing that "pursuing a rigorous investigation into the CSE construct at both the general and task-specific levels is of significant value" (Marakas et al., 1998, p. 157).

Over two decades and hundreds of citations later, their study has dramatically influenced CSE research. What is not so clear is whether its foundation has resulted in a systematic program of inquiry into CSE. Although many studies have utilized CSE, few have answered the call to rigorously investigate the methods, measures, and models of CSE; its boundary conditions; and its impact on consumers, employees, and learners. Instead, its synthesis has been used to justify CSE as an ad hoc or control variable serving as an antecedent to IT adoption decisions (e.g., Venkatesh, 2000). Although it is an important contributor to understanding why individuals adopt new technologies, it does not help scholars gain a deeper understanding of the construct or how it evolves and affects the performance of computing tasks.

Marakas et al. (1998) called for empirical replications to confirm relationships in their model, but to date, few have occurred. One exception is the replication study of Compeau and Higgins's (1995a) work conducted by Torres et al. (2022), which confirmed most paths in the model but produced weaker findings than the original study, underscoring the changing nature of the computing domain, where measures and conceptualization of CSE continue to evolve.

The shift from the use of computers as the principal domain of technicians to one widely used by employees and consumers (Petter et al., 2012) has implications for how CSE shapes the use of computers in organizations and society. The information technology (IT) context today is quite different from the computing context that existed when CSE was first investigated. The current IT environment includes devices such as desktop and laptop computers, smartphones, tablets, self-service kiosks, and work devices (e.g., inventory scanners, self-checkout machines) using software as simple as an online alarm timer to a fully integrated, multifunction organizational enterprise resource planning (ERP) system. To function properly, many devices and software depend on access to the internet and other networks. As a result, the increased complexity of the computing use context and the growth in its user base constitute boundary conditions for how CSE frames the use of consumer, enterprise, productivity, and other software.

Vancouver and colleagues (Vancouver & Kendall, 2006; Vancouver et al., 2008) have suggested that when self-efficacy is extremely high, overconfidence can lead to a lack of preparation and cognitive effort, resulting in negative performance, although this line of thought has yet to be examined in the CSE literature. Although CSE researchers have generally found consistent relationships between antecedents and performance, some primary findings have proven countertheoretical. For example, Cazan et al. (2016) found that CSE was positively related to computer anxiety. Staples et al. (1999) and Johnson et al. (2016a) saw negative correlations between CSE and performance, although these may have been due to a measurement mismatch or lack of experience. Without a complete set of CSE studies, we cannot determine whether such findings are artifactual or substantive. Thus, to move the literature forward in a systematic way, an examination of the current state of CSE research is needed.

To ensure a rigorous reflection of CSE, we employed meta-analysis to empirically summarize the literature, identify understudied topics, and articulate an agenda for future work. The assessment makes several contributions to the literature. First, it identifies which portions of the Marakas et al. (1998) model have received support, which have not, and which have yet to be investigated. Second, it considers changes to the relationship between efficacy, antecedents, and consequences that include research design (survey/experiment, cross-sectional/longitudinal), sample characteristics (students/employees, gender), and use contexts (computing/internet, consumer/corporate/education and training). We also considered the economic development of the country in which research was conducted, as well as local culture (individualism/collectivism, power/distance).

Our meta-analysis encompasses 683 papers and aggregated results across 749 independent samples. As such, it represents the most complete and comprehensive review to date, intended to provide a robust understanding of CSE. Based on its findings, we articulate an updated model of CSE that includes advances in self-efficacy and changes to the context of computing use. Finally, we offer a contemporary agenda to guide future research, identifying important but underresearched variables and articulating directions for research. The findings may guide researchers as they seek innovative ways to examine CSE (e.g., blue ocean theorizing), given the diverse contexts of IT use.

2 Computer Self-Efficacy

CSE is an estimation of an individual's ability to use a computer (Compeau & Higgins, 1995b). Researchers have explored the role that CSE plays during software training (Compeau & Higgins, 1995a), e-learning (Santhanam et al., 2008), and task performance (Looney et al., 2006). CSE has also been examined in such software contexts as text editing (Hasan, 1998), office productivity (Yi & Davis, 2003), and enterprise systems (Hwang & Grant, 2011).

These studies have found that people with higher CSE may outperform those with lower CSE, set higher goals, and be more committed to them (Johnson, 2005). Individuals with higher self-efficacy tend to put more effort into completing tasks, are more likely to persist when they face difficulties, and respond better to feedback than those with a lower level of self-efficacy (Bandura & Cervone, 1983; Martocchio & Webster, 1992). Researchers have argued that CSE exists at multiple levels of specificity (Marakas et al., 2007) and have examined its role at the software application level (Santhanam et al., 2008; Yi & Davis, 2003), the application environment (e.g., Windows, iOS, and Linux) (Agarwal & Karahanna, 2000; Marakas et al., 2007), as well as more general levels (Compeau et al., 2022). Overall, research findings suggest that CSE may play a significant role in how individuals learn to use computers, perform computer-based tasks, and respond to new technology.[1]

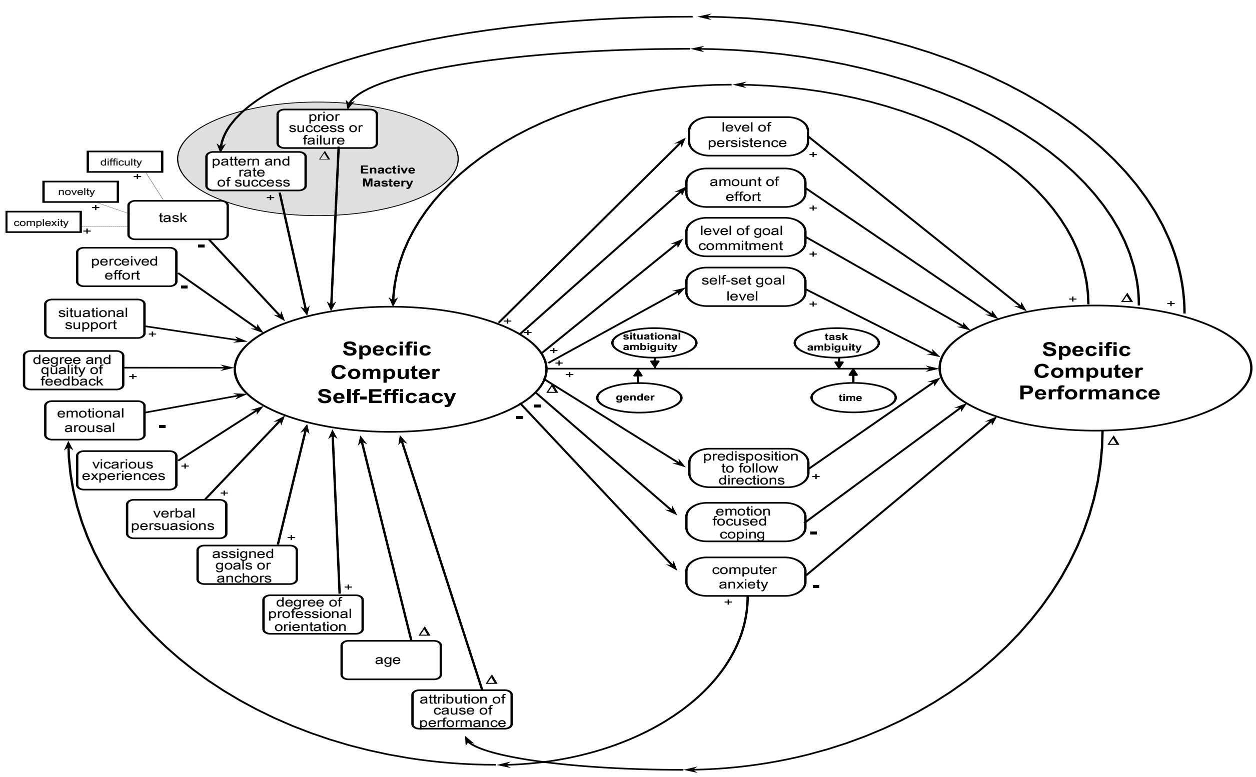
[1] A full theoretical derivation of CSE is beyond the scope of this paper but has been undertaken by other researchers. Interested readers are encouraged to review the work of Marakas et al. (1998) and Compeau et al. (2006).

2.1 The Nomological Net of CSE

Self-efficacy theory (Bandura, 1997) identifies four factors that can affect someone's efficacy estimations, namely enactive mastery (actual experience), vicarious experience, verbal persuasion, and emotional arousal (anxiety). Each has received support in the literature on self-efficacy (Bandura, 1997) and CSE (Marakas et al., 1998). Compeau and Higgins (1995a) showed that enactive mastery and vicarious experience (e.g., behavioral modeling training) as part of a spreadsheet training program can contribute to increases in CSE, and Smith (1994) found that verbal persuasion improved women's estimations of CSE. Researchers have also reported that computer anxiety (emotional arousal) affects CSE estimations (Thatcher & Perrewe, 2002). Building on these four antecedents, Marakas et al. (1998) developed a model of variables that can affect CSE or mediate the relationship between CSE and performance (see Figure 1), including demographic characteristics (age, gender, etc.), motivation and goal-setting variables, causal attributions, and task characteristics.

Although the Marakas et al. (1998) model has greatly influenced how we study CSE, the rationale for including specific variables is often based on a single study, which suggests the need to update the inclusion rationale for variables to be included. Since their review, the technology we use and the contexts in which we use it have evolved significantly. The population of interest for early CSE research was mainly comprised of software programmers, developers, or technical staff because most people had limited familiarity with computers. Today, employees are expected to transition seamlessly between PCs, laptops, tablets, smartphones, kiosks, and other forms of computing technology (Johnson et al., 2016b). Technology has also been embedded into consumer artifacts such as automobiles or smartwatches that are capable of processing and acting on data without human intervention.

Given these changes, researchers have argued that we must carefully assess CSE and its relevance to contemporary organizations and society (Compeau et al., 2022). The need for such assessment is underscored by the self-efficacy literature, which has identified boundary conditions and other factors that shape CSE and its relationship to performance (Vancouver et al., 2008) but have yet to be incorporated into the IS literature.



Note: (+) Increase in factor results in an *increase* in dependent variables. (−) Increase in factor results in a *decrease* in the dependent variable. (Δ) Relationship to the dependent variable is *disordinal* in nature. Source: Marakas, G. M., Yi, M. Y., & Johnson, R. D. (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), 126-163.

Figure 1. Extant Model of Specific Computer Self-Efficacy

Table 1. Comparison of CSE and ISE

Construct	Brief definition	Sample item
Computer self-efficacy	Ability to use computers or computing software	I believe I have the ability to manipulate the way a number appears in a spreadsheet (Johnson & Marakas, 2000).
Internet self-efficacy	Ability to navigate, use, and evaluate content on the Internet	I feel confident finding information on the world wide web (Torkzadeh & Van Dyke, 2001).

2.2 Computer Self-Efficacy and Internet Self-Efficacy

Since the 1998 publication of the Marakas et al. review, research on internet self-efficacy (ISE), a related yet distinct construct, has grown dramatically. Because individuals access the internet using a computer, it is tempting to view ISE as part of CSE. However, because ISE is conceptually and empirically distinct (Eastin & Larose, 2000; Hsu & Chiu, 2004; Torkzadeh & Van Dyke, 2001), a unique literature has arisen around this construct. ISE is an individual's perceived ability to navigate, use, and evaluate content on the internet (Daugherty et al., 2005; Tsai, 2004), whereas CSE is an individual's belief in their ability to use a computer (Compeau & Higgins, 1995b). These constructs are related because most software applications run on or require an internet connection and can focus on the networked computing domain. However, CSE focuses on one's skill in using a computer or software, while ISE focuses on such tasks as navigating the internet, searching for information, generating and disseminating information online, and using the internet to communicate (Chuang et al., 2015; Eachus & Cassidy, 2006; Eastin & Larose, 2000; Tsai, 2004) Table 1 provides brief definitions of these terms and sample items.

2.3 Previous Reviews of CSE

The extant reviews of the CSE literature are limited, either focusing on a subset of variables or being broad and narrative in nature. For example, Karsten et al. (2012) conducted a meta-analysis that focused on CSE's correlation with seven adoption variables, including ease of use, usefulness, computer anxiety, behavioral intention, and adoption behavior. They found statistically significant and positive relationships between CSE and six of the variables, as well as a negative relationship with anxiety. However, it is important to note that five of the seven relationships had credibility intervals that included zero. Although the Karsten study shed light on the empirical relationships between CSE and variables in adoption contexts, it did not speak to CSE in different training and use contexts. In addition, Oliver and Shapiro (1993) presented a brief overview of CSE research conducted in the late 1980s, while Compeau et al. (2006) conducted a narrative review of the CSE literature and found that much of the research was focused on performance rather than the formation of CSE.

Each narrative review improved our understanding of CSE formation, but because they are decades old, they may not reflect the richer technological environments in which users now engage. As a result, the field lacks an updated integrative theoretical understanding of the implications in training users and assessing how they perform when using information and computing technologies. To address this gap, our work examines a much greater period, allowing us to examine whether the role of CSE has changed over time. Second, we employ meta-analytic techniques to examine the largest set of variables in the CSE nomological network compiled to date. Third, complementing the Karsten et al. (2012) review, our study focuses on the role of CSE in training and use rather than adoption. We thus draw on previous studies, identify variables that have emerged since they were published, and consider a far broader set of constructs.

2.4 Moderators

Meta-analytic techniques allow scholars to assess whether method or context affects the variation across CSE studies (Gerow et al., 2014; Schmidt & Hunter, 2015). Meta-analysis is increasingly employed in studies of the adoption and use of IS (Blut et al., 2016, 2022). Drawing on theory (Bandura, 1997), previous CSE reviews (Compeau et al., 2006; Marakas et al., 1998), meta-analyses of self-efficacy (Gegenfurtner et al., 2013; Karsten et al., 2012; Stajkovic & Luthans, 1998), and IS meta-analyses (Blut et al., 2022; Hess et al., 2014), we identified a variety of potential demographic, methodological, and substantive moderators, utilizing three main criteria to determine which to include. First, a moderator had to have a solid theoretical rationale in either the self-efficacy or the CSE literature. Second, it had to have compelling empirical evidence supporting its inclusion. And third, there had to be sufficient k ($k \geq 10$) for each level. Based on these criteria, we identified 11 moderators that may be relevant. Each is discussed below.

