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Self-Efficacy and Work-Related Performance: A Meta-Analysis

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This meta-analysis (114 studies, k = 157, N = 21,616) examined the relationship between self-efficacy and work-related performance. Results of the primary meta-analysis indicated a significant weighted average correlation between self-efficacy and work-related performance, $G(r_+) = .38$, and a significant within-group heterogeneity of individual correlations. To account for this variation, the authors conducted a 2-level theory-driven moderator analysis by partitioning the k sample of correlations first according to the level of task complexity (low, medium, and high), and then into 2 classes according to the type of study setting (simulated–lab vs. actual–field). New directions for future theory development and research are suggested, and practical implications of the findings are discussed.

Although different lines of research have documented the existence of many cognitive factors that have motivational effects on human action (e.g., George, 1992; Weiss & Adler, 1984), only a few cognitive determinants of behavior (e.g., goal setting) have received as ample and consistent empirical support as the concept of self-efficacy (Bandura, 1986, 1997b; Maddux, 1995). Self-efficacy is defined as a personal judgment of "how well one can execute courses of action required to deal with prospective situations" (Bandura, 1982, p. 122). Expectations of personal efficacy determine whether an individual's coping behavior will be initiated, how much task-related effort will be expended, and how long that effort will be sustained despite disconfirming evidence (Bandura, 1977a, 1986). Individuals who perceive themselves as highly efficacious activate sufficient effort that, if well executed, produces successful outcomes, whereas those who perceive low self-efficacy are likely to cease their efforts prematurely and fail on the task (Bandura, 1986, 1997b).

Two decades of empirical research have generated a great number of studies that demonstrated the positive relationship between self-efficacy and different motivational and behavioral outcomes in clinical (e.g., Bandura, Adams, Hardy, & Howells, 1980), educational (e.g., Lent, Brown, & Hackett, 1994; Schunk, 1995), and organizational settings (e.g., Bandura, 1988; Wood & Bandura, 1989b). Regarding the relationship between self-efficacy and performance in organizational settings, in the initial years of self-efficacy research only a few studies were conducted. They revealed that self-efficacy was related to job search (Ellis & Taylor, 1983), insurance sales (Barling & Beattie, 1983), and research productivity of university faculty members (Taylor, Locke, Lee, & Gist, 1984). Even though, considering their limited number, these studies did not enhance much of the understanding of the organizational correlates of self-efficacy, they did provide an initial impetus for subsequent research examining the relationship between self-efficacy and work-related performance.

Empirical research over the last decade has demonstrated that self-efficacy is related to a number of other work-performance measures such as adaptability to advanced technology (Hill, Smith, & Mann, 1987), coping with career related events (Stumpf, Brief, & Hartman, 1987), managerial idea generating (Gist, 1989), managerial performance (Wood, Bandura, & Bailey, 1990), skill acquisition (Mitchell, Hopper, Daniels, George-Falvy, & James, 1994), newcomer adjustment to an organizational setting (Saks, 1995), and naval performance at sea (Eden & Zuk, 1995). Although there have been several conceptual reviews regarding the application of self-efficacy to organizational settings (Bandura, 1988, 1991; Gist, 1987; Gist & Mitchell, 1992; Wood & Bandura, 1989b), no study, to date, has quantitatively synthesized, tested, and compared the variations in the self-efficacy–work-related performance pattern of results as a function of moderating effects of various studies' characteristics across the population of all available studies.

The purpose of this study was to meta-analytically aggregate and analyze individual research findings pertaining to the relationship between self-efficacy and work-related performance. In particular, we first present the theory that guided the choice of moderators. Next, we outline the study collection procedures and specify the selection criteria. Finally, we test the derived hypotheses in the primary and the two-level moderator meta-analyses. In the primary meta-analysis we investigate the overall magnitude of relationship between self-efficacy and work-related performance, and in the moderator meta-analysis we test the proposed two-level moderation model. On the basis of the implications of our analyses, we conclude by suggesting new directions for future theory development and research and provide practical guidelines for more effective management of human resources in today's organizations.

Theoretical Foundations

The analytical portion of our study starts with the primary meta-analysis in which we examine three research questions:

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(a) what is the weighted average correlation between self-efficacy and work-related performance? (b) is that weighted average correlation significantly different from zero? and (c) are individual correlations between self-efficacy and performance homogeneous across all studies contributing to the overall weighted average correlation? On the basis of the conceptual foundations of social cognitive (Bandura, 1986) and self-efficacy theories (Bandura, 1997b), and existing empirical evidence, we hypothesized that there is an overall positive relationship between self-efficacy and work-related performance as represented by the weighted average correlation calculated across all available studies (Hypothesis 1), and that given the large number and different properties of the examined studies, magnitudes of the individual self-efficacy–performance correlation estimates are significantly heterogeneous for the initial sample of all studies (Hypothesis 2). Because we hypothesized that individual correlation magnitudes would deviate among each other beyond what may be expected by chance, we next turn to theoretical explanations for potential sources of systematic variations among the examined studies.

Moderator Analysis

In the following sections, we provide the theory-driven rationale for the variables proposed to moderate the relationship between self-efficacy and work-related performance. The conceptual framework proposed was largely construed from social cognitive (Bandura, 1986) and self-efficacy (Bandura, 1997b) theories, with emphasis on both self-reactive and contextual influences in the regulation of efficacy perceptions (see Bandura, 1991). We also based our arguments on conceptual guidelines for the application of social cognitive theory to organizational settings (Bandura, 1988; Wood & Bandura, 1989b), and theoretical analysis of the malleability of self-efficacy (Gist & Mitchell, 1992). A comprehensive review of this literature indicates that one variable of potential moderating importance regarding the relationship between self-efficacy and work-related performance is task complexity.

Task Complexity

Bandura and other self-efficacy researchers (e.g., Bandura, 1986, 1997b; Bandura et al., 1980; Gist & Mitchell, 1992; Wood & Bandura, 1989a) have repeatedly pointed out that in addition to the regulative potential of self-efficacy for successful performance, the relative contribution of the complexity of the task to be performed must also be considered. An important aspect of the conceptual analysis of task complexity, as it relates to self-efficacy, is to recognize that complex tasks typically represent multifaceted constructs with different implications for behavioral, information processing, and cognitive facilities of the task performer (Bandura, 1997b). Thus, we approached the analysis of task complexity and self-efficacy by providing a process-oriented analysis of how task complexity varies, as the multidimensional construct, on the various factors identified by Bandura (1986, 1997b) that can affect the magnitude of the relationship between self-efficacy and task performance. In particular, we related task complexity to the changes in self-referent thought, such as (a) faulty assessment of performance and self-efficacy, (b) mismatch between self-efficacy and performance domains, (c) limited scope of self-efficacy assessment, and (d) lowered self-efficacy and distorted self-knowledge.

Task Complexity and Changes in Self-Referent Thought

Faulty assessment of performance and self-efficacy. In order for self-efficacy to regulate effort effectively, performers must have an accurate knowledge of the tasks they are trying to accomplish (Bandura, 1986, 1991, 1997b). However, different tasks vary extensively in the level of their complexity (Wood, 1986). In comparison to lower complexity tasks, highly complex tasks require different skills necessary for their successful execution by placing greater demands on (a) required knowledge, (b) cognitive ability, (c) memory capacity, (d) behavioral facility, (e) information processing, (f) persistence, and (g) physical effort (Bandura, 1986). Given the multitude of different task demands, complex patterns of behaviors do not lend themselves to easy appraisal (Bandura, 1997b). This can lead to a faulty assessment of task performance enticing misleading self-efficacy referent thoughts regarding how much effort needs to be extended, how long to sustain it, and when to make corrective actions (Bandura, 1986).[1] As a consequence, whenever people "act on faulty judgment of their efficacy, they suffer adverse consequences" (Bandura, 1997b, p. 70).

Mismatch between self-efficacy and performance domains. A related problem caused by complex task demands is exemplified in instances when both self-efficacy and performance are, say, accurately assessed, but they relate to different types of competencies (Bandura, 1997b; Pajares & Miller, 1994). In addition to a simple error in the specification of domains (e.g., Lachman & Leff, 1989), the more latent example of this problem is when complex tasks involve the use of certain means (as they usually do) to achieve the desired level of performance. In particular, the mismatch between the domains of self-efficacy and task performance may occur when self-efficacy for performing certain means is used as a singe predictor, whereas the whole performance sequence also depends on the posited influence of the selected means (Bandura, 1997b). As a result, capabilities assessed in perceived efficacy (means efficacy) are different from those that govern performance (more inclusive, attainment efficacy; see Bandura & Cervone, 1986; Wood & Bandura, 1989a).

Limited scope of self-efficacy assessment. Complex tasks are typically multifaceted, requiring a variety of capabilities necessary for their successful execution (Bandura, 1986, 1997b). Thus, to estimate the full magnitude of the relationship between self-efficacy and complex task performance, multidimensional self-efficacy predictors are needed (e.g., Lent, Brown & Larkin, 1986, 1987). However, because self-efficacy assessment is rarely inclusive of all of the aspects (e.g., behavioral, informational, etc.) that constitute a complex task (Bandura, 1997b), the "true" relationship between self-efficacy and performance is, most likely, usually underestimated in formal tests. It should be noted that this represents artifactual attenua-

[1] Faulty assessment of self-efficacy and task performance also includes using inappropriate measures of both constructs in empirical research such as measuring self-efficacy as a global trait (e.g., general self-efficacy) or using proxy measures of task performance (e.g., self-reports, rating of others, etc.; see Bandura, 1997b, for more details).

tion caused by the limited scope of self-efficacy assessment for the complex task (multifaceted nature of the complex task assessed by the single-faceted efficacy predictor), rather than the lack of the "true" relationship between the two variables (Bandura, 1997b).

Lowered self-efficacy and distorted self-knowledge. Finally, greater informational and skill demands imposed by complex undertakings may lead to two scenarios in which self-efficacy is either lowered or where personal knowledge is self-distorted (Bandura, 1986, 1997b). First, given the high task complexity demands, task performers may simply not perceive enough personal capabilities (e.g., adequate skills, cognitive processing capacity) to successfully execute complex tasks, which can, in turn, induce them to judge themselves as incompetent (e.g., Langer, 1979). Perceptions of personal incompetence usually result in self-debilitating effects on the beliefs of personal efficacy (Bandura, 1986, 1997b). Second, as a result of the high pressure of complex undertakings on individual facilities, personal knowledge can be self-distorted by adverse cognitive processes such as selective recall of personal failures and inefficacious behaviors, and/or distortions in perceptions of efficacy-relevant past experiences (Bandura, 1997b), both with relevant implications for efficacy estimation.

