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A Tale of Two Transfers: Disentangling Maximum and Typical Transfer and Their Respective Predictors

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Abstract

Purpose Research on transfer of training has been characterized by a lack of precision in distinguishing between the ability to transfer (i.e., "can do"), and the motivation to transfer (i.e., "will do"). Drawing from job performance research that has made this distinction, we argue that transfer of training can fall along a maximum/typical continuum, with one end reflecting how much trainees *could* potentially transfer (maximum) and the other capturing how much trainees *will* transfer (typical).

Design/Methodology/Approach A meta-analysis was conducted to identify relationships among four learning outcomes (declarative knowledge, skill acquisition, posttraining self-efficacy, and motivation to transfer), three stable antecedents (cognitive ability, conscientiousness, and workplace support), and transfer of training. 144 papers provided input for a meta-analytic correlation matrix, which formed the basis of regression analyses for hypothesis testing.

Findings Maximum and typical transfer were only weakly correlated and, as hypothesized, were predicted by different antecedents. Specifically, ability factors including declarative knowledge, skill acquisition, and cognitive ability were stronger predictors of maximum transfer, whereas motivation factors including posttraining self-efficacy, motivation to transfer, conscientiousness, and workplace support were stronger predictors of typical transfer. Additional mediation analyses revealed that learning outcomes mediated the effects of stable antecedents differently on maximum/typical transfer.

Implications These findings refine the understanding of the transfer construct space and suggest that future work on transfer should explicitly consider the maximum/typical continuum.

Originality/Value This is the first paper to demonstrate the maximum/typical transfer distinction, thus offering potential explanation to inconsistent findings and highlighting the need for increased precision in transfer measurement.

Keywords Transfer of training · Training evaluation · Learning outcomes · Maximum/typical performance

Introduction

Training researchers have advanced the understanding of what is meant by learning (Gagné 1984; Kraiger et al. 1993) and the factors that impact learning during training (Arthur et al. 2003; Chen and Klimoski 2007; Salas et al. 2012). Researchers have also examined transfer of training—the extent to which an individual can generalize the

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knowledge and skills acquired in a learning context to a performance context. Those interested in understanding the link of learning outcomes and transfer outcomes often examine the application of the learning to a variety of settings, situations, and people not faced in the learning context. However, one key distinction is whether a trainee is in a learning or performance context when the outcomes are measured (Baldwin and Ford 1988; Blume et al. 2010). In a learning context, it is clear to the trainee that they are in a setting where they are to gain some specific knowledge and skills. In a performance context, the trainee is being asked or expected to apply learning to accomplish a task (i.e., training transfer) given the knowledge and skills gained in the learning context.

In their influential review, Baldwin and Ford (1988) identified trainee characteristics and work environmental factors as two important categories of antecedents to learning outcomes and subsequent transfer. Ensuing research has shed light on the nomological relationships among input, learning outcomes, and transfer. For example, Colquitt et al.'s (2000) meta-analytic path analysis showed that skill acquisition and posttraining self-efficacy contributed uniquely to impacting transfer while declarative knowledge did not. They also found evidence for direct and indirect effects for trainee characteristics (e.g., conscientiousness) and workplace support on learning and transfer outcomes.

Although Colquitt et al. (2000) provided preliminary evidence of the effects of factors impacting transfer, many of their estimates were based on a very small number of studies (e.g., three studies examined the relationship between transfer and both posttraining self-efficacy and climate; one study examined the relationship between conscientiousness and transfer). Research in the past decade on learning and transfer outcomes affords the opportunity to update the cumulative knowledge and derive more accurate meta-analytic estimates for the effects of trainee characteristics, workplace support, and learning outcomes, and enables a closer examination of the multidimensionality of learning outcomes. Recent advances on posttraining motivation (see Cheng and Hampson 2008) allow for the inclusion of motivation to transfer as an additional learning outcome variable in a meta-analytic study.

More importantly, transfer research has not addressed the difference between measuring transfer as a "can do" versus a "will do" construct. Yet, at the end of the training, organizations are not only concerned with trainees' enhanced capacity to apply the newly acquired knowledge and skills, but also the extent to which trainees utilize such enhanced capacity on the job. Such distinction has not been made salient in the training literature and deserves systematic investigation to better understand the nomological network of relationships of training input, learning, and transfer outcomes. This distinction between maximum and typical transfer is useful to researchers when conceptualizing and operationalizing training transfer as well as to practitioners when planning for assessment of training impact.

In this study, we draw from extant research that has distinguished between maximum and typical performance (e.g., Klehe and Anderson 2007a; Sackett et al. 1988) so as to separate transfer of training into "can transfer" (maximum transfer) and "will transfer" (typical transfer). Grounded in theories of performance that emphasize the ability $\times$ motivation interaction (Campbell et al. 1993; McCloy et al. 1994), we align learning outcomes and stable antecedents into ability versus motivational clusters and formulate hypotheses regarding their relative contributions in predicting maximum versus typical transfer. By extricating the roles of learning outcomes (knowledge acquisition, skill acquisition, self-efficacy, and motivation to transfer) and stable antecedents (cognitive ability, conscientiousness, and workplace support) in predicting maximum and typical transfer, we seek to clarify the nomological network leading to transfer of training.

Maximum Transfer and Typical Transfer

Maximum and typical *transfer* are direct extensions from prior research on maximum and typical *performance.* Sackett et al. (1988) defined a maximum performance situation as one in which performers (a) explicitly understand that they are being evaluated, (b) accept implicit or explicit instructions to maximize effort, and (c) are evaluated for a relatively short time. A typical performance situation is characterized by a setting in which individuals are not aware that their performance is being evaluated, are not consciously attempting to perform to the best of their ability, and are loosely monitored over an extended period of time (Sackett et al. 1988). For maximum transfer, trainees are given explicit or implicit prompts to maximize effort while demonstrating the skill transfer, typically for a short period of time. On the other hand, typical transfer occurs when trainees transfer skills without prompts, typically over an extended period of time and without focusing on the fact that the skill transfer is being evaluated.

A number of research studies have documented that maximum and typical performance are structurally distinct (Marcus et al. 2007; Ployhart et al. 2001; Witt and Spitzmuller 2007). That is, the empirical findings show that performance across these two conditions shares only a modest positive correlation (Beus and Whitman 2012; DuBois et al. 1993; Klehe and Latham 2006; Sackett et al. 1988). It is worth noting that maximum and typical performance are often described as falling along a conceptual continuum (Sackett et al. 1988). Aside from the influence of measurement situations, variation along the maximum/typical performance continuum has been associated with characteristics of the person (e.g., experience and ability—Barnes and Morgeson 2007; Deadrick and Gardner 2008) and of the tasks within a job (e.g., the degree to which each task component is emphasized—Mangos et al. 2007).

Analogously, transfer outcomes—in which trainees apply newly acquired knowledge and skills to a novel environment (e.g., work environment)—can be categorized along a maximum/typical continuum. In particular, some situations provide trainees with explicit or implicit instructions to maximize effort in transferring training for a short period of time, whereas other situations involve the measurement of transfer over an extended period without any explicit instructions to maximize transfer. As one empirical example, consider the Baldwin (1992) study where transfer was assessed in both maximum and typical contexts. Study participants were trained on assertive communication skills and then participated in a short role-play exercise within the lab setting where they were aware that they were being evaluated and were likely to maximize effort—a measure of maximum transfer. Approximately 1 month later, participants returned to the lab to complete a post-study questionnaire to examine their learning retention. Upon leaving the lab, participants were approached by a confederate who asked them to purchase business publications. This represents typical transfer in that they did not realize they were being evaluated and would not necessarily maximize their effort to demonstrate their assertive communication skills when responding to the confederate. Exploring the difference between maximum and typical transfer provides the basis for developing a conceptual framework, as well as addressing some of the inconsistencies in the literature regarding the strength of various predictors of transfer (e.g., Burke and Hutchins 2007; Cheng and Hampson 2008).

