Internal and External Dimensions of Computer Self-Efficacy: An Empirical Examination

Jason Bennett Thatcher, J. Christopher Zimmer, Michael J. Gundlach, and D. Harrison McKnight

Abstract—Researchers have found computer self-efficacy (CSE) to be important to technology adoption. Past research has treated CSE as a unitary concept. This paper proposes that CSE has two dimensions—internal and external. The idea that CSE has internal and external dimensions is based on attribution theory, which identifies the human tendency to attribute events to causes that are either internal or external to the self. The internal CSE dimension focuses on how individuals perceive their capacity to use computers independently (i.e., without help). The external CSE dimension focuses on how individuals perceive their ability to use computers with human assistance and other forms of external support. Using items drawn from the Compeau and Higgins’ CSE instrument, this paper examines each dimension’s relationship to computer anxiety and perceived ease-of-use of information technology. The paper also reports on six studies that examine this proposal, and contributes to the literature by identifying two distinct CSE dimensions, developing theory-driven explanations for their relationships to constructs within the CSE’s nomological network, and empirically establishing that they have distinct effects. Implications for research and practice are presented.

Index Terms—Attribution theory, computer anxiety, computer self-efficacy (CSE), perceived ease-of-use (EOU), social cognitive theory.

I. INTRODUCTION

Effectively adopting technologies is crucial for successful enterprises, and past research shows that computer self-efficacy (CSE) is a key adoption factor. At the individual level of analysis, understanding information technology (IT) use factors has been of great interest to information systems researchers [2]–[4]. Numerous studies have demonstrated that CSE plays an important role in influencing IT perceptions and use [5]–[7]. CSE refers to a “judgment of one’s capability to use a computer” [1, p. 195]. Past research suggests that CSE is an important antecedent to beliefs and emotions that influence IT use. For example, CSE positively influences the perceived ease of use (EOU) of IT [8] and negatively influences computer anxiety [2].

Although CSE has been frequently researched, CSE scholars suggest that, “the results obtained to date have, in some cases, been either equivocal or contradictory” [7], [9]. One such counterintuitive finding is that organizational support negatively relates to CSE [2]. Compeau and Higgins [2] originally hypothesized that organizational support should foster efficacy. To explain this finding, they surmised that: 1) those with lower CSE are more aware of organizational support and 2) high support may “hinder the formation” of high CSE either by making it so that one does not have to solve one’s own computer problems or by making one feel less able than the computer-savvy person who solved it. Compeau and Higgins conclude that these two reasons have “very different implications” and that “additional research is needed” to find out which is correct [2, p. 204]. Leading thinkers on CSE argue that such research could potentially strengthen our understanding of the theory and measurement of CSE [7], [9], [10].

Based on such commentary and our own review of the CSE literature (for reviews of CSE research see [7] and [9]), we believe that problematic findings in CSE research are likely rooted in how studies have measured the construct. Inconsistencies among diverse self-developed measures [10]–[12] or modified measures of CSE (e.g., [13] and [14]) illustrate the need for revisiting how we conceptualize and measure the construct. For example, in contrast to Compeau and Higgins’ [1] broad CSE measure, Marakas et al. [79] recently suggested using first-order, formative, application-specific, CSE measures. These inconsistencies in measurement are one likely source of problematic findings in CSE research.

To advance CSE research, scholars need to change how they think about and measure efficacy. Instead of a unitary construct, we argue that CSE reflects distinct beliefs about one’s ability to perform tasks either: 1) on one’s own (internal CSE) or 2) with the support of others (external CSE). As found in other domains (e.g., [15]), using unitary measures to operationalize multidimensional concepts can render building a comprehensive body of knowledge problematic. For example, a broad CSE measure would render it difficult to compare results across studies because the salience of distinct CSE subdimensions within a given sample could not be ascertained. In this case, the dimension that has the greater effect on the dependent variable would not be known. Furthermore, if two dimensions of CSE existed within a unitary CSE measure, their influence could be confounded such that either no effects would be found or the effects found would be hard to interpret.

In light of these issues, this paper examines two questions: 1) what are the conceptual dimensions of CSE? and 2) can the Compeau and Higgins’ [1] CSE scale be adapted to operationalize these conceptual dimensions? In response to these questions, this paper first contributes by providing a firm conceptual basis for the two CSE dimensions using attribution theory, a well-developed cognitive psychology domain. Specifically, it identifies internally and externally attributable subdimensions of
CSE. Second, the paper also tests the convergent and discriminant validity of the two dimensions. Further, it demonstrates that CSE has two dimensions by showing that each CSE dimension has a distinct effect on EOU and computer anxiety. Finally, we identify four three-item CSE measures that demonstrate equal or greater predictive power than a ten-item single dimension CSE measure.

The paper unfolds as follows. First, it develops the theoretical underpinnings for a multidimensional CSE construct. Then, it empirically tests the validity of the CSE dimensions. The paper concludes with a discussion of implications for research and practice.

A. Theoretical Framework

When approaching a task, individuals make three main CSE assessments [16], [17]. First, they analyze task requirements, focusing on resources required to perform the task. Second, individuals assess their personal ability to perform the task. This analysis evaluates prior experience and the conditions under which task outcomes occurred. Third, individuals assess the probability that they will achieve outcomes given their ability and the situation (e.g., skills, effort, experience) [18]. By understanding the sources of beliefs about ability, research can provide stronger prescriptions for improving task performance.

Social cognitive theory (SCT) ties beliefs about ability to individual performance. SCT posits that there are two kinds of expectations salient to understanding performance—outcome and efficacy [19]. Outcome expectations refer to the connections individuals make between specific behaviors and task outcomes. Efficacy expectations refer to whether individuals believe they can perform the behaviors required to produce those outcomes [19], [20]. When individuals are highly efficacious, they believe they can influence or control an outcome. Research suggests that self-efficacy provides a powerful explanation for individual behavior and task performance.

SCT-driven research focuses on how to foster efficacy beliefs and how to understand their implications. SCT identifies four sources of efficacy beliefs [18], [19]—enactive mastery, emotion, vicarious experiences, and social persuasion [21]. Internally, enactive mastery and emotion influence individuals’ efficacy. Enactive mastery refers to an individual successfully performing the task without assistance. Emotion links individuals’ mood to their efficacy judgments. For example, regardless of domain, individuals report higher efficacy beliefs when happy than when sad [22]. Vicarious experiences refer to seeing someone similar to oneself succeed by sustained effort. Social persuasion occurs when individuals are persuaded by others that they have the necessary skills and ability to succeed. By manipulating these efficacy beliefs, SCT research demonstrates that one may improve performance in general and specific situations [18], [19].

While SCT speaks to how efficacy can be influenced, attribution theory provides a causal explanation for sources of efficacy beliefs. Consistent with SCT, attribution theory research suggests that individuals’ beliefs about performance vary with the controllability of an outcome [17], [23]. Based on experience, attribution theory explains how individuals develop a lens, or attributional tendency for causality, through which they anchor assessments of their future ability to perform the same or similar sets of behaviors. Attributions are closely tied to one’s efficacy beliefs. Attributions of effort, ability, and luck draw on beliefs about past successes or failures, whereas efficacy beliefs pertain to future performance capabilities [18].

Where SCT directs attention to internal sources of efficacy [24], an attribution theory approach to efficacy suggests that individuals’ efficacy may also be rooted in external sources. Attribution research suggests that individuals may believe that success (or failure) originates within themselves (i.e., internal) or from other factors in the environment (i.e., external) [17]. For example, if attributing success internally, an individual would believe that completing a complex Excel formula was the result of hard work. Alternately, if failing to execute the formula properly, an individual might complain they lacked training or the interface was too complex. Individuals usually believe successes are caused by internal sources while failures are caused by external sources [25]. Distinguishing between internal and external efficacy beliefs is important because individuals who make internal attributions express more confidence in their ability to perform a task and report more positive beliefs and attitudes than do those who make external attributions [26]–[29]. This is because they have more control over internal factors.