Self-Efficacy and Performance as a Function of Task Complexity

The above conceptual arguments suggest that task complexity may be a categorical variable moderating the relationship between self-efficacy and performance. Thus, on the basis of the theory posited, we hypothesized that the relationship between self-efficacy and performance is moderated by the level of task complexity; the higher the task complexity, the weaker the relationship between self-efficacy and performance (Hypothesis 3).

Of course, self-efficacy has been found to be positively related to tasks of different complexities, varying from simple brainstorming (e.g., Locke, Frederick, Lee, & Bobko, 1984) to very complex scientific work (Taylor et al., 1984). However, these findings cannot be a priori accepted as evidence that the level of task complexity does not moderate the relationship between self-efficacy and performance without considering the magnitudes of these relationships for different levels of task complexity (see Wood, Mento, & Locke, 1987). For example, it is possible, for the reasons extended in the theory proposed, that the relationship between self-efficacy and performance is the strongest for low levels of task complexity but incrementally weaker, yet still significant, for the moderate and high levels of task complexity. If this was the case, then the appropriate test of the moderation would be to quantitatively compare the magnitudes of the relationships between self-efficacy and performances among all studies that used tasks of low, moderate, and high levels of complexities. The moderator meta-analysis provides analytical procedures for such comparisons.

Environment in Judgment of Self-Efficacy

Bandura (1986) suggested that the differences in magnitudes of the relationships between self-efficacy and performance could also "arise when efficacy is judged for performance in actual situations but performance is measured in simulated situations that are [usually] easier to deal with than the actualities" (p. 397; see also Bandura, 1997b). Thus, another categorical variable that may moderate the relationship between self-efficacy and performance is the type of setting in which the study is conducted. As with task complexity, in the next section we provide another process-oriented analysis of the multifaceted nature of this moderator.

Simulated Versus Actual Environments

In contrast to real world settings, the mechanisms for assessing the magnitude of the relationship between self-efficacy and performance in simulated settings does not always allow for capturing all relevant environmental elements. Also, these contextual factors tend to significantly vary in their nature between the two settings (Bandura, 1986, 1997b; Wood & Bandura, 1989b). Specifically, the different environmental context (actual vs. simulated) can produce disparities in the magnitude of the relationship between self-efficacy and performance due to the different situational characteristics such as (a) performance constraints, (b) ambiguity of task demands, (c) deficient performance information, (d) consequences of efficacy misjudgment, and (e) temporal disparities between self-efficacy and action (Bandura, 1986, 1997b; Gist & Mitchell, 1992).

Performance constraints. Gist and Mitchell (1992) pointed out that individuals' estimates of self-efficacy will be different in actual settings because they have to include considerations of several performance constraints usually not present in simulated settings. These constraints include (a) the amount of available resources (e.g., material resources, time, staff) necessary to complete the task, (b) interdependence of the particular task with other functions in the organization, (c) physical distractions (e.g., noise, interruptions), and (d) the amount of physiological and/or psychological danger present in the environment (see Bandura, 1997b). Thus, as Bandura (1986) pointed out, "when performances are impeded by . . . inadequate resources or external constraints, self-judged efficacy will exceed the actual performance" because "the execution of skills is hindered by external factors" (p. 396).

Ambiguity of task demands. Bandura (1986, 1997b) also argued that discrepancies between the judgment of self-efficacy and performance will more likely arise in actual settings because tasks and surrounding circumstances (e.g., situational unpredictability) tend to be more ambiguous when compared to highly controlled, simulated laboratory experiments. As a result of ambiguously defined tasks and less clear context under which they are performed, appraisals of self-efficacy will diverge from action more in actual settings because people may not be able to fully understand what they have to do and what means to use, and thus will lack the accurate information to correctly "assess the veridicality of their self-appraisals" (Bandura, 1986, p. 398). In Bandura's (1997b) words, "if one does not know what demands must be fulfilled in a given endeavor, one cannot accurately judge whether one has the requisite abilities to perform the task" (p. 64).

Deficient performance information. Related to the above discussion, Wood and Bandura (1989b) also suggested that, in comparison to mostly well-defined simulated lab experiments in which individual effort can be directly related to the level of performance, in actual settings (especially in business organizations) performance accomplishments are, most of the time, accomplished through some form of group effort. When performance outcomes are achieved through interdependent actions, the aspects of one's performance may not be as clearly observable, and one has to rely on others (or other similar situations) to find how one is doing (Bandura, 1986, 1997b). Both in this case, and in the case when performance outcomes are socially judged due to either the unknown or ill-defined objective criteria, estimates of personal efficacy tend to be more socially dependent and thus more inaccurate (Bandura, 1986, 1997b; Bandura & Cervone, 1983; Cervone, Jiwani, & Wood, 1991).

Consequences of efficacy misjudgment. Bandura (1986) also pointed out that "situations in which misjudgments of capabilities carry no consequence provide little incentive for accurate appraisal of self-efficacy" (p. 396). Wood and Bandura (1989b) made this point most clearly when they analyzed the differences in the magnitudes of the relationships between self-efficacy and performance in actual versus simulated settings by arguing that "unlike subjects in decision experiments, managers [and others] must live with the consequences of their errors in judgment and faulty decisions" (p. 369). As Bandura (1997b) also simply put it, "people take their self-appraisal [more] seriously when they must chose between courses of action that have significant personal consequences" (p. 68). Any natural setting, and especially organizational ones where employees' actual performance is measured, would be an example (see Wood & Bandura, 1989b). On the other hand, studies in simulated settings rarely entail any serious negative consequences for the participants involved.

Temporal disparities between self-efficacy and action. Bandura (1986, 1997b) noted that task performance is best predicted by self-efficacy beliefs that operate in close proximity to the time of the performance. In contrast, to predict performance on the basis of dated perceptions of self-efficacy may create discordances if the existing reality (e.g., factors causing reappraisal of personal efficacy) has changed in the interim with adverse effects on efficacy beliefs (e.g., Lachman & Leff, 1989). The effect of intervening factors on self-efficacy beliefs, however, does not depend on the amount of time elapsed, but on the nature and potency of the efficacy-related intervening experiences (Bandura, 1997b). Thus, proximal measures of self-efficacy tend to reveal the actual relationship between self-efficacy and performance, whereas dated efficacy measures may underestimate it (Bandura, 1986, 1997b).

Relating these arguments to the simulated versus actual study settings, it is more likely that the simulation studies will have closer matching of items, used in the efficacy measures, with the actual behavioral acts the study participants are asked to perform. On the other hand, naturalistic settings usually involve much longer temporal disparities in the assessment of self-efficacy and performance. This longer time period allows for a higher possibility that environmental changes, either with adverse effects on efficacy beliefs or a direct impact on the task, may occur between the administration of the measure and the actual performance (see Bandura, 1997b).

Self-Efficacy and Performance as a Function of Study Setting

The above conceptual arguments indicate that in addition to the task complexity, the study setting may be another categorical variable moderating the relationship between self-efficacy and performance. Thus, we hypothesized that the relationship between self-efficacy and performance is further moderated by the type of study setting (actual vs. simulated) for each level of task complexity; simulated settings produce stronger relationships between self-efficacy and performance, as compared to actual settings, for each level of task complexity (Hypothesis 4).

Study Collection for Meta-Analysis and Selection Criteria

Collection of the Studies

The collection of studies was initiated by computerized searches of specialized databases such as the *Business Periodicals Index, PsycLIT, Sociofile,* and *Social Science Index* covering the published literature from 1977 to 1996. The key words used were *self-efficacy, perceived self-efficacy, self-efficacy beliefs, self-efficacy expectations, social cognitive theory,* and *social learning theory.* Next, we searched the *Expanded Academic Index,* the ERIC database, *Dissertation Abstracts,* and *Dissertation Abstracts International* using the same time period (1977–1996) and the same key words. Relevant articles that were not covered by computerized databases (e.g., the most recent ones) were manually searched for in journals such as *Academy of Management Journal, Academy of Management Review, Cognitive Therapy and Research, Journal of Applied Psychology, Journal of Personality and Social Psychology, Organizational Behavior and Human Decision Processes, Personnel Psychology, Psychological Bulletin,* and *Psychological Review.* Searches were also conducted using the reference sections of earlier reviews of and books on self-efficacy, social learning theory, and social cognitive theory (e.g., Bandura, 1977b, 1986, 1991; Gist, 1987; Gist & Mitchell, 1992; Wood & Bandura, 1989b). In addition, several unpublished manuscripts were also included in the analysis. The search was limited to articles in the English language.

Selection Criteria

Because the research on self-efficacy has been conducted across various disciplines over a 20-year period, we started by defining the boundaries of our work. This study is about the relationship between self-efficacy and work-related performance. This purpose places several specific boundaries on the scope and nature of this meta-analysis. They are identified in terms of inclusion requirements and exclusion criteria.

Inclusion Requirements

To be included in this meta-analysis, a study was required to have self-efficacy operationalized according to the conceptual premises defined by Bandura (1977a, 1977b, 1986, 1997b). Considering operationalization of self-efficacy, two dimensions of task specific self-efficacy have been widely used in empirical research: self-efficacy magnitude (belief in the level of accomplishment), and self-efficacy strength (certainty about task accomplishment; Bandura, 1986, 1997b; Gist & Mitchell, 1992). Because of the high intercorrelations between these two dimensions of self-efficacy (see Cervone & Peake, 1986; Earley & Lituchy, 1991; Lee & Bobko, 1994; Locke et al., 1984), and their low discriminant validity, many researchers have combined these two dimensions into one overall index of self-efficacy (e.g., Earley, 1993, 1994; Earley & Erez, 1991; Gist, Schwoerer, & Rosen, 1989). Given the high convergent validity between self-efficacy strength and magnitude, we used estimates of these two dimensions, or an index of both as interchangeably representative measures of self-efficacy.

Criterion (dependent for experiments) variables for each study had to be examined in the form of work-related performance measures. Using Wood's (1986) theory of task as a conceptual guideline, task performance was defined "in terms of the *behavioral responses* [italics added] a person should emit in order to achieve some specified level of performance" (p. 62). Task performance was defined as work-related if three essential components of any task, namely (a) product of the task, (b) required acts necessary to perform the task, and (c) information cues on which a person can base the judgment about the execution of the task (Campbell, 1988; Naylor, Pritchard, & Ilgen, 1980; Wood, 1986), could be assumed to be plausibly related to tasks performed in organizational settings (see Kluger & DeNisi, 1996; Wood et al., 1987).