Ability and motivation have been modeled as interacting antecedents to job performance (Campbell et al. 1993; McCloy et al. 1994). Campbell et al. (1993) noted two factors that relate to an individuals' ability to perform (a) declarative knowledge—understanding of facts; and (b) procedural knowledge and skills—knowing how to do things. Another general factor, motivation, pertains to the choices individuals make to perform and the level and persistence of effort they apply to their work (Campbell et al. 1993). According to Campbell and colleagues, variation on both ability and motivation drives variation in performance.

While an individual's ability factors are thought to be relatively stable, the motivational antecedents to performance are more subject to influence by performance situations at work. In particular, the continuum ranging from maximum to typical performance situations can directly affect performance through choices made regarding motivation levels and persistence of those efforts (DuBois et al. 1993; Klehe and Anderson 2007a).

Job performance research has documented that maximum and typical performance outcomes have different predictors (e.g., Beus and Whitman 2012; DuBois et al. 1993; Klehe and Anderson 2007a, b; Marcus et al. 2007; Witt and Spitzmuller 2007). Maximum performance results from the elevated motivation to perform up to one's best ability, whereas typical performance stems more from each individual's volition to apply one's ability in work tasks over time. As such, maximum performance outcomes are predicted more by ability-related factors, and typical performance outcomes are better predicted by motivational factors.

To better understand the variance in maximum versus typical transfer outcomes, we examined the following ability and motivation-related predictors: (a) learning outcomes, namely knowledge acquisition, skill acquisition, posttraining self-efficacy, and motivation to transfer; and (b) stable antecedents, including cognitive ability, conscientiousness, and workplace support for transfer. We summarize the expected relationships between these predictors and transfer outcomes in a heuristic model in Fig. 1.

Learning Outcomes and Maximum/Typical Transfer

Defined as "persistent states that make possible a variety of human performance" (Gagné 1984, p. 377), learning outcomes have long been considered important precursors to transfer of training (Baldwin and Ford 1988; Noe 1986; Rouiller and Goldstein 1993; Tannenbaum et al. 1991). Kraiger et al. (1993) proposed a multidimensional taxonomy, consisting of cognitive, skill-based, and affective learning outcomes. According to Kraiger et al. (1993), cognitive outcomes include verbal knowledge, knowledge structures, and cognitive strategies. Skill-based outcomes involve the procedural reproduction of trained skills. Affective outcomes include attitudinal changes and changes in motivational tendencies. At the conceptual level, cognitive and skill-based outcomes correspond to Campbell et al.'s (1993) ability-related antecedents of declarative knowledge and skills, while affective outcomes correspond more to the motivational component. At the operational level, training research has usually assessed declarative knowledge as the cognitive outcome, skill acquisition/reproduction as the skill-based outcome, and posttraining self-efficacy and (posttraining) motivation to transfer as the affective outcomes.

We draw from job performance research to elucidate the way in which these ability (i.e., declarative knowledge and

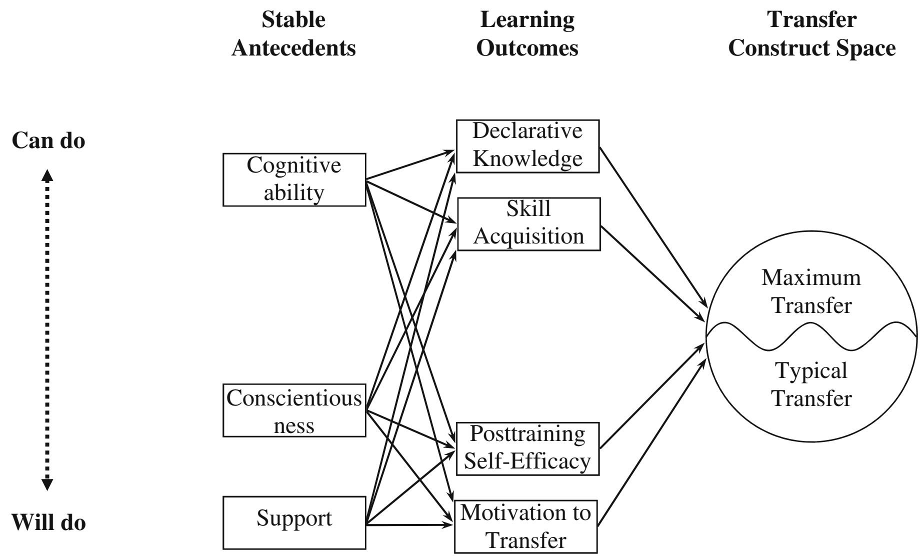

Fig. 1 Heuristic framework of current investigation. *Note* Stable antecedents may have direct effects on maximum/typical transfer not graphed here. Curved division between maximum and typical transfer suggests that the two components may be interrelated

skill acquisition) and motivation-related (i.e., posttraining self-efficacy and motivation to transfer) learning outcomes may differentially predict maximum and typical transfer. Klehe and Anderson (2007a) assessed the degree to which declarative knowledge, procedural skills, and motivation predicted maximum and typical performance outcomes. Participants compared product prices via the Internet in a laboratory, with typical performance induced when participants were working alone without explicit instruction to maximize effort. An experimenter manipulated maximum performance by observing participants work on the task for a short period of time. As expected, Klehe and Anderson (2007a) demonstrated that motivation was more strongly associated with typical than maximum performance, while declarative knowledge and procedural skills were both more strongly associated with maximum than typical performance.

Consistent with these findings, we expect that maximum transfer outcomes will be predicted by the deliberate application of learned knowledge and skills (Smith-Jentsch et al. 2001). The focus on maximizing effort under these conditions will likely diminish the effects of affective learning outcomes that are largely motivational in nature (Kraiger et al. 1993). In contrast, in predicting typical transfer outcomes, the degree to which trainees are motivated to put forth effort to apply the knowledge and skills they acquired will play a more important role in determining the success of transfer than the knowledge and skill-related outcomes.

Hypothesis 1(a) Cognitive and skill-based learning outcomes (i.e., declarative knowledge and skill acquisition) will be better predictors of maximum transfer than affective learning outcomes (i.e., posttraining self-efficacy and motivation to transfer).

Hypothesis 1(b) Affective learning outcomes (i.e., posttraining self-efficacy and motivation to transfer) will be better predictors of typical transfer than cognitive and skill-based outcomes (i.e., declarative knowledge and skill acquisition).

Stable Antecedents and Maximum/Typical Transfer

Aside from learning outcomes, stable individual difference variables and the workplace environment can also affect transfer (Baldwin and Ford 1988; Blume et al. 2010). Following Noe's (1986) proposition that training outcomes are the function of ability, motivation, and perceptions of the work environment, we identified cognitive ability, conscientiousness, and workplace support as distal antecedents of transfer (Colquitt et al. 2000). Those three constructs have been shown to consistently affect transfer (Blume et al. 2010) and allow for an examination of both trainee characteristics and the workplace environment (see Baldwin and Ford 1988). More importantly, these three predictors have been clearly implicated in the maximum versus typical job performance distinction. For example, cognitive ability has been found to be a significant predictor of maximum performance outcomes (Marcus et al. 2007; Witt and Spitzmuller 2007), whereas conscientiousness and organizational support have been found to be better predictors of typical performance outcomes (Klehe and Anderson 2007b; Marcus et al. 2007; Witt and Spitzmuller 2007).