By combining SCT and attribution theory, we build a strong theoretical and practical foundation for understanding how individuals form efficacy beliefs and how these beliefs affect performance. Attribution theory underscores locus of causality as a means to classify internal and external dimensions of efficacy. In terms of locus of causality, enactive mastery and emotion may be mapped as sources of the internal dimension of efficacy because they result primarily from individual experiences or responses to a situation. Vicarious experience and social persuasion may be mapped as sources of the external dimension of efficacy. They depend on the ability to model or interact with other individuals.

II. ATTRIBUTIONS AND COMPUTER SELF-EFFICACY

Revisiting the conceptual foundations of self-efficacy in light of attribution theory may assist in resolving equivocal findings in CSE research. Attribution theory suggests that CSE consists of two distinct, yet related, beliefs about control—internal and external.

Internal CSE taps into individuals’ beliefs about their ability to independently accomplish a task using a computer. Not unlike a small child who broadcasts efficacy by proudly saying, “Look, Mom, I can do it all by myself,” or a sophisticated computer user claiming to “never need help” learning a new software package, technology users develop individual efficacy based on prior mastery experiences. When high on internal CSE, one is less reliant on external support to learn or apply ITs. Hence, we define internal CSE as the belief that one has the ability to independently accomplish a task using a computer.

External CSE taps into individuals’ beliefs about their ability to perform a computer task with support such as human assistance. Efficacy research suggests that beliefs about ability are
influenced by other social actors upon whom they can model their behavior [26], [30]. Recent research suggests that individuals regard both humans and computers as social actors who influence their computing beliefs [31], [32]. External CSE rests on individuals’ beliefs about being able to perform a task when external support is available, be it from another person or from the software itself. When one relies on human or a software support to use technology, one assumes that there is a degree of interactivity and social presence that enables one to perform a task. For example, a person or software package may provide step-by-step guidance in an interactive manner that allows one to complete a task. Hence, we define \textit{external CSE} as the belief that one has the ability to perform a task on a computer with support from a social actor.

CSE measures often combine internal and external dimensions. For example, when assessing behavioral modeling and outcome expectancy, Compeau and Higgins [33] used a broadly defined CSE measure to assess training’s influence on individuals’ beliefs about their ability to use IT. To do so, they used items focused on enactive mastery, vicarious learning, and social persuasion, and thus, combined internal and external sources of CSE into a single measure. Hence, we define \textit{external CSE} as the belief that one has the ability to perform a task on a computer with support from a social actor.

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|}
\hline
\textbf{Author(s) and Year} & \textbf{CSE Measure} & \textbf{Number of Items} \\
\hline
(Hunton & Beeler, 1997) & (Hunton, 1996) & 4 \\
(Compeau, Higgins, & (Compeau & Higgins, 1995) & 10 \\
& & (Compeau & Higgins, 1995) & 10 \\
(Venkataseh, 1999) & (Compeau & Higgins, 1995) & 10 \\
(Aganwal & Karahanna, 2000) & (Compeau & Higgins, 1995) & 10 \\
(Piccoli, Ahmad, & (Compeau & Higgins, 1995) & n.a. \\
& Ives, 2001) & (Compeau & Higgins, 1995) & n.a. \\
(Thatcher & Perrewe, 2002) & (Compeau & Higgins, 1995) & 10 \\
(Speier & Morris, 2003) & (Compeau & Higgins, 1995) & n.a. \\
(Venkataseh, & (Compeau & Higgins, 1995) & n.a. \\
& Davis, & (Compeau & Higgins, 1995) & n.a. \\
& 2003) & & 8 \\
(Marcolin, Compeau, Munro, & (Compeau & Higgins, 1995) & 8 \\
& & & 10 \\
(Venkataseh, 2000) & (Compeau & Higgins, 1995) & 10 \\
(Aganwal, Sambamurthy, & (Compeau & Higgins, 1995) & 10 \\
& Stair, 2000) & & Author created for specific SE \\
(Yi & Davis, 2003) & (Johnson & Marakas, 2000) & 7 \\
(Galletta, Henry, McCoy, & (Compeau & Higgins, 1995) & 10 \\
& Polaak, 2006) & (Compeau & Higgins, 1995) & 10 \\
(Webster & Hackley, 1997) & (Hollenbeck & Brief, 1987) & 5 \\
(Kuo, Chu, Hu, & (Hollenbeck & Brief, 1987) & Author created for specific SE \\
& Hsieh, 2004) & & 7 \\
(Heu & Chiu, 2004) & (Torkzadeh & van Dyke, 2001) & 30 \\
(Stafford, 2003) & (Compeau & Higgins, 1995) & 10 \\
(Frayne & Gerring, 2000) & & Author created for specific SE \\
(Hong, Thong, Wong, & (Compeau & Higgins, 1995) & 8 \\
& Tam, 2001) & & \\
\hline
\end{tabular}
\caption{Review of Prior Works Using CSE and the Scales Used to Measure CSE}
\end{table}

However, a broadly defined CSE measure may be inadequate for predicting context-specific IT feelings, beliefs, or performance. For example, an IT training program may increase users’ confidence in their ability to use IT with assistance (i.e., external CSE); however, it may not increase users’ confidence in their ability to use IT on their own (i.e., internal CSE). Because internal and external CSE may not covary, a broad measure may mask the effect of a training program on a specific dimension of efficacy and performance. If internal and external CSE are combined in one measure and if they do represent distinct dimensions, then combining them may actually reduce their predictive power. When efficacy is evaluated in specific task domains such as IT, internal and external dimensions may conflict and may not yield a clear picture of how CSE relates to other constructs.

In addition, failing to distinguish the types of CSE may yield a limited view of the sources of CSE beliefs. For example, Johnson and Marakas [10] employed a measure of internally attributable CSE beliefs and found support for the link between CSE and outcome expectancy. However, their measure neither controlled for nor captured the influence of external CSE, which may also be germane in the workplace. As a result, their findings do not speak to how firms may positively influence external CSE beliefs and performance through technical support. Hence, employing too broad or too narrowly focused CSE measures may lead to incomplete results. The implication is that variations in how we measure the CSE concept limits researchers’ ability to build a cumulative body of knowledge about the efficacy’s implications for technology use in organizations.

In order to build on an existing body of CSE research, this study focuses on refining an existing CSE scale. Because of the frequency with which it has been used, we selected the Compeau and Higgins’ [1] measure. This measure has been referenced in at least 274 refereed journal publications (see, for example, [2], [34], and [35]). Compeau and Higgins’ ten-item scale has been used in its entirety as well as reduced to a smaller subset (see Table I). Other CSE scales have been used much less extensively. The Compeau and Higgins instrument was designed to capture

\footnote{Cited reference search on Information Sciences Institute (ISI) Web of Science on August 31, 2008.}
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Fig. 1. Proposed research model.

the magnitude and strength of CSE across situations [1]. By carefully evaluating the dimensionality of its items, we will possess more effective tools to evaluate CSE’s development and implications. Hence, the next section develops hypotheses that predict the multidimensionality of Compeau and Higgins’ instrument (H1) and evaluates how CSE relates to computer anxiety and EOU (H2–H4).

A. Research Model and Hypotheses

The research model was developed as follows (see Fig. 1). First, the researchers examined the face validity of the Compeau and Higgins’ CSE instrument to determine whether items fell within the internal and external dimensions. Face validity is most often used to assess whether measurement items adequately represent their concept. This assures the important logical link between empirical measures and theoretical concepts on which the veracity of logical positivist science depends. Face validity was assessed prior to empirical analysis in order to identify a priori which items best measured each attributional CSE dimension.