Exclusion Criteria

Specific versus general self-efficacy. General self-efficacy has been used recently as another dimension of self-efficacy in empirical research (e.g., Eden & Aviram, 1993; Eden & Kinnar, 1991; Eden & Zuk, 1995). However, theory and research to date have indicated that task-and-situation specific self-efficacy and general self-efficacy represent separate constructs that differ in the two major ways: (a) conceptually (Bandura, 1986, 1997b; Eden, 1988; Eden & Kinnar, 1991; Eden & Zuk, 1995) and (b) psychometrically (Bandura, 1997b; Cervone, 1997; Eden & Aviram, 1993; Sherer & Adams, 1983; Sherer et al., 1982; Wang & Richarde, 1988).

Regarding the conceptual difference between the two variables, Bandura (1986, 1997b) argued that specific self-efficacy represents task and situation (domain) *specific cognition.* On the other hand, general self-efficacy is defined as a "*generalized trait* [italics added] consisting of one's overall estimate of one's ability to effect requisite performances in achievement situations" (Eden & Zuk, 1995, p. 629). Thus, in contrast to specific self-efficacy, which represents "a dynamic, multifaceted belief system that operates selectively across different activity domains and under different situational demands, rather than being a decontextualized conglomerate" (Bandura, 1997b, p. 42), general self-efficacy consists of trait-like characteristics that are "not tied to specific situations or behavior" but that generalize to a "variety of situations" (Sherer et al., 1982, p. 664).

The above differences are simply summarized by Bandura (1997b) who stated that "an efficacy belief is not a decontextualized trait" (p. 42) as is general self-efficacy. It is, however, important to note that it is not that specific self-efficacy appraisals do not generalize at all. Rather, they generalize in different ways in different circumstances, across different tasks, and for different people (Bandura, 1997b; Cervone, 1997). In fact, in contrast to general efficacy beliefs that do not account for the variability in self-perceptions across diverse domains (Mischel & Shoda, 1995), the highly variable patterns of generalizations are obtained when individuals' idiosyncratic patterns of social and self-referent beliefs are assessed (Cervone, 1997).

Although Bandura (1986, 1997b) clearly differentiated between specific and general self-efficacy, Lazarus (1991) also provided theoretical arguments congruent with Bandura's conceptualizations. In particular, he differentiated between knowledge and appraisal as separate constructs. Knowledge refers to beliefs about the world (including oneself) in general (e.g., "I am a good worker"), whereas appraisals are relational assessments regarding oneself in a social context (e.g., "I will fail on this task"; Lazarus, 1991, 1995). Specific self-efficacy beliefs are performance-related appraisals of a person within a context, that is, how well one believes he or she can perform given the specific social context and the particular task. Decontextualizing specific efficacy expectations replaces them with abstract beliefs (general self-efficacy) that then become incongruent with the defined premises of social cognitive theory (Bandura, 1986, 1997b).

Psychometric differences regarding the assessment of the two variables include questionable relevance of global measures of general self-efficacy (e.g., Sherer et al., 1982) to a specific domain of functioning typically explored by specific self-efficacy (Bandura, 1997b; Cervone, 1997). These measures mostly include items that, in psychometric terms, "contaminate" (Nunnally & Bernstein, 1994) the assessment of the task-and-situation specific efficacy beliefs, by being related to unspecified, general domains of human functioning (Wang & Richarde, 1988). In particular, whereas Bandura (1997b) argued that "in no case are efficacy items disassociated from context and the level of task demands" (p. 50), a typical general self-efficacy item is exemplified by a statement such as "I do not seem capable of dealing with most problems that come up in life" (Sherer et al., 1982, p. 666). By making nomothetic assumptions about the nature of the construct (see Cervone, 1997), general self-efficacy measures are incompatible with those assessing the task-and-domain specific efficacy beliefs as defined by social cognitive theory (Bandura, 1986, 1997b). Thus, it seems to follow that empirical evidence has shown high discriminant validity between the measures of specific and general self-efficacy (Eden & Kinnar, 1991; Smith, 1989; Wang & Richarde, 1988).

Considering all of the above arguments, individual correlations representing the relationship between general self-efficacy and performance were excluded from this meta-analysis. This exclusion represented 10 studies and 14 individual correlations.

Nonrelated settings. The focus of this meta-analysis on work-related performance as an outcome measure placed further restraints on the scope of applicable studies. In particular, studies were excluded if they (a) examined the relationship between self-efficacy and behaviors clearly unrelated to performances in organizational settings (e.g., discussions on death, participating in political demonstrations), (b) used samples from clinical institutions that would rarely be found as a majority of the workforce in a common organizational setting (e.g., agoraphobics, individuals with disabilities), (c) investigated the relationship between self-efficacy and performance in the field of sports psychology and medicine (e.g., modified back-dive, field hockey), and (d) included study participants who, considering their age, legally cannot be in the workforce (e.g., those younger than 15).

Final selection of the studies. Any other form of task performance that was not clearly nonapplicable as described above was included in the analysis (see also Kluger & DeNisi, 1996). Thus, out of 2,099 studies (adjusted for reference overlaps among databases) identified in the initial search of outlined sources, 202 (10%) met the selection criteria. After closely examining each of these studies, an additional 88 (43%) studies were excluded for other methodological or conceptual reasons such as (a) the use of secondary data from previous studies already selected for the analysis, (b) not reporting the description of the task, (c) examining behavioral intentions, or choice options rather than task performance as the criterion (dependent) variable(s), and finally (d) analyzing self-efficacy as a criterion (dependent) rather than a predictor (independent) variable. No relevant studies were excluded because of lack of statistics. The final sample consisted of $s = 114$ studies, generating $k = 157$ correlations estimates, and the total sample size of $N = 21{,}616$. The average sample size per correlation estimate was 138 study participants.

Primary Meta-Analysis

Method

Analytical Procedures

Point estimation of single correlation magnitude. Because meta-analysis represents the quantitative summary of individual study findings across an entire body of research (Cooper & Hedges, 1994), the first analytical step was to compute the index of correlation magnitude between self-efficacy and performance for each individual study. For this and other analyses, we used Hedges and Olkin's (1985) meta-analytic procedures. Following the common practice in meta-analytic synthesis (e.g., Hedges & Olkin, 1985; Hunter & Schmidt, 1995), we used Pearson's correlation coefficient r as an estimate of population correlation ρ. If studies did not report an estimate of r, we used computational adjustments, provided by Hedges (1981, 1982b) and Rosenthal (1991, 1994), to transform different statistics to correlation estimate r.

Estimation of individual correlations from correlated estimates. One of the first analytical questions in estimating individual correlations was how to treat multiple correlation estimates if they resulted from a single study (see Rosenthal, 1991). If significance testing for homogeneity assumptions is not performed, the most explicit way is to either average the correlation estimates, or to include all correlation estimates as if they were obtained from different studies (e.g., Glass, McGaw, & Smith, 1981). However, when homogeneity testing using the chi-square distribution is performed (e.g., Hedges & Olkin, 1985), combining correlation estimates from the same studies that used stochastically dependent samples leads to dependent multivariate distribution of estimated correlations (Gleser & Olkin, 1994; Hedges & Olkin, 1985). Because correlated end-point measures represent a major violation of chi-square analysis (see Cervone, 1987; Hedges & Olkin, 1985; Hunter & Schmidt, 1995), if some studies provided k correlations, we performed adjustments for stochastically dependent correlations (Hedges & Olkin, 1985), which allowed us to obtain an independent correlation estimate from each study.

Unbiased point estimation of single correlations. Because r tends to underestimate the magnitude of the population correlation ρ (Hedges & Olkin, 1985; Hotelling, 1953), to correct for this bias, we calculated an unbiased estimator of r, labeled $G(r)$, which provides a more stable and accurate (in terms of mean squared error) estimate of the population correlation ρ (Hedges & Olkin, 1985). Hedges and Olkin have shown that $G(r)$ represents an accurate approximation of r to within 0.01 if $n \geq 8$, and to within 0.001 if $n \geq 18$. The unbiased estimator $G(r)$ has the same range of -1 to $+1$, and, consequently, the same asymptotic distribution as r. Because the variance of r and thus $G(r)$ is largely dependent on the unknown value of the population correlation ρ, to further stabilize the distribution of $G(r)$, and to make its variance independent of an unknown population parameter ρ, as suggested by Hedges and Olkin, we next converted $G(r) \cong r$ to the standard normal deviate z.

Estimating common correlation from a group of studies. In estimating the weighted average correlation for the entire group of studies, we used z transformations to convert each $G(r_1) \ldots G(r_k)$ to $z_1 \ldots z_k$, and then calculated the weighted average (Z_+). We next tested whether the weighted average estimate of the common population correlation between self-efficacy and performance (Z_+) across k studies occurred beyond chance by comparing the value of the test statistic $Z_+ \times$ SQR $(n - 3k)$ to critical values of the standard normal distribution (Hedges & Olkin, 1985). We also constructed confidence intervals for the population correlation ρ by first obtaining 95% lower and upper confidence limits for z population parameter ζ, and then using two transformational equations (see Hedges & Olkin, 1985) to obtain 95% upper and lower confidence limits for population correlation ρ.

Testing for within-group homogeneity of individual correlations. By this test, we intended to determine whether the variability of correlations relating self-efficacy and performance across all examined studies was higher than would be expected by chance (Hedges & Olkin, 1985). If heterogeneity of k sample correlations was present, that would indicate that single estimates of individual correlations were drawn from different populations, and that we could not represent the data with the model of the common weighted correlation. For this test, we used the Q_t homogeneity statistic (Hedges & Olkin, 1985), where the Q_t value was compared to the chi-square distribution for $df = (k - 1)$, where k = number of individual correlations.

Outlier Analyses

We conducted two outlier analyses: for correlation magnitudes and sample sizes. The problem with the presence of high correlation values is that, considering the high sensitivity of the chi-square test, they may cause constant significant within-group heterogeneity of individual correlations, which will keep on indicating systematic variance that, in fact, may not be, in the words of Hunter and Schmidt (1995), meaningful in the organizational reality. The problem with the presence of large sample sizes is that when the weighted averages are used in meta-analysis, they tend to give exceedingly larger weight to studies with large sample sizes than is given to any other study, which can cause the entire meta-analysis to be defined by one or a few studies (Hunter & Schmidt, 1995). Small sample sizes were not a concern because the negative bias in the distribution of r was stabilized by transforming r to $G(r)$ and z.