We formulate an analogous pattern of predictions for maximum and typical transfer outcomes. Considering that motivation is constrained at a high level in maximum transfer, the degree to which trainees have the ability and capability to transfer should have a larger impact on maximum transfer. In contrast, given that conscientious individuals are more motivated and more likely to set goals (Judge and Ilies 2002), we expect conscientiousness to be a better predictor for typical transfer. These predictions are consistent with hypotheses and meta-analytic findings from Beus and Whitman (2012). They found that ability had a stronger relationship with maximum performance than with typical performance. Results also revealed that conscientiousness was also more strongly associated with typical relative to maximum performance, although this difference was not significant (Beus and Whitman 2012). In addition, we expect that workplace support for transfer will promote the ease and consistency of typical transfer behavior (Witt and Spitzmuller 2007).

Hypothesis 2(a) Cognitive ability will be a stronger predictor of maximum transfer than conscientiousness and workplace support.

Hypothesis 2(b) Conscientiousness and workplace support will be stronger predictors of typical transfer than cognitive ability.

Once stable antecedents are identified as significant predictors of maximum/typical transfer, the juxtaposition of stable antecedents and training-induced learning outcomes enables us to explore the degree to which antecedents influence maximum/typical transfer through learning outcomes.[1] Learning outcomes serve as multiple mediators (Preacher and Hayes 2008) that may simultaneously convey the effects of stable antecedents on transfer. Following Colquitt et al.'s (2000) finding that antecedents can influence transfer both directly and through mediated mechanisms, we expect the effects of cognitive ability, conscientiousness, and workplace support to be partially mediated by learning outcomes.

We utilized meta-analytic techniques to examine these hypotheses. Specifically, we derived a meta-analytic correlation matrix among predictors and transfer and assessed maximum/typical transfer as an outcome level moderator. We further employed meta-analytic regression techniques (Viswesvaran and Ones 1995) to evaluate the importance of our selected predictors across maximum and typical transfer outcomes. Finally, to assess mediated effects, we utilized Selig and Preacher's (2008) Monte Carlo simulation approach, which has been shown to outperform the Sobel test in a large scale simulation study (MacKinnon et al. 2004).

Method

Literature Search

To construct a correlation matrix consisting of meta-analyzed population estimates, we conducted an extensive literature search for primary studies reporting a correlation between any pair of the eight study variables: transfer of training, cognitive ability, conscientiousness, workplace support, declarative knowledge, skill acquisition, post-training self-efficacy, and motivation to transfer.

The search proceeded in three phases. First, we obtained the primary studies included in Blume et al. (2010) and updated the search for papers using the same search method. We also obtained journal articles and dissertations reported in Colquitt et al. (2000). Second, we searched in the PsycInfo and ERIC databases using any pair of the study variables as keywords while specifying "training" or "learning" in the title of papers. For three variables that had more than one common name in the literature, we used additional keywords: "mental ability" for cognitive ability; "support for training," "support for transfer," "supervisor support," "peer support," and "subordinate support" for workplace support; and "intention to transfer" for motivation to transfer. For posttraining self-efficacy, we searched for "self-efficacy" as the keyword and manually screened for posttraining self-efficacy in the papers.

After coding of all relevant correlations (to be described later), we searched for existing meta-analyses conducted on the relationships of interest. The search identified a meta-analysis on the relationship between cognitive ability and conscientiousness that included more primary studies than we had located in the training literature (Judge et al. 2007), and thus, the meta-analytic estimate from Judge et al. (2007) was used in our analyses. This practice is consistent with recent meta-analytic theory-testing in organizational psychology and management literature (e.g., DeChurch and Mesmer-Magnus 2010; Ilies et al. 2009).

Inclusion Criteria and Coding

Consistent with the study focus, we limited the studies to training studies conducted on healthy adult samples. In addition, the study had to have a learning context and a performance context. Two criteria were applied to inclusion of study variables. First, as we were interested in workplace support specific for training and transfer (but used various search terms for support to be more inclusive), we screened and excluded studies that reported relationships with support variables that were general in scope and did not focus on training and transfer (e.g., perceived organizational support; Ferris et al. 2009). Second, we considered measures of knowledge, skills, self-efficacy, and motivation to transfer as learning outcomes only when they were measured immediately after training. The inclusion criteria resulted in a sample of 144 journal articles and unpublished manuscripts (listed in Appendix 1).

We based our coding of transfer measures upon the distinction above between learning and performance

[1] We thank an anonymous reviewer for this suggestion.

contexts. A transfer measure was coded as such when (a) authors noted key changes in task context that makes it a transfer task; (b) participants were informed of the completion of the learning phase, including assessment of learning; and/or (c) participants were informed of the start of the performance phase. In coding the maximum and typical transfer distinction, we followed the definition provided by Sackett et al. (1988) and determined whether the trainees were expected to maximize their effort in transferring trained content over a limited period of time, or a typical context where trainees decided if and when to utilize the training they received. The first author coded all 144 studies, while the second author independently coded a random sample of 36 studies.[2] The coding agreement was 100 % for maximum/typical transfer, with a mean overall agreement of 96 % for the other coded variables (i.e., sample size, reliabilities, and effect sizes). A table that contains the coding information (e.g., maximum/typical transfer, sample size, effect size, etc.) for each of the studies in the meta-analysis can be found in Appendix 2.

Additional Moderating Variables

We included other potential moderators to examine the strength of the meta-analytic results on the maximum/typical transfer distinction in comparison with other moderators. Specifically, we considered three moderating variables: (a) *student sample* (1 = student sample; 0 = organizational/military sample); (b) *relevance of training program* (1 = relevant as part of one's job/education in a field setting; 0 = contrived for a research study in a laboratory setting); and (c) *time elapsed from training to transfer assessment* (ranging from 0 to 52 weeks, $M = 6$, $Mdn = 4$, SD = 8).

Meta-analyses

We followed the meta-analytic procedures described in Hunter and Schmidt (2004) to analyze the corrected population estimates between any pair of study variables. To correct for measurement errors, we performed study-level correction when reliability information was available for all studies involved in a particular bivariate relationship; when reliability information was reported sporadically for a bivariate relationship, we used artifact distribution instead (see Table 1 for summary statistics).

A primary study's correlation may deviate from the other studies due to atypical study features and/or errors in reporting (Huffcutt and Arthur 1995). We employed the

[2] There could be more than one transfer measure coded for the maximum/typical dimension in a given study.

Table 1 Reliability distributions for study variables

Study variable	Reliability *M*	Reliability SD	*K*
Declarative knowledge	.79	.10	32
Skill acquisition	.85	.10	12
Posttraining self-efficacy	.86	.08	42
Motivation to transfer	.85	.08	35
Cognitive ability	.85	.08	9
Conscientiousness	.81	.07	23
Workplace support	.82	.09	29
Transfer	.84	.08	51

sample-adjusted meta-analytic deviancy statistic (Huffcutt and Arthur 1995; Beal et al. 2002) to detect severe outliers. In addition, we also decided to exclude Oakes et al. (2001) due to the study's large sample size ($N = 9{,}721$). We also excluded 18 estimates that assessed predictor and transfer using the same source and the same measurement context (SS/SMC), following Blume et al.'s (2010) finding of their biasing effect. In the present study, all 18 excluded effect sizes were based on self-report measures taken at a single point in time.[3]

Results

Results of the meta-analytic correlations among study variables are presented in Table 2. Among learning outcomes, skill acquisition had the highest association with overall transfer ($\rho = .48$), followed by declarative knowledge ($\rho = .29$), posttraining self-efficacy ($\rho = .23$), and motivation to transfer ($\rho = .16$). Stable antecedents had moderate zero-order associations with overall transfer (i.e., ρ's ranged from .18 for conscientiousness to .37 for cognitive ability). For descriptive purposes, we compare the current meta-analytic estimates with estimates from prior meta-analytic studies (i.e., Blume et al. 2010; Colquitt et al. 2000). The current estimates are consistent with the relationships reported in Blume et al. (2010). The largest discrepancy was observed in the effect of conscientiousness, $\rho = .18$ vs. .37. Larger differences were observed when compared against Colquitt et al.'s (2000) estimates, which is likely due to the inclusion of more studies in the current meta-analysis and the fact that we eliminated studies that assessed the predictor and transfer

[3] Such design has been shown to be particularly susceptible to the inflation effect due to common method variance (Podsakoff et al. 2003; also see Huang et al. 2014a). It is worth noting that inclusion of these 18 effects did not substantially change the support for the study hypotheses.