Two of the researchers separately examined the wording and phrasing of the instrument in order to identify items that implied different sources of attributional causation. The researchers consistently identified six items that uniquely represented internal and external dimensions of CSE (Table II). Overall, the researchers agreed on the placement of all but one item (Cohen’s kappa = 0.92).

The two researchers then met and discussed the coding. They agreed that the remaining four items did not have sufficient clarity to be clustered with either dimension or to form a third conceptual dimension; rather, each item represented a separate belief like time availability or built-in help facility. Excluding these items (coded O in Table II), the scale demonstrated the presence of two distinct dimensions representing internal and external CSE. Although the Compeau and Higgins measure did include one item that could be interpreted as measuring ability with support from software (i.e., the help function), it did not include a sufficient number of items required to assess software as a distinct external source of efficacy beliefs. Thus, the Compeau and Higgins measure demonstrated a dimension representing external CSE rooted in human support as well as a dimension representing internal CSE. In sum, an analysis of these measures in light of attribution theory suggests the following:

Hypothesis 1: The Compeau and Higgins’ [1] CSE instrument measures two distinct dimensions of efficacy beliefs.

The information systems literature was then reviewed to identify concepts that might relate to the internal and external CSE dimensions. In this way, nomological validity of the constructs could be demonstrated. Nomological validity refers to whether or not a construct relates as expected with other constructs [36], as suggested by theory [14]. If two constructs behave differently in their nomological network, this provides additional evidence that they are discriminant.

To establish CSE’s nomological validity, we examined two well-established correlates of CSE—perceived EOU and computer anxiety. We selected EOU and computer anxiety for three reasons. First, CSE exhibits distinct relationships with EOU and computer anxiety. We selected EOU and computer anxiety for three reasons. First, CSE exhibits distinct relationships with EOU and computer anxiety. When individuals express high levels of CSE, research suggests that they report high levels of EOU [8], [37]. By contrast, when individuals have high levels of CSE, studies consistently show that individuals report low levels of computer

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Second, EOU and computer anxiety are used as outcome variables in important CSE research. In an important extension of the technology acceptance model, Venkatesh [37] found that CSE was a significant positive correlate of EOU. Also, in their seminal CSE research, Compeau and coworkers [2], [33] found that CSE was a negative correlate of computer anxiety. Third, recent research suggests that self-efficacy best predicts beliefs and feelings that lead to behavior. According to the Unified Theory of Acceptance and Use of Technology (UTAUT) [38], EOU should mediate the influence of efficacy on actual usage behavior. Similarly, computer anxiety may be modeled as an outcome of efficacy beliefs [7], [26].\footnote{We thank an anonymous reviewer for this observation.} As a result, we examine nomological validity using EOU and computer anxiety.

EOU is defined as “the degree to which the prospective user expects the target system to be free of effort” [39]. Venkatesh and Davis [8] found that CSE was a significant positive correlate of EOU of IT. Since belief that one can independently accomplish a computer task (internal CSE) will make a system seem simple to use, we believe that the internal CSE dimension will positively affect EOU. In other words, when individuals have higher levels of internal CSE, they should report higher levels of EOU because they have confidence in their personal ability to use IT.

**Hypothesis 2a:** Internal CSE will have a significant, positive influence on perceived EOU.

External CSE reflects beliefs about the ability to use IT with external assistance. When individuals believe that they can perform a task with assistance, they may still not believe that a technology will be easy for them to use. Beliefs linked to ability should improve as the sources of successful performances are attributed to internal causes grounded within one’s self (e.g., ability or effort) rather than external conditions [4], [26], [29], [40]–[42]. Because perceptions of EOU should be based primarily on beliefs in individuals’ capabilities without potentially receiving the assistance external social actors, we believe that external CSE should not influence the perceived EOU of IT.

**Hypothesis 2b:** External CSE will not significantly affect perceived EOU.

Computer anxiety reflects negative emotional arousal linked to actual or potential computer use [43]. Computer anxiety stems from irrational fears about the implications of computer use such as the fear of losing important data or the fear of making other mistakes [44]. Compeau et al. [2] found that CSE was a significant negative correlate of computer anxiety. Given that computer anxiety reflects irrational fears about IT use, it is reasonable to expect that it will be influenced by internal and external beliefs about using IT, i.e., the dimension of CSE should influence computer anxiety. A high level of internal CSE should lower anxiety about using the computer because it implies that one has personal control over the computer. High external CSE should lower anxiety because one would feel more assured (and thus less anxious), knowing that external support is available when performing computer-based tasks. As a result, we expect that the internal and external CSE dimensions will demonstrate significant negative relationships with computer anxiety.

**Hypothesis 3a:** Internal CSE will demonstrate a significant negative relationship with computer anxiety.

**Hypothesis 3b:** External CSE will demonstrate a significant negative relationship with computer anxiety.

Even if the hypothesized relationships to EOU and computer anxiety are demonstrated, to be a useful extension of CSE research, the dual-construct (internal and external) CSE measures must be more explanatory than the original CSE instrument. According to the measurement theory, a broad CSE scale that taps into distinct dimensions may confound the actual relationship between the dimensions of efficacy and related variables [45]. If combined into one measure, the distinct explanatory power of internal and external CSE will be masked, resulting in less

### TABLE II

**DIMENSION CODING OF THE COMPEAU AND HIGGINS CSE ITEMS**

<table>
<thead>
<tr>
<th>Computer Self Efficacy Items</th>
<th>Rater 1</th>
<th>Rater 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. I could complete my job using the technology if ...</td>
<td>I</td>
<td>I</td>
</tr>
<tr>
<td>2. ... there was no one around to tell me what to do. (I)</td>
<td>I</td>
<td>I</td>
</tr>
<tr>
<td>3. ... I had never used a package like it before. (I)</td>
<td>I</td>
<td>I</td>
</tr>
<tr>
<td>4. ... I had only the software manuals for reference. (I)</td>
<td>E</td>
<td>O</td>
</tr>
<tr>
<td>5. ... I had seen someone else using it before trying it myself.</td>
<td>E</td>
<td>E</td>
</tr>
<tr>
<td>6. ... I could call someone for help if I got stuck. (E)</td>
<td>E</td>
<td>E</td>
</tr>
<tr>
<td>7. ... someone else helped me get started. (E)</td>
<td>O</td>
<td>O</td>
</tr>
<tr>
<td>8. ... I had a lot of time to complete the job for which the software was provided.</td>
<td>E</td>
<td>O</td>
</tr>
<tr>
<td>9. ... someone showed me how to do it first. (E)</td>
<td>O</td>
<td>O</td>
</tr>
<tr>
<td>10. ... I used similar packages like this one before to do the job.</td>
<td>O</td>
<td>O</td>
</tr>
</tbody>
</table>

\footnotetext{(I)—Items comprising the internal dimension of CSE. (E)—Items comprising the external dimension of CSE. (O)—Other sources of efficacy such as resource availability or experience. Cohen’s Kappa, a measure of interrater reliability, was 0.92.}
explained variance. Alternatively, by modeling these dimensions as two distinct constructs, this should result in greater explained variance in the endogenous variables. Hence, if internal and external CSE are distinct, they should explain more variance in EOU and computer anxiety.

Hypothesis 4a: The hypothesized dimensions of CSE will explain more variance in perceived EOU than will the original measure of CSE.

Hypothesis 4b: The hypothesized dimensions of CSE will explain more variance in computer anxiety than will the original measure of CSE.