2.4.1 Methodological Moderators

We examined study design (experiment vs. survey), type (longitudinal vs. cross-sectional), and sample (students vs. non-students). Each moderator had been examined in previous meta-analyses and was argued to potentially affect research findings (Mitchell et al., 1994; Schepers et al., 2011; Shadish et al., 2002). We also examined the type of scale, general versus specific. Marakas et al. (1998) argued that a mismatch in the level of measurement of CSE and performance could contribute to "a weakening in the observed relationship between CSE and performance" (p. 154), an argument supported by Johnson and Marakas (2000), who found that a specific CSE measure correlated more strongly with performance than a general CSE measure. Others have maintained that as skills are mastered over time, CSE reflects an overall efficacy toward computers on which users anchor as they make future efficacy judgments (Downey et al., 2008; Marakas et al., 2007). Thus, scale level may affect the strength of the relationship between CSE and other variables.

2.4.2 Year of Study

Given the evolution of computers and how we interact with them, the year in which a study is conducted can serve as a moderator. When the first CSE studies were conducted, mainframe and minicomputers were the dominant forms of computing. As the domain has evolved to include large-scale, web-based ERP systems, personal computers, laptops, tablets, and smartphones, the types of tasks computers perform have also changed. Unlike early systems that focused on basic data processing, today's ubiquitous devices enable individual and organizational decision-making, consumer transactions, communication, and social connections.

The user base of computing has also changed. Most early users were technical experts trained to design and deploy IS, while today's users come from many backgrounds and age groups and are not primarily technical. Thus, the current computing environment is vastly different than the one in which the CSE construct was first assessed (Compeau et al., 2022; Johnson et al., 2016b; Petter et al., 2012). Based on this, we propose the following hypothesis:

H1: The strength of the relationship with CSE will be stronger in earlier studies.

2.4.3 Gender (Masculinity/Femininity)

Some researchers have noted that women tend to have lower CSE than men (e.g., Wei et al., 2011). Gender has also been identified as a variable that may moderate the relationship between CSE and performance (Marakas et al., 1998) as well as IT adoption (Blut et al., 2022). One reason for this could be women's tendency to underestimate their abilities (Sieverding & Koch, 2009), which can reduce the strength of the relationship between CSE and other variables.

It is important to note, however, that findings on the moderating role of gender have been mixed, with some studies observing a stronger moderating effect (Siddiq & Scherer, 2016) than others (Mäntymäki & Salo, 2013). One explanation is that it is not biological sex but rather gender role that affects the relationships with CSE. One study presented evidence that once a gender role had been statistically controlled for, other gender differences became nonsignificant (Ogletree & Williams, 1990). Based on the above, and the small k for gender, we assess gender using the masculinity/femininity dimension of culture.

Hofstede (1991) defined culture as a "collective programming of the mind which distinguishes the members of one group or category of people from another" (p. 5). Culture captures a group's values, beliefs, communication patterns, assumptions, and social norms that together manifest in an individual's beliefs about what they can, should, or should not do (Srite & Karahanna, 2006). Masculinity/femininity focuses on the extent to which a culture reflects highly structured male and female gender roles. Characteristics typically associated with masculine gender roles are assertiveness, competitiveness, and toughness. From a career standpoint, characteristics associated with masculine gender roles are a focus on earnings, recognition, advancement, and the importance of challenging work. The characteristics typically associated with feminine gender roles include caring for people, children, and the home. Career-related behaviors include cooperation, management of relationships, and living in a location desirable for family and employment security. Countries with distinct gender roles are generally considered masculine, while those where gender roles overlap are considered more feminine (Hofstede, 1991). In countries that are considered masculine, individuals may be likely to develop skills and pursue careers that fit cultural gender roles, whereas in more "feminine" cultures, such distinctions may not be as strong, suggesting a greater variation in computing skills and CSE between men and women in masculine countries. Thus, we propose the following hypothesis:

H2: Masculinity/femininity will moderate the relationship between CSE and the variables examined in this study, such that the relationship will be stronger in more masculine countries.

2.4.4 Individualism/Collectivism

Bandura (1997) suggested that differences in individualism/collectivism shape how individuals develop self-efficacy and its relationship to performance. Individualism/collectivism refers to the extent to which group identity is shaped by personal choices or the group to which a person belongs (Hofstede, 1991). Consistent with this, Earley (1993) found that managers in individualistic countries such as the US exhibited higher self-efficacy and performance when an individual-focused management system was put into place, and lower efficacy and performance when a group management system was used. By comparison, managers in collectivist countries such as China exhibited greater self-efficacy working in teams that shared the same cultural background (e.g., collectivism).

Although efficacy estimations reflect an individual's skill assessment, they also reflect an assessment relative to others, particularly in collectivistic countries. Thus, the role of the group in an individual's assessment of self-efficacy may be more pronounced in collectivist cultures (Earley, 1993, 1994). Research has also shown that people from individualist cultures respond differently to questions regarding the self-competence aspects of self-esteem, a concept similar to self-efficacy (Baranik et al., 2008). Thus, those from individualist and collectivist cultures may differ in how CSE relates to other variables. Individualism/collectivism was measured for each study using the scores of the sample country in which the research was conducted (Hofstede, 2010). Thus, we propose the following hypothesis:

H3: Individualism/collectivism will moderate the relationship between CSE and the variables examined in this study, such that the relationships will be stronger in more individualistic countries.

2.4.5 Power/Distance

The power/distance dimension of culture reflects the extent to which a culture accepts inequality. A higher score reflects a higher tolerance for inequalities. In lower power/distance cultures, relationships are more consultative and less hierarchical. Subordinates are more likely to engage with, contradict, and challenge supervisors, whereas in higher power/distance countries, relationships are more hierarchical, managers direct subordinates' work, and relationships are less consultative. Thus, performance may be less dependent on individual skills and competence and more dependent on relationships. Based on such differences, CSE may be seen as less important in higher power distance cultures. In support of these arguments, Almukhlifi et al. (2018) found that the Middle Eastern concept of *wasta* moderated the relationship between ISE and intention to use eGovernment services. According to Harbi et al. (2017), *wasta* can be understood through the lens of individual/collectivism and power/distance.

H4: Power/distance will moderate relationships between CSE and the variables in the model such that relationships will be stronger in lower power/distance countries than in higher power/distance countries.

2.4.6 Country Development

The extent of a country's human development can also moderate the relationship between CSE and the variables examined in this study, with the populations of more developed countries generally having higher levels of income, education, and life expectancy. Individuals in these countries should thus have greater access to and experience using computers and other digital devices. Thus, CSE estimates may have lower variance in more developed countries than in less developed countries. This can weaken CSE's relationship with the variables of interest. Conversely, studies conducted in less developed countries may show weaker relationships with CSE because their populations will likely have less exposure to computers, resulting in less calibrated CSE estimates. A country's level of development was assessed using the Human Development Index (HDI), assessed on a 0-1 scale. Those with higher scores had higher income, education, life expectancies, and economic opportunities. Thus, we propose the following hypothesis:

H5: Country development will moderate the relationships between CSE and the variables examined in this study.

2.4.7 Technology Context

As noted previously, researchers maintain that ISE and CSE represent different constructs of related but separate domains. As Bandura (1997) and Marakas et al. (2007) observed, CSE measures that are closely aligned with the domain of interest will more accurately reflect the relationship between CSE and other variables in a model. When the measure of CSE and outcomes of interest are less aligned, it will weaken the relationship between CSE and the variables of interest (Marakas et al., 1998), so that when CSE is measured for an internet-based task, the relationship with other variables will be weaker than when it is measured for a computer-based task. Thus, we propose the following hypothesis:

H6: The strength of the relationships with CSE will be weaker in an internet use context than in a computing use context.

2.4.8 Use Context

The context in which CSE is measured may also serve as a moderator. We categorized studies into three contexts: corporate, consumer, and education and training. Studies of the corporate context tend to focus on IS used in an organization. These can be individual systems that focus on office productivity or organizational systems such as ERPs. Such systems are instrumental, concerned with improving employee performance. Studies in the consumer context emphasize fulfilling social or personal needs. Most involve online shopping and factors that motivate consumers to purchase or consume goods. Finally, the context of education and training focuses on formal settings where individuals learn to use software.

These contexts differ substantially and could moderate the relationships between CSE and the variable of interest. The education and training setting may feature motivational factors, skills, and experience that are more highly correlated with CSE than the other two contexts. However, they may be weaker in the consumer context, i.e., less important in purchase decisions. In consumer contexts, which are often hedonic, personality states such as personal innovativeness with information technology (PIIT) and playfulness play a greater role than in other contexts. Finally, in the corporate context, instrumental factors such as experience or performance are often more related to CSE. Thus, we propose the following hypothesis:

H7: The strength of the relationships with CSE will be moderated by the use context.

3 Method

3.1 Data Collection and Coding

Our sample of studies was drawn from journals, books, conference papers, and dissertations. Dissertations and conference papers were included to reduce the so-called "file drawer problem" (Rosenthal, 1979).[2] In addition, we reached out to scholars, asking them to supply unpublished studies. Multiple keywords were utilized in our search, including *computer self-efficacy, software self-efficacy, e-learning and self-efficacy*, and *technology and self-efficacy*. We searched over 80 databases, including the ACM Digital Library, the AIS e-Library, Academic Search Complete, Business Source Complete, ERIC, ProQuest Dissertations and Theses, and Web of Science. Fields spanned by this search included IS, education, e-learning, management, and psychology. Finally, we reviewed the bibliographies of each work for additional references.

A trained undergraduate student and two of the authors conducted the search, which ultimately yielded an initial sample of 3,513 papers.

3.2 Pool of Primary Studies

Five inclusion criteria were established for our meta-analysis. First, a study had to contain some form of CSE. Several studies identified in the search mentioned CSE but did not in fact examine it (e.g., Carlson & Zmud, 1999). We also screened out studies that focused solely on ISE, information privacy self-efficacy, or general self-efficacy since, as noted, ISE is a distinct construct with its own scales and measures (Eastin & Larose, 2000). Information privacy self-efficacy and general self-efficacy studies were not included because neither encompasses technology. Second, the measurement of CSE and its correlated construct had to correspond with definitions found in the broader literature. Table 2 lists the constructs examined in this meta-analysis and their definitions. It also contains hypotheses for their theorized relationship with CSE. Two examples of studies that did not meet criteria for inclusion are Hakverdi et al. (2007), which measured system use as self-reported expertise on software, and Teo et al. (2002), which claimed to measure performance as self-directed learning, but upon review actually measured course utility.

Third, the study had to report correlation coefficients (r) or similar statistics that allowed us to estimate r (such as d, t, or F). If the study was empirical but statistics were not available, we contacted the authors by email. We contacted 253 authors and received correlation matrices from 16 (a 6.32% response rate).

Fourth, studies had to provide independent samples to avoid dependent data and prevent problematic weighting (Bobko & Roth, 2013; Downey & McMurtrey, 2007). Thus, if the same correlation was reported in a dissertation, conference paper, and/or journal publication, it was only included once. When data were presented multiple times, we chose the published journal version (Downey & McMurtrey, 2007) versus a conference proceeding or dissertation (Downey & DeLooze, 2006). Some studies included multiple measures of a construct. For these, we created a composite correlation using Hunter and Schmidt's (2004) formula and a composite reliability that used Mosier's (1943) formula.

Fifth, any time there are fewer than 10 studies, a greater sense of uncertainty regarding interpreting conclusions may arise (Switzer et al., 1992). For this reason, we analyzed variables that correlated with CSE in 10 or more studies. Although not a criterion for inclusion per se, it reduced the number of variables included in the meta-analysis. For a summary of the article inclusion process, please see Table 3.

Our final sample consisted of 489 journal articles, 83 dissertations, and 111 conference papers. In all, 683 empirical studies met the criteria and included 479 independent samples (overall $N = 279{,}414$). Appendix A contains a complete list of studies, Appendix B contains the sample characteristics (users, technology, use context, and country) where data were collected, and Appendix C contains all included effect sizes.[3]

[2] The file drawer problem reflects the challenge that, in any field, researchers "cannot tell how many studies have been conducted but never reported" (Rosenthal, 1979, p. 638).

[3] Due to space constraints, all appendices can be found at https://osf.io/xyqbw/overview

Table 2. Constructs and Hypotheses

Construct	Description	Hypothesis	Rationale
Age	Age of the individual respondent (often measured in years)	H1: Age will be negatively related to CSE, such that older individuals have lower CSE than younger individuals.	Younger individuals are argued to have broader and fuller experiences with a variety of technologies, which should increase their confidence in using computers and other computing devices (e.g., smartphones) and mobile apps. Research has also found a negative correlation between age and CSE (Brown et al., 2010; Burkhardt, 1994)
Agreeableness	Personality trait that reflects an individual's desire to maintain harmonious relationships with others	H2: Agreeableness will be positively related to CSE.	Agreeableness is a Big 5 personality trait. Researchers have argued that agreeableness makes it easier for individuals to pursue new activities, such as learning to use new computing devices or software, which can increase their CSE (Judge et al., 2007; Stajkovic et al., 2018). Research has found that agreeableness and CSE are positively correlated (Rupp et al., 2018; Venkatesh & Windeler, 2012).
Computer anxiety	An effective state where an individual feels fear and apprehension about interacting with computers or technology	H3: Computer anxiety will be negatively related to CSE.	Higher levels of anxiety (e.g., emotional arousal) signal to the individual that he or she may not have the skills to complete the computer task, which will reduce CSE. Computer anxiety and CSE are reported to be negatively related (McKenna et al., 2013; Thatcher & Perrewe, 2002).
Computer experience	Experience using computing technology; includes experience with spreadsheets, databases, ERP software, computing in general, computer programming, teaching with computers, etc.	H4: Computer experience will be positively related to CSE.	Enactive mastery is one of the strongest sources of efficacy information. Those with mastery experiences will be more confident in their use of computers (Marakas et al., 1998). Researchers have also found that CSE and performance are positively correlated (Compeau & Higgins, 1995a; Johnson, 2005).
Computer knowledge	Knowledge about a specific software package or computer application	H5: Computer knowledge will be positively related to CSE.	When individuals have greater knowledge about computers, software, and other apps, they should also be more confident in their ability to use these tools. Research has also found that knowledge is positively related to CSE (He & Freeman, 2010; Martocchio, 1992)
Computer skill	Subjective or objective assessment of an individual's skills in completing technology tasks	H6: Computer skills will be positively related to CSE.	Computer skills are developed over time as individuals build skills. As they develop skills, they should become more confident and better able to calibrate their CSE (Johnson & Marakas, 2000). Researchers have also reported that computer skills and CSE are positively correlated (Pavlou & Fygenson, 2006; Yang & Cheng, 2009).
Conscientiousness	Personality trait characterized by being thorough, careful, and task and achievement/goal-focused	H7: Conscientiousness will be positively related to CSE.	Individuals who are more conscientious will set higher goals and be more dedicated to these goals. Martocchio and Judge (1997) suggest that "self-efficacy represents the mechanism through which the generalized tendencies of conscientiousness manifest