Table 2 Meta-analytic correlations among study variables

	Knowledge	Skill	Self-efficacy	Motivation	Cognitive ability	Conscientiousness	Support
Knowledge	–						
Skill	.32, **.40**	–					
	16/1967						
Self-efficacy	.17, **.21**	.31, **.38**	–				
	32/4,051	10/1,441					
Motivation	.16, **.19**	.23, **.28**	.46, **.52**	–			
	18/2,143	3/338	14/2,274				
Cognitive ability	.31, **.39**	.33, **.40**	.17, **.19**	−.15, −**.17**	–		
	13/2,438	8/1,180	9/2,013	2/790			
Conscientiousness	.10, **.13**	.00, **.00**	.16, **.18**	.21, **.26**	–, −**.04**[a]	–	
	13/2,629	5/853	3/361	4/762	56/15,429		
Support	.05, **.09**	.24, **.29**	.20, **.25**	.32, **.39**	.04, **.05**	.11, **.13**	–
	17/2,209	1/43	5/835	15/2,129	1/180	1/362	
Overall transfer	.23, **.29**	.40, **.48**	.20, **.23**	.13, **.16**	.30, **.37**	.15, **.18**	.18, **.22**
	52/6,163	12/1,336	28/3,383	24/2,515	14/2,321	7/690	17/1,358
Maximum transfer	.36, **.44**	.55, **.67**	.26, **.30**	−.02, −**.02**	.32, **.39**	.03, **.03**	.00, **.00**
	21/2,581	7/914	10/1,397	5/698	13/2,234	4/393	1/65
Typical transfer	.14, **.17**	.09, **.10**	.16, **.18**	.19, **.22**	−.14, −**.17**	.31, **.36**	.19, **.23**
	31/3,582	5/422	18/1,986	19/1,817	1/87	3/297	16/1,293
Fisher's *Z*-test	11.64***	12.04***	3.65***	−5.46***	5.25***	−4.49***	−1.80

Sample size-weighted mean correlation ($\bar{r}$) and population corrected correlations (ρ, in bold) are presented on the first row; the number of independent samples (k) and the total sample size (N) are presented on the second row. *** $p < .001$

Knowledge = declarative knowledge; Skill = skill acquisition; Self-efficacy = posttraining self-efficacy; Motivation = posttraining motivation to transfer. Fisher's *Z*-test: Testing the difference of correlations between maximum and typical transfer

SD_r and SD_ρ is available upon request from the first author

[a] ρ estimate obtained from Judge et al. (2007), which did not report $\bar{r}$

at the same time using the same measurement source. For example, we found zero-order associations between posttraining self-efficacy and overall transfer of $\rho = .23$ ($K = 28$), whereas Colquitt et al. reported a corrected correlation of .50 ($K = 3$).

Five primary studies in the current sample, including two lab studies and three field studies, assessed both maximum and typical transfer and reported their correlations. These five studies allowed us to obtain a meta-analytic estimate of the average relationship between maximum and typical transfer: $K = 5$, $N = 253$, $\rho = .04$, $SD_\rho = .15$, 80 % credibility interval −20, .29. In comparison, Beus and Whitman's (2012) meta-analytic correlation between maximum and typical performance was .42. Additional analysis revealed that the maximum–typical transfer relationship appeared stronger in the three field studies using employee samples and job relevant training materials ($K = 3$, $N = 116$, $\rho = .18$, $SD_\rho = .00$) and weaker in the two lab studies using undergraduate samples and contrived tasks ($K = 2$, $N = 137$, $\rho = -.07$, $SD_\rho = .14$). Although these estimates above came from a small number of cases, the evidence available suggests that maximum and typical transfer are indeed distinct.[4]

We proceeded to examine the degree to which predictors (i.e., learning outcomes and stable antecedents) had differential zero-order correlations with maximum versus typical transfer. The results (Table 2) indicate that learning outcomes and stable antecedents indeed had differential relationships with maximum and typical transfer. Specifically, declarative knowledge, skill acquisition, and self-efficacy all had stronger effects on maximum transfer (ρs = .44, .67, and .30) than on typical transfer (ρs = .17,[5] .10, and .18;

[4] These results above should be interpreted with caution, as the results were based on a small number of studies with small sample sizes. The low maximum–typical correlation we obtained could be due to second-order sampling error or some unknown moderating effect, and therefore may not represent the true overall relationship between maximum and typical transfer.

[5] Based on the sample-adjusted meta-analytic deviancy statistic, two studies were detected as outliers for the relationship between declarative knowledge and typical transfer. When excluding these two outliers, $\rho = .11$. Because the inclusion of these two outliers did not affect the pattern of results in subsequent analyses, we retained

Table 3 Weighted least square regression comparing joint influence of maximum/typical transfer with another moderator

Predictor	K	Model 0	Model 1		Model 2		Model 3	
		Maximum	Maximum	Student	Maximum	Relevance	Maximum	Time
Knowledge	52	.27***	.24**	.05	.27**	−.01	.15*	−.02*
Skill	12	.47**	.53**	−.12	.53*	.09	.54*	.01
Self-efficacy	28	.11†	.04	.10	−.03	−.17	.08	−.01
Motivation	24	−.22*	−.22*	.01	−.28*	−.13	−.18	.01
Cognitive ability	14	.45**	.56**	−.14	.34	−.12	n/a	n/a
Conscientiousness	7	−.27*	n/a	n/a	−.14	.20	−.54***	−.02
Support	17	−.19	−.19	−.01	−.19	.00	−.19	.01

Maximum: maximum transfer = 1; typical transfer = 0. Student: student sample = 1, organizational/military sample = 0. Relevance: training relevant to trainees' job/education in a field setting = 1; training contrived for a research study in a laboratory setting = 0. Time: number of weeks elapsed from end of training to transfer assessment

n/a: WLS regression is not performed because maximum/typical and the other moderator showed perfect collinearity in the current analysis. For example, when estimating conscientiousness–transfer relationship, all maximum transfer studies were based on student samples

WLS regression results for each of the three moderators (i.e., student, relevance, and time) in isolation are available from the first author

† $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$. Weighted least square regression on observed correlation coefficients (see Lipsey and Wilson 2001), with unstandardized regression coefficient (Bs) reported

Fisher's Zs = 11.64, 12.04, and 3.65, ps < .001). In addition, cognitive ability shared a larger association with maximum transfer than with typical transfer (ρs = .39 and −.17, respectively; Fisher's $Z = 5.25$, $p < .001$). In contrast, motivation to transfer and conscientiousness was each correlated more strongly with typical transfer (ρs = .22, and .36) than with maximum transfer (ρs = −.02, and .03; Fisher's $Z = -5.46$ and -4.49, $p < .001$). Finally, support's associations with maximum and typical transfer did not differ significantly (ρs = .00 and .23, respectively; Fisher's $Z = -1.80$, $p = .07$).

Although maximum and typical transfer appeared to share different relationships with the antecedents and learning outcomes, it is important to examine if the differential effects were accounted for by other moderating variables. As noted above, we included three additional moderators: (a) student sample; (b) relevance of training program, and (c) time elapsed from training to transfer assessment. Given our theoretical focus, we expected maximum/typical transfer to account for significant variation in observed relationships across studies, even after controlling for other moderating variables. We examined maximum/typical transfer moderating effect by itself (see Model 0 in Table 3) as well as simultaneously with each one of the three moderators (see Models 1–3 in Table 3) in weighted least square regression (Lipsey and Wilson 2001). It is worth noting that we could not examine all four moderating variables simultaneously because the moderators were correlated ($\bar{r}$s = .51, −.63, and −.60 for maximum transfer association with student, relevance, and time, respectively, averaged across seven antecedent-transfer relationships), making multicollinearity an issue in the current small sample analysis (median $k = 17$).