III. METHOD

We examined six datasets to investigate CSE’s dimensionality. We present sample characteristics, methods, and target technologies in Table III. Although all samples were drawn from student populations, the target technologies varied in levels of specificity and difficulty with a focus on technologies commonly used in the workplace such as Excel, Oracle Developer, and Internet applications. Also, data were collected at four different universities. Across samples, we captured information from respondents with diverse ethnicities, ages, and computer experience. By using a multistudy approach to evaluate efficacy’s dimensionality, we felt our analysis: 1) would present a rigorous examination of efficacy’s dimensionality and 2) if multidimensionality was established, would be a robust test of CSE’s nomological net.

A. Construct Measures

In addition to the ten-item Compeau and Higgins’ [1] CSE scale, we used two other established scales. To measure EOU, we used items from the work of Davis [3]. Depending on the sample, either three or four items were used. Computer anxiety was measured using the computer anxiety rating scale (CARS) [46]. We used the four items identified by Compeau and Higgins [1] that best predict anxiety associated with computer use. These items have been used in subsequent computer anxiety research [2], [47]. All study items are reported in Table IV.

IV. RESULTS

We followed Anderson and Gerbing’s [48] guidelines, estimating the measurement model prior to evaluating the structural model. To analyze the data, we used EQS version 6.1, build 90 [49]. We first evaluated the dimensionality of the Compeau and Higgins’ [1] CSE measure (H1). Next, we examined how CSE influences EOU and computer anxiety (H2 and H3). Then, we evaluated the predictive validity of our two-factor structure of CSE (H4).

A. Hypothesis 1 Results

Hypothesis 1 states that Compeau and Higgins’ [1] CSE instrument measures two distinct dimensions of efficacy beliefs. To formally test this, we collected data from six independent samples. Rather than present six separate analyses, we tested the six samples for invariance [50] so that the samples can be combined. We then conducted an exploratory factor analysis, and the results were used to conduct a confirmatory factor analysis.

To test whether the six independent samples could be aggregated, we analyzed the samples for invariance. If these groups show invariance, then the data can be aggregated and tested as a single sample [50], [51]. Invariance is demonstrated by showing good fit across all models when they are analyzed.
TABLE IV
EFA RESULTS FOR TEN ITEMS AND FOR SIX INTERNAL/EXTERNAL CSE ITEMS

<table>
<thead>
<tr>
<th>Computer Self Efficacy Items</th>
<th>E.F.A. 10 Items</th>
</tr>
</thead>
<tbody>
<tr>
<td>I could complete my job using the technology if ...</td>
<td>1</td>
</tr>
<tr>
<td>1. ... there was no one around to tell me what to do. (I)</td>
<td>0.185</td>
</tr>
<tr>
<td>2. ... I had never used a package like it before. (I)</td>
<td>0.196</td>
</tr>
<tr>
<td>3. ... I had only the software manuals for reference. (I)</td>
<td>0.320</td>
</tr>
<tr>
<td>4. ... I had seen someone else using it before trying it myself.*</td>
<td>0.681</td>
</tr>
<tr>
<td>5. ... I could call someone for help if I got stuck. (E)</td>
<td>0.790</td>
</tr>
<tr>
<td>6. ... someone else helped me get started. (E)</td>
<td>0.804</td>
</tr>
<tr>
<td>7. ... I had a lot of time to complete the job for which the software was provided.*</td>
<td>0.480</td>
</tr>
<tr>
<td>8. ... I had just the built-in help facility for assistance*</td>
<td>0.205</td>
</tr>
<tr>
<td>9. ... someone showed me how to do it first. (E)</td>
<td>0.733</td>
</tr>
<tr>
<td>10. ... I had used similar packages like this one before to do the job.*</td>
<td>0.560</td>
</tr>
</tbody>
</table>

* These items were not included in six item EFA.

simultaneously with increasing restrictions. The first step is a baseline model in which the samples are analyzed simultaneously with no restrictions. In step two, configural invariance constrains the factor loadings to be equivalent across all groups. The final step, structural invariance, retains the constraint from the previous step and includes the further restriction that the covariances between factors are equivalent across all samples. If all three models have good fit, then the samples are invariant and can be combined. We found that all three models demonstrated good fit, thus supporting sample aggregation. The baseline invariance statistics were a Satorra–Bentler $\chi^2$ = 454.06, comparative fit index (CFI) = 0.94, root mean square error of approximation (RMSEA) = 0.08. The configural invariance statistics were a Satorra–Bentler $\chi^2$ = 529.01, CFI = 0.93, and RMSEA = 0.08. The structural invariance statistics were a Satorra–Bentler $\chi^2$ = 610.73, CFI = 0.91, and RMSEA = 0.08.

For the aggregated sample, when all ten items were subjected to an exploratory factor analysis, the items exhibited an unacceptable amount of cross loading (see Table IV). Looking at the pattern of cross-loading and the face validity results, items 4, 7, 8, and 10 (see Table II) that did not conceptually map to either individual or human-assisted efficacy were removed and the exploratory factor analyses (EFAs) were run again with the remaining six items. As shown in Table V, when these six items are used, the EFAs show clear indication of CSE being composed of two dimensions, with only item 3 demonstrating a problematic cross-loading. Based on the results of the factor analysis, we then conducted a confirmatory factor analysis (CFA).

We conducted two different CFAs. First, we used all ten items and estimated CFAs using a single-factor and a three-factor model. Second, we used the six items in Table V and compared a single-factor to a two-factor model.

$^3$ The data were also analyzed separately and the findings across all six samples were identical, further supporting the invariance findings and the aggregation of the samples. The results of the six separate analyses are available from the corresponding author.

TABLE V
EFA RESULTS FOR TEN ITEMS AND FOR SIX INTERNAL/EXTERNAL CSE ITEMS

<table>
<thead>
<tr>
<th>Computer Self Efficacy Items</th>
<th>E.F.A. 6 Items</th>
</tr>
</thead>
<tbody>
<tr>
<td>I could complete my job using the technology if ...</td>
<td>Int.</td>
</tr>
<tr>
<td>1. ... there was no one around to tell me what to do. (I)</td>
<td>0.864</td>
</tr>
<tr>
<td>2. ... I had never used a package like it before. (I)</td>
<td>0.867</td>
</tr>
<tr>
<td>3. ... I had only the software manuals for reference. (I)</td>
<td>0.578</td>
</tr>
<tr>
<td>4. ... I could call someone for help if I got stuck. (E)</td>
<td>0.133</td>
</tr>
<tr>
<td>5. ... someone else helped me get started. (E)</td>
<td>0.126</td>
</tr>
<tr>
<td>6. ... someone showed me how to do it first. (E)</td>
<td>0.178</td>
</tr>
</tbody>
</table>

CFA works best when items are multivariate normal. The normalized kurtosis estimates in EQS provide a measure of multivariate normality. According to DeCarlo [52], values over 10 may be a problem and values over 20 indicate a more serious problem. Hence, we used robust estimators that correct for multivariate nonnormality to evaluate the CFA whenever the exhibited kurtosis estimates were greater than 10.

When analyzing all ten items, the three-factor model was superior to the one-factor model. The robust fit indexes for the CFI and RMSEA show better fit for the three-factor model (Fig. 2). A CFI greater than 0.90 and an RMSEA below 0.08 is desirable [53]–[55]. While the CFI for the one-factor model showed good fit (CFI = 0.90) the CFI for the three-factor model was higher (CFI = 0.96). Further, the RMSEA for the one-factor model did not show acceptable fit (RMSEA = 0.101), while the three-factor RMSEA did show good fit (RMSEA = 0.068). A chi-square difference test was conducted and this test showed that the three-factor model was superior to the one-factor model ($\chi^2$ difference = 267.16, df$\text{diff} = 3$, p < 0.0001).