			themselves" (p. 766). Research has also found that conscientiousness is positively related to CSE (Devaraj et al., 2008; Rupp et al., 2018).
Education	Formal education level of the participant	H8: Education will be positively related to CSE.	Often used as a control variable. The more education an individual has received, the greater the breadth/depth of their experiences. Those with more education should be more open and confident when they are exposed to new software, apps, and devices. Although several studies have found educational attainment and CSE are positively correlated (Bakke & Henry, 2015; Beas & Salanova, 2006), some have not (Oostrom et al., 2013).
Gender	Gender of the participant; male or female	H9: Males will have higher CSE than females.	Females are argued to have lower CSE than males because they have fewer experiences using technology than males. Research has also found that women have lower CSE than men (Wei et al., 2011). However, some research suggests that when experience is controlled, any sex differences are not significant (Ogletree & Williams, 1990).
Interaction	Interactions and collaboration among participants and/or instructors in a classroom setting; most often within an online classroom	H10: CSE will be positively related to the amount of interaction with others that an individual has in an e-learning setting.	Individuals with higher CSE should be more comfortable interacting with others online and should communicate more (Johnson & Brown, 2017). CSE is reported to be positively correlated with e-learning interactions (Choi et al., 2007; Johnson et al., 2008).
Locus of control	Degree to which an individual believes that they control events in their life versus an external entity	H11: Individuals with an internal locus of control will have higher CSE than individuals with an external locus of control.	When individuals believe that they have the resources and capabilities to exert control over their environment, they should be more confident that they can perform tasks within that environment (Wood & Bandura, 1989). Research has found that individuals with an internal locus of control have higher CSE (Johnson et al., 2009; Workman et al., 2008).
Metacognition	An individual's awareness of and ability to regulate cognitive processes during learning	H12: CSE will be positively related to metacognitive behavior.	When individuals have higher CSE, they should be able to dedicate greater cognitive resources to learning and not navigating the online learning environment. When individuals have lower CSE, they are more likely to focus more cognitive efforts on the learning environment itself, reducing their ability to engage in metacognition. CSE and metacognition are said to be positively related (Johnson et al., 2009; Schmidt & Ford, 2003).
Microcomputer playfulness	Degree of cognitive spontaneity when using a computer	H13: CSE will be positively related to microcomputer playfulness	Individuals with higher cognitive playfulness are more likely to utilize software, apps, and devices in creative and innovative ways, which suggests that they are more comfortable and confident with these tools than those with lower cognitive playfulness. Researchers have

			also found that CSE and playfulness are positively correlated (Agarwal & Karahanna, 2000; Webster & Martocchio, 1992).
Motivation to learn	Desire to learn or master the content of a training program	H14: CSE will be positively related to an individual's motivation to learn.	When individuals believe that they are learning or performing effectively, it increases their motivation to continue engaging in that behavior. Specifically, when individuals have higher CSE, their motivation to learn is higher than when they have lower CSE. This increased motivation signals that they may have stronger skills, which in turn increases CSE. Research has found that CSE and motivation to learn are positively correlated (Martocchio & Webster, 1992; Yi & Davis, 2003).
Neuroticism	Personality trait characterized by feelings such as anxiety, insecurity, worry, and fear	H15: Neuroticism will be negatively related to CSE.	Individuals with greater neuroticism more frequently feel a lack of control and higher anxiety. Given that self-efficacy is about exercising control in a specific environment (Bandura, 1997), neuroticism should be negatively related to CSE. Empirical evidence suggests neuroticism and CSE are negatively related (Davis & Yi, 2012; Saleem et al., 2011).
Openness to experience	Personality trait characterized by flexibility of thought and tolerance of new ideas	H16: Openness to experience will be positively related to CSE.	Individuals with higher openness to experience view new experiences as opportunities rather than challenges and should approach the use of new software, apps, and devices positively. These positive perceptions can enhance CSE estimations (Stajkovic et al., 2018). Openness to experience and CSE are reported to be positively related (Devaraj et al., 2008; Saleem et al., 2011).
Outcome expectancy	An individual's assessment that a specific behavior will lead to specific outcomes	H17: CSE will be positively related to outcome expectancy.	When individuals believe that they have the capabilities to successfully complete tasks, they will also be more likely to believe that it will lead to stronger outcomes. Research has found that CSE and outcome expectancy are positively correlated (Compeau et al., 2022; Compeau & Higgins, 1995b).
Performance	An individual's task(s) performance; measured as a score on individual tasks or overall course performance	H18: CSE will be positively related to performance.	When individuals are more confident in their ability to use software, apps, or devices, they will put in more effort, work harder, and ultimately perform better than those with lower confidence. Research has found that CSE and performance are positively related (Compeau & Higgins, 1995a; Johnson, 2005).
Personal innovativeness with it	Willingness of an individual to try new information technology	H19: CSE will be positively related to personal innovativeness with IT.	Individuals with higher PIIT will be more likely to experiment and take risks with new software, apps, or devices, which will provide more opportunities to learn and perform effectively, which will increase CSE. Research has found that CSE and PIIT are positively related (Agarwal et al., 2000; Venkatesh & Windeler, 2012).

Training satisfaction	The degree to which an individual is satisfied with the training	H20: CSE will be positively related to training satisfaction.	When individuals have higher CSE, they will be able to navigate the learning environment and overcome obstacles more successfully. In turn, this will create a more positive learning environment, leading to higher satisfaction with training. Research has found that CSE and training satisfaction are positively correlated (Hu & Hui, 2012; Martocchio & Webster, 1992).
Self-efficacy	An individual's belief about their ability to perform a specific task	H21: CSE will be positively related to self-efficacy.	Individuals who have higher generalized self-efficacy should also have higher self-efficacy in specific domains. For this reason, CSE and CSE in another domain may also be related. However, it is possible that high efficacy in one domain is not related to efficacy in another domain of functioning. Research indicates that task domain efficacy and CSE are positively related (Sang et al., 2010; Santhanam et al., 2008).
Self-regulated learning	An individual's ability to understand, manage, control, and leverage the available resources in the learning environment	H22: CSE will be positively related to the use of self-regulated learning strategies.	When individuals can self-manage their learning, they should be more likely to seek feedback and assess their progress, which should lead to higher CSE. CSE and self-regulated learning are reported to be positively correlated (Gravill & Compeau, 2008; Yilmaz, 2017).
Support	Perception of the extent to which an organization is providing the resources necessary to support use of the system	H23: CSE will be positively related to the amount of actual or perceived support provided.	When individuals perceive that they have the support they need to be successful, this will increase their CSE. However, although most research has found that support is statistically significantly positively related to CSE (Compeau & Higgins, 1995b; Scott & Walczak, 2009), some studies have not found this relationship (Lewis et al., 2003; Sykes, 2020).
User competence	An individual's breadth and depth of knowledge, skill, and abilities regarding information technology and their ability to apply this knowledge	H24: User competence will be positively related to CSE.	User competence is developed over time as individuals build knowledge and skills about software, apps, and devices. As competence develops, individuals should become more confident and better able to calibrate their CSE. User competence and CSE have been found to be positively correlated (Munro et al., 1997; Schmidt & Ford, 2003).
Utility judgment	Extent to which individuals believe that training/coursework provides them with relevant knowledge or skills	H25: CSE will be positively related to an individual's utility judgments about training.	Relative to those with lower CSE, individuals with higher CSE will be able to navigate the learning environment more successfully, which will allow more cognitive resources to be available to focus on learning tasks. This should allow them to see the value of the content of the course. Research indicates that CSE and utility judgments are positively correlated (Johnson et al., 2008; Webster & Martocchio, 1995).

Table 3. Inclusion Criteria

Criteria	Illustrative study	Studies excluded	Percentage excluded
1. Includes some form of computer self-efficacy	Barnoy et al. (2008)	1395	39.7%
2. Empirical data available	Brinkerhoff (2006)	1176	33.5%
3. Non-duplicate studies	Gupta (2017)	12	0.4%
4. At least ten (10) studies have a correlation with CSE	Cagirgan Gulten et al. (2011)	247	7.0%
Original pool of studies		3,513	
Total excluded studies		2,830	80.5%
Total included unique sample studies		683	19.5%

3.3 Coding of Study Characteristics and Interrater Agreement

We randomly selected 40 studies, and two of the authors independently coded the subjects (student versus non-student), technology (software, general, e-learning, etc.), study type (survey, experiment), analysis used (SEM, regression, etc.), sample size, country, CSE measure source, and CSE level (general or specific). The intercoder agreement was 94.68%. Disagreements were resolved by reexamining the article in question. In each case, the disagreement was the result of a coding error by one of the authors and did not require a coding update to correct.

4 Analysis

To integrate the studies' quantitative findings, we used Schmidt and Hunter's (2015) psychometric approach to meta-analysis. This is a technique that applies coding and statistical procedures to combine results from independent studies that use similar constructs; it has been employed in studies on the adoption and use of IT (e.g., Blut et al., 2022; Blut et al., 2016; Gerow et al., 2014). For a discussion of this technique, see Glass (1981), Hunter and Schmidt (2004), or Lipsey and Wilson (Lipsey & Wilson, 2001). Calculations were conducted using the Schmidt-Le program (Schmidt & Le, 2005).

A key advantage of the Hunter-Schmidt approach is that it allows a researcher to correct measurement errors that can downwardly bias population correlation estimates (i.e., make them too small). To account for this, we corrected the correlations for unreliability using an artifact distribution of internal consistency measures of reliability for CSE and the related variable (Hunter & Schmidt, 2004). We thus made sure our results would produce a conservative correction of the correlations (Hunter & Schmidt, 2004).

We calculated three effect size estimates and the variability of these estimates. The first is the mean effect size ($\hat{p}$), which estimates the mean true population correlation and reflects the magnitude of the relationship with CSE. Second, credibility intervals (CVs) reflect the distribution of the parameter estimates. Typically, 80% CVs are reported. When the CV includes zero, the researcher cannot be sure whether the true population estimates from various studies are positive, negative, or zero. Confidence intervals (CIs) reflect the accuracy and likelihood of error in $\hat{p}$. When the 95% CI does not include zero, the mean effect is assumed to be statistically significant (Gerow et al., 2014).

For categorical moderators, we used *t*-tests to assess whether the mean effect (e.g., $\hat{p}$) of one group differed from another's mean effect.[4] A significant *t*-test indicates that the mean effect of each group differs from the other (Nastjuk et al., 2024). As continuous moderators, we used linear regression, with the correlation as the dependent variable and continuous moderators as the independent variables. To compute these regressions, we took the sampling error as the WLS weight using SPSS version 28. A significant result would indicate that the moderator does influence the correlation (Gonzalez-Mulé & Aguinis, 2018).

Before conducting the main analysis of the study, further analyses of publication bias, sample size outliers, and effect size outliers were conducted (Blut, 2021; Geyskens et al., 2009; Grewal et al., 2018).[5] Publication bias and related issues were assessed using fail-safe N (FSN) (Rosenthal, 1979) and funnel plots. FSN reflects the number of studies with nonsignificant results that are needed to render the results of the relationship nonsignificant (see McDaniel et al., 2006, for details). Of the 26 relationships examined, the FSN varied between 1 and 453. Other than neuroticism (FSN = 1), FSN was k = 18 or greater for all other variables.

[4] We thank an anonymous reviewer for suggesting these analyses.

[5] We thank an anonymous reviewer for suggesting these analyses.

A second method for assessing publication bias is the use of funnel plots, a graphical approach to assessing bias that plots effect size on the horizontal axis and sample size on the vertical axis. The interpretation of funnel plots is based on the assumption that the average effect size may be similar in both large and small studies, with greater variation shown in small samples. Ultimately, funnel plots are an "eyeball test," where the researcher assesses the extent to which plots reflect an inverted funnel (Sabherwal et al., 2006). Our analysis revealed that for many relationships, the risk of publication bias was minimal.

Sample size outliers were assessed using box plots and funnel plots. For any correlation in which the box plot identified a sample size outlier, a funnel plot was reviewed to determine if the correlation was an outlier. This was not the case in any instance, providing further evidence that sample size did not present an overall threat to our results.

Finally, effect size outliers were assessed using box plots. Two options are available when effect size outliers are indicated. Some scholars recommend removing studies with outliers and testing the relationships to see if they have been materially affected by outliers (Geyskens et al., 2009). Others argue that the existence of an outlier does not necessarily mean that it is inaccurate or incorrect (Grewal et al., 2018). That is, extreme values (outliers) may occur purely by chance (Baker & Jackson, 2008) and are difficult to identify as "true outliers [or] legitimate but extreme values" (Schmidt & Hunter, 2015, p. 23). Extreme values can occur naturally due to sampling errors in studies with a small or moderate *N* and should not be eliminated from the data (Schmidt & Hunter, 2015). Our analysis showed that only two correlations (agreeableness and conscientiousness) were potentially influenced by extreme outliers, both from the same study. For these correlations, we removed the outlier from further analysis. (Please see Appendix D at https://osf.io/xyqbw/overview for further details).

5 Results

Analyses are reported in four sections. First, we discuss the results with respect to CSE and the original four core self-efficacy antecedents (Bandura, 1997). Second, we report results for additional antecedents investigated by CSE researchers. Third, we report the outcomes of CSE in the context of training and performance. Fourth, we report the analysis of moderating variables. Table 4 presents the correlation matrix for all the variables investigated. Table 5 provides the results of our main analysis.