Results in Model 0 generally support maximum/typical transfer as a significant moderating variable. For example, maximum transfer effect on knowledge–transfer relationship was $B = .27$, $p < .001$, indicating that declarative knowledge had a significantly stronger relationship with maximum transfer than with typical transfer. Across Models 1–3, the general pattern of results indicate that, when simultaneously considering maximum/typical transfer and any of the three moderating variables, maximum/typical distinction tended to be the factor accounting for greater variation across studies. The general non-significance of the other three moderators also obviated the need to include them in further analysis.

Hypothesis 1(a) states that cognitive and skill-based learning outcomes will be better predictors of maximum transfer than affective outcomes. A regression on maximum transfer revealed that declarative knowledge, skill acquisition, and posttraining self-efficacy positively predicted transfer in a maximum transfer context, while motivation to transfer had a negative effect. The negative effect for motivation to transfer appeared to be a statistical suppressor effect (Bobko 2001), given the small, nonsignificant −.02 zero-order correlation between motivation to transfer and the transfer outcome. We further utilized relative weights (LeBreton et al. 2007) to discern the difference in importance among predictors, as standardized regression coefficients may fail to indicate predictor importance in the presence of correlated predictors. As shown in Table 4, the raw relative weights indicate that

Footnote 5 continued
these two studies. Results without these two outliers are available from the first author.

declarative knowledge and skill acquisition accounted for a combined 47 % of variance in maximum transfer, compared to the combined 10 % variance by self-efficacy and motivation to transfer. With the relative weight rescaled to percentage of total variance accounted for, cognitive and skill-based outcomes were almost five times as important as affective outcomes (83 vs. 17 %).

Hypothesis 1(b) states that affective learning outcomes will be better predictors of typical transfer than cognitive and skill-based outcomes. A multiple regression analysis on typical transfer showed that motivation to transfer had a positive unique effect, followed by declarative knowledge and self-efficacy, while skill acquisition had no influence on typical transfer. Next, we examined predictor importance in typical transfer. Self-efficacy and motivation to transfer together explained 5 % variance in transfer, relative to the 2 % variance by declarative knowledge and skill acquisition combined. The rescaled relative weights indicated that affective outcomes were more than five times more important than cognitive and skill-based outcomes combined (67 vs. 33 %). Taken together, *Hypotheses 1*(*a*) and (*b*) were both supported.

Hypothesis 2 states that cognitive ability will be a better predictor for maximum transfer (*2a*), whereas conscientiousness and workplace support will be better predictors for typical transfer (*2b*). Two multiple regression and with relative weights analyses were conducted (see Table 5) to examine these hypotheses. In support of *Hypothesis 2(a)*, cognitive ability was the sole stable antecedent that uniquely predicted maximum transfer, accounting for 15 % of the variance in transfer and outweighing conscientiousness and workplace support in importance. Neither conscientiousness nor support significantly predicted maximum transfer.

As for typical transfer, conscientiousness and workplace support both had positive unique effects, whereas cognitive ability had a negative effect. Evaluation of relative weights revealed that conscientiousness accounted for 12 % variance in typical transfer, followed by the 4 % by workplace support. Taken together, the combined effects of conscientiousness and workplace support were more than five times as important as the effect of cognitive ability, providing support for *Hypothesis 2(b)*.

After identifying cognitive ability as significant predictor of maximum transfer and conscientiousness, workplace

Table 4 Simultaneous effects of learning outcomes across transfer measurement contexts

	Overall	Maximum transfer			Typical transfer		
	β	β	Raw RW	% RW	β	Raw RW	% RW
Declarative knowledge	.11***	.23***	.12	21	.14**	.01	29
Skill acquisition	.41***	.60***	.35	62	−.03	.00	4
Posttraining self-efficacy	.05*	.20***	.06	10	.08*	.02	22
Motivation to transfer	−.01	−.33***	.04	7	.16***	.03	45
Model R^2	.24***		.57***			.07***	
N[a]	1,445		1,118			1,109	

Raw RW = relative weight in R^2 units; % RW = relative weight re-expressed in percentage of total R^2

* $p < .05$; ** $p < .01$; *** $p < .001$

[a] N based on harmonic mean of all Ns for each analysis

Table 5 Simultaneous effects of stable antecedents across transfer measurement contexts

	Overall	Maximum transfer			Typical transfer		
	β	β	Raw RW	% RW	β	Raw RW	% RW
Cognitive ability	.37***	.39***	.15	99	−.17**	.03	15
Conscientiousness	.17***	.05	.00	1	.32***	.12	62
Support	.18***	−.03	.00	0	.19**	.04	23
Model R^2	.20***		.15***			.19***	
N[a]	457		187			209	

Raw RW = relative weight in R^2 units; % RW = relative weight re-expressed in percentage of total R^2

* $p < .05$; ** $p < .01$; *** $p < .001$

[a] N based on harmonic mean of all Ns for each analysis

support, and (unexpectedly) cognitive ability as predictors of typical transfer, we proceeded to evaluate their direct versus mediated effects. As noted above, we utilized the Monte Carlo simulation approach (see Preacher and Selig 2012) to estimate the significance and confidence interval of indirect effects. We conducted two sets of regression analyses to obtain the parameter estimates as input for the simulation. First, we regressed maximum and typical transfer separately onto both stable antecedents and learning outcomes simultaneously (see Table 6). Second, we regressed each learning outcome separately onto the three antecedents simultaneously (see Table 7). Using these input values, we generated 20,000 simulated values for each indirect effect and reported the empirical 95 % confidence interval (Table 8). Mediation is detected when a stable antecedent (e.g., cognitive ability) has a significant indirect effect on transfer through a learning outcome variable (e.g., declarative knowledge).

The mediation analyses shed additional light on the influence of stable antecedents on maximum and typical transfer. When predicting maximum transfer, the effect of cognitive ability was fully mediated by declarative knowledge, skill acquisition, posttraining self-efficacy, and motivation to transfer, as indicated by a nonsignificant direct effect ($\beta = -.04$, n.s.). In contrast, conscientiousness and workplace support appeared to influence maximum transfer through inconsistent mediation (i.e., when one indirect effect has a different sign from the direct effect or other indirect effects; MacKinnon et al. 2007). Given conscientiousness and workplace support had null total effects (βs = .05 and −.03, n.s.) on maximum transfer, such inconsistent mediation could be due to motivation to transfer statistical suppressor effect and should be interpreted with caution.

When predicting typical transfer, posttraining self-efficacy partially mediated the influence of cognitive ability, conscientiousness, and workplace support. In addition, declarative knowledge partially mediated the effects of cognitive ability and conscientiousness. However, these indirect effects were weaker relative to the direct effects. The partial mediation results are consistent with the relative weights analysis (see Table 6), which indicate that stable antecedents tended to have greater importance in predicting typical transfer than learning outcomes.