For both outlier analyses, we used schematic plot analysis (Light, Singer, & Willett, 1994) because of its accuracy in determining outlier and extreme values. In this analysis, values examined that are positioned 1.5 to 3 lengths from the upper or lower edge of the 50% interquartile range of all values (e.g., Tukey's hinges) are considered outliers, and values that are more than 3 lengths from the interquartile range are considered extreme values (e.g., Tukey, 1977). Upper and lower boundaries represent the highest and lowest values that are not considered outliers. We conducted three analyses: with the entire set of studies (Set 1), with magnitude outliers excluded (Set 2), and with sample size outliers excluded (Set 3).

Results

Complete results of the primary meta-analysis for all data sets are shown in Table 1. Because most of the studies examined in this meta-analysis used a correlational design, and the meta-analytic procedures applied were respectively concordant, the

Table 1
Results of Primary Meta-Analysis for All Three Data Sets

Set[a]	Z_+	Z^b	ζ_l	ζ_u	$G(r_+)$	ρ_l	ρ_u	$\sigma^2_{(\rho)r+}$	σ^2_e	σ^2_ρ	% SE[c]	σ_ρ	$G(r_+)/\sigma_\rho$[d]	Q_t
1	.35	50.89**	.3365	.3634	.34	.3265	.3534	.034547	.005733	.028825	17	.17	2.00	1129.08**
2	.35	50.84**	.3365	.3634	.34	.3265	.3534	.033895	.005709	.028186	17	.17	2.00	1113.72**
3	.40	50.56**	.3845	.4154	.38	.3645	.3954	.031812	.006649	.025163	31	.16	2.38	888.12**

Note. Confidence intervals were calculated at the 95% certainty level.
[a] Data Set 1 = complete data with no outliers removed (s = 114, k = 157, N = 21,616); Data Set 2 = complete data with one correlation magnitude outlier removed (s = 113, k = 156, N = 21,568); Data Set 3 = complete data with sample size outliers removed (s = 109, k = 148, N = 16,441). [b] Value of the test statistic. [c] % SE = percentage of variance attributable to sampling error. [d] Distance from zero value of population correlation expressed in standard deviations.
** $p < .01$.

results of this meta-analysis should be interpreted as representing the magnitude of the relationship between self-efficacy and work-related performance and not as indicators of causal effects of self-efficacy on performance.

Estimating Common Correlation

For the first set of studies, the weighted average correlation between self-efficacy and performance, corrected for attenuation, was $G(r_+) = .34, p < .01$. First outlier analysis for correlation magnitudes indicated one outlier correlation value $r = -.23$). However, removing that correlation coefficient in the second set of studies did not produce any change in the results (see Table 1); thus, the estimate was kept in the analysis. Second outlier analysis for sample sizes indicated five extreme (n = 927, n = 734, n = 666, n = 666, n = 565) and four outlier (n = 410, n = 410, n = 410, n = 387) sample size values. After removing sample size outliers and extreme values in the third set of studies, the weighted average correlation, corrected for attenuation, was $G(r_+) = .38$, $p < .01$, which supported Hypothesis 1.

Implications of Sample Size Outlier Analysis

Removing sample size outliers and extreme values in Set 3 produced changes, as compared to the entire set of studies, in the magnitude of the average correlation, $G(r_+) = .38$ versus $G(r_+) = .34$, and in the proportion of the variance attributable to sampling error (31% vs. 17%). Hunter and Schmidt (1995) have shown that the changes in meta-analytic results due to the removal of extreme sample sizes are not surprising because the weighted averages always give greater weight to studies with large sample sizes. In this study, had the outlier sample size values not been excluded, the weighted average correlation coefficient would have given, on average, over five times the weight to the studies with extreme sample sizes as compared to any other study.[2]

Thus, to avoid a bias toward larger weights for the sample size deviant studies, further analyses were conducted with sample size outliers and extreme values removed. This exclusion accounted for the reduction of 4% in the number of studies (s = 114 to 109), 6% in the number of correlations (k = 157 to 148), and 24% in the total sample size (N = 21,616 to 16,441). These reductions represent below average reductions in the social sciences (10%; Hunter & Schmidt, 1995), and notably below average reductions in the "exact" sciences (40%; Hedges, 1987).

[2] The average extreme (n = 712) and outlier (n = 404) sample size values were, respectively, 5.2 and 3 times as large when compared to the average sample size per effect with outlier and extreme values included (n = 137) and 6.44 and 3.64 times as large when compared with an average sample size with outlier and extreme values excluded (n = 111). Conceptually, in addition to having extreme or outlier sample sizes, another characteristic of all of the extreme or outlier sample size studies was the possibly unusual ways of obtaining the study participants. In particular, all of these studies had obtained their samples through some form of institutional backing (e.g., military setting, home care facility, state employment compensation offices), which, in most cases, included required or hard to reject participation.

Within-Group Homogeneity Assumption

Given the diverse attributes and the large number of studies included in this meta-analysis, as expected, the assumption of within-group homogeneity of correlations across the studies was rejected for each data set (see Table 1), which supported Hypothesis 2. Although the value of the homogeneity statistic for Set 3 (used in further analyses) decreased as a result of the removal of outlier studies, it still showed significant within-group heterogeneity of individual correlations. This finding indicated that individual correlation magnitudes deviated among each other beyond what may be expected by chance, and, therefore, that it was inappropriate to specify the predictive model by a single estimate of the weighted average correlation (Hedges & Olkin, 1985). Thus, we next engaged in a meta-analytic moderator analysis in which we tested the conceptually derived two-level moderation model.

Meta-Analytic Moderator Analysis

Moderators

Hedges and Olkin's (1985) moderator meta-analytic procedures involve coding and partitioning the entire set of studies into moderator groups as a first step in the moderator analysis. As previously discussed, our first theory-driven moderator variable identified was task complexity. However, although tasks are an inherent part of any study of human performance (Campbell, 1988; Naylor et al., 1980; Wood, 1986), and characteristics of the task have been examined as moderators in a number of areas in organizational behavior such as job design (Hackman & Oldham, 1980), goal setting (Wood et al., 1987), and feedback interventions (Kluger & DeNisi, 1996), no theoretical approach has emerged as an agreed upon way of defining task complexity (Aldag & Brief, 1979; Campbell, 1988; Hackman, 1969; Wood, 1986). In fact, "little consensus exists among researchers concerning the properties that make a task complex" (Campbell, 1988, p. 40). Thus, we first profile some of the conceptual approaches to the study of task complexity, and then justify the choice taken in this meta-analysis.

Definitional Approaches to Task Complexity

Subjective task complexity. According to this approach, task complexity is viewed as a subjective, psychological experience of the task performer (Aldag & Brief, 1979; Ford, 1969; Miner, 1980). In particular, task characteristics and the inherent task complexity are derived from an individual's perception of the psychological dimensions of the task, usually using some multivariate technique (e.g., factor analysis), and are not based on formal definitions of the task (Dunham, Aldag, & Brief, 1977; McCormick, 1976; Peterson & Bownas, 1982; Taylor, 1981). Subjectively identifying task characteristics inevitably confounds task and nontask elements (Wood, 1986), which makes it difficult to establish construct validity of the task as an empirical variable (Shaw, 1963) and to reliably differentiate one task from another (e.g., Dunham et al., 1977; McCormick, 1976; Peterson & Bownas, 1982).

Relational task complexity. In contrast to the subjective approach, the relational view of task complexity recognizes the importance of both characteristics of the task performer and those of the task itself (Frost & Mahoney, 1976; Hammond, 1986; Tversky & Kahneman, 1981). According to this approach, task complexity is determined by a person–task interaction (Campbell, 1988), representing the person's estimate regarding the extent to which the perceived task demands match the perceived individual attributes (e.g., available skills, information processing ability, etc.; March & Simon, 1958). Thus, because task complexity represents an "experienced" construct by the task performer, these perceptions are inherently judgmental views of the task to be performed (Campbell, 1988; Locke, Shaw, Saari, & Latham, 1981). Because of the lack of a standardized definition, the subject-judgmental aspect of the relational approach to task complexity represents an obstacle in generalizing empirical assessments of the properties of a task (Hammond, 1992; Kluger & DeNisi, 1996; Wood, 1986), and has caused inconsistencies in the studies examining effects of task complexity (see Wood et al., 1987, for details).

Objective task complexity. As defined by Wood's (1986) general theory of task, according to this approach, task complexity is determined by the "objective" attributes of the task, which represent an independent phenomenon of the individual performing the task, and are described (coded) from the position of the detached, objective observer (see also Hackman, 1969; Naylor et al., 1980). Basic attributes of the task include (a) task product, (b) behavioral acts, and (c) information cues. Wood (1986) defined task product as a set of observable task attributes assembled in some recognizable form pertaining to either an object (e.g., audit balance report), or event (e.g., training a worker). Task behavioral acts represent a pattern of behaviors with an identifiable purpose, direction, and strength necessary to execute the task in question (Wood, 1986). Finally, information cues are defined as "pieces of information about the attributes of stimulus objects [or events] upon which an individual can base judgments he or she is required to make during the performance of a task" (Wood, 1986, p. 65). Basic task attributes represent important inputs in determining task complexity because they set the upper limits on the knowledge, ability, effort, and skills necessary for successful performance (Wood, 1986).

In addition to the basic task attributes, task complexity is also determined by the relationship between task attributes. Wood (1986) defined overall task complexity in terms of its constituting subcomplexities: component, coordinative, and dynamic. Component complexity represents the number of distinguishable behavioral acts that need to be executed for successful performance of the task, and the number of distinct information cues that need to be processed to perform those acts (Naylor, 1962; Wood, 1986). Coordinative complexity portrays the nature of the relationship among sequential steps (e.g., timing, frequency, location) between task inputs and task products necessary to perform the task (Gist & Mitchell, 1992; Wood, 1986). Finally, if the nature of the relationship between behavioral acts and information cues necessary to perform the task changes in the means-end sequencing, then the accomplishment of the task must also involve taking into account the dynamics (dynamic complexity) of that change (Wood, 1986).

Selecting an Approach

To summarize, subjective and relational approaches to task complexity are limited by the lack of standardization of definitions pertaining to what constitutes task complexity as a result of the variable and empirically hard to determine confounding nature of the person–task interaction (Campbell, 1988; Fleishman, 1975; Hackman, 1969; Weick, 1965; Wood, 1986; Wood et al., 1987). This leads to low (task) construct validity (e.g., Dunham et al., 1977; McCormick, 1976; Peterson & Bownas, 1982; Shaw, 1963), differences in predictive properties of task effects (e.g., Baumler, 1971; Frost & Mahoney, 1976; Jackson & Zedeck, 1982), and, importantly, questionable feasibility of task-complexity operationalization (Campbell, 1988; Naylor et al., 1980; Wood, 1986; Wood et al., 1987), especially in meta-analyses that use secondary data.