Table 4. Study Correlations

	1	2	3	4	5	6	7	8	9
1. Computer self-efficacy	----								
2. Computer experience	$\hat{\rho} = 0.416$ $k = 147$	---							
3. Computer anxiety	$\hat{\rho} = -0.353$ $k = 141$	$\hat{\rho} = -0.302$ $k = 34$	---						
4. Age	$\hat{\rho} = -0.116$ $k = 81$	$\hat{\rho} = 0.043$ $k = 39$	$\hat{\rho} = 0.073$ $k = 17$	---					
5. Gender	$\hat{\rho} = -0.071$ $k = 83$	$\hat{\rho} = -0.065$ $k = 31$	$\hat{\rho} = 0.096$ $k = 16$	$\hat{\rho} = -0.008$ $k = 48$	---				
6. Education	$\hat{\rho} = 0.108$ $k = 32$	$\hat{\rho} = 0.156$ $k = 14$	$\hat{\rho} = -0.086$ $k = 4$	$\hat{\rho} = 0.118$ $k = 22$	$\hat{\rho} = -0.090$ $k = 17$	---			
7. Support	$\hat{\rho} = 0.264$ $k = 68$	$\hat{\rho} = 0.062$ $k = 13$	$\hat{\rho} = 0.021$ $k = 11$	$\hat{\rho} = -0.028$ $k = 7$	$\hat{\rho} = -0.028$ $k = 14$	$\hat{\rho} = -0.319$ $k = 1$	---		
8. Conscientiousness	$\hat{\rho} = 0.197$ $k = 18$	$\hat{\rho} = 0.143$ $k = 5$	$\hat{\rho} = -0.216$ $k = 3$	$\hat{\rho} = 0.139$ $k = 5$	$\hat{\rho} = -0.101$ $k = 5$	---	$\hat{\rho} = 0.128$ $k = 2$	---	
9. Openness to experience	$\hat{\rho} = 0.319$ $k = 10$	---	$\hat{\rho} = -0.179$ $k = 2$	$\hat{\rho} = 0.028$ $k = 3$	$\hat{\rho} = -0.104$ $k = 2$	---	---	$\hat{\rho} = 0.403$ $k = 10$	---
10. Locus of control	$\hat{\rho} = 0.106$ $k = 12$	$\hat{\rho} = 0.021$ $k = 2$	$\hat{\rho} = -0.197$ $k = 2$	$\hat{\rho} = -0.107$ $k = 1$	$\hat{\rho} = -0.130$ $k = 2$	---	---	---	---
11. Neuroticism	$\hat{\rho} = -0.209$ $k = 17$	$\hat{\rho} = -0.150$ $k = 4$	$\hat{\rho} = 0.462$ $k = 3$	$\hat{\rho} = -0.002$ $k = 5$	$\hat{\rho} = -0.010$ $k = 6$	$\hat{\rho} = -0.050$ $k = 2$	---	$\hat{\rho} = -0.304$ $k = 11$	$\hat{\rho} = -0.221$ $k = 9$
12. Playfulness	$\hat{\rho} = 0.407$ $k = 31$	$\hat{\rho} = 0.484$ $k = 5$	$\hat{\rho} = -0.215$ $k = 16$	$\hat{\rho} = -0.067$ $k = 7$	$\hat{\rho} = -0.014$ $k = 3$	$\hat{\rho} = -0.092$ $k = 3$	---	$\hat{\rho} = 0.003$ $k = 3$	$\hat{\rho} = -0.263$ $k = 3$
13. Personal innovativeness in IT	$\hat{\rho} = 0.451$ $k = 60$	$\hat{\rho} = 0.375$ $k = 15$	$\hat{\rho} = -0.191$ $k = 19$	$\hat{\rho} = -0.164$ $k = 12$	$\hat{\rho} = -0.230$ $k = 9$	$\hat{\rho} = -0.127$ $k = 6$	$\hat{\rho} = 0.124$ $k = 4$	$\hat{\rho} = -0.054$ $k = 5$	$\hat{\rho} = -0.236$ $k = 4$
14. Domain self-efficacy	$\hat{\rho} = 0.397$ $k = 27$	$\hat{\rho} = 0.230$ $k = 10$	$\hat{\rho} = -0.145$ $k = 2$	$\hat{\rho} = 0.016$ $k = 6$	$\hat{\rho} = -0.004$ $k = 7$	$\hat{\rho} = -0.059$ $k = 1$	$\hat{\rho} = 0.093$ $k = 1$	$\hat{\rho} = 0.039$ $k = 2$	$\hat{\rho} = -0.395$ $k = 1$
15. Interaction	$\hat{\rho} = 0.275$ $k = 20$	$\hat{\rho} = 0.192$ $k = 4$	$\hat{\rho} = 0.039$ $k = 7$	$\hat{\rho} = 0.131$ $k = 2$	$\hat{\rho} = -0.470$ $k = 1$	---	$\hat{\rho} = 0.604$ $k = 3$	---	
16. Outcome expectations	$\hat{\rho} = 0.431$ $k = 38$	$\hat{\rho} = 0.373$ $k = 12$	$\hat{\rho} = -0.200$ $k = 10$	$\hat{\rho} = -0.015$ $k = 3$	---	$\hat{\rho} = -0.006$ $k = 1$	$\hat{\rho} = 0.292$ $k = 6$	---	---
17. Performance	$\hat{\rho} = 0.256$ $k = 121$	$\hat{\rho} = 0.210$ $k = 40$	$\hat{\rho} = -0.189$ $k = 24$	$\hat{\rho} = 0.000$ $k = 25$	$\hat{\rho} = -0.015$ $\hat{\rho} = -21$	$\hat{\rho} = -0.115$ $k = 6$	$\hat{\rho} = 0.205$ $k = 8$	$\hat{\rho} = 0.252$ $k = 7$	$\hat{\rho} = 0.081$ $k = 3$
18. Training satisfaction	$\hat{\rho} = 0.340$ $k = 21$	$\hat{\rho} = 0.237$ $k = 17$	$\hat{\rho} = -0.132$ $k = 13$	$\hat{\rho} = 0.090$ $k = 8$	$\hat{\rho} = 0.191$ $k = 10$	$\hat{\rho} = 0.049$ $k = 3$	$\hat{\rho} = 0.353$ $k = 4$	$\hat{\rho} = 0.195$ $k = 2$	---
19. Utility judgment	$\hat{\rho} = 0.455$ $k = 16$	$\hat{\rho} = 0.315$ $k = 3$	$\hat{\rho} = -0.062$ $k = 3$	$\hat{\rho} = 0.010$ $k = 2$	$\hat{\rho} = 0.092$ $k = 5$	$\hat{\rho} = 0.185$ $k = 1$	$\hat{\rho} = 0.053$ $k = 4$	---	---

20. Metacognition	$\hat{p}$ = 0.323 k = 15	$\hat{p}$ = 0.179 k = 2	$\hat{p}$ = 0.323 k = 1	---	---	---	---	---	---
21. Self-regulated learning	$\hat{p}$ = 0.430 k = 13	$\hat{p}$ = 0.187 k = 2	$\hat{p}$ = 0.163 k = 1	$\hat{p}$ = 0.259 k = 1	$\hat{p}$ = -0.044 k = 2	---	$\hat{p}$ = -0.002 k = 1	---	---
22. Agreeableness	$\hat{p}$ = 0.236 k = 13	$\hat{p}$ = 0.494 k = 2	$\hat{p}$ = -0.421 k = 3	$\hat{p}$ = 0.130 k = 3	$\hat{p}$ = 0.126 k = 2	---	---	$\hat{p}$ = 0.434 k = 12	$\hat{p}$ = 0.391 k = 10
23. Engagement	$\hat{p}$ = 0.344 k = 13	$\hat{p}$ = -0.061 k = 1	$\hat{p}$ = 0.109 k = 1	$\hat{p}$ = 0.281 k = 3	$\hat{p}$ = 0.068 k = 3	---	$\hat{p}$ = 0.579 k = 2	---	---
24. Competence	$\hat{p}$ = 0.412 k = 11	$\hat{p}$ = 0.184 k = 2	$\hat{p}$ = -0.270 k = 4	$\hat{p}$ = -0.121 k = 2	$\hat{p}$ = -0.010 k = 2	---	$\hat{p}$ = 0.085 k = 2	---	---
25. Skill	$\hat{p}$ = 0.480 16	$\hat{p}$ = 0.764 k = 5	$\hat{p}$ = -0.235 k = 1	$\hat{p}$ = -0.191 k = 5	$\hat{p}$ = 0.335 k = 5	$\hat{p}$ = 0.248 2	---	---	---
26. Knowledge	$\hat{p}$ = 0.603 k = 22	$\hat{p}$ = 0.460 k = 1	$\hat{p}$ = 0.081 k = 5	$\hat{p}$ = -0.200 k = 4	$\hat{p}$ = -0.188 k = 3	---	$\hat{p}$ = 0.625 k = 2	$\hat{p}$ = -0.010 k = 1	---
27. Motivation to learn	$\hat{p}$ = 0.401 k = 14	$\hat{p}$ = 0.399 k = 4	$\hat{p}$ = 0.019 k = 4	$\hat{p}$ = -0.165 k = 3	$\hat{p}$ = 0.180 k = 2	$\hat{p}$ = 0.042 1	---	---	---

	10	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
10. Locus of control	---								
11. Neuroticism	$\hat{p}$ = 0.313 k = 3	---							
12. Microcomputer playfulness	---	$\hat{p}$ = -0.099 k = 3	---						
13. Personal innovativeness in IT	$\hat{p}$ = -0.431 k = 1	$\hat{p}$ = -0.100 k = 5	$\hat{p}$ = 0.672 k = 12	---					
14. Domain self-efficacy	---	$\hat{p}$ = -0.279 k = 1	$\hat{p}$ = 0.053 k = 2	$\hat{p}$ = 0.861 k = 1	---				
15. Interaction	$\hat{p}$ = -0.063 k = 1	---	$\hat{p}$ = 0.074 k = 4	$\hat{p}$ = 0.180 k = 5	---	---			
16. Outcome expectations	$\hat{p}$ = 0.268 k = 2	---	---	---	---	---	---		
17. Performance	$\hat{p}$ = -0.074 k = 3	$\hat{p}$ = -0.164 k = 3	$\hat{p}$ = 0.111 k = 9	$\hat{p}$ = 0.317 k = 7	$\hat{p}$ = 0.288 k = 15	$\hat{p}$ = 0.475 k = 2	$\hat{p}$ = 0.363 k = 10	---	
18. Training satisfaction	---	---	$\hat{p}$ = 0.262 k = 2	$\hat{p}$ = 0.292 k = 7	$\hat{p}$ = 0.296 k = 6	$\hat{p}$ = 0.241 k = 1	$\hat{p}$ = 0.669 k = 2	$\hat{p}$ = 0.456 k = 21	---
19. Utility judgment	---	---	$\hat{p}$ = 0.321 k = 1	---	---	$\hat{p}$ = 0.312 k = 3	---	$\hat{p}$ = 0.651 k = 6	$\hat{p}$ = 0.526 k = 3
20. Metacognition	$\hat{p}$ = -0.020 k = 1	---	---	$\hat{p}$ = 0.196 k = 1	$\hat{p}$ = 0.464 k = 3	$\hat{p}$ = 0.220 k = 2	---	$\hat{p}$ = 0.203 k = 8	$\hat{p}$ = 0.400 k = 3
21. Self-regulated learning	---	---	---	---	$\hat{p}$ = 0.640 k = 4	---	---	$\hat{p}$ = 0.376 k = 4	$\hat{p}$ = 0.657 k = 2
22. Agreeableness	---	$\hat{p}$ = -0.320 k = 11	$\hat{p}$ = 0.234 k = 3	$\hat{p}$ = 0.107 k = 4	---	---	---	$\hat{p}$ = 0.085 k = 3	---
23. Engagement	---	---	$\hat{p}$ = 0.180 k = 2	---	$\hat{p}$ = 0.290 k = 2	---	---	0.441 k = 4	---
24. Competence	$\hat{p}$ = -0.224 k = 1	---	---	---	---	---	$\hat{p}$ = 0.229 k = 1	$\hat{p}$ = 0.630 k = 4	$\hat{p}$ = 0.064 k = 1
25. Skill	---	---	---	$\hat{p}$ = 0.720 k = 1	$\hat{p}$ = 0.482 k = 1	---	$\hat{p}$ = 0.400 k = 1	$\hat{p}$ = 0.145 k = 1	---
26. Knowledge	---	---	$\hat{p}$ = 0.368 k = 2	---	---	---	- $\hat{p}$ = 0.022 k = 1	$\hat{p}$ = 0.526 k = 4	$\hat{p}$ = 0.103 k = 1
27. Motivation to learn	---	---	$\hat{p}$ = 0.320 k = 1	---	$\hat{p}$ = 0.844 k = 1	---	- $\hat{p}$ = 0.097 k = 1	$\hat{p}$ = 0.154 k = 8	$\hat{p}$ = 0.606 k = 5

	19	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**
19. Utility judgment	---								
20. Metacognition	$\hat{p}$ = 0.430 k = 2	---							
21. Self-regulated learning	$\hat{p}$ = 0.437 k = 1	$\hat{p}$ = 0.796 k = 2	---						
22. Agreeableness	---	---	---	---					
23. Engagement	---	---	$\hat{p}$ = 0.702 k = 2	---	---				
24. Competence	---	$\hat{p}$ = 0.073 k = 1	---	---	---	---			
25. Skill	---	---	---	---	---	$\hat{p}$ = 0.497 k = 1			
26. Knowledge	---	---	---	---	---	---	$\hat{p}$ = 0.750 k = 2	---	
27. Motivation to Learn	---	$\hat{p}$ = 0.545 k = 3	$\hat{p}$ = 0.551 k = 3	---	---	---	$\hat{p}$ = 0.133 k = 1	$\hat{p}$ = 0.613 k = 1	---

Note: $\hat{p}$ = corrected population correlation point estimate; k = number of studies; --- Constructs that did not have any correlations.