Discussion

What stands out most in this study is the empirical validation of the intuitive difference between maximum and typical transfer and the identification of the different predictors of each. Consistent with prior research in the domain of job performance (DuBois et al. 1993; Klehe and Latham 2006; Sackett et al. 1988), our findings show that

Table 6 Simultaneous effects of stable antecedents and learning outcomes across transfer measurement contexts

	Overall	Maximum transfer			Typical transfer		
	β	β	Raw RW	% RW	β	Raw RW	% RW
Cognitive ability	.23***	−.04	.05	8	−.31***	.05	20
Conscientiousness	.17***	.07	.00	0	.30***	.10	41
Workplace support	.07	−.14***	.02	3	.17***	.03	13
Declarative knowledge	.03	.22***	.10	17	.20***	.03	12
Skill acquisition	.35***	.65***	.34	57	.08	.01	4
Posttraining self-efficacy	−.02	.20***	.05	9	.13*	.02	7
Motivation to transfer	.03	−.31***	.03	5	−.10	.01	4
Model R^2	.31***		.59***			.24***	
N[a]	520		388			403	

Raw RW = relative weight in R^2 units; % RW = relative weight re-expressed in percentage of total R^2

* $p < .05$; ** $p < .01$; *** $p < .001$

[a] N based on harmonic mean of all Ns for each analysis

Table 7 Standardized regression coefficients of stable antecedents simultaneously predicting each learning outcome

	DV = Declarative knowledge	DV = Skill acquisition	DV = Posttraining self-efficacy	DV = Motivation to transfer
Cognitive ability	.39***	.38***	.19***	−.18***
Conscientiousness	.14**	−.02	.16***	.20***
Workplace support	.05	.28***	.22***	.37***
Model R^2	.17***	.23***	.12***	.23***
N[a]	523	149	391	440

* $p < .05$; ** $p < .01$; *** $p < .001$

[a] N based on harmonic mean of all Ns for each analysis

Table 8 Direct and indirect effect of stable antecedents on maximum and typical transfer

	IV = Cognitive ability		IV = Conscientiousness		IV = Workplace support	
	β	95 % CI	β	95 % CI	β	95 % CI
Maximum transfer						
Direct effect	−.04	–	.07	–	−.14***	–
Indirect effect via						
Declarative knowledge	.09***	.05, .12	.03**	.01, .05	.01	−.01, .03
Skill acquisition	.25***	.15, .35	−.01	−.11, .08	.18***	.08, .27
Posttraining self-efficacy	.04***	.01, .07	.03**	.01, .06	.04***	.02, .07
Motivation to transfer	.05***	.03, .09	−.06***	−.10, −.03	−.11***	−.16, −.08
Typical transfer						
Direct effect	−.31***	–	.30***	–	.17**	–
Indirect effect via						
Declarative knowledge	.08***	.04, .12	.03***	.01, .05	.01	−.01, .03
Skill acquisition	.03	−.01, .08	.00	−.02, .01	.02	−.01, .06
Posttraining self-efficacy	.02*	.00, .05	.02*	.00, .05	.03*	.00, .06
Motivation to transfer	.02	−.00, .04	−.02	−.05, .00	−.04	−.08, .01

95 % CI = 95 % confidence interval obtained from Monte Carlo simulation with 20,000 replications. Monte Carlo confidence intervals were not estimated for direct effects

* $p < .05$; ** $p < .01$; *** $p < .001$

maximum and typical transfer are empirically distinct. When examining learning outcomes, we found that knowledge and skill are much more important predictors of maximum transfer, whereas motivation and self-efficacy are much better predictors of typical transfer. We also found that cognitive ability had a strong, significant effect on maximum transfer, whereas conscientiousness and workplace support did not. Consistent with the notion that work behavior is driven by an ability × motivation interaction (Campbell et al. 1993; McCloy et al. 1994), our findings identify ability factors as the most important determinants of the degree to which trainees *can transfer*, whereas motivation factors are most instrumental to the degree to which trainees actually *will transfer*.

Implications for Research

Our findings provide important clarifications to the transfer literature and extend existing findings in several ways. First, the maximum/typical distinction offers a plausible explanation for the weak and inconsistent effects of declarative knowledge on transfer found in past meta-analyses (Alliger et al. 1997; Colquitt et al. 2000). While declarative knowledge has a sizeable unique effect on maximum transfer, its influence on typical transfer is much less pronounced. If one collapses across maximum and typical transfer and predicts overall transfer as a whole (i.e., Overall column in Table 2), the observed effects become much more difficult to interpret. These findings help resolve some of the confusion in the transfer literature and should encourage training researchers to more explicitly identify what distinguishes the learning from the transfer context and whether maximum or typical transfer is being examined. Second, in their qualitative review of transfer studies, Gegenfurtner et al. (2009) observed mixed findings regarding the linkage between motivation to transfer and transfer. Our findings offer a clear explanation for that observation in that motivation to transfer is likely to have a weak and nonsignificant effect on transfer *when maximum transfer is assessed.*

Given the distinction between maximum and typical transfer, examining maximum transfer is likely to be most useful if researchers are interested in the learning process and the cognitive and skill development involved. On the other hand, if researchers are interested in understanding trainees' choice and autonomous effort in transferring, they would be best advised to assess typical transfer as their outcome variable of interest. For example, Smith-Jentsch et al. (2001) found that transfer measured on the job was more highly correlated with ratings on a simulation for those in the typical rather than the maximum performance condition. The broad implication is that future transfer researchers would be well-advised to seek measurement of both maximum and typical transfer and to further consider including measurement of moderators (e.g., the length and duration of performance assessment; see Beus and Whitman 2012) in their research protocol.

The findings also suggest that training researchers need to incorporate both maximum and typical transfer situations in their research to better understand the factors impacting transfer outcomes. For example, future training research in more controlled settings would benefit from the incorporation of both maximum conditions and of "typical" conditions that elicit typical transfer behaviors. Based on Sackett et al. (1988), the key is to simulate the underlying dimensions of a typical transfer setting. These could include examining transfer over longer periods of time, reducing the explicit prompts to participants to transfer what they have learned, and obtaining measures of transfer from participants when they do not think they are being evaluated.

Future transfer research in the field setting should seek to further advance the understanding of the maximum–typical continuum. For example, following Klehe and Anderson's (2007a) suggestion that supervisor ratings of job performance may exhibit more characteristics of the maximum dimension than coworker ratings, it is possible that supervisor ratings of transfer are "more maximum" than peer ratings, as supervisors are more likely to observe trainees for shorter periods of time and trainees may increase their transfer effort when being observed by a supervisor.

Our findings also suggest that although it makes intuitive sense to think learning outcomes are a necessary condition for transfer to occur, it does not have to be the case. For example, someone high on conscientiousness may continue to practice and rehearse newly trained skills, and, despite initial low learning, may still transfer well. Modeling transfer over time will enable training researchers to better discern the potential cumulated effect of predictors over time.

At a minimum, the present findings confirm that it is imperative that authors of future transfer studies provide more details regarding the transfer context. For example, authors should include whether the context resembles more of a maximum or typical setting based on the conditions discussed above. This could be done by evaluating the context on each of the three conditions outlined by Sackett et al. (1988). Based on this type of analysis, researchers could indicate where on the continuum of maximum or typical transfer they are investigating.

Practical Implications

Organizations interested in training transfer could benefit from more active consideration of the maximum/typical transfer continuum. For example, consider a company that wants to evaluate the effectiveness of their safety training. A maximum transfer assessment would be obtained by sending out a safety officer to observe someone operating a forklift to see if all procedures are followed. On the other hand, a typical transfer assessment might be obtained by utilizing a hidden video camera or asking peers to report how often colleagues follow certain safety rules. In this example, it is easy to see that employees who 'can transfer' adherence to safety guidelines may not be the same as whether they 'will transfer.' As another example, when evaluating transfer of customer service training, trainer or supervisor's observations of customer service interactions can constitute evaluation of maximum transfer, whereas assessment from mystery shoppers (Wilson 2001) can shed light on typical transfer. Furthermore, the assessment of both maximum and typical transfer can provide important feedback for an organization's training efforts. While trainees' failure to transfer in a maximum context indicates problems in the training design and delivery process, the failure to transfer in a typical context points to the need to better support and motivate trainees after the training has been completed. Thus, training practitioners are encouraged to consider the use of transfer measurement in conjunction with maximum/typical transfer measurement context.