To qualify the last statement, a relational approach to task complexity could yield an independent estimate of the level of task complexity if one can determine, in addition to the task attributes, the availability and the nature of the performer's skills. In this case, an independent observation can be made as to whether the task is an easy or complex one for a given performer without having to rely on the performer's subjective judgment. However, although feasible for designing individual experiments, this scenario represents a rare possibility when operating with secondary data. This is because most studies do not report sufficiently detailed sample descriptions to be able to determine what particular skills study participants may have (e.g., study participants were college students enrolled at the local university).

Thus, because task complexity, as defined by subjective and relational approaches, is not amenable (or not practically so) to a quantifiable definition while operating with secondary data (meta-analysis), we approach task complexity from the point of view of the general theory of task as defined by Wood (1986). In addition to the above arguments, this approach to task complexity is preferable for three other reasons. First, the relationship between task attributes can be described (coded) from the position of outside observers (meta-analysts). Second, this approach to task complexity also has been used in most studies examining moderating effects of task complexity on the relationship between self-efficacy and task performance (e.g., Bandura & Jourden, 1991; Bandura & Wood, 1989; Cervone & Wood, 1995; Wood & Bandura, 1989a; Wood et al., 1990) and in some other meta-analyses (e.g., Kluger & DeNisi, 1996; Wood et al., 1987). Finally, an objective approach to task complexity also allows for integration of evidence regarding task effects not only from a given area, but also from studies in different fields.

Coding of the Studies

Each study that met the selection criteria was coded for two moderators on the basis of the theory proposed. The following section outlines the coding procedures and provides the reliabilities (interrater and "effective") obtained.

Task complexity. As suggested by Bandura (1997b, p. 42), this moderator included the categories of low, medium, and high task complexity. Task complexity levels were coded independently by one of the investigators (Stajkovic) of this analysis and another trained rater (a graduate student with about 20 hr of training on Wood's, 1986, approach to task complexity). After the training, a copy of the description of the task for each study was given to the trained rater who independently rated each task on a 3-point complexity scale (e.g., *low, medium, high*). The complexity scale was based on the definitions of task complexity provided by Wood (1986) and outlined above.

Type of study setting. This moderator included the categories of simulated–laboratory and actual–field study settings. A simulated–laboratory setting was defined as a study conducted under controlled conditions in laboratories or similar settings that are not naturally conducive to the activity performed (e.g., managerial decision making simulations in college classrooms). An actual–field study setting was defined as actual settings in which activities are naturally expected to be performed (e.g., managerial decision making in practicing organizations).

Interrater and effective reliability. The interrater agreement was Rho = .929 and .974, respectively, for each moderator group, with the mean agreement between raters when coding was aggregated across the moderator groups of Rho = .948. The effective reliability, defined as an estimate of the reliability of the variables coded with a comparable group of judges (Rosenthal, 1991), was .973, and was determined using the Spearman–Brown formula provided by Rosenthal (1991). Determining the effective reliability indicated the probability that a similar group of two other raters would reach the same conclusions regarding the variables coded.

Method

To explain the nature of moderation, we next performed three sets of tests: (a) the test for homogeneity of weighted average correlations between moderator groups, (b) orthogonal comparisons among moderator groups, and (c) the test for homogeneity of individual correlations within moderator groups. The same tests were used for the second-level moderator analysis.

Homogeneity of weighted average correlations between moderator groups. This test was performed in the moderator analysis to determine if the weighted average correlations differed beyond chance across moderator groups. For this test, we used the Q_b homogeneity statistic where the Q_b value was compared to the chi-square distribution for $df = (p - 1)$, where p = number of groups (Hedges, 1982a, 1982b). We further examined the pairwise differences between weighted average correlations for different moderator groups by means of linear combinations using orthogonal polynomials (Hedges & Olkin, 1985).

Homogeneity of individual correlations within moderator groups. To determine whether the moderator variable explained systematic variations among individual correlations within newly created groupings, we next tested for the homogeneity of individual self-efficacy–performance correlations within moderator groups by using the Q_w homogeneity statistic. The Q_w procedures represented an overall test of homogeneity of single correlations within the partitioned groups across k studies (Hedges & Olkin, 1985). The value of the Q_w homogeneity statistic was compared to the chi-square distribution for $df = (k - p)$, where k = number of studies and p = number of groups. Individual Q_{w1} to Q_{wp} homogeneity statistics were also calculated, as if each group was an entire collection of studies (Hedges & Olkin, 1985), to determine which individual homogeneity value contributed the most to the heterogeneity of the entire moderator grouping.

Considering the sensitive nature of the chi-square test (due to the high statistical power generated by the large number of studies in the meta-analysis) in detecting even the slightest violations from within-group homogeneity of individual correlations (Cervone, 1987; Hedges & Olkin, 1985; Hunter & Schmidt, 1995), we also used Hunter and Schmidt's (1995) 75% rule as another validation of the obtained results based on Hedges and Olkin's approach. The 75% rule represents Hunter and Schmidt's (1995) method for determining the percentage of sampling error variance as a part of residual variance (heterogeneity of within-group/class individual correlations). In particular, we first estimated the sampling error variance of the weighted average correlations for the moderator group, and then we estimated the corresponding variance of the population correlation by adjusting the variance of the weighted average correlation for its sampling error variance (see Hunter & Schmidt, 1995).

Second-level homogeneity adjustments. Testing for between-and-within moderator group fit continued in the second-level moderator analysis until the within-group homogeneity of individual correlations was achieved (Hedges & Olkin, 1985). For those moderator classes (second-level partitioning) that still exhibited significant within-class heterogeneity of individual correlations, we performed homogeneity adjustments by using microanalytic statistical within-class homogeneity procedures to determine extreme values that mostly contributed to the heterogeneity of individual correlations for that particular class (Hedges & Olkin, 1985). In performing individual homogeneity tests for every level of adjustment, we used moving averages of weighted average correlations and overall class homogeneity statistics to achieve an accurate representation of the value statistics after the removal of each extreme homogeneity value. Hunter and Schmidt's (1995) homogeneity method was also included in these procedures.

Results

First-Level Moderator Analysis

Using task complexity as the first moderator, the entire set of studies (Set 3) was split into three moderator groups reflecting low, medium, and high levels of task complexity. Table 2 shows the complete results for the first-level moderator analysis.

The weighted average correlations indicated that self-efficacy is a significant predictor of performance for each level of task complexity. The between-group homogeneity test revealed that magnitudes of the average correlations for each moderator group were significantly different among each other ($Q_{bI} = 375.63$, $p < .01$), indicating that task complexity was a categorical variable significantly related to the magnitude of average correlations between self-efficacy and performance. As shown in Table 2, magnitudes of the weighted average correlations were the highest at the low level of task complexity, further decreasing as the task complexity approached medium and high levels. These results supported Hypothesis 3. We further compared the average correlations for each level of task complexity, by means of three linear combinations, using orthogonal polynomials (Hedges & Olkin, 1985) to determine pairwise differences among moderator groups. Significant differences were detected for Comparison I contrasting magnitudes of average correlations for low and medium levels of task complexity ($\gamma_I = .19$, $p < .01$), Comparison II comparing magnitudes of average correlations for low and high levels of task complexity ($\gamma_{II} = .35$, $p < .01$), and Comparison III which distinguished between average correlation magnitudes for medium and high levels of task complexity ($\gamma_{III} = .16$, $p < .01$).

The test of overall homogeneity of individual correlations indicated significant heterogeneity of individual correlations within the partitioned groups across k studies ($Q_{wI} = 512.49$, $p < .01$). The analysis of homogeneity of individual correlations within each moderator group separately indicated significant heterogeneity for each level of task complexity. Hunter and Schmidt's (1990) 75% rule also confirmed the results of the previous analysis using Hedges and Olkin's (1985) chi-square

Table 2
Results of the First-Level Task Complexity Moderator Meta-Analysis

LTC[a]	Z_+	z[b]	ζ_l	ζ_u	$G(r_+)$	ρ_l	ρ_u	$\sigma^2_{(r)r+}$	σ^2_e	σ^2_ρ	% SE[c]	σ_ρ	$G(r_+)/\sigma_\rho$[d]	Q_{wi}
Low	.59	38.72**	.5601	.6198	.53	.5001	.5598	.016575	.006306	.010270	38	.10	5.23	173.97**
Medium	.40	30.92**	.3775	.4283	.38	.3546	.4053	.015459	.005903	.009555	38	.09	3.80	179.45**
High	.24	18.28**	.2141	.2659	.24	.2141	.2659	.020260	.006886	.013373	34	.12	2.00	159.07**

Note. Confidence intervals were calculated at the 95% certainty level. $Q_{wI} = 512.49$** (within-moderator groups overall homogeneity statistic); $Q_{bI} = 375.63$** (between-moderator groups homogeneity statistic).
[a] LTC = level of task complexity: low ($k = 54$, $N = 4,470$); medium ($k = 49$, $N = 6,123$); high ($k = 45$, $N = 5,848$). [b] Value of the test statistic. [c] % SE = percentage of variance attributable to sampling error. [d] Distance from zero value of population correlation expressed in standard deviations.
** $p < .01$.

Table 3
Results of the Second-Level Study Setting Moderator Meta-Analysis

TC/SS[a]	Z_+	z^b	ζ_l	ζ_u	$G(r_+)$	ρ_l	ρ_u	$\sigma^2_{(g)r+}$	σ^2_e	σ^2_ρ	% SE[c]	σ_ρ	$G(r_+)/\sigma_\rho$[d]	Q_{wi}
LL	.61	37.28**	.5779	.6420	.54	.5079	.5720	.016618	.006046	.010572	36	.10	5.40	153.36**
LF	.58	13.88**	.4981	.6618	.52	.4381	.6018	.016661	.007193	.009467	43	.10	5.20	17.98*†[e]
ML	.48	24.62**	.4417	.5182	.44	.4017	.4782	.022732	.006568	.016163	29	.13	3.38	129.46**
MF	.34	19.66**	.3061	.3738	.32	.2861	.3538	.005794	.005231	.000562	90	.02	24.44	24.44††
HL	.34	13.41**	.2903	.3897	.32	.2703	.3697	.046048	.009591	.036456	21	.19	1.68	105.13**
HF	.20	12.89**	.1696	.2303	.20	.1696	.2303	.005968	.005688	.000379	95	.02	0.05	27.33††

Note. Confidence intervals were calculated at the 95% certainty level. Q_{wII} = 457.74** (within-moderator classes overall homogeneity statistic); Q_{bII} = 54.75** (between-moderator classes homogeneity statistic).
[a] TC/SS = level of task complexity by study setting: LL = low task complexity–laboratory setting (k = 46, N = 3,873), LF = low task complexity–field setting (k = 8, N = 597); ML = medium task complexity–laboratory setting (k = 27, N = 2,712); MF = medium task complexity–field setting (k = 22, N = 3,411); HL = high task complexity–laboratory setting (k = 19, N = 1,612); HF = high task complexity–field setting (k = 26, N = 4236). [b] Value of the test statistic. [c] % SE = percentage of variance attributable to sampling error. [d] Distance from zero value of population correlation expressed in standard deviations. [e] This value is homogeneous at $p > .01$ but not at $p > .05$ (i.e., $p > .01$† but $p < .05$*).
** $p < .01$. * $p < .05$. †† $p > .05$. † $p > .01$.

test approach (see Table 2). Although the levels of task complexity accounted for significant between-group variance, significant within-group heterogeneity of individual correlations indicated that the model of task complexity as a moderator of the relationship between self-efficacy and performance cannot be fully specified because significant variation was still present within each moderator group. To account for this variation, we proceeded with the second-level moderator analysis using the second moderator, type of study setting.