Table 5. Main Analysis

Analysis	$\hat{p}$	*k*	*N*	Var.	80% CV		95% CI		% Art.	FSN
					10% CV	90% CV	lower CI	upper CI		
Core four antecedents										
Computer experience	0.416	147	40528	0.061	0.099	0.733	0.372	0.460	14%	453
Computer anxiety	-0.353	141	40054	0.076	-0.705	-0.000	-0.400	-0.305	7%	108
Demographic antecedents										
Age	-0.120	81	21704	0.046	-0.391	0.160	-0.166	-0.066	9%	34
Gender	-0.071	83	34971	0.036	-0.315	0.173	-0.114	-0.027	9%	54
Education	0.108	32	7891	0.032	-0.121	0.337	0.041	0.175	13%	49
Personality										
Agreeableness	0.118	12	2153	0.006	0.016	0.220	0.090	0.381	56%	19
Conscientiousness	0.132	17	4248	0.008	0.018	0.246	0.095	0.299	42%	286
Openness to experience	0.319	10	1734	0.003	0.298	0.340	0.264	0.374	96%	26
Locus of control	0.106	12	3837	0.092	-0.283	0.494	-0.072	0.283	5%	18
Neuroticism	-0.209	17	3300	0.050	-0.496	0.077	-0.324	-0.094	12%	1
Microcomputer playfulness	0.407	31	5048	0.017	0.238	0.576	0.350	0.464	32%	94
Personal innovativeness in IT	0.451	60	15215	0.040	0.194	0.707	0.396	0.506	13%	195
Knowledge & skills										
Competence	0.412	11	2997	0.093	0.022	0.803	0.226	0.599	4%	34
Computer knowledge	0.603	22	3665	0.094	0.212	0.995	0.467	0.532	10%	88
Computer skill	0.480	16	4500	0.027	0.271	0.688	0.392	0.567	15%	54
Additional antecedents										
Domain self-efficacy	0.397	27	7619	0.050	0.120	0.674	0.310	0.484	9%	81
Support	0.264	68	23785	0.062	-0.054	0.582	0.202	0.322	7%	158
CSE outcomes										
Engagement	0.344	13	2464	0.037	0.099	0.590	0.231	0.458	14%	35
Interaction	0.275	20	5312	0.051	-0.014	0.565	0.170	0.380	9%	48
Metacognition	0.323	15	3637	0.048	0.042	0.604	0.204	0.443	11%	39
Motivation to learn	0.401	14	2602	0.056	0.098	0.704	0.267	0.536	13%	42
Outcome expectations	0.431	38	11197	0.087	0.052	0.809	0.334	0.528	5%	120
Performance	0.256	121	31893	0.029	0.036	0.475	0.221	0.291	17%	277
Self-regulated learning	0.430	13	8957	0.038	0.179	0.680	0.319	0.540	5%	41
Training satisfaction	0.340	21	6717	0.032	0.113	0.567	0.258	0.422	12%	57
Utility judgments	0.455	16	13751	0.014	0.306	0.603	0.389	0.521	23%	52

Note: $\hat{p}$ = corrected population correlation point estimate; k = number of studies; N = number of observations; Var. = variance of true score correlations; 80% CV = lower and upper bounds of the 80% credibility value for $\hat{p}$; 95% CI = lower and upper bounds of the 95% confidence interval for $\hat{p}$, % Art. = percent of variance in observed correlations attributable to sampling and measurement errors, FSN = failsafe N.

5.1 Core CSE Antecedents

Of the four key sources of efficacy information—enactive mastery (experience), verbal persuasion, vicarious experience, and emotional arousal (anxiety)—only enactive mastery and computer emotional arousal had been researched sufficiently for inclusion in the meta-analysis. As shown in Table 5, the corrected mean population correlation point estimate between enactive mastery and CSE was $\hat{p} = 0.42$ ($k = 147$, $N = 40{,}528$). This represents the sample-weighted average correlation across all results. The mean correlation was corrected for unreliability in the variables. The 80% CVs ranged from 0.10 to 0.73, while 14% of the variance in correlations was due to measurement and sampling errors, suggesting that moderators might be present. A negative mean population correlation point estimate was found for emotional arousal ($\hat{p} = -0.35$, $k = 141$, $N = 40{,}054$). The 80% CVs ranged from 0.71 to 0.00. In each case, the results are consistent with social cognitive theory (SCT) (Bandura, 1997) and provide support for these antecedents of CSE.

5.2 Additional CSE Antecedents

These results suggest that additional factors may serve as antecedents to CSE. Consistent with Marakas et al. (1998), negative mean corrected population correlation estimates were observed for age ($\hat{p} = -0.12$, $k = 81$, $N = 27{,}704$) and gender ($\hat{p} = -0.07$, $k = 83$, $N = 34{,}971$), which suggests that women and older individuals may have lower CSE than men and younger individuals, though the gender effect was weak. In addition, education (a component of an individual's professional orientation) ($\hat{p}$ = 0.11, k = 32, N = 7891) and support ($\hat{p}$ = 0.26, k = 68, N = 23,785) were positively correlated with CSE, suggesting that more educated members of the population and those who receive situational support will have higher CSE than those who do not.

The meta-analysis also identified several antecedents not examined in previous reviews. These include user personality traits and states, as well as knowledge and skill. With respect to personality, the meta-analysis found mean positive corrected population correlation point estimates for agreeableness ($\hat{p}$ = 0.12, k = 12, N = 2153), conscientiousness ($\hat{p}$ = 0.13, k = 17, N = 4248), openness to experience ($\hat{p}$ = 0.320, k = 10, N = 1734), and locus of control ($\hat{p}$ = 0.11, k = 12, N = 3837). A mean negative populated correlation point estimate was observed for neuroticism ($\hat{p}$ = −0.21, k = 17, N = 3300), and mean positive correlations were found for microcomputer playfulness ($\hat{p}$ = 0.41, k = 31, N = 5048), personal innovativeness in IT ($\hat{p}$ = 0.451, k = 60, N = 15,215), and domain self-efficacy[6] ($\hat{p}$ = 0.40, k = 28, N = 5824). Finally, computer knowledge ($\hat{p}$ = 0.60, k = 22, N = 3665), skills ($\hat{p}$ = 0.48, k = 16, N = 4500), and competence ($\hat{p}$ = 0.41, k = 11, N = 2997) were positively correlated with CSE. Neither the CIs nor the CVs for these variables included zero.

Though most CVs did not include zero, some did, such as age, gender, education, locus of control, and neuroticism. CVs that include zero suggest that the true correlations between variables may be zero, positive, or negative (Gerow et al., 2014). For locus of control, the CI also included zero. Thus, we cannot determine if the relationship between CSE and locus of control is significant.

5.3 Outcomes of CSE

The results of the meta-analysis of the relationship between CSE and training processes and outcomes can be seen in the CSE outcomes section of Table 5. Mean positive corrected population correlation point estimates were found for interaction ($\hat{p}$ = 0.27, k = 20, N = 5312), engagement ($\hat{p}$ = 0.34, k = 13, N = 2464), metacognition ($\hat{p}$ = 0.32, k = 15, N = 3637), motivation to learn (MTL) ($\hat{p}$ = 0.40, k = 14, N = 2602), outcome expectations ($\hat{p}$ = 0.43, k = 38, N = 11197), self-regulated learning strategies ($\hat{p}$ = 0.43, k = 13, N = 8957), performance ($\hat{p}$ = 0.26, k = 121, N = 31,893), satisfaction with training ($\hat{p}$ = 0.34, k = 21, N = 6717), and utility judgments ($\hat{p}$ = 0.46, k = 16, N = 13,751). These findings are consistent with the broader training literature, in which these variables are related to self-efficacy (Colquitt et al., 2000). The correlations were universally positive, and CIs did not include zero. Thus, researchers can conclude that the relationships are statistically significant (however, caution should be used in interpreting results regarding interaction, since the CV includes zero). For most variables, the percentage of variance attributable to artifacts was low (35% or below), suggesting that moderators may exist.

5.4 Moderator Analysis

As in the main analysis, we compared moderators only when categories contained 10 or more studies for comparison (e.g., $k \geq 10$). Study method, sample, time frame, self-efficacy scale level (e.g., general vs. specific), technology context, and use context were coded as categorical. Year of study, culture (e.g., masculinity/femininity, individualism/collectivism, and power/distance), and economic development were coded as continuous variables.

5.4.1 Categorical Moderators

Although the results suggested that categorical moderators were present (see Table 6), the analysis presents a more nuanced picture. Most of the mean corrected correlation CIs did not include zero and could thus be considered significant. Some CVs did include zero, which suggests variability across studies. *t*-tests were used to assess whether the mean of each moderator condition was significantly different.[7] We also examined whether the CV included zero for any condition. The results suggest that $\hat{p}$ for the relationship between domain self-efficacy and CSE was higher for non-journal publications (t = −2.21, $p \leq$ 0.05) (the CV did not include zero in either condition). In addition, the $\hat{p}$ for the relationship between education and CSE was higher for journal publications (t = −2.49, $p \leq$ 0.05). The results also indicate that the CV for articles published in journals included zero for computer anxiety and support, whereas the CV included zero for outcome expectancy in articles that were not published in journals.

The results for computer experience were similar. Again, CIs did not include zero, although the CVs for employees did, suggesting greater variance in individual studies on employees. The results exhibit a similar pattern for computer anxiety and performance, meaning that CIs did not include zero, but several CVs did. For computer anxiety, $\hat{p}$ was more negative for surveys (t = −2.40, $p <$ 0.05) relative to experiments. For gender and support, the CIs did not include zero, but a pair of the CVs included zero for cross-sectional studies. In addition, for general CSE, the CIs did not include zero, but the CV included zero for specific CSE and support. However, for computer anxiety, the CV included zero for specific CSE. For both computer anxiety and support, the CV included zero for internet use context, and $\hat{p}$ was more negative in the computing context (t = 3.58, $p \leq$ 0.001).

[6] In this study, domain self-efficacy reflects individual self-efficacy in completing an educational or business task without concern for technology, i.e., many e-learning studies focus on how individuals learn academic subjects such as math or reading (Spence & Usher, 2007; Tsai & Yen, 2014).

[7] We thank an anonymous reviewer for suggesting this analysis.

Table 6. Results of Categorical Moderator Analyses

Analysis	$\hat{\rho}$	*k*	*N*	Var.	SDrho	80% CV		95% CI		% art.	*t*
						10% CV	90% CV	lower CI	upper CI		
Journal vs. Other											
Computer anxiety											
Journal	-0.336	95	29720	0.075	0.273	-0.690	0.014	-0.390	-0.279	6%	
Non-journal	-0.394	46	10334	0.075	0.274	-0.740	-0.043	-0.480	-0.310	8%	
Domain self-efficacy											
Journal	0.339	16	5147	0.026	0.1619	0.131	0.546	0.252	0.425	14%	-2.21 *
Non-journal	0.519	11	2472	0.070	0.2625	0.183	0.855	0.356	0.682	8%	
Education											
Journal	0.164	22	5092	0.038	0.1946	-0.085	0.413	0.077	0.252	12%	2.49*
Non-journal	0.006	10	2799	0.006	0.0758	-0.092	0.103	-0.057	0.068	42%	
Outcome expectancy											
Journal	0.459	18	5287	0.044	0.209	0.191	0.726	0.356	0.561	9%	
Non-journal	0.406	20	5910	0.125	0.354	-0.047	0.859	0.246	0.566	3%	
Performance											
Journal	0.258	56	16270	0.017	0.130	0.092	0.424	0.219	0.298	25%	
Non-journal	0.256	65	15365	0.043	0.206	-0.008	0.520	0.201	0.311	14%	
Support											
Journal	0.274	51	18372	0.070	0.265	-0.065	0.613	0.198	0.350	6%	
Non-journal	0.231	17	5413	0.031	0.176	0.005	0.456	0.140	0.322	13%	
Students vs. Employees											
Computer experience											
Student	0.441	81	21752	0.051	0.227	0.151	0.732	0.387	0.496	17%	
Employee	0.355	43	11413	0.079	0.280	-0.004	0.714	0.266	0.445	10%	
Outcome expectancy											
Student	0.472	21	6164	0.045	0.212	0.200	0.745	0.376	0.569	9%	
Employee	0.388	15	4647	0.146	0.382	-0.101	0.876	0.190	0.586	3%	
Experiment vs. Survey											
Computer anxiety											
Experiment	-0.232	22	7900	0.095	0.308	-0.626	0.162	-0.365	-0.099	4%	-2.40*
Survey	-0.380	119	32154	0.066	0.258	-0.710	-0.051	-0.429	-0.332	8%	
Performance											
Experiment	0.181	12	3162	0.045	0.213	-0.092	0.453	0.051	0.310	11%	
Survey	0.266	109	28473	0.027	0.164	0.056	0.475	0.231	0.300	19%	
Cross-sectional vs. Longitudinal											
Gender											
Cross-sectional	-0.059	73	31087	0.038	0.195	-0.309	0.1913	-0.106	-0.011	8%	
Longitudinal	-0.166	10	3884	0.012	0.107	-0.303	-0.0294	-0.246	-0.087	29%	
Outcome expectancy											
Cross-sectional	0.402	56	19116	0.071	0.267	-0.093	0.5898	0.176	0.321	6%	
Longitudinal	0.571	12	4669	0.018	0.134	0.157	0.5003	0.243	0.414	20%	
GCSE vs. CSE											
Computer anxiety											
GCSE	-0.354	115	33506	0.070	0.265	-0.693	-0.0142	-0.405	-0.303	7%	
CSE	-0.344	14	2392	0.119	0.334	-0.784	0.0971	-0.532	-0.156	6%	
Support											
GCSE	0.246	50	17879	0.064	0.252	-0.076	0.570	0.173	0.319	6%	
CSE	0.380	10	3653	0.030	0.172	0.160	0.600	0.264	0.496	14%	
Technology context											
Computer anxiety											
Computer	-0.405	93	27575	0.065	0.254	-0.731	-0.080	-0.460	-0.351	8%	3.58***
Internet	-0.237	48	12479	0.081	0.285	-0.602	0.129	-0.321	-0.152	6%	
Support											
Computer	0.250	42	14885	0.038	0.194	0.002	0.498	0.187	0.312	11%	
Internet	0.288	26	8900	0.101	0.318	-0.119	0.695	0.162	0.415	4%	
Use context											
Computer experience											
Education & training	0.454	83	25794	0.058	0.240	0.147	0.761	0.397	0.510	15%	2.78**[2] 3.02**[3]
Consumer	0.298	22	4799	0.042	0.204	0.037	0.560	0.203	0.394	18%	
Corporate	0.298	29	6121	0.057	0.24	-0.008	0.604	0.203	0.393	14%	

Computer anxiety										
Education & training	-0.341	69	19936	0.081	0.285	-0.705	0.023	-0.411	-0.271	6%	
Consumer	-0.357	26	8366	0.091	0.301	-0.743	0.028	-0.478	-0.2371	5%	
Corporate	-0.368	32	7610	0.068	0.261	-0.703	-0.034	-0.464	-0.273	8%	
Performance										
Education & training	0.236	68	20295	0.021	0.144	0.052	0.420	0.197	0.275	21%	-3.26**[1]
Consumer	0.172	18	3732	0.044	0.209	-0.096	0.439	0.066	0.277	14%	-
Corporate	0.360	30	6550	0.034	0.184	0.124	0.596	0.286	0.434	19%	3.59***[3]
Personal innovativeness in IT										
Education & training	0.511	22	5275	0.014	0.118	0.361	0.662	0.451	0.572	32%	
Consumer	0.413	17	5756	0.042	0.205	0.151	0.675	0.309	0.517	10%	2.34*[3]
Corporate	0.354	14	2527	0.078	0.280	-0.004	0.712	0.199	0.509	9%	
Support										
Education & training	0.285	25	10353	0.035	0.186	0.046	0.523	0.207	0.363	10%	
Consumer	0.207	12	5018	0.143	0.379	-0.278	0.692	-0.013	0.427	3%	
Corporate	0.276	27	6728	0.052	0.228	-0.015	0.568	0.184	0.368	10%	

Note: $\hat{p}$ = corrected population correlation point estimate; k = number of studies; *N* = number of observations; Var. = variance of true score correlations; 80% CV = lower and upper bounds of the 80% credibility value for $\hat{p}$; 95% CI = lower and upper bounds of the 95% confidence interval for $\hat{p}$, % Art. = percent of variance in observed correlations attributable to sampling and measurement errors; t = t-value. * $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$. [1]consumer vs. corporate; [2]consumer vs. education & training; [3]corporate vs. education & training.