The finding that affective/motivational factors carry significantly more weight than cognitive and skill-based learning outcomes in predicting typical transfer should also prompt training professionals to consider posttraining efforts to facilitate transfer. Specifically, training professionals may need to increase trainees' 'will do' attitude once they are back on the job. This may include interventions that target trainees' motivation after training (e.g., Stevens and Gist 1997) or directly solicit support from work units (e.g., Tews and Tracey 2008). On the other hand, organizations may increase the frequency of supervisory observations and communicate the explicit expectation for transfer to reinforce the maximum transfer of knowledge and skills.

Our study highlights the notion that learning outcomes such as knowledge and skills acquisition are necessary but not sufficient for organizations to receive a return on their training investment, and have further implications for the selection of trainees. That is, an organization may get a better return on their training investment by training an employee with average ability but high motivation, rather than a high-ability employee with low motivation. Taking the human resource management perspective at a higher level and recognizing the connection between training activities and other human resource management functions (Aguinis and Kraiger 2009), an organization's selection procedure that emphasizes employees' adaptive dispositions and motivation (Huang et al. 2014b) can prove beneficial in enhancing transfer of training.

Limitations

As with all meta-analytic investigations, the present study has some limitations that stem largely from the nature of the sample of included studies. First, some of our results (e.g., cognitive ability and typical transfer; support and maximum transfer) were based on few studies and may therefore be subject to second-order sampling error (Hunter and Schmidt 2004). Thus, we caution against interpreting these effects in isolation and emphasize the overall pattern of support for the hypotheses. As our hypotheses were grounded in theories of job performance and the results provide consistent support to the hypotheses, the concern on second-order sampling error is somewhat mitigated. Nevertheless, more stable estimates based on a larger number of primary studies are desirable as more research efforts are directed toward understanding transfer.

Second, given our focus on delineating the maximum and typical transfer distinction, we did not include several predictors that could potentially influence transfer. For example, mastery goal orientation, neuroticism, and job involvement have been identified in prior work as significant antecedents to transfer of training (Blume et al. 2010). Although these predictors are not central in the current hypothesis testing, it could have been beneficial to explore their effects across maximum and typical transfer. However, inclusion of these predictors was not viable due to the limited number of primary studies to estimate a predictor's relationship with either maximum or typical transfer.

Finally, we operationalized maximum and typical transfer as two distinct categories, although the distinction exists on a conceptual continuum. Constrained by the number of primary studies available and the amount of information about transfer measurement provided in the studies, we were unable to offer a fine-grained analysis by rating studies on a continuous maximum–typical scale. We do recognize that additional work within the training transfer arena may be needed in order to rate transfer context on a continuum. A finer understanding of the maximum–typical continuum may be gained by assessing variations of transfer as a within-person effect (Ford and Oswald 2003) across transfer contexts and task dimensions over time.

Conclusion

One of the maxims of military battle planning is that "no plan ever survives contact with the enemy." The transfer of training challenge is analogous in that, while trained capability is critically important, it is ultimately the willingness of trainees to adapt, generalize, and find opportunities to apply their learning that ultimately determines training success. Prior research on transfer has too often failed to disentangle the "can do" and "will do" elements of transfer, and the present study empirically validates the importance of doing so. Future transfer research and interventions will benefit from more intentional and overt recognition of the distinction between maximal and typical transfer.

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Appendix 1: References for Studies Included in Meta-analysis

Ackerman, P. L., & Kanfer, R. (1993). Integrating laboratory and field study for improving selection: Development of a battery for predicting air traffic controller success. *Journal of Applied Psychology, 78*, 413–432.

Ackerman, P. L., Kanfer, R., & Goff, M. (1995). Cognitive and noncognitive determinants and consequences of complex skill acquisition. *Journal of Experimental Psychology: Applied, 1*, 270–304.

Al-Ammar, S. A. (1995). The influence of individual and organizational characteristics on training motivation and effectiveness. *Dissertation Abstracts International, 55*, 4099.

Axtell, C. M., Maitlis, S., & Yearta, S. K. (1997). Predicting immediate and longer-term transfer of training. *Personnel Review, 26*, 201–213.

Ayres, H. W. (2005). *Factors related to motivation to learn and motivation to transfer learning in a nursing population.* (Unpublished doctoral dissertation), North Carolina State University, Raleigh, NC.

Baldwin, T. T. (1992). Effects of alternative modeling strategies on outcomes of interpersonal-skills training. *Journal of Applied Psychology, 77*, 147–154.

Bates, R. A., Holton, E. F., III, & Burnett, M. F. (1999). Assessing the impact of influential observations on multiple regression analysis on human resource research. *Human Resource Development Quarterly, 10*, 343–363.

Bell, B. S., & Ford, J. K. (2007). Reactions to skill assessment: The forgotten factor in explaining motivation to learn. *Human Resource Development Quarterly, 18*, 33–62.

Bell, B. S., & Kozlowski, S. W. J. (2002). Goal orientation and ability: Interactive effects on self-efficacy, performance, and knowledge. *Journal of Applied Psychology, 87*, 497–505.

Bell, B. S., & Kozlowski, S. W. J. (2008). Active learning: Effects of core training design elements on self-regulatory processes, learning, and adaptability. *Journal of Applied Psychology, 93*, 296–316.

Borowski, J. L. (2001). The social influence of work organizations on training transfer. *Dissertation Abstracts International, 61*, 3926.

Bourgeois, N. T. (2008). Error training: An examination of metacognition, emotion control, intrinsic motivation, and knowledge as mediators of performance effects. *Dissertation Abstracts International, 68*, 4873.

Brown, T. C. (2005). Effectiveness of distal and proximal goals as transfer-of-training interventions: A field experiment. *Human Resource Development Quarterly, 16*, 369–387.

Brown, T. C., & de Leon, S. (2008, August). *Evaluation of a leadership development program for union and management leaders: A comparison of two self-management techniques*. Paper presented at the annual meeting of the Academy of Management, Anaheim, CA.

Brown, T. C., & Warren, A. M. (2009). Distal goal and proximal goal transfer of training interventions in an executive education program. *Human Resource Development Quarterly, 20*, 265–284.

Burke, L. A. (1997). Improving positive transfer: A test of relapse prevention training on transfer outcomes. *Human Resource Development Quarterly, 8*, 115–128.

Burke, L. A., & Baldwin, T. T. (1999). Workforce training transfer: A study of the effect of relapse prevention training and transfer climate. *Human Resource Management, 38*, 227–241.

Carter, M., & Beier, M. E. (2010). The effectiveness of error management training with working-aged adults. *Personnel Psychology, 63*, 641–675.

Chen, G., Donahue, L. M., & Klimoski, R. J. (2004). Training undergraduates to work in organizational teams. *Academy of Management Learning & Education, 3*, 27–40.

Chen, G., Thomas, B., & Wallace, J. C. (2005). A multilevel examination of the relationships among training outcomes, mediating regulatory processes, and adaptive performance. *Journal of Applied Psychology, 90*, 827–841.

Chiaburu, D. S., Sawyer, K. B., & Thoroughgood, C. N. (2010). Transferring More than Learned in Training: Employees' and managers' (over)generalization of skills. *International Journal of Selection and Assessment, 18*, 380–393.

Chiaburu, D. S., & Tekleab, A. G. (2005). Individual and contextual influences on multiple dimensions of training effectiveness. *Journal of European Industrial Training, 29*, 604–626.

Chiaburu, D. S., Van Dam, K., & Hutchins, H. M. (2010). Social Support in the Workplace and Training Transfer: A longitudinal analysis. *International Journal of Selection and Assessment, 18*, 187–200.

Clasen, P. S. (1997). Expectancy theory predictions of the transfer of training skills to the job. *Dissertation Abstracts International, 58*, 2163.