Second-Level Moderator Analysis

Each of the initial three moderator groups (low, medium, and high task complexity) was further partitioned into two classes according to the type of setting in which the study was conducted: (a) simulated–laboratory, and (b) actual–field settings. Table 3 shows the complete results for all levels of task complexity further partitioned by each category of study setting.

The weighted average correlations indicated that self-efficacy is a significant predictor of performance for each level of task complexity further partitioned into laboratory and field settings. Results of the between-classes homogeneity test indicated that the magnitudes of the weighted average correlations among moderator classes were significantly different from each other (Q_{bII} = 54.75, $p < .01$), indicating that the study setting was another categorical variable, in addition to task complexity, significantly related to the magnitudes of average correlations between self-efficacy and performance. The average correlations exhibited the strongest magnitude for the low level of task complexity and laboratory settings, with the further decrease in magnitudes reaching the lowest level for high task complexity and field settings (see Table 3).[3] With the only exception to this downward spiral in magnitudes of average correlations between medium task complexity and field studies and high task complexity and laboratory settings, these findings supported Hypothesis 4.

Pairwise analysis of the average correlations further revealed that the difference between average correlations for laboratory and field settings was the lowest (.02) for the low level of task complexity (.54 and .52), with a further increase (.12) as the analysis approached the medium level of task complexity, however, at the lower overall levels of correlation magnitudes (.44 and .32). The difference between average correlations for laboratory and field studies remained the same for the high level of task complexity (.12), however, at an even lower level of correlation magnitudes (.32 and .20). We tested the pairwise

[3] If these analyses were to be performed with sample size extreme and outlier values included, the notable differences in results would occur for the low task complexity–field studies class. In particular, the total sample size for this class of N = 597 increases 3.5 times after the inclusion of the two extreme sample size values (n = 927; n = 565) to N = 2,089. Consequently, given their lower individual correlations than the average correlation for the entire class obtained without these studies, it is not surprising (as suggested by Hunter & Schmidt, 1995) that the weighted average procedures had given much larger weight to these two studies, which, in turn, reduced the average class correlation to Z_+ = .23 and $G(r_+)$ = .23. The significance level of this average correlation remained the same ($p < .01$), whereas the class homogeneity statistic (Q_w) increased to $p < .01$.

differences between average correlations by orthogonal polynomials with three ad hoc linear combinations. Results indicated significant differences for Comparison II, contrasting average correlations between laboratory and field settings for the medium level of task complexity, ($\gamma_{\mathrm{II}} = .12, p < .01$), and Comparison III, comparing average correlations between laboratory and field settings for the high level of task complexity, ($\gamma_{\mathrm{III}} = .14, p < .01$). Average correlations for the low level of task complexity did not reach a significant difference level.

Finally, analysis of the confidence limits corresponding to each weighted average correlation revealed that each weighted estimate of the population correlation had relatively narrow 95% confidence limits, thus increasing the accuracy of the estimation and stability of the average correlations. The only exception was slightly wider confidence limits for low task complexity and field studies, which was due to the composition of that moderator class ($k = 8; N = 597$) in comparison to other classes. The examination of the confidence limits (see Table 3) also confirmed the downward trend in both average correlations and the confidence limits within which corresponding population correlations are placed.

Using the same analytical procedures as in the first-level moderator analysis, the overall within-classes test of homogeneity of individual correlations indicated significant heterogeneity of individual correlations within the partitioned classes across k studies ($Q_{w\mathrm{II}} = 457.74, p < .01$). However, further analyses of individual within-classes homogeneity statistics ($Q_{w\mathrm{III}-6}$) indicated that within-class homogeneity of individual correlations was immediately achieved for a low level of task complexity and field studies, a medium level of task complexity and field studies, and a high level of task complexity and field studies (see Table 3). Heterogeneity of average correlations was still present for all three laboratory average correlations for low, medium, and high levels of task complexity. Hunter and Schmidt's (1990) 75% within-group homogeneity rule confirmed the results obtained by using Hedges and Olkin's (1985) within-classes homogeneity procedures.

Because three moderator classes exhibited significant heterogeneity of individual correlations, we performed homogeneity adjustments for each heterogeneous class. For removing deviant data, "Tukey (1960) and Huber (1980) recommended deletion of the most extreme 10% of data points—the largest 5% and the smallest 5%—of values" (Hunter & Schmidt, 1990, p. 207). However, because removing a priori 10% of the most extreme heterogeneity values may be more than is needed to achieve within-class homogeneity of individual correlations, we used analytic procedures based on the values of individual $Q_{w\mathrm{II}i-p}$ homogeneity statistics (see Hedges & Olkin, 1985) and corresponding moving $Z_{\mathrm{II}+i-p}$ weighted averages to analyze the within-class homogeneity of individual correlations while removing the most extreme heterogeneity values one at a time (e.g., Kluger & DeNisi, 1996). Table 4 shows the complete results, which indicated that within-class homogeneity of individual correlations was achieved for each of the remaining three moderator classes.[4]

Although obtaining within-class homogeneity of individual correlations allowed us to provide, in the words of Behrens (1997), "sensible description of the remaining data" (p. 145), it also called our attention to the aspects of the studies' processes or contexts that may have generated the extreme heterogeneity values. Thus, we next conceptually analyzed every study from which these estimates were obtained by focusing on whether the examined studies entailed any systematically occurring common characteristics (e.g., methods used, study participants, study settings, etc.), or some other unusual properties (e.g., unique research-related process, errors, etc.) that may have provided additional conceptual insights into the deviant data. However, besides random deviations in particular properties of individual studies that may have explained respective heterogeneity value, we had not found any systematic, across-studies, variations that may have provided more parsimonious explanations of the deviant data from which conceptual conclusions could be drawn. This indicated that extreme heterogeneity values were simply inconsistent with the rest of the data (see Barnett & Lewis, 1994), and, importantly, that they did not represent any, either statistically or conceptually, identifiable underlying mechanism that may have caused their generation (see Behrens, 1997, for a detailed discussion of these issues).

Adjusted Second-Level Moderator Analysis

Because the homogeneity adjustments required removal of several extreme within-class homogeneity values, and thus corresponding $Z_{\mathrm{II}+i-p}$ weighted averages (see Table 4), we reran the second level moderator analysis with the data as it appeared after all within-class homogeneities of individual correlations were achieved. Table 5 shows the complete results for all levels of task complexity partitioned by each category of the study setting.

After all methodological corrections, outlier analyses, and homogeneity adjustments, each weighted average correlation, classified by task complexity and type of study setting, still exhibited statistical significance indicating that self-efficacy is a strong predictor of performance. Results of the between-classes homogeneity test revealed that magnitudes of adjusted weighted average correlations among moderator classes were significantly different from each other ($Q_{b\mathrm{II}A} = 344.94, p < .01$), reaffirming the findings from the unadjusted second-level moderator analysis that study setting was another categorical variable that significantly moderated the relationship between self-efficacy and performance. As in the unadjusted second-level moderator analysis, however even more pronounced, the adjusted weighted average correlations exhibited the same downward trend from the strongest magnitudes for the low level of task complexity and laboratory settings to the lowest levels for the high task complexity and field settings (see Figure 1). In contrast to one exception in the unadjusted second-level moderator analysis, in this analysis there were no exceptions to this downward trend, which fully supported Hypothesis 4.

Further analysis of the average correlations revealed that the difference between the average correlations for laboratory and field settings (.50 and .48), when compared to the unadjusted second-level moderator analysis, remained the lowest for the

[4] The low task complexity–field studies class was immediately homogeneous at $p > .01$ but not at $p > .05$. Although the homogeneity for this class was achieved ($p > .01$), because we microanalyzed each class statistically and conceptually, we tried to determine why this class did not reach the homogeneity level as the other two classes including field studies did ($p > .05$), and, thus, we included it in this analysis too (see Table 4 for details).

Table 4
Adjustments for the Within-Class Homogeneity of Correlations

Adjustments	$Q_w ext.$	$Q_w \bar{X}$	$Q_w min.$	$Q_w max.$	Z_+	$(G)r_+$	k	Q_{wiA}
TC–LS								
Unadjusted		3.33	.00	51.14	.61	.54	46	153.36**
First	51.14	2.24	.00	26.38	.59	.53	45	100.88**
Second	26.38	1.63	.00	9.06	.56	.51	44	71.65**
Third	9.06	1.45	.00	5.57	.55	.50	43	62.36†
LTC–FS								
Unadjusted		2.25	.00	8.56	.58	.52	8	17.98*†
First	8.56	1.18	.00	4.97	.53	.48	7	8.23††
MTC–LS								
Unadjusted		4.79	.01	61.47	.48	.44	27	129.46**
First	61.47	2.37	.00	40.49	.42	.40	26	61.61**
Second	40.94	0.75	.00	4.37	.40	.38	25	18.80††
HTC–LS								
Unadjusted		5.53	.02	22.27	.34	.32	19	104.98**
First	22.27	4.50	.00	19.05	.32	.31	18	80.99**
Second	19.05	3.60	.01	12.56	.29	.28	17	61.15**
Third	12.56	3.01	.00	10.44	.31	.30	16	48.17**
Fourth	10.44	2.50	.00	10.21	.30	.29	15	37.56**
Fifth	10.21	1.89	.00	7.66	.27	.27	14	26.47†

Note. $Q_w ext.$ = Highest extreme value of the individual homogeneity statistic within the moderator class; $Q_w \bar{X}$ = mean value of the individual homogeneity statistic within the moderator class after $Q_w ext.$ has been removed; $Q_w min.$ = minimum value of the individual homogeneity statistic within the moderator class after the $Q_w ext.$ has been removed; $Q_w max.$ = maximum value of the individual homogeneity statistic within the moderator class after $Q_w ext.$ has been removed; Z_+ = average correlation for the moderator class (expressed as standard normal deviate) after $Q_w ext.$ has been removed; $(G)r_+$ = average correlation for the moderator class after $Q_w ext.$ has been removed; k = number of correlations after $Q_w ext.$ has been removed; Q_{wiA} = overall homogeneity value for the moderator class after $Q_w ext.$ has been removed; LTC = low task complexity; LS = laboratory setting; FS = field setting; MTC = medium task complexity; HTC = high task complexity.
* $p < .05$. ** $p < .01$. † $p > .01$. †† $p > .05$.

low level of task complexity (.02), however, with a smaller difference increase (.06) as the analysis approached the medium level of task complexity, and also at the lower overall levels of correlation magnitudes (.38 and .32). The difference between weighted average correlations for laboratory and field studies also slightly increased, when compared to the medium level of task complexity, for the high level of task complexity (.07), furthermore, at an even lower overall level of correlation magnitudes (.27 and .20). Using the same procedures as in the unadjusted second-level moderator analysis, we tested the pairwise differences by performing three planned comparisons. Significant differences were found for Comparison II, comparing average correlations between laboratory and field settings for the medium level of task complexity, ($\gamma_{II} = .06$, $p < .01$), and Comparison III, contrasting average correlations between laboratory and field settings for the high level of task complexity, ($\gamma_{III} = .08$, $p < .01$). Average correlations for the low level of task complexity did not reach a significant difference level.