The technology use context reveals several interesting differences. For computer experience, $\hat{p}$ for the education and training context was higher than in both the consumer ($t = 2.78$, $p \leq 0.01$) and corporate ($t = 3.02$, $p \leq 0.01$) use contexts. The CV included zero for studies conducted in the corporate setting. For computer anxiety, the corporate context was the only context where the CV did not include zero, and for performance, $\hat{p}$ was higher in the corporate setting than in both education and training ($t = -3.26$, $p \leq 0.01$) and consumer settings ($t = -3.59$, $p \leq 0.001$). In addition, the CV included zero only for the consumer setting. There was also a difference in $\hat{p}$ for personal innovativeness in IT, with $\hat{p}$ for education and training context higher than for the corporate context ($t = 2.34$, $p \leq 0.05$). The CV included zero only for the corporate context. For support, there were no significant mean differences for use context, but the CV in both the consumer and corporate contexts included zero.

Only 9 of nearly 300 relationships (3%) had statistically significant *t*-tests. In addition, 14 relationships had one condition that contained zero. This suggests that moderators associated with characteristics of the study (e.g., sample, study time frame, research design, and technology context) may significantly affect relationships. Although we agree with Marakas and colleagues (Marakas et al., 1998, 2007) that researchers should seek to measure CSE and constructs of interest at the same level of analysis, the lack of statistically significant moderators for each type of scale, general or specific, suggests that a more general measure may "reflect estimates of ability closer to the individual than the tool" (Marakas et al., 2007, pp. 40-41) and could be equally effective in predicting performance as a specific measure for non-novice computer users.

Thus, researchers may not need to develop a new measure for each research study and context. However, it is important to note that a more specific measure could capture fine-grained changes in CSE (Johnson & Marakas, 2000) and be more appropriate for novice users in specific contexts. Overall, these findings suggest that although it is good practice for researchers to consider potential study artifacts in designing studies, in the case of CSE, the risk of design artifacts affecting relationships is small, and their inclusion should be based on study considerations rather than recommended as best practice.

5.4.2 Subgroup Analysis

We also conducted a subgroup analysis for categorical moderators. The sample was split into subgroups, and the effect sizes for each group were compared (Blut, 2021; Grewal et al., 2018). Researchers have argued that "power is very low for most subgroup analyses" (Cuijpers et al., 2021, p. 1) and "may require dozens to hundreds of studies for realizing sufficient statistical power" (Cuijpers et al., 2021, p. 3). Others have argued that comparisons of groups with $k > 10$ can produce sufficiently stable results (Gerow et al., 2014; Nastjuk et al., 2024; Switzer et al., 1992). For this reason, we discuss the results for those moderators that had a sufficient number of studies (see Table 7) below. However, because other researchers in IS were less concerned with sample size and presented subgroup analyses with $k < 10$ (Blut et al., 2022; Hess et al., 2014), we include the results for all relationships in Appendix E.[8]

[8] Available at https://osf.io/xyqbw/overview. We thank an anonymous reviewer for suggesting the subgroup analysis.

Table 7. Subgroup Analysis

Analysis	$\hat{\bar{p}}$	*k*	*N*	80% CV	95% CI	*t*
Computer experience						
Publication outlet & use setting						
Journal/training	0.40	43	16605	12-.68	.33-.47	3.29**[1]
Journal/corporate	0.36	11	2384	-.01-.73	.18-.55	
Non-journal/training	0.50	40	9179	18-.82	.42-.59	
Non-journal/corporate	0.28	18	3737	.01-.55	.17-.39	
Publication outlet & sample						
Journal/students	0.41	37	12157	.13-.70	.33-.49	2.37*[2]
Journal/employees	0.38	27	8017	.02-.73	.27-.49	
Non-journal/students	0.47	44	9595	.18-.75	-.06-.66	
Non-journal/employees	0.30	16	3396	.39-.54	.15-.45	
Computer anxiety						
Use context & technology context						
Training/internet	-0.30	25	6446	-.72-.12	-.43-.17	3.79***[3]
Training/computer	-0.36	44	13490	-.69-.03	-.44-.28	
Consumer/internet	-0.17	13	4110	-.39-.05	-.27-.07	
Consumer/computer	-0.52	13	4256	-.90-.15	-.69-.36	
Publication outlet & use context						
Journal/training	-0.29	47	13772	-.63-.05	-.37-.21	2.05*[4]
Journal/corporate	-0.38	19	5716	-.75-.01	-.51-.24	
Non-journal/training	-0.44	22	6164	-.85-.03	-.65-.13	
Non-journal/corporate	-0.39	13	1994	-.58-.30	-.51-.27	
Publication outlet & sample						
Journal/students	-0.33	52	13625	-.72-.06	-.42-.25	-2.80*[5]
Journal/employees	-0.36	28	10491	-.59-.14	-.32-.13	
Non-journal/students	-0.49	19	5595	-.81-.16	-.61-.37	
Non-journal/employees	-0.24	16	2846	-.59-.12	-.38-.09	
Sample & technology context						
Students/internet	-0.23	26	7348	-.64-.18	-.36-.10	3.47***[6]
Students/computer	-0.47	15	3467	-.53-.06	-.36-.11	
Employees/internet	-0.24	45	11872	-.78-.15	-.54-.39	
Employees/computer	-0.36	29	9870	-.72-.01	-.47-.26	
Performance						
Publication outlet & use setting						
Journal/training	0.25	28	10741	.09-.42	.20-.31	2.04*[7]
Journal/corporate	0.25	40	9554	.12-.42	.16-.27	
Non-journal/training	0.22	15	3187	.15-.35	.19-.31	
Non-journal/corporate	0.50	15	3363	.26-.73	.39-.61	
Publication outlet & sample						
Journal/students	0.28	33	10464	.13-.42	.23-.32	-2.80**[8]
Journal/employees	0.19	35	8999	.03-.44	.17-.29	
Non-journal/students	0.23	18	8009	.13-.40	.12-.27	
Non-journal/employee	0.38	23	4255	.09-.67	.28-.48	
Publication outlet & use context						
Training/internet	0.24	18	8009	.13-.40	.21-.32	3.79***[9]
Training/computer	0.23	16	4892	-.04-.32	.06-.22	
Consumer/internet	0.11	38	8261	.05-.43	.18-.29	
Consumer/computer	0.20	49	10473	.05-.59	.25-.39	
Age						
Publication outlet & use setting						
Journal/training	-0.15	17	7163	.48-.19	27-.02	
Journal/corporate	-0.19	14	2631	.53-.14	.34-.13	
Non-journal/training	-0.13	15	2414	.30-.04	.21-.05	
Non-journal/corporate	-0.05	15	2968	.28-.17	-.15-.04	
Publication outlet & sample						
Journal/students	-0.23	20	6411	.50-.05	.33-.13	-2.42*[10] -2.42*[11]
Journal/employees	-0.04	14	3919	.29-.22	.14-.08	
Non-journal/students	-0.09	20	2915	.27-.09	.21-.05	
Non-journal/employee	-0.01	12	3439	.24-.21	.12-.09	

Publication outlet & technology context						
Journal/internet	-0.20	13	3797	.52-.12	.34-.05	
Journal/computer	-0.13	30	9426	.43-.16	.22-.05	4.87***[12]
Non-journal/internet	0.05	12	3823	.12-.21	.04-.13	-3.01**[13]
Non-journal/computer	-0.15	26	4658	.28-.01	.20-.09	
Use setting & sample						
Training/students	-0.28	13	4695	.51-.05	.38-.17	
Training/employees	0.02	13	3450	.22-.26	.08-.17	-4.15***[14]
Corporate/students	-0.11	15	1898	.29-.07	.20-.02	-2.74*[15]
Corporate/employees	-0.07	10	2778	.34-.20	.21-.07	

Note: For clarity, the table only includes variables for which the subgroup analysis suggests that there were meaningful differences based upon both moderators. Full analyses are available in Appendix E. [1]non-journal: training vs. corporate; [2]non-journal: student vs. employees; [3]consumer: internet vs. computer; [4]training: journal vs. non-journal; [5]non-journal: students vs. employees; [6]students: internet vs. computers; [7]training: journal vs. non-journal; [8]non-journal: students vs employees; [9]consumer: internet vs. computers; [10]journal: students vs. employees; [11]students: journal vs. non-journal; [12]non-journal: internet vs. computers; [13]internet: journal vs. non-journal; [14]training: students vs. employees; [15]students: training vs. corporate. * $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$.

Although less than 2% of all subgroup pairs examined were found to potentially have meaningful subgroup differences, there was a consistent finding in these analyses. Specifically, the findings suggest that the publication outlet (journal or non-journal) interacted with several other moderators. For research published in non-journal publications, there were statistically significant effect size differences between student and employee samples for computer experience ($t = 2.37$, $p \leq 0.05$), computer anxiety ($t = -2.80$, $p \leq 0.05$), and performance ($t = -2.80$, $p \leq 0.05$). In non-journal publications, the use context for computer experience ($t = 3.29$, $p \leq 0.01$) and the technology context for age ($t = 4.87$, $p \leq 0.001$) each had statistically significant differences. For age, statistically significant differences were present between students and employees for articles published in a journal ($t = -2.40$, $p \leq 0.05$). For computer anxiety and training ($t = 2.05$, $p \leq 0.05$) and performance and training ($t = 2.04$, $p \leq 0.05$), the effect size was stronger in non-journal publications. However, for age, the effects were reversed, with larger negative effect sizes in journal publications for student samples ($t = -2.42$, $p \leq 0.05$) and the internet technology context ($t = -3.01$, $p \leq 0.01$).

Other statistically significant differences in effect sizes include differences between the internet and computer context in several contexts, including the consumer context for computer anxiety ($t = 3.79$, $p \leq 0.001$) and performance ($t = 3.79$, $p \leq 0.001$) and student samples for computer anxiety ($t = 3.47$, $p \leq 0.001$). Finally, for age, two additional subgroups analyses suggested group differences. For student samples, the effect size was stronger in training settings than in corporate settings ($t = -2.74$, $p \leq 0.05$), and for the training setting, the effect size was negative for student samples and positive in employee samples ($t = -4.15$, $p \leq 0.001$).

In addition, in training settings, the effect size for the CSE-experience relationship for articles published in journals ($\hat{\rho} = 0.40$; CI [0.33, 0.47]) was meaningfully smaller than for articles appearing in non-journal outlets ($\hat{\rho} = 0.50$; CI [0.42, 0.59]). The t-test results also suggest there may be meaningful differences ($t = -1.95$, $p = 0.054$). Further, for computer anxiety, the effect size for students was weaker (less anxiety) when the article was published in a journal ($\hat{\rho} = -0.33$; CI [−0.42, −0.25]) as opposed to a non-journal outlet ($\hat{\rho} = -0.49$; CI [−0.61, −0.37]). The t-test results also suggest meaningful differences ($p = 0.50$).

Another way to identify potentially meaningful effect size differences is to compare the critical intervals. When critical intervals do not significantly overlap, it suggests that the effect size differences may be meaningful, even if t-test results are not statistically significant. We found one such relationship. In the internet context, the relationship between CSE and anxiety was meaningfully lower in the consumer context ($\hat{\rho} = -0.17$; CI [−0.27, −0.07]) relative to the training context ($\hat{\rho} = -0.30$; CI [−0.43, −0.17]). Together, the results of the subgroup analysis suggest that the effects of moderators such as sample, use context, and technology may be affected by the type of publication in which research appears. Specifically, the magnitude of the relationships may be larger in non-journal outlets. Although, in general, the relationships with CSE are robust across conditions, a possible difference exists between students and employees based on whether a study focuses on the internet or a computing context.

5.4.3 Continuous Moderators

Analysis suggests that the year of the study and the culture in which it was conducted may serve as moderators (Table 8). The relationships between CSE and support ($r = 0.25$, $p \leq 0.05$), engagement ($r = 0.66$, $p \leq 0.01$), interaction ($r = 0.65$, $p \leq 0.001$), and utility judgments ($r = 0.50$, $p \leq 0.051$) have grown stronger over time. However, the relationships between CSE and neuroticism ($r = -0.44$, $p \leq 0.05$) and metacognition ($r = -0.59$, $p \leq 0.01$) have grown weaker over time.

The extent of a country's economic development also moderated relationships between CSE and other variables. The relationships between CSE and computer experience (r = 0.17, $p \leq 0.05$) and microcomputer playfulness (r = 0.67, $p \leq 0.001$) were stronger in more developed countries, while those between CSE and computer anxiety (r = −0.19, $p \leq 0.05$), engagement (r = −0.50, $p \leq 0.05$), interaction (r = −0.43, $p \leq 0.05$), and utility judgments (r = −0.51, $p \leq 0.05$) were weaker in more developed countries.

Culture also moderates the relationship between CSE and other variables. The relationships between CSE and microcomputer PIIT (r = 0.35, $p \leq 0.001$) and engagement (r = 0.56, $p \leq 0.05$) were stronger in countries with more individualistic cultures. Conversely, the relationships between CSE and computer experience (r = −0.45, $p \leq 0.05$), neuroticism (r = −0.64, $p \leq 0.01$), and computer anxiety (r = −0.17, $p \leq 0.05$) were weaker in more collectivist cultures. In addition, power/distance moderated several relationships with CSE. For computer anxiety (r = 0.27, $p \leq 0.001$), support (r = 0.25, $p \leq 0.05$), interaction (r = 0.62, $p \leq 0.01$), engagement (r = 0.49, $p \leq 0.05$), and utility judgment (r = 0.71, $p \leq 0.001$), effect sizes were stronger in cultures with greater power/distance, but in cultures that had lower power/distance, effect sizes were stronger for conscientiousness (r = −0.44, $p \leq 0.05$), microcomputer playfulness (r = −0.51, $p \leq 0.01$), and PIIT (r = −0.70, $p \leq 0.001$). Finally, in masculine cultures, effect sizes were stronger for microcomputer playfulness (r = 0.46, $p \leq 0.01$) and PIIT (r = 0.23, $p \leq 0.05$) but weaker for conscientiousness (r = −0.44, $p \leq 0.05$), computer knowledge, (r = −0.40, $p \leq 0.05$), interaction (r = −0.48, $p \leq 0.05$), and utility judgment (r = −0.62, $p \leq 0.01$).