To test Hypothesis 1, we used the six items from the EFAs that yielded a two-factor structure (see Fig. 3 and Table VII). We subjected the aggregated sample to a CFA comparing a one-and two-factor solution. When the data were analyzed as a single factor, the normed fit index (NFI) was above the commonly used 0.90 heuristic; however, the CFI was not [56]. Further, the RMSEA was above the generally accepted 0.08 guideline (see Fig. 2 and Table VII) [56]. We then estimated a two-factor solution—internal and external. The two-factor solution yielded
better measures of fit—the CFI and NFI were above 0.90 and the RMSEA was lower than the one-factor solution. Further, the chi-square difference test was significant ($\chi^2$ difference = 120.35, df$_{diff}$ = 1, $p$ < 0.0001), meaning the two-factor solution fits the data significantly better than the one-factor solution [56]. Hence, H1 is supported: the Compeau and Higgins’ [1] CSE measure encompasses two distinct dimensions.

### B. Hypotheses 2 and 3 Results

Since Hypotheses 2 and 3 investigate CSE’s relationship with computer anxiety and perceived EOU, we used a two-step approach to evaluate the structural model. First, the measurement model was evaluated, and then, the structural hypotheses were tested [48]. Furthermore, while the same measures of CSE were used across all four samples, different numbers of items for EOU and computer anxiety were used for some of the samples. Because of the different items used for these constructs, we cannot aggregate the data as we did for H1.

1) **Measurement Model:** Because Sample 1 and Sample 2 did not include computer anxiety or EOU, we used other datasets to test Hypotheses 2 and 3. Samples 3 and 4 evaluated efficacy beliefs about computers at a general level in the workplace and across work, home, and school. Samples 5 and 6 evaluated specific CSE toward Oracle Developer and Microsoft Excel.

2) **Reliability and Validity:** We assessed reliability and dimensionality in three steps. First, reliability was assessed using Cronbach’s alpha [57]. All construct measures were reliable, with Cronbach’s alphas above the 0.70 threshold [58].

Second, to evaluate convergent validity, we conducted an EFA that included our proposed measures of internal CSE and external CSE as well as computer anxiety and EOU. A principal components analysis with a varimax rotation was conducted on each of the four samples. Four factors emerged for each sample and we observed only one cross-loading greater than 0.40 between

---

**TABLE VI**

<table>
<thead>
<tr>
<th>Sample</th>
<th>S-B$^2$</th>
<th>df</th>
<th>CFI</th>
<th>RMSEA</th>
<th>S-B$^2$</th>
<th>df</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>3 unconstrained</td>
<td>57.03</td>
<td>48</td>
<td>0.99</td>
<td>0.03</td>
<td>96.28</td>
<td>5</td>
<td>0.000</td>
</tr>
<tr>
<td>3 constrained</td>
<td>155.31</td>
<td>53</td>
<td>0.84</td>
<td>0.11</td>
<td>135.41</td>
<td>5</td>
<td>0.000</td>
</tr>
<tr>
<td>4 unconstrained</td>
<td>110.90</td>
<td>71</td>
<td>0.98</td>
<td>0.04</td>
<td>135.41</td>
<td>5</td>
<td>0.000</td>
</tr>
<tr>
<td>4 constrained</td>
<td>246.31</td>
<td>76</td>
<td>0.91</td>
<td>0.08</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>5 unconstrained</td>
<td>102.90</td>
<td>71</td>
<td>0.96</td>
<td>0.05</td>
<td>72.09</td>
<td>5</td>
<td>0.000</td>
</tr>
<tr>
<td>5 constrained</td>
<td>174.99</td>
<td>76</td>
<td>0.88</td>
<td>0.09</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>6 unconstrained</td>
<td>143.42</td>
<td>71</td>
<td>0.95</td>
<td>0.07</td>
<td>222.36</td>
<td>6</td>
<td>0.000</td>
</tr>
<tr>
<td>6 constrained</td>
<td>365.78</td>
<td>77</td>
<td>0.79</td>
<td>0.13</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
</tbody>
</table>

---

**TABLE VII**

<table>
<thead>
<tr>
<th>Sample</th>
<th>10 item R$^2$</th>
<th>lower C.I.</th>
<th>upper C.I.</th>
<th>2 factor R$^2$</th>
<th>significant</th>
<th>R$^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>3 unconstrained</td>
<td>0.20</td>
<td>0.15</td>
<td>0.26</td>
<td>0.24</td>
<td>no</td>
<td>0.04</td>
</tr>
<tr>
<td>3 constrained</td>
<td>0.26</td>
<td>0.22</td>
<td>0.30</td>
<td>0.23</td>
<td>no</td>
<td>-0.02</td>
</tr>
<tr>
<td>5 unconstrained</td>
<td>0.11</td>
<td>0.06</td>
<td>0.16</td>
<td>0.34</td>
<td>yes</td>
<td>0.23</td>
</tr>
<tr>
<td>5 constrained</td>
<td>0.18</td>
<td>0.14</td>
<td>0.23</td>
<td>0.41</td>
<td>yes</td>
<td>0.22</td>
</tr>
<tr>
<td>3 unconstrained</td>
<td>0.17</td>
<td>0.11</td>
<td>0.22</td>
<td>0.25</td>
<td>yes</td>
<td>0.08</td>
</tr>
<tr>
<td>3 constrained</td>
<td>0.12</td>
<td>0.09</td>
<td>0.16</td>
<td>0.16</td>
<td>yes</td>
<td>0.04</td>
</tr>
<tr>
<td>5 unconstrained</td>
<td>0.06</td>
<td>0.02</td>
<td>0.09</td>
<td>0.26</td>
<td>yes</td>
<td>0.21</td>
</tr>
<tr>
<td>5 constrained</td>
<td>0.68</td>
<td>0.65</td>
<td>0.72</td>
<td>0.79</td>
<td>yes</td>
<td>0.10</td>
</tr>
</tbody>
</table>

**Notes:**

- The RMSEA for this model is 0.088, which is above the commonly used heuristic of 0.08. It misses the cutoff by 0.008 and is much closer to 0.08 than the one-factor model RMSEA of 0.156.

---

**Note:**

- CFI shows performance of specified model relative to an uncorrelated model. Higher is better.
- RMSEA shows the discrepancy between the observed and reproduced covariance matrices. Lower is better.
- The $\chi^2$ difference test is the result when unconstrained $\chi^2$ and df is subtracted from the constrained. This value is then tested for significance using the df in column E and the p-value associated with this test is shown in column F. A significant result demonstrates the model with the lower $\chi^2$ is significantly better.
the hypothesized CSE dimensions, indicating good convergent validity [58].

Third, we evaluated the discriminant validity of the measure. Discriminant validity suggests that construct measures should be distinct from each other. To test for this, the correlations between pairs of constructs were allowed to vary in one instance, and in another, were set to unity. By constraining the correlation between latent factors to 1, the constructs are, in essence, measuring the same thing. Discriminant validity is established if the chi-square difference test for the unconstrained model is significantly lower than for the constrained model [54]. Results presented in Table VI provide strong evidence of discriminant validity across all four samples. Based on the results of our analysis, the reliability, convergent, and discriminant validity of the measurement models across all four samples were sound.

3) Structural Model\textsuperscript{5}: A structural equation model using maximum likelihood estimation was used to test Hypotheses 2 and 3. The structural equation model evaluates the relationships among constructs and provides an assessment of predictive validity [59]. As with the samples used to test Hypothesis 1, the normalized kurtosis estimates were all above 20 save sample 6, which still exceeded 10 (normalized estimates 28.81, 31.12, 21.26, and 13.51 for samples 3–6, respectively), so the robust estimates that correct for multivariate nonnormality were used [56].