Finally, analysis of the confidence limits corresponding to each adjusted weighted average correlation indicated that each estimate of the population correlation also had relatively narrow 95% confidence limits (see Figure 1), with similar accuracy of estimation of average correlations. This analysis also confirmed the downward trend in both average correlations and the confidence limits within which the corresponding population correlations are placed.

Discussion

The main purpose of this study was to provide a meta-analytic review of the relationship between self-efficacy and work-related performance. By synthesizing the results of the empirical studies conducted over the past 20 years, we intended to answer two major questions: (a) what was the overall magnitude of the relationship between self-efficacy and performance? and (b) were there any study characteristics that systematically moderated the relationship between these two variables. We answered these questions in primary and moderator meta-analyses.

Primary Meta-Analysis

With regard to the overall magnitude of the relationship between self-efficacy and work-related performance, the results of the primary meta-analysis indicated a significant weighted average correlation (adjusted for sample size outliers and extreme values) of .38. This finding was not an artifact of the point estimation, correlated individual estimates, or sampling error. To this point, this average correlation represents the first time that an indicator of the overall relationship between self-efficacy and work-related performance has been meta-analytically derived, analyzed, and compared to other studies.

For comparison purposes with other meta-analyses, if the obtained average correlation in this study (.38) was to be converted to the commonly used effect size estimate (*d.*; Hedges, 1986), the transformed value would be $d. = .82$ which represents a 28% gain in performance (see Glass, 1976). This 28% increase in performance due to self-efficacy represents a greater gain than, for example, those obtained in meta-analyses examining the effect on performance of goal-setting (10.39%; Wood et al., 1987), feedback interventions (13.6%; Kluger & DeNisi,

Table 5
Results of the Adjusted Second-Level Study Setting Moderator Meta-Analysis

TC/SS[a]	Z_+	z^b	ζ_l	ζ_u	$G(r_+)$	ρ_l	ρ_u	$\sigma^2_{(\rho)r+}$	σ^2_e	σ^2_ρ	% SE[c]	σ_ρ	$G(r_+)/\sigma_\rho$[d]	Q_{wi}
LL	.55	31.15**	.5190	.5892	.50	.4653	.5346	.010679	.007302	.003376	68	.06	8.33	62.36†
LF	.53	11.09**	.4434	.6179	.48	.3927	.5672	.011118	.008003	.003114	72	.06	8.00	8.23††
ML	.40	19.09**	.3589	.4410	.38	.3389	.4210	.006231	.007871	−.001640	100	.00	3,800	18.80††
MF	.34	19.66**	.3061	.3738	.32	.2861	.3538	.005794	.005231	.000562	90	.02	24.44	24.44††
HL	.27	9.40**	.2149	.3274	.27	.2137	.3262	.017720	.009657	.008063	55	.08	3.37	26.47††
HF	.20	12.89**	.1696	.2303	.20	.1696	.2303	.005968	.005688	.000379	95	.02	0.05	27.37††

Note. Confidence intervals were calculated at the 95% certainty level. Q_{wTadj} = 167.94† (also $p > .025$; within-moderator classes overall homogeneity statistic); Q_{bTadj} = 344.94** (between-moderator classes homogeneity statistic).
[a] TC/SS = level of task complexity by study setting: LL = low task complexity–laboratory setting (k = 43, N = 3,336), LF = low task complexity–field setting (k = 7, N = 526); ML = medium task complexity–laboratory setting (k = 25, N = 2,353); MF = medium task complexity–field setting (k = 22, N = 3,411); HL = high task complexity–laboratory setting (k = 14, N = 1,255); HF = high task complexity–field setting (k = 26, N = 4,236). [b] Value of the test statistic. [c] % SE = percentage of variance attributable to sampling error. [d] Distance from zero value of population correlation expressed in standard deviations.
** $p < .01$. †† $p > .05$. † $p > .01$.

1996), or organizational behavior modification (17%; Stajkovic & Luthans, 1997). These comparisons appear particularly important because, historically, it has been proven difficult to predict objective behavioral outcomes from self-reports (Stone-Romero, 1994).

The meta-analytically derived average correlation of .38 also seems to indicate that self-efficacy may be a better predictor of work-related performance than much of the personality trait-based constructs commonly used in organizational research (see Adler & Weiss, 1988; George, 1992; Ghiselli, 1971; Weiss & Adler, 1984). Although many interpretations of the findings from that literature can be made (e.g., Davis-Blake & Pfeffer, 1989; Ilgen, Major, & Tower, 1994; Lord & Maher, 1991; Mischel, 1968; Pervin, 1985, 1994), there still does not appear to be clear, systematic evidence indicating that self-report trait measures predict specific behavioral outcomes at levels approaching those found in this meta-analysis (e.g., Bass, 1981; Davis-Blake & Pfeffer, 1989; Eden & Zuk, 1995; George, 1992; Ilgen et al., 1994; Muchinsky & Tuttle, 1979; Pervin, 1994; Weiss & Adler, 1984; White, 1978).

One may argue, however, that the average correlation of .38 between self-efficacy and performance does not represent a much higher gain than what is typically found with generalized trait measures. This argument could be countered by two points. First, people do not tend to enter into challenging environments that they find to be beyond their perceived capabilities. In fact, they may take actions to avoid being engaged in such endeavors. Thus, because there is no performance measure for this, the correlation between self-efficacy and performance found in this study may be even quite conservative. Second, as we postulated in the theory driving our moderator analysis, complex, naturalistic environments introduce variables that moderate the relationship between self-efficacy and performance. Thus, if the obtained average correlation between self-efficacy and performance for the lowest levels of task and environmental complexity was to be selected for comparison purposes (because there are fewer intervening factors), the predictive power of self-efficacy would increase substantially.

First-Level Moderator Meta-Analysis

Results from this analysis provided supporting evidence for our hypothesis that task complexity moderates the relationship between self-efficacy and work-related performance. Although several studies have examined the relationship between self-efficacy and performance on complex tasks (e.g., Ackerman, Kanfer, & Goff, 1995; Taylor et al., 1984; Wood et al., 1990), our findings indicate that task complexity is a strong moderator of the relationship between self-efficacy and performance also when meta-analyzed across the body of relevant literature (e.g., N = 16,441). Although the relationship between self-efficacy and performance was significant for each level of task complexity, the magnitude of the relationship was the greatest for simple tasks, decreasing for moderate and high levels of task complexity.

Although we found a strong moderating effect of task complexity, it is possible that the difference in the magnitudes of the relationship between self-efficacy and performance between simple and complex tasks may decrease, or even disappear (thus increasing the predictive power of self-efficacy) over repeated

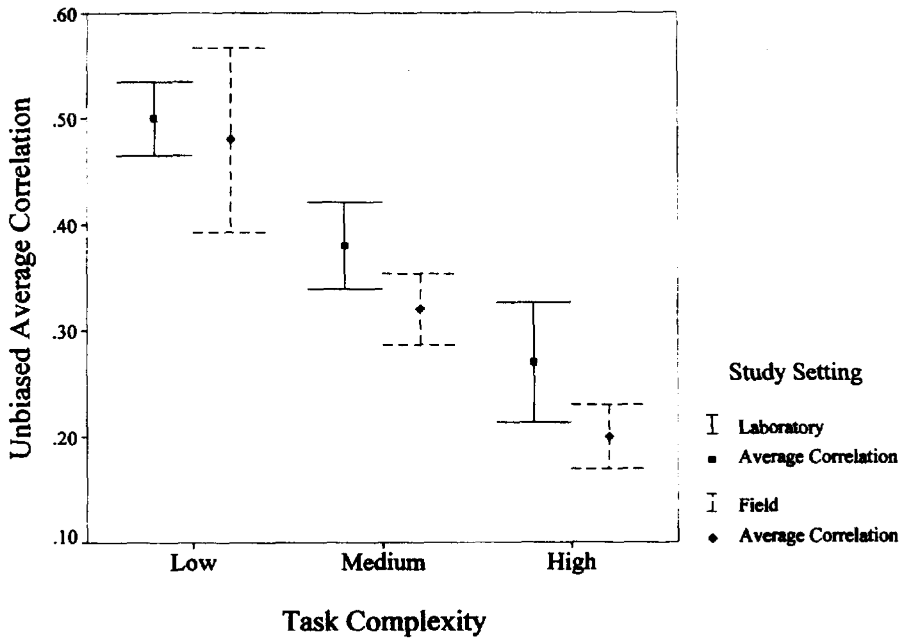

Figure 1. Average correlations and confidence intervals for the levels of task complexity and study settings.

performance trials, as individuals become more familiar with the intricacies of the complex tasks. Thus, we suggest several underlying mechanisms that may further explain the nature of the relationship between self-efficacy and performance for the different levels of task complexity.

Task strategies. The lagged effects between self-efficacy and performance for the different levels of task complexity may be due to the over-time development of effective strategies to cope with the intricate demands of the complex undertakings. Moreover, perceptions of higher self-efficacy may lead to the development of more effective strategies necessary for successful performance on the complex task. In fact, studies using Wood's dynamic decision making task (Wood & Bailey, 1985) shed light on these processes by indicating that individuals low on self-efficacy tend to develop poorer task strategies then those high on self-efficacy (e.g., Bandura & Wood, 1989; Wood & Bandura, 1989a; Wood et al., 1990).