Unlike categorical moderators, there was greater evidence of the importance of continuous moderators. However, less than 30% of the relationships had a significant moderator effect as suggested by t-tests and effect sizes. Consistent with Bandura (1997) and Earley (1993), the individualism/collectivism dimension moderated several relationships. Surprisingly, the results were in the opposite direction from that theorized for anxiety and computer experience. That is, the relationships with CSE were weaker in more individualist countries than they were in collectivist countries. The results also illustrate that although a country's economic development and the cultural dimensions of power/distance and masculinity/ femininity moderate relationships in the model, no consistent pattern was found. In addition, no continuous moderator affected the relationship between CSE and performance.

These findings suggest that although the country in which a study is conducted may moderate relationships with CSE, it is unclear how important such moderators are or how they play a role. As with categorical moderators, inclusion in future research should be based on the needs of the study itself. This is especially important because no moderator was found to affect the CSE and performance relationship.

Table 8. Results of Continuous Moderators

Variable	Year		Country: Country development		Country: Individualism/ collectivism		Country: Power/ distance		Country: Masculinity/ femininity		# of countries
	r	*k/N*	*r*	*k/N*	*r*	*k/N*	*r*	*k/N*	*r*	*k/N*	
Antecedents											
Computer experience			0.17*	142/39740	-0.45*	141/39335					25
Computer anxiety			-0.19*	134/38487	-0.17*	136/38565	0.27***	134/38487			25
Conscientiousness							-0.44*	17/4330	-0.44*	17/4330	11
Neuroticism	-0.44*	17/3300			-0.64**	15/3073					8
Computer knowledge									-0.40*	21/3597	6
Microcomputer playfulness			0.67***	29/4828			-0.51**	29/4828	0.46**	29/4828	8
Personal innovativeness in IT					0.35**	60/15215	-0.70***	57/14727	0.23*	57/14727	19
Support	0.25*	68/23785					0.25*	61/22272			20
Outcomes											
Engagement	0.66**	13/2464	-0.50*	13/2464	0.56*	13/2464	0.49*	13/2464			7
Interaction	0.65***	20/5312	-0.43*	20/5312			0.62**	20/5312	-0.48*	20/5312	8
Metacognition	-0.59**	15/3637									6
Utility judgement	0.50*	16/13751	-0.51*	15/13683	-0.59**	16/13751	0.71***	15/13683	-0.62**	15/13683	6

Note: For clarity, the table only includes variables for which the moderators were statistically significant. * $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$.

6 Discussion

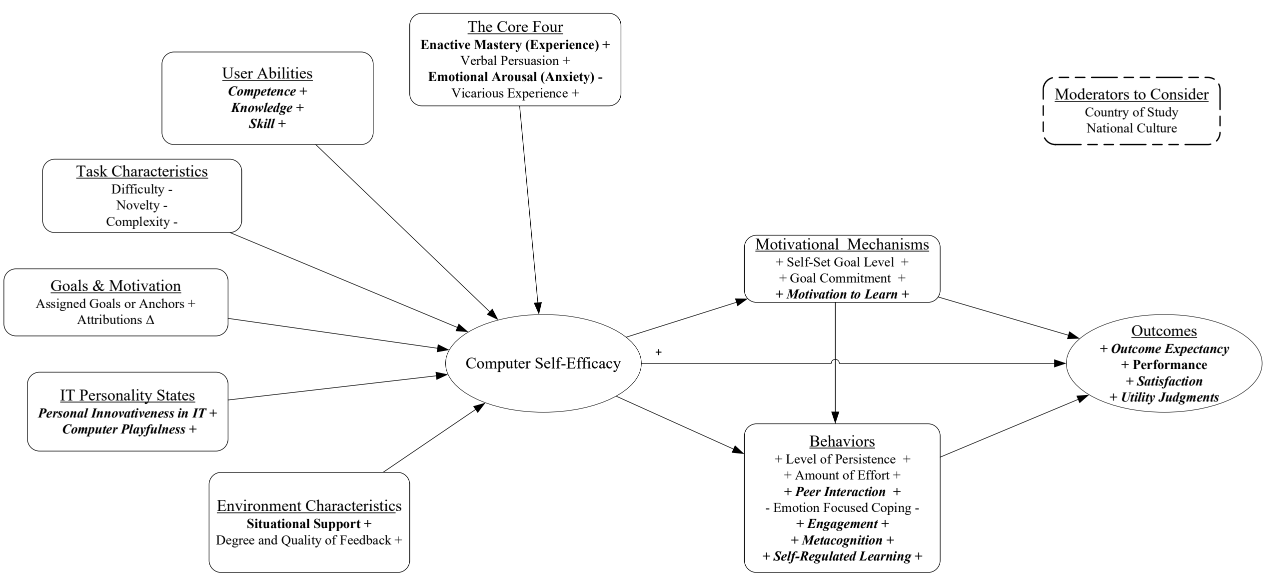
This study uses meta-analysis to articulate an updated view of CSE's nomological network and offers a path for future research to follow. It draws on studies from multiple disciplines based on an initial pool of over 2,000 studies, 400 effect sizes, and 26 variables. To our knowledge, it is the largest study conducted on CSE. In comparison, Karsten et al. (2012) had an initial pool of 194 studies and analyzed only seven variables. These findings should elicit fresh insight into CSE and chart a way forward for CSE research.

Our review found that only 7 of the 30 variables identified in the Marakas et al. (1998) review appeared in a sufficient number of studies to warrant inclusion in an empirical meta-analysis, meaning that much of their theoretical model still needs to be investigated further. Our review also identified 18 variables that were not examined in previous summative studies. Some variables, such as peer interaction and MTL, reflect the growing importance of e-learning and training, while others are focused on more distal traits related to computer use. The emergence of new variables suggests that to reflect the latest advances in SCT and training research, current models of CSE may require updating. The meta-analysis also revealed that several factors thought to affect CSE have CVs that include zero (age, education, gender, etc.), suggesting that additional attention to such variables may not be fruitful.

By using meta-analysis, we were able to leverage insights from an empirical examination of the relationship between 26 variables and CSE to develop a new, theory-driven model (see Figure 2) that builds on empirical results as well as recent advances in SCT research. We triangulated results from our meta-analysis and theoretical advances to justify including 10 new variables relevant to the role of CSE in training and performance. Based on the meta-analytic findings and on advances in SCT, our updated model divides variables into separate categories and identifies the source of their relationship (meta-analysis, previous reviews, new variables). For each variable, we have noted whether the relationship is positive, negative, or dependent upon the context. Recommendations for each variable are presented in Table 9 and summarized in the following sections.

6.1 Core Antecedents

The meta-analysis revealed that of the four core antecedents, only two—enactive mastery and emotional arousal (e.g., anxiety)—appeared in a sufficient number of studies to merit inclusion in the meta-analysis. Consistent with SCT, the results indicate that individuals with greater experience using computers have higher CSE and that individuals with higher computer anxiety have lower CSE. Although vicarious experience (often implemented as behavioral modeling training) has not been investigated extensively in the IS literature, extant research has shown its effectiveness in training settings (Compeau & Higgins, 1995b; Johnson & Marakas, 2000; Yi & Davis, 2003). The results also illustrate that CSE is related to knowledge, skills, and competence. Just as CSE increases with enactive mastery experiences, so do these variables. In many ways, they reflect the extent to which individuals have enactive mastery experiences. It is not enough to simply use a computer; it is successful experiences that help individuals gain mastery when using one. This, in turn, can enhance competence and skill.



Note: Meta-analytically supported variables are in bold, and newly identified variables are italicized. (+) Increase in variable results in an increase of dependent variable. (−) Increase in the variable leads to a decrease in the dependent variable. (Δ) Nature of the relationship between variables is context dependent.

Figure 2. Updated Model of Specific Computer Self-Efficacy

Table 9. Meta-Analysis Informed Recommendations

Category	Examples	Findings and recommendations
Core four	Enactive mastery Emotional arousal Vicarious experience Verbal persuasion	• Original sources of self-efficacy information have received strong support across multiple domains • Enactive mastery experiences should always be considered • Opportunities remain to research how each of these four antecedents of CSE may relate to the other types of CSE antecedents
Demographics	Age Gender Education Professional orientation	• Evidence suggests that they are not as important as previously thought • Likely to be proxies for other factors, such as experience • Include in models only when there is a compelling theoretical reason that cannot be explained by other antecedents to CSE
Personality traits	Agreeableness conscientiousness Locus of control Neuroticism Openness to experience	• Non-malleable and inconsistent relationship with CSE for some personality factors • Consider using more proximal and malleable personality states instead
Personality states	PIIT Microcomputer playfulness Self-efficacy Computer anxiety	• Proximal relationship with CSE • Although not all personality states may be malleable with respect to the computing environment, researchers should include them in studies to better understand how a specific intervention works better for some individuals than others
Goals & motivation	Assigned goals Self-set goals Goal commitment Learning goal orientation Motivation to learn	• Strong, consistent, and mutually influencing relationship with self-efficacy • Include goal-related factors to understand how CSE and goal-related behaviors influence each other and to improve training/e-learning outcomes • Research should consider how individuals' self-set goals and anchoring affect CSE
Task characteristics	Difficulty Complexity Novelty Ambiguity	• Identified as important in both SE and CSE literature but have received limited attention in the CSE literature • Given the growing importance of technology in support of a variety of consumer and organizational tasks, understanding how task characteristics affect CSE is important • Need to investigate how domain self-efficacy and CSE interact for complex, domain-spanning tasks that are common to business and consumer settings
Environment	Situational support Feedback	• To improve CSE and performance, organizations should provide resources supporting individuals as they learn to use new software • Research should assess how different types of feedback, and the timing of feedback may enhance or diminish CSE estimations
Behaviors	Engagement Interaction Metacognition Persistence & effort Self-regulated learning	• CSE can lead to higher engagement and interaction in e-learning environments • Individuals with higher CSE are more likely to engage in stronger metacognitive and self-regulated learning behaviors, which can help them better navigate the online learning environment • Although theory suggests that CSE leads to greater persistence and effort, more research is needed to confirm this
Moderators	National culture Country of study	• Researchers should consider that the national culture and economic development of the country may affect how individuals develop and maintain CSE, as well as the success of interventions meant to enhance CSE

6.2 Demographic Characteristics

Our meta-analysis revealed that individual demographic characteristics such as age, education, and gender are related to CSE. However, all had CVs that contained zero, implying substantial variance from study to study and suggesting that demographic variables may play a more nuanced role in CSE estimations than when computers first appeared in organizations. It is also possible that these variables were convenient proxies for computing experience rather than actual demographic differences. Therefore, we encourage scholars to go beyond demographic differences to focus on more malleable factors that affect CSE.

6.3 Personality Traits and States

The meta-analysis identified personality traits and states of interest to CSE researchers. Specifically, agreeableness, conscientiousness, openness to experience, and locus of control were positively related to CSE, while neuroticism was negatively related to CSE. While the CIs did not typically include zero, the CVs for locus of control and neuroticism did. The results also identified two additional domain-specific personality traits, namely PIIT and microcomputer playfulness, that were positively related to CSE.

To integrate personality traits into a contemporary model of CSE, we leveraged the work of Locke and Latham (2004), Davis and Yi (2012), and Thatcher and Perrewe (2002), who argued that a hierarchy of personality traits and states affect specific behaviors. The most distal are personality traits, which are seen as broad, stable, and not generally malleable (Barrick & Mount, 1991). Thus, organizations cannot introduce interventions to change them. Our results suggest that because the relationship of some traits with CSE may be zero, the field may be better served by focusing on proximal, malleable, and IT-focused traits, such as PIIT and microcomputer playfulness.

6.3.1 Personal Innovativeness With Information Technology

PIIT refers to "the willingness of an individual to try out new information technology" (Agarwal & Prasad, 1998, p. 206). Innovative individuals are more likely to seek new and stimulating experiences, take risks, and engage in creative IT use (Agarwal & Karahanna, 2000). In general, they are more confident as they approach new tasks and have higher CSE (Agarwal & Karahanna, 2000; Davis & Yi, 2012). Given the strong positive relationship between PIIT and CSE, interventions that raise PIIT may positively affect change in CSE. However, because PIIT is a more stable IT-specific trait (Davis & Yi, 2012), it may not be as conducive to intervention. Although these arguments are tenable, more research is needed to test this proposition.

6.3.2 Microcomputer Playfulness

Microcomputer playfulness is "an individual's tendency to interact spontaneously, inventively, and imaginatively with microcomputers" (Webster & Martocchio, 1992, p. 202). Playfulness is also considered a more enduring IT-specific trait (Davis & Yi, 2012). The cognitive spontaneity of those with a more playful perspective toward computers can enhance their CSE (Davis & Yi, 2012). In addition, individuals with higher playfulness tend to explore and learn new features to a greater extent than those who are less playful. In turn, this can enhance CSE (Davis & Yi, 2012; Webster & Martocchio, 1992, 1995). Thus, researchers should focus on the conditions under which playfulness affects CSE estimations and determine its relative importance to other motivational, task, and environmental characteristics.

6.4 Goals and Motivations

Given the centrality of self-efficacy to the goal-setting process (Locke & Latham, 1990), it is surprising that goals have received such limited attention in the IS literature. Goals are one of the strongest and most generalized predictors of performance, and self-efficacy is a key mechanism in the goal-setting process (Locke & Latham, 1990). "People's beliefs in their efficacy determine the goals they adopt and the strength of their commitment to them" (Bandura, 1997, p. 461). Thus, individuals with higher self-efficacy tend to set higher goals (Bandura & Cervone, 1983) and remain committed to those goals (Locke et al., 1984). Some research has examined the relationship between self-set goals, goal commitment, goal orientation, and CSE (Johnson, 2005; Yi & Hwang, 2003; Yi & Im, 2004), but it has been limited in scope. Given the importance of the relationships between goals and CSE in training, the need for a nuanced, contextualized investigation of the relationship between CSE, goals, and performance remains.

In addition, the meta-analysis suggests the need to incorporate MTL into our models of CSE in the training context. MTL represents the desire to master training materials (Hicks & Klimoski, 1987). Those with higher MTL tend to be more focused and engaged, put in more effort, have greater self-efficacy, and outperform those with lower MTL (Schunk, 1991; Webster & Martocchio, 1992). Given the positive relationship between goals, MTL, and CSE, future researchers should consider the role played by CSE in a broader training framework, such as that derived by Colquitt et al. (2000).