\textsuperscript{5}While previous research has demonstrated a relationship between computer anxiety and perceived EOU, we chose to leave this relationship out of our model because our research objective is to demonstrate the multidimensionality of CSE and to situate it into the nomological network. We did model the EOU–CSE relationship separately during our analyses and found that its inclusion does not impact any of our conclusions. These results are available from the authors.
For sample 3, the model fit indexes were all acceptable, the Satorra–Bentler $\chi^2 = 61.96$. The CFI for sample 3 was 0.98 indicating a very good fit, and the RMSEA was 0.042 indicating a close fit. For sample 4, the model fit indexes were also acceptable. The Satorra–Bentler $\chi^2 = 106.72$, the CFI was 0.96, which is above the 0.90 threshold and the RMSEA was 0.07 indicative of a good fit. For sample 5, the Satorra–Bentler $\chi^2 = 143.45$, the CFI was 0.95, again indicating a good fit, and the RMSEA was 0.071 indicating a good fit [60], [61].

Since all four samples demonstrated good fit, we used the path coefficients to evaluate Hypotheses 2 and 3. As reported in Fig. 4, we generally found support for the hypotheses. In the interest of clarity, we only present the structural paths in Fig. 4. Each path contains four numbers. These numbers represent the values for samples 3, 4, 5, and 6, respectively.

Hypothesis 2a states that a positive relationship exists between internal CSE and perceived EOU. This was supported across all samples ($\beta = 0.53$, $p < 0.05$; $\beta = 0.38$, $p < 0.05$; $\beta = 0.58$, $p < 0.05$; $\beta = 0.94$, $p < 0.05$ for samples 3–6, respectively). Support indicates that when individuals believe they may accomplish a task on a computer task independently, this positively influences how easy they perceive it is to use computer technology.

Hypothesis 2b states that no relationship exists between the external dimension of CSE and EOU. In the general CSE samples (3 and 4), we found support for H2b. Our analysis indicates that there was no significant relationship between external CSE and EOU ($\beta = -0.05$, $p = n.s.$ for Sample 3 and $\beta = 0.04$, $p = n.s.$ for sample 4). For specific CSE, we found mixed support for H2b. In sample 6, we found no relationship between external CSE and EOU ($\beta = -0.06$, $p = n.s.$), supporting H2b. In sample 5, which used Oracle Developer, we found that external CSE had a negative influence on EOU ($\beta = -0.19$, $p = 0.05$). The more respondents relied on others to complete an Oracle Developer task, the more they reported it was difficult to use.

Hypothesis 3a states that internal CSE is negatively related to computer anxiety. The internal dimension of CSE shows a clear, strong negative relationship with computer anxiety across all four samples ($\beta = -0.33$, $p < 0.05$; $\beta = -0.37$, $p < 0.05$; $\beta = -0.34$, $p < 0.05$; $\beta = -0.35$, $p < 0.05$ for samples 3–6, respectively). Support indicates that when individuals believe they may accomplish a task on a computer task independently, this positively influences how easy they perceive it is to use computer technology.

Hypothesis 3b states that no relationship exists between the external dimension of CSE and computer anxiety. In the general CSE samples (3 and 4), we found support for H3b. Our analysis indicates that there was no significant relationship between external CSE and computer anxiety ($\beta = 0.04$, $p = n.s.$ for Sample 3 and $\beta = 0.03$, $p = n.s.$ for sample 4). For specific CSE, we found mixed support for H3b. In sample 6, we found no relationship between external CSE and computer anxiety ($\beta = 0.01$, $p = n.s.$), supporting H3b. In sample 5, which used Oracle Developer, we found that external CSE had a positive influence on computer anxiety ($\beta = 0.19$, $p = 0.05$). The more respondents relied on others to complete an Oracle Developer task, the more they reported it was difficult to use.
Fig. 4. Results of the structural model for Hypotheses 2 and 3 for samples 3/4/5/6, respectively. Note: Values marked with * are significant at $\alpha < 0.05$.

$\beta = -0.64, p < 0.05; \beta = -0.93, p < 0.05$ for samples 3–6, respectively. As our respondents’ internally derived efficacy increases, they report lower levels of anxiety. This is consistent with research on stress in organizations that suggests when outcomes are less ambiguous and tasks are within the range of individuals’ skills, they will report lower levels of stress and anxiety [62].

Hypothesis 3b states that external CSE negatively impacts computer anxiety. In contrast to H3a, support for H3b varied with the specificity of the target technology. For samples 3 and 4, we found consistent support for H3b. External CSE demonstrated a negative relationship with computer anxiety when thinking about computers in general ($\beta = -0.21, p < 0.05; \beta = -0.17, p < 0.05$ for samples 3 and 4, respectively). Contrary to expectations, when using a specific target technology, we found external CSE demonstrated either no relationship with computer anxiety ($\beta = 0.14, p = \text{n.s. sample 5}$) or a positive relationship ($\beta = 0.46, p < 0.05, \text{sample 6}$).

C. Hypothesis 4 Results

Hypothesis 4 states that the two dimensions of CSE will explain more variance in EOU and computer anxiety than the original, unidimensional conceptualization of CSE. To formally test H4, we estimated confidence intervals to determine whether the 2-D models’ $R^2$-value was greater than or equal to the full CSE measure models. If the value of $R^2$ falls within the 95% confidence interval of the full CSE measure model, then there is no difference between the full and 2-D models’ ability to predict computer anxiety or EOU [63], [64]. If $R^2$ is above the 95% confidence interval, the multidimensional model explains greater variance than the full CSE model. We used this approach to test H4 because there is no other method to formally test for differences in $R^2$ across structural models with different measurement models [65].

Using the baseline $R^2$ of the full ten-item Compeau and Higgins measure, we estimated 95% confidence intervals to determine if the two-factor solution falls within the confidence interval. Much like any confidence interval, it is calculated as standard error plus and minus around the $R^2$-value. The formula to calculate the squared standard error of $R^2$ was [63]

$$SE_{R^2}^2 = \frac{4R^2(1 - R^2)^2(N - K - 1)^2}{(N^2 - 1)(N + 3)}.$$  (1)

By taking the square root of formula (1) and adding and subtracting that number from the $R^2$, the confidence interval is estimated. If the $R^2$-value for the 2-D model value is above the upper limit, it can be concluded that it is greater than $R^2$ for the unidimensional model. We present the analysis for each sample in Table VII.

For H4a, we found consistent support. The $R^2$ test for EOU demonstrates that the 2-D CSE model had greater predictive power than the unidimensional CSE model. Across all four samples, the two-factor conceptualization had significantly higher $R^2$-values than the ten item measure. The 2-D CSE model explained more variance in EOU.

For H4b, we found mixed support (see Table VII). $R^2$ for computer anxiety in the two-factor models of samples 5 and 6 supported H4b. However, $R^2$ for the two-factor solution for samples 3 and 4 did not. Sample 3 had a higher $R^2$, but it fell...
TABLE VIII
REVIEW OF SUPPORT FOR HYPOTHESES 1–4

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Sample 1</th>
<th>Sample 2</th>
<th>Sample 3</th>
<th>Sample 4</th>
<th>Sample 5</th>
<th>Sample 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1: The Compeau and Higgins' [1] computer self-efficacy instrument measures two distinct dimensions of efficacy beliefs.</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>H2a: The individual dimension of computer self-efficacy will have a significant, positive influence on EOU.</td>
<td>X</td>
<td>X</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>no</td>
</tr>
<tr>
<td>H2b: The human-assisted dimension of computer self-efficacy will not significantly affect perceived ease of use.</td>
<td>X</td>
<td>X</td>
<td>yes</td>
<td>yes</td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>H3a: Individual computer self-efficacy will demonstrate significant negative relationships with computer anxiety.</td>
<td>X</td>
<td>X</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>H3b: External computer self-efficacy will demonstrate significant negative relationships with computer anxiety.</td>
<td>X</td>
<td>X</td>
<td>yes</td>
<td>yes</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>H4a: The hypothesized dimensions of computer self-efficacy will explain more of the variance in EOU than will the original measure of computer self-efficacy.</td>
<td>X</td>
<td>X</td>
<td>no(^*$)</td>
<td>no(^*$)</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>H4b: The hypothesized dimensions of computer self-efficacy will explain more of the variance in computer anxiety than will the original measure of computer self-efficacy.</td>
<td>X</td>
<td>X</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

\(^*$\) This Hypothesis was supported with the aggregated data as well as each individual sample as well. For the sake of parsimony only the aggregated results were formally presented as advocated by [80]–[81]. The full results are available from the authors.