Task focus. A further analysis suggests that whether task performers develop effective task strategies on complex tasks also depends on the relationship between self-efficacy and an individual self-orientation (Wood & Bandura, 1989a). Low self-efficacy tends to cause people to become more self-focused rather than task-diagnostic, which interferes with the optimal deployment of the cognitive resources necessary to develop and test complex task strategies. This is because self-focused individuals tend to "dwell on their personal deficiencies and cognize environmental demands as more formidable than they really are" (Wood & Bandura, 1989a, p. 408). As a result, there is more focus on personal deficiencies and possible adverse task outcomes, rather than on sustained attention to complex task demands requisite for development of effective task strategies (Sarason, 1975).

Ability conception. To complicate matters further, self-orientation (self-focused vs. task-diagnostic) also depends on people's conception of ability with which they approach complex undertakings (Dweck & Elliot, 1983). There are two identified approaches to ability perception (see Elliot & Dweck, 1988). According to the first one, ability is perceived as an incremental skill that could be progressively improved by learning and acquisition of new competencies. In contrast, another perspective views ability mostly as a fixed entity with strong self-evaluative concerns about a given intellectual capacity (Nicholls, 1984). Wood and Bandura (1989a) have shown that people with ability as an acquirable skill orientation tend to sustain perceptions of high personal efficacy and subsequently develop effective analytic strategies for the performance of a complex task (see also Wood et al., 1990).

Skill acquisition. Learning can be considered as another explanation of possible lagged effects between self-efficacy and performance for the different levels of task complexity. In particular, self-efficacy theory (Bandura, 1997b) distinguishes between performance efficacy beliefs and beliefs in one's efficacy to acquire new competencies. Research shows that perceived learning efficacy is a good predictor of the acquisition of complex skills necessary for successful execution of complex tasks (e.g., Kanfer & Ackerman, 1989). However, when complex tasks are examined in a temporal sequence, research shows mixed results. For example, Mitchell et al. (1994) found that self-efficacy is a more important determinant of performance earlier in learning or performing a task than in later learning during routine performance after the study participants have become more familiar with the task. Eden and Zuk (1995) reported similar findings. In contrast, Wood and associates have repeatedly found opposite results (e.g., Bandura & Wood, 1989; Wood & Bandura, 1989a; Wood et al., 1990).

Second-Level Moderator Analysis

Results of the second-level moderator analysis provided support for the hypothesis that the relationship between self-efficacy and performance is further moderated by the type of study setting for each level of task complexity. The findings showed a downward movement in the magnitude of the relationship between self-efficacy and performance from the most pronounced levels for the low task complexity and simulated settings to the high task complexity and actual settings. A major implication of the adjusted second-level moderator analysis is not only that it confirmed the hypothesis, but it did so while achieving full homogeneity of individual correlations for each moderator class. Because this analysis reduced residual variances to a statistical nil, as Hunter and Schmidt (1995) pointed out "if chi square is not significant, this is strong evidence that there is no true variation across studies" (p. 112).

Regarding the finding from this analysis that situational factors present in naturalistic environments tend to further (in addition to impact of task complexity) lower the strength of the relationship between self-efficacy and performance, there are two important questions yet to be addressed. First, which of the environmental factors outlined in the theory proposed exerts the greatest influence on the relationship between self-efficacy and performance for each level of task complexity. Only the design of an individual research study has the capacity to examine the influence of each individual factor while holding others constant. The second question is how these factors influence the relationship between self-efficacy and performance. For example, do they influence the accuracy of the self-efficacy judgment (e.g., the "noisier" the environment the less task performers are able to accurately estimate their personal efficacy), which then leads to lower performance levels, or do they directly influence the performance level, irrespective of efficacy judgment, by imposing environmental constraints on the efficient performance? These questions represent interesting avenues for further inquiry.

Practical Implications

Part of the reason self-efficacy theory has been eagerly embraced by management scholars and even practitioners is the potential of its applicability to work-related performances and organizational pursuits. The nature and the scope of the studies included in this meta-analysis support this development. Thus, it seems important to recognize the implications of this study's results, and the theory on which they are based, as they relate to practicing managers.

General Guidelines

Two general findings appear particularly important for organizational practitioners. First is the understanding that, overall, self-efficacy was found to be positively and strongly related to work-related performance. Given the scope of this meta-analysis, and the extensive theoretical foundation of the whole research stream (Bandura, 1986, 1997b), the above findings represents something that usually skeptical practicing professionals may rely on with a reasonable amount of confidence. This is particularly noteworthy considering that some frequently examined areas in organizational behavior have, over the years, in fact shown weak (e.g., Iaffaldano & Muchinsky, 1985; Wahba & Bridwell, 1976) or mixed results (e.g., Cotton, Vollrath, Froggatt, Lengnick-Hall, & Jennings, 1988; King, 1970).

Second is the awareness that the relationship between self-efficacy and work-related performance is moderated by task complexity and locus of performance. The identification of these two moderators particularly relates to organizational settings because it appears that task complexity and situational factors present in work environments tend to weaken the relationship between self-efficacy and performance. Especially in light of the finding that the relationship between self-efficacy and performance tends to be the weakest for the higher levels of task complexity and field settings, we suggest several specific suggestions to improve the performance of human resources in the complex undertakings found in today's organizations in an efficient and relatively inexpensive manner.

Specific Suggestions

First, managers should provide accurate descriptions of the tasks employees are asked to perform. Unless the definitions of the task and task circumstances are provided in a clear and concise manner, employees may not be able to accurately assess the complex task demands, may not fully know what they have to do, and thus will lack accurate information for regulating their effort. As a result, this may lead employees to a faulty assessment of their perceived efficacy.

Second, employees should also be instructed as to what (technological) means are necessary for successful performance, and how to use those means (e.g., Gist et al., 1989). Because complex tasks usually involve several possible paths for their execution, the appropriateness of the selected means should also be ensured. Otherwise, even the strongest employee belief that he or she can execute the means may not lead to the successful performance, which can in turn result in unjustifiably lowered personal efficacy.

Third, the work environment should be free from undesirable factors such as physical distractions that may cause either digression in information processing, behavioral acts, or both. If physical distractions are present, they may increase thoughts of failure and amount of stress (Gist & Mitchell, 1992) and reduce coping mechanisms (Bandura, 1986, 1997b), all of which can reduce the magnitude of the relationship between self-efficacy and performance.

Fourth, due to the greater cognitive and behavioral demands imposed by complex tasks, employees may not perceive enough personal capabilities to perform successfully at complex undertakings. Thus, managers may provide programs designed to enhance employee's self-efficacy. However, the main idea here is not necessarily to train workers at new skills, but to enhance their beliefs as to what they can do with the skills they already have (see Bandura, 1997b).

Fifth, in addition to programs designed to enhance self-efficacy, managers may have to provide additional training in developing effective behavioral and cognitive strategies for coping with complex tasks. This training should also include helping employees to become more task-diagnostic (Kanfer, 1987) and to establish the conception of ability as an incremental skill (Wood & Bandura, 1989a). This is important because if ability is perceived as a given entity (Elliot & Dweck, 1988), any mistakes are likely to be perceived as indicative of intellectual (in)capacity, which may imply lack of personal control (Bandura, 1991). The perceived lack of control leads to personal anxiety (Thompson, 1981), which, in turn, diminishes learning

(Martocchio, 1992; Wine, 1971). The final result is likely to be a lessened belief of self-efficacy for subsequent performance.

Sixth, if efficacy enhancement programs are to be implemented, their timing should be close to the task employees are asked to perform. If not, given the complexity of organizational reality, many factors with negative influence on self-efficacy or direct impact on performance may occur in the interim, which can, in turn, diminish the magnitude of the relationship between an employee's efficacy and his or her performance (Bandura, 1986, 1997b). As a consequence, the entire efficacy enhancement program may be judged as ineffective, whereas the actual problem may have been the timing of it. This is especially important for cost-conscious management of today's organizations.

Seventh, managers should provide clear and objective standards against which employees can gauge the level of their performance accomplishment (see Bandura & Cervone, 1983, 1986). This suggestion is particularly relevant if performance is to be accomplished through some form of interdependent (sequencing of several tasks) or group effort. If specific performance standards are not available in these instances, task performers may be forced to rely on similar situations (which may not have existed or employees may not recall it well), others (who may be biased), or some informal social criteria (that may vary depending on the person providing it) to determine how they are doing (Bandura, 1997b). In any case, estimates of self-efficacy tend to be less accurate because they would be based on information that is either not readily available or apparent, or is socially dependent.

Finally, if no personal consequences are contingently attached to employees' performance, they may have little incentive to seriously engage in an accurate appraisal of their perceived self-efficacy (Bandura, 1986, 1997b; Wood & Bandura, 1989b). In fact, in his latest work, Bandura (1997b) argued that "it is because people see outcomes as contingent on the adequacy of their performance, and care about those outcomes, that they rely on efficacy beliefs in deciding which course of action to pursue and how long to pursue it" (p. 24). We would note that implementing some of the behavioral interventions (e.g., Kluger & DeNisi, 1996; Stajkovic & Luthans, 1997) may prove useful here because, as Bandura (1997b) suggested, "in social cognitive theory, people exercise control for the benefits they gain by it" (p. 16).

Conclusion

Although there have been numerous reviews of self-efficacy literature, meta-analyses of the relationship between self-efficacy and work-related performance have been lacking. We narrowed down the literature to yield a manageable number of studies, formed a domain-meaningful group, and meta-analyzed the results from available studies. Because they pertain to work-related performance, results from our meta-analysis should not be taken as an encompassing index of the overall importance of self-efficacy perceptions in human functioning. Self-efficacy has been demonstrated to influence other areas of human affairs such as, but not exclusively, vocational choice and career pursuits (Hackett, 1997; Hackett & Betz, 1995), health behavior and physical functioning in sports psychology and medicine (Holden, 1991; Maddux, Brawley, & Boykin, 1995), educational achievement of children and adolescents (Holden, Moncher, Schinke, & Barker, 1990), and human adaptation and adjustment (e.g., Bandura, 1997a; Maddux, 1995).

Finally, by this meta-analysis, we hope to have changed the focus from the general question of whether self-efficacy is related to performance (which was clearly answered in this study), to more specific questions regarding the nature and underlying mechanisms of the relationship between self-efficacy and work-related performance. These are the lines of research that can best clarify the size of the contribution of efficacy beliefs to human action.

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