6.5 Task Characteristics

Despite the attention paid in the broader self-efficacy literature and CSE reviews (Compeau et al., 2006; Marakas et al., 1998), a dearth of research remains regarding task difficulty, complexity, and ambiguity. This represents an opportunity for researchers to focus on how task characteristics affect CSE formation. One area of interest is how CSE interacts with domain efficacy in completing complex domain-spanning tasks—for example, in the move to e-learning that took place at universities during the COVID-19 pandemic. Successful e-learning requires not only CSE but also self-efficacy in the domain of study. Consistent with Marakas et al. (2007), successful outcomes depend upon individuals having both higher CSE and domain self-efficacy (deNoyelles et al., 2014; Looney et al., 2006). To advance our knowledge of CSE and its role in organizational and consumer settings, we must examine more complex and domain-spanning tasks than we currently do, with the goal of understanding how CSE and functional domain self-efficacy interact to improve task outcomes.

6.6 Feedback

The self-efficacy and training literature has demonstrated the importance of feedback in skill development. How feedback is conveyed can enhance or undermine an individual's sense of efficacy (Bandura, 1997). For example, researchers found that emphasizing training success led to higher efficacy estimations than when performance deficiencies were highlighted (Bandura & Cervone, 1983). Although limited research has focused on the role of feedback in CSE (Martocchio & Dulebohn, 1994; Webster & Martocchio, 1992), in redressing that deficit, scholars must consider the ethical implications of manipulating feedback (Marakas et al., 1998). That is, artificially lowering CSE estimations in an experimental context may lead subjects to generalize decreases to the software used outside of the training context (Johnson et al., 2016a), which can have unintended practical implications for job performance, while raising CSE to high levels may cause overconfidence that results in counterproductive learning behaviors (Moores & Chang, 2009).

6.7 User Behaviors

6.7.1 Effort & Attributions

According to theory, CSE can affect the behaviors individuals employ when learning to use computers. For example, individuals with higher CSE put in greater effort and are more persistent than those who demonstrate lower CSE. However, in some situations, this may not lead to sustained efficacy increases but, counterintuitively, may result in reduced efficacy estimations in the future (Bandura, 1986). One way to explain the complex relationship between effort and CSE is through the lens of attribution theory, which focuses on how individuals interpret the causes of behavior and outcomes (Weiner, 1972). Thus, the interpretation of success, failure, or effort will determine CSE change (Silver et al., 1995; Stajkovic & Sommer, 2000) so that efficacy estimations are more likely to change in response to internal and stable attributions regarding performance compared to external and unstable attributions (Johnson et al., 2006; Schunk & Gunn, 1986). In turn, self-efficacy affects how an individual makes attributions (Stajkovic & Sommer, 2000).

Additional studies are needed that focus on the relationship between CSE and causal attributions. Studies might focus on how attribution processes operate differently for those with high vs. low CSE and affect how people learn new technology and recover from poor software performance and on how task characteristics affect the attribution-CSE relationship. This is particularly important in today's computing environment, where employees are expected to move seamlessly between software applications and an individual's performance using one type of software may affect their CSE for other types (Johnson et al., 2016a).

6.7.2 Training & Development Behaviors

The growth of corporate and educational e-learning has continued with an examination of the role of CSE. Our meta-analysis identified several variables of interest to researchers, including engagement, peer and instructor interaction, metacognition, and self-regulated learning behaviors. Metacognitive behaviors focus on an individual's awareness and regulation of cognitive processes (Flavell, 1979). Self-regulated learning behaviors keep people "focused on a task … to monitor their task-completion progress" (Santhanam et al., 2008, p. 30).

Engagement is a major challenge facing e-learning students because instruction is often individually focused and isolating (Johnson & Brown, 2017), and the drop-out rate tends to be high. The results of the meta-analysis suggest that activities that enhance efficacy may also improve engagement. One potential advantage of e-learning is that it can provide an enhanced ability to manage and control learning (DeRouin et al., 2004), but only those students with stronger metacognition and self-regulated learning strategies can effectively leverage this control (Santhanam et al., 2008; Sitzmann et al., 2009). This meta-analysis suggests that CSE may be a key mechanism for enhancing engagement and metacognition behaviors.

The meta-analytic results also indicate that individuals with higher CSE are more likely to engage and interact with their peers online. Interaction can improve learning performance by helping individuals process information more deeply, receive greater peer feedback, and evaluate training progress (Piccoli et al., 2001). Individuals with greater CSE should be more confident in leveraging technology for better quality communication, which allows them to receive the benefits of interaction (Johnson & Brown, 2017). However, the strength of the relationship between CSE and interaction depends on the context in which training occurs. If the online environment is not pedagogically designed to encourage interaction, individuals may have strong CSE but may fail to communicate with peers (Hornik et al., 2007). Thus, researchers need to consider specific contexts and the pedagogical design of e-learning to understand how to leverage CSE to improve peer interaction and understand the contexts where peer interaction and CSE offer differential predictability regarding performance.

6.7.3 Training Outcomes

With the growth of e-learning, researchers are examining outcomes beyond performance—including training satisfaction and utility judgments, also called course instrumentality. These reflect individual beliefs about content and knowledge gained in a course and whether it is valuable or relevant (Alliger et al., 1997). Individuals who are more satisfied with e-learning are more likely to enroll in courses in the future (Lim, 2001). In addition, when individuals find the training to be relevant and valuable, they will be more likely to transfer their knowledge to the job (Sitzmann et al., 2008). Given the strong correlations between these variables and CSE and their importance in developing effective e-learning and training initiatives, they have been added to the CSE model.

7 Future Research Opportunities

Advances in self-efficacy theory, as well as in the breadth and depth of technology use, require an updated understanding of CSE. In an environment where software is designed for use on multiple devices and operating systems, a more complete understanding of CSE will help organizations develop resilient users who can seamlessly move from one type of software or platform to another and bounce back from unsuccessful experiences. To this end, three additional areas of research are suggested: the boundary conditions of CSE, the growing importance of CSE generality, and expanding the levels of CSE.

7.1 Boundary Conditions

Some have argued that in some contexts, self-efficacy may be negatively related to future performance (Bandura & Jourden, 1991; Vancouver & Kendall, 2006; Vancouver et al., 2001). When individuals are highly efficacious, they may become overconfident in their abilities and put less effort into learning. Extremely high efficacy may cause individuals to ignore cautionary feedback and commit to questionable courses of action (Audia et al., 2000; Whyte et al., 1997), which may ultimately lead to poor learning outcomes (Moores & Chang, 2009). When CSE is too high, an individual may consider a task easy and not invest resources in preparing for and completing the task (Vancouver et al., 2008). Thus, research is needed on the conditions in which CSE may negatively affect effort, motivation, and performance. For example, scholars could investigate whether those who rely on smartphones and office productivity software are sufficiently equipped to use complex business ERP software and what, if any, negative outcomes may result.

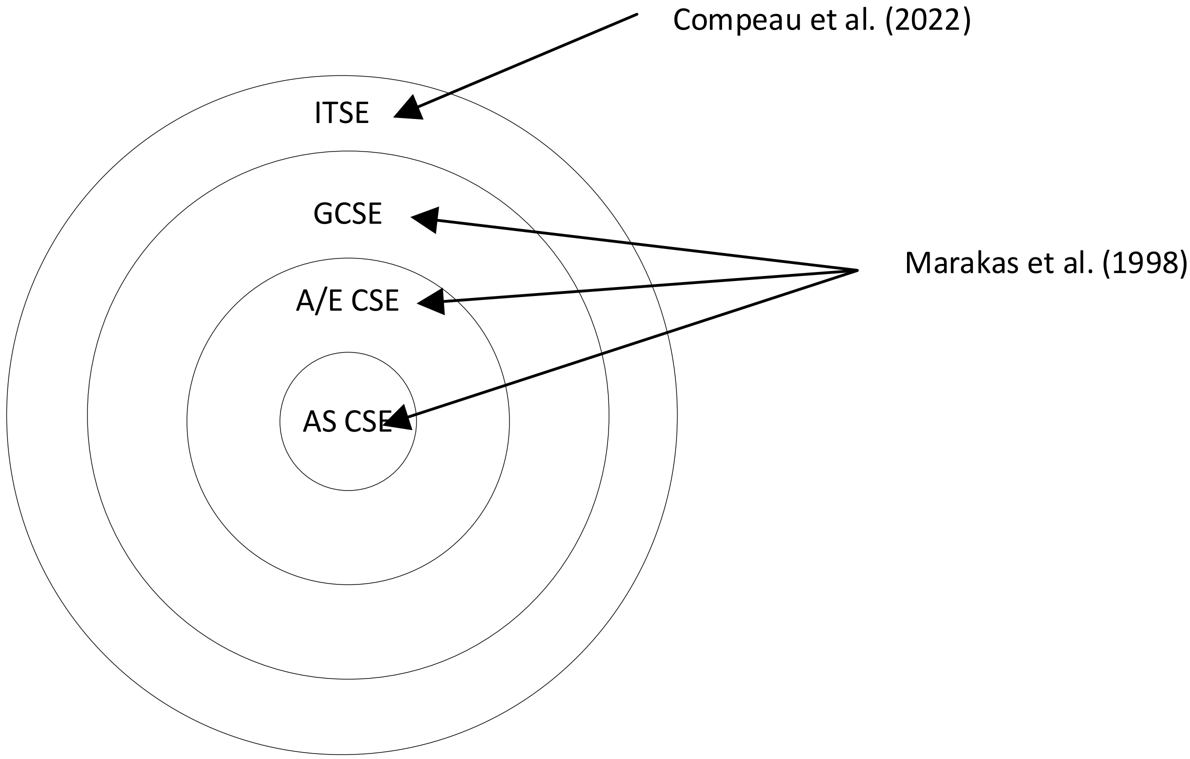
7.2 CSE Generality

CSE generality reflects the extent to which self-efficacy beliefs associated with one activity may generalize to others. It is an important concept in the computing context, where employees and consumers use a myriad of devices to access, manipulate, integrate, and share data from cloud-based and traditional software. Through generality, successful experiences with one software package can increase efficacy estimations for software packages that are perceived to be similar. However, negative experiences with one software package can lower self-efficacy for other packages (Johnson et al., 2016a). Negative experiences may have an exaggerated impact on efficacy estimations, as an unexpected negative experience can create an emotional reaction in the user and can increase the salience of this event in the user's mind (Berntsen, 2002).

This risk is particularly relevant for those who have grown up with personal and mobile technologies and must learn to use complex ERP systems in the course of employment. Since people often base their efficacy estimations on the use of personal technologies and mobile devices that are simpler and easier to use, they may overestimate their capabilities to use ERPs. In turn, this could reduce the user's preparatory effort as they are learning and could lead to an unexpected failure, which could, in turn, reduce that individual's CSE across multiple software applications. For this reason, we believe research should investigate how to calibrate new employees' CSE for organizational ERPs and how CSE generalizes across organizational systems and use contexts. It could be interesting to see how efficacy evolves for digital natives exposed to more complex ERP systems and whether training mitigates the risks of overconfidence when learning to use complex business systems.

7.3 Extending the Conceptualization of CSE

The variety and complexity of hardware, software, and data tools have proliferated since CSE was first conceptualized. Some scholars have suggested that the computing environment has evolved to the point where the effectiveness of CSE's conceptualization and measurement should be reassessed (Compeau et al., 2022). However, given that a computer is simply "a programmable … electronic device that can store, retrieve, and process data" (Merriam-Webster Dictionary, 2018), the IT tools used today may be viewed as extensions of the traditional computing environment. Rather than identifying a fundamentally different construct, Compeau et al. (2022) may have identified a more general level of CSE focused on the broader IT environment (Figure 3).



Note: ITSE = Information technology self-efficacy; GCSE = General computer self-efficacy; A/E CSE = Application environment computer self-efficacy; AS CSE = Application specific computer self-efficacy

Figure 3. Levels of CSE Specificity

Tablets and smartphones require different user interaction methods and reflect a different software application environment, one that may differ fundamentally from traditional computing environments. We concur with Compeau et al. that an updated conceptualization of CSE may be needed to allow researchers to investigate the multiple levels of CSE, how application-specific CSE estimates generalize from one type of software or device to another, and whether new measures are warranted.

7.4 Limitations

Like all research, our work has limitations. Our in-depth review of the literature restricts attention to studies that examine CSE and the constructs in CSE's nomological network using specific definitions taken from the literature. When coding these studies, we included data that referenced constructs by generally accepted names (e.g., CSE, age, and anxiety) and data whose conceptual definitions mapped to our conceptual/theoretical definitions (e.g., software self-efficacy, relative advantage, and social influence).

Because our initial sample included a wide variety of studies, we may have introduced noise into our dataset that could have attenuated correlations (Hunter & Schmidt, 2004). However, in coding the data, we focused on how closely the measurement of a construct mapped to its definition. Thus, we are confident that the data adequately represent the constructs. Finally, due to the triadic reciprocal nature of SCT (Bandura, 1997), it was not possible to test all variables concurrently in a path model. Care should be taken in interpreting the relationships specified in the model, as more research is needed to assess the incremental validity of each variable.

Another limitation, which is common to many meta-analyses, is that we were unable to fully examine the categorical and continuous moderator relationships and how they mutually affect one another. The major issues that arose with respect to conducting these analyses were sample size limitations (lower *k*), the use of proxy variables (cultural variables), and scaling differences in the moderators, each of which could lead to untrustworthy assessments (Schmidt & Hunter, 2015). As more studies are conducted and researchers continue to assess CSE, we encourage a fuller examination of the moderators.

8 Conclusion

This article represents the broadest and most thorough investigation into the antecedents and consequences of CSE to date. Our findings indicate that CSE remains a crucial factor in the adoption of new technology and IT training processes. Despite a strong interest in CSE, several important variables remain understudied (i.e., goals, task characteristics, and the environment). We have identified several new variables for CSE scholars to consider, such as PIIT, playfulness, MTL, interactions, and engagement. Our findings also underscore the value of considering how a sample's country of origin and its cultural and technological context may moderate the relationship between CSE and variables of interest.

Finally, we present directions in which CSE scholars may go to expand their understanding of the nature of CSE, its role in training and use of technology, and the interdisciplinary tasks involved in using computers and other advanced IT. Although we have learned much about CSE, the findings that emerged from this meta-analysis suggest the need to continue investigating the construct with the goal of understanding its conceptualization and role in today's complex computing and technology environments.

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