X = this sample was not used to test this hypothesis.\(^*$\)

While the two dimensions of CSE are not more effective than unidimensional conceptualization, they are equivalent.

within the upper confidence interval. Sample 4 had a slightly lower $R^2$-value, but within the lower confidence interval. While the two factor conceptualization does not outperform the original ten items, it explains an equivalent amount of variance in computer anxiety in the general samples. The overall analysis supports the notion that the 2-D model either outperforms (six out of eight times) or performs as well as (two out of eight times) the unidimensional conceptualization of CSE.

Given that our 2-D model offers a more parsimonious and focused theoretical conceptualization of CSE, we believe that the findings have important implications for efficacy-related research as well as for the design and evaluation of IT training programs. In the next section, we discuss the implications of the findings and the limitations of the study.

V. DISCUSSION

The findings of this study suggest that CSE is a multifaceted construct comprising two dimensions with distinct attributional sources. In general, results supported the hypotheses (see Table VIII for a summary). Our findings suggest that the Compeau and Higgins’ CSE measure taps into two distinct sources of efficacy beliefs (H1). Several independent samples, operationalizations of CSE, and analytic techniques (i.e., EFA and CFA) supported the notion that the Compeau and Higgins’ scale provided distinct measures of internal CSE and external CSE. Separately, each study could be deemed anomalous. However, these studies provide support for two dimensions of CSE at different levels of specificity (i.e., general and specific) and using different target technologies. Overall, the findings suggest that IT users’ CSE is attributed to internal and external sources.

We found that the internal and external CSE dimensions behave differently. Analysis supported the idea that internal CSE exerts a significant positive effect on EOU (H2a). This hypothesis was consistently supported across four different samples spanning general CSE and specific CSE. These findings are consistent with studies using SCT and attribution theory (e.g., [17], and [66]–[68]), which have shown that individuals who perceive themselves as sources of control in their lives should have positive beliefs about their abilities [17], [69].

By contrast, external CSE’s influence varied with the target technology. In three samples, we found that external CSE did not affect EOU. This finding is also consistent with SCT and attribution theory, which suggest that when individuals believe that successes are externally derived, they will not believe that they are more likely to succeed in the future. Note that for Oracle Developer, a complex software development tool, we found that external CSE diminished one’s belief about EOU. Attribution research provides a useful explanation for this counterintuitive finding. When one fails or is likely to fail, Weiner [17] argues that one blames external sources. Consistent with this notion, when one’s ability to perform a task using complex software package is dependent upon external support, our results suggest that individuals are pessimistic about the software’s EOU.

Our findings may also explain the anomalous result mentioned in the motivation of this paper [2] that organizational support negatively influenced CSE. Our findings suggest that this counterintuitive result can be accounted for by the following explanation. The ability to use more complex software when
organizational support is present should produce external attributions that would not positively affect beliefs about the EOU of IT [70]. Rather, these context-dependent attributions for success may diminish beliefs about individual ability and EOU, which explains why Compeau and Higgins [2] found CSE to correlate negatively with organizational support. In contrast, when one uses a comparatively simpler software tool such as Excel (sample 6), it is not surprising that external CSE does not diminish the EOU. This finding underscores the importance of building individuals’ sense of independent competence for using software. Although this finding is not what we expected, it does indicate that for the task-specific situation, internal CSE behaves differently from external CSE, supporting the overall thesis that these constructs are distinct.

Our findings highlight the importance of building internal CSE beliefs about using IT. Internal CSE negatively influenced computer anxiety across general or specific IT usage in four samples. These findings suggest that computer anxiety can be offset by internally derived efficacy beliefs. For general technology usage, external CSE also demonstrated a negative relationship with computer anxiety. This suggests that external support in the form of human assistance is useful for diminishing anxiety about IT in general.

For specific technologies, our findings suggest that external CSE may have negative implications. Analysis of samples 5 and 6 suggests that external CSE positively influenced computer anxiety, with this being significantly so in Sample 6. Intuitively, external support should diminish computer anxiety. Research in fields such as psychology, sociology, and organizational behavior suggest that having human support reduces one’s anxiety when in difficult, risky, or challenging situations [62]. However, relying on another person often incurs a social cost that can make individuals less likely to turn outward for assistance [71]–[73]. When considering efficacy and IT, it appears that external CSE can magnify computer anxiety. Perhaps having to turn to the support of another to complete a task intensifies anxious feelings about specific IT because it reveals an inability to complete the task alone as well as their lack of control over completing a task. Recent research has shown that the socialization process an individual experiences upon joining the organization impacts self-efficacy [74]. This socialization process could adversely impact an individual’s efficacy in subsequent situations once she is integrated into the organization, particularly if the socialization process is critical of showing a lack of knowledge or skills [71]–[74]. For example, individuals who require help to use a well-known software tool such as Microsoft (MS) Excel may fear they will be perceived as inept or inadequate, which may increase anxiety about IT. Ego defense research shows that individuals tend to deny internal shortcomings, instead preferring to focus on external causes for failing in a particular task [25]. Further, by acknowledging that they lack ability, individuals express feelings of qualitative overload (i.e., they lack the skills required to complete necessary work) [75]. Feelings of overload that require external support to resolve are well-established antecedents to anxiety, strain, and diverse negative outcomes in the workplace [62]. Hence, our findings suggest that if organizations focus on building resource-dependent CSE, users will experience anxiety when using a specific IT.

Although the internal and external dimensions used six items instead of ten, they still offered either comparable or superior explanatory power to the full CSE instrument (H4). In fact, as results showed, the 2-D CSE scales were as effective in explaining variance in EOU for the general samples. Reviewing the structural models for the four samples, the specific technology target samples demonstrated a positive relationship with anxiety for the external dimension and a negative relationship with anxiety for the internal dimension. By allowing these dimensions to independently impact computer anxiety, the predictive validity increases because when they are all combined, the distinct influence of each dimension is confounded. In the unidimensional model, the effects of these opposite relationships mask each other, resulting in a lower $R^2$. In the specific samples, the 2-D CSE scales were more effective than the unidimensional scales, and across all samples, the multidimensional scales explained more variance in computer anxiety than the full CSE instrument. This suggests that these two distinct CSE measures may offer a more parsimonious and predictive set of CSE scales for future research.

A. Limitations

Like all research, this study has limitations. First, we used several cross-sectional samples to test the hypotheses. Cross-sectional designs are prone to common method variance, which may result in inflating results. However, we employed several tactics to limit the influence of common-method variance. First, we employed different anchors. CSE required respondents to rate their ability and rank their confidence on a scale of 1–10. Computer anxiety and EOU used different Likert-type anchors (1–7). Second, we sampled a range of target objects, from broad definitions of technology to specific applications. Finally, inspection of the correlation of items and constructs shows that the relationships varied within and across studies. As a result, we are confident that our results are robust to issues related to common-method variance.

Second, research using student subjects has been criticized for lacking generalizability to broader populations in workplace settings. Although a recent meta-analytic work suggests that students’ beliefs and attitudes toward IT do not differ from employed workers [76], we addressed this concern through using data collected from students exhibiting diversity in terms of their location, majors, and expertise with IT (see Table III) [76]. We drew samples from students at four universities in three states, from numerous majors, and from the general population of business students as well as management information systems (MIS) majors. Thus, we believe this element enhances the generalizability of our results.

Finally, this study examines only one possible source of external CSE. In the current study, we developed a theoretical framework that suggests that there may be more than one external source of efficacy. For example, one’s beliefs about ability with the support of the help function in software could very well constitute a distinct dimension of external efficacy. Although our
B. Implications for Research

This paper offers several avenues for future research. First, while we have examined two CSE consequences, this study has not examined CSE antecedents. For example, personal innovativeness has been identified as an antecedent to CSE [35]. Future research could examine whether personal innovativeness and other personality variables exert different influences on internal and external CSE. For example, social anxiety may negatively influence external CSE and not affect internal CSE. Through gaining a deeper understanding of antecedents to CSE beliefs, research will provide insight into how to better manage IT implementations.

Second, our findings suggest that additional research is necessary to examine the relationship between internal and external CSE and their relationship with other variables leading to computer use. For example, it is unclear how external CSE relates to key constructs such as the perceived usefulness of IT. It is plausible that external efficacy could negatively influence perceived EOU and positively relate to perceived usefulness. For example, one may perceive a software package as difficult to use, but with human support, perceive it as a useful tool for enabling productivity, and consequently, form a high intention to use the technology. Given that relatively little is known about external efficacy, reexamining efficacy’s influence constitutes a rich direction for future research.

Third, while our research suggests that external CSE may diminish EOU and magnify computer anxiety, future research should examine situations in which external CSE could have positive implications. For example, during the initial stages of an IT innovation’s implementation in an organization, external social support may be a necessary prerequisite for individual use of IT. Initially, users of a new IT may have no qualms about turning to another for help. However, as the innovation becomes more infused in the workplace, human assistance may become a detriment to individual innovation and independent use of IT. Alternatively, external CSE’s influence may vary with organizational tenure. New employees may not be bothered by having to reach out for help with unfamiliar technologies. Established employees may find relying on external support troubling and report higher levels of anxiety. Gaining a deeper understanding of how external CSE’s influence evolves, research may better inform how to reap the benefits of technology.

Fourth, the findings respond to concerns about the validation of instruments used in Information Systems research (e.g., [77] and [78]). Our findings clarify CSE’s theoretical underpinnings and present parsimonious measures of internal and external CSE dimensions. Moreover, specifying the CSE dimensions in which researchers are interested can only strengthen the internal, external, and nomological validity of future studies. By identifying reliable, parsimonious measures of CSE, and related constructs, results within and across studies may be more effectively interpreted and compared. It is important to note that our conceptualization of CSE as having different sources and being multidimensional does not rule out a formative operationalization of the construct (see [79]). If one is interested in a global measure of efficacy, researchers may operationalize CSE’s diverse dimensions as a second-order formative construct comprising internal, external, and other externally derived dimensions. Our theoretical approach is consistent with a formative operationalization of the general CSE construct because we do not believe that internal and external dimensions of efficacy necessarily covary. Hence, our refined measures could be used to operationalize a formative, second-order, operationalization of CSE in future research.

Finally, this study contributes to an ongoing discussion about the conceptual foundations of efficacy. Bandura and other efficacy researchers argue that efficacy should be primarily conceived as derived from internal sources [21], [80]. However, many contemporary thinkers on efficacy and task performance argue that beliefs about ability should be more broadly rooted in the task at hand, the job, and the overarching work environment [2], [70], [81]–[83]. Differing from Bandura’s perspective, it has been shown that self-efficacy is rooted in internal and external sources of control, and that evidence of this is implied in Bandura’s definition of the construct [83]. This position resonates with attribution theory. The present study provides a conceptual framework for integrating these competing perspectives regarding efficacy’s sources, meaning, and implications. Our findings suggest that internally and externally derived beliefs about control are distinct and have divergent influences on beliefs that lead to performance. Having provided initial evidence of efficacy’s dimensions, future research should consider theoretically and empirically examining the interrelationship between internal and external efficacy beliefs. However, this is a difficult issue to specify fully, since these concerns apply to both CSE researchers and the broader community of efficacy researchers [40]. Our work contributes to this discussion by theoretically and empirically examining distinct sources of efficacy beliefs.

C. Implications for Practice

For managers, this research directs attention to how firms evaluate IT training programs. CSE is a frequently used measure of IT training programs’ effectiveness. If programs seek to raise participants’ overall level of IT competence, trainers should evaluate trainees’ general self-efficacy. However, if trainers seek to encourage independent use of IT, our findings suggest that trainers should evaluate training programs based on internal CSE attributions. To build internal efficacy attributions, education research suggests that programs emphasize providing
positive feedback on prior performance and ability [84], [85]. However, because this study does not link training or CSE to performance with IT, additional research is needed that ties CSE to outcomes such as IT use.

Second, our research suggests that engineering managers carefully consider the nature of the technology and training offered to users of ITS. A common truism among practitioners is that if appropriate support is available, users of an IT innovation will effectively and quickly appropriate the technology. However, our research suggests that external support may not be a silver bullet for addressing challenges and issues related to encouraging IT use. In particular, our analysis suggests that for users of complex technologies like Oracle Developer, efficacy beliefs dependent on human assistance may have negative implications for perceptions of the technology (i.e., EOU) and may magnify anxiety evoked by the technology. Hence, managers should build internal CSE beliefs that directly affect antecedents to technology use [38].

Third, when managers seek to encourage routine use of IT, they may want to foster efficacy dependent upon human assistance and other external sources. Although innovation is often perceived as desirable, firms frequently do not want employees “innovating” or “exploring” new uses of required technologies. Consider employees working in a nuclear power plant. Because the implications of failure are so extreme, a firm may want such employees to use new ITs in a very specific manner. In such a circumstance, fostering dependence on external support may be desirable. Employees who are dependent on external support should perceive technology as difficult to use and feel more anxiety about a technology. These employees may be less likely to innovate with IT. In fact, they may be more likely to turn to anxiety about a technology. These employees may be less likely to perceive technology as difficult to use and feel more anxiety about a technology. Therefore, fostering dependence on external support may be desirable.

VI. CONCLUSION

Overall, our findings suggest that the internal and external dimensions of CSE, when isolated, relate in distinct ways to EOU and computer anxiety—two important information systems variables. This occurred because each dimension is attributed to a different source. The internal dimension of CSE measured an individual’s beliefs about CSE attributable to one’s own ability or effort. This conceptualization resonates with the CSE definition most frequently used in previous studies regarding individuals’ assessments of their computer capabilities (e.g., [33] and [41]). Revisiting Compeau and Higgins’ CSE definition reiterates this point: “computer self-efficacy, then, refers to a judgment of one’s capability to use a computer” [1]. Alternatively, the external dimension measured an individual’s beliefs about CSE that are attributable to external social support. Although the external dimension relates to users’ beliefs about their capabilities, our findings suggest that it may be a unique dimension of CSE. To more effectively understand how different forms of CSE influence individual behavior, researchers should carefully identify context factors and use the operationalization most germane to the CSE dimension under investigation. By doing so, future CSE research may yield less fragmented findings and extend our understanding of the construct’s implications for IT-related beliefs and behavior. Such research will not only lead to a better understanding of CSE, but it will also further clarify and demonstrate the importance of CSE in influencing other constructs within its nomological network.

REFERENCES


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