Colquitt, J. A., & Simmering, M. J. (1998). Conscientiousness, goal orientation, and motivation to learn during the learning process: A longitudinal study. *Journal of Applied Psychology, 83*, 654–665.

Combs, G. M., & Luthans, F. (2007). Diversity training: Analysis of the impact of self-efficacy. *Human Resource Development Quarterly, 18*, 91–120.

Coyne, T. H. (2009). Examining the systemic influences of trainee, training design and work environment characteristics on learning, retention, and transfer. *Dissertation Abstracts International, 69*, 2982.

Cruz, B. J. (1995). *An empirical investigation of the validity of self-report assessment versus and instructionally aligned assessment to measure training transfer.* (Unpublished doctoral dissertation), University of San Francisco, San Francisco, CA.

Davis, F. D., & Yi, M. Y. (2004). Improving Computer Skill Training: Behavior Modeling, Symbolic Mental Rehearsal, and the Role of Knowledge Structures. *Journal of Applied Psychology, 89*, 509–523.

Davis, M. A., Curtis, M. B., & Tschetter, J. D. (2003). Evaluating Cognitive Training Outcomes: Validity and Utility of Structural Knowledge Assessment. *Journal of Business and Psychology, 18*, 191–206.

Davis, W. D., Fedor, D. B., Parsons, C. K., & Herold, D. M. (2000). The development of self-efficacy during aviation training. *Journal of Organizational Behavior, 21*, 857–871.

Day, E. A., Arthur Jr, W., & Gettman, D. (2001). Knowledge structures and the acquisition of a complex skill. *Journal of Applied Psychology, 86*, 1022–1033.

Dean, M. A., Conte, J. M., & Blankenhorn, T. R. (2006). Examination of the predictive validity of Big Five personality dimensions across training performance criteria. *Personality and Individual Differences, 41*, 1229–1239.

Devos, C., Dumay, X., Bonami, M., Bates, R., & Holton, E. (2007). The Learning Transfer System Inventory (LTSI) translated into French: internal structure and predictive validity. *International Journal of Training and Development, 11*, 181–199.

Dierdorff, E. C., & Surface, E. A. (2008). If you pay for skills, will they learn? Skill change and maintenance under a skill-based pay system. *Journal Of Management, 34*, 721–743.

Dierdorff, E. C., Surface, E. A., & Brown, K. G. (2010). Frame-of-reference training effectiveness: Effects of goal orientation and self-efficacy on affective, cognitive, skill-based, and transfer outcomes. *Journal of Applied Psychology, 95*, 1181–1191.

Essary, V. L. (2001). The influences of self-efficacy on training transfer. *Dissertation Abstracts International, 62*, 1626.

Fagan, E. C. (1998). *Effects of self-management training and self-efficacy on assistive device trainees' transfer of training*. (Unpublished doctoral dissertation), The Johns Hopkins University, Baltimore, MD.

Fisher, S. L., & Ford, J. K. (1998). Differential effects of learner effort and goal orientation on two learning outcomes. *Personnel Psychology, 51*, 397–420.

Fitzgerald, C. G. (2002). *Transfer of training and transfer climate: The relationship to the use of transfer maintenance strategies in an autonomous job context.* (Unpublished doctoral dissertation), The University of Connecticut, Storrs, CT.

Ford, J. K., QuiÑOnes, M. A., Sego, D. J., & Sorra, J. S. (1992). Factors affecting the opportunity to perform trained tasks on the job. *Personnel Psychology, 45*, 511–527.

Ford, J. K., Smith, E. M., Weissbein, D. A., Gully, S. M., & Salas, E. (1998). Relationships of goal orientation, metacognitive activity, and practice strategies with learning outcomes and transfer. *Journal of Applied Psychology, 83*, 218–233.

Foster, J., & Hoff Macan, T. (2002). Attentional Advice: Effects on Immediate, Delayed, and Transfer Task Performance. *Human Performance, 15*, 367–380.

Frash, R. E., Jr. (2004). *Modeling the context and transfer relationship for blended elearning instructional design and delivery in hospitality.* (Unpublished doctoral dissertation), Purdue University, West Lafayette, IN.

Gist, M. E. (1989). The influence of training method on self-efficacy and idea generation among managers. *Personnel Psychology, 42*, 787–805.

Gist, M. E., Schwoerer, C., & Rosen, B. (1989). Effects of alternative training methods on self-efficacy and performance in computer software training. *Journal of Applied Psychology, 74*, 884–891.

Gist, M. E., Stevens, C. K., & Bavetta, A. G. (1991). Effects of self-efficacy and post-training intervention on the acquisition and maintenance of complex interpersonal skills. *Personnel Psychology, 44*, 837–861.

Gjestland, C. (2001). Applying cognitive skill acquisition theory to the training needs assessment of information technology professionals: An initial study. *Dissertation Abstracts International, 61*, 3250.

Goldberg, C., & Perry, E. L. (2009, April). *Training HR managers to handle sexual harassment complaints: Context matters*. Paper presented at the annual meeting of the Society for Industrial and Organizational Psychology, New Orleans, LA.

Gorman, C. A., & Rentsch, J. R. (2009). Evaluating frame-of-reference rater training effectiveness using performance schema accuracy. *Journal of Applied Psychology, 94*, 1336–1344.

Green, E. C. (2002). The influence of individual and work environment characteristics on trainee motivation and training effectiveness measures. *Dissertation Abstracts International, 62*, 4025.

Guardiola, R. J. (2001). A transfer of training evaluation study: Investigating differences between goal setting and relapse prevention. *Dissertation Abstracts International, 61*, 5037.

Hanisch, K. A., & Hulin, C. L. (1994). Two-stage sequential selection procedures using ability and training performance: Incremental validity of behavioral consistency measures. *Personnel Psychology, 47*, 767–785.

Helle, L., Nivala, M., Kronqvist, P., Ericsson, K. A., & Lehtinen, E. (2010). Do prior knowledge, personality and visual perceptual ability predict student performance in microscopic pathology? *Medical Education, 44*, 621–629.

Herold, D. M., Davis, W., Fedor, D. B., & Parsons, C. K. (2002). Dispositional influences on transfer of learning in multistage training programs. *Personnel Psychology, 55*, 851–869.

Hertenstein, E. J. (2001). Goal orientation and practice condition as predictors of training results. *Human Resource Development Quarterly, 12*, 403–419.

Hicks, E. T. (2006). *Individual and situational factors affecting transfer of training in a call center environment.* (Unpublished doctoral dissertation), University of Louisville, Louisville, KY.

Holladay, C. L., Anderson, D. J., Gilbert, S. M., & Turner, S. L. (2008, April). *Evaluating diversity training effectiveness: Self-efficacy as an enabler of transfer*. Paper presented at the annual meeting of the Society for Industrial and Organizational Psychology, San Francisco, CA.

Holladay, C. L., & Quiñones, M. A. (2003). Practice variability and transfer of training: The role of self-efficacy generality. *Journal of Applied Psychology, 88*, 1094–1103.

Holton Iii, E. F., Bates, R. A., Bookter, A. I., & Yamkovenko, V. B. (2007). Convergent and divergent validity of the learning transfer system inventory. *Human Resource Development Quarterly, 18*, 385–419.

Huang, L. (2012). A multifocal framework of personality applied to training and transfer. *Dissertation Abstracts International, 73*, 2553.

Hutchins, H. M. (2004). *Enhancing skill maintenance through relapse prevention strategies: A comparison of two models.* (Unpublished doctoral dissertation), University of North Texas, Denton, TX.

Keith, N., & Frese, M. (2005). Self-Regulation in Error Management Training: Emotion Control and Metacognition as Mediators of Performance Effects. *Journal of Applied Psychology, 90*, 677–691.

Kelleher, D., Finestone, P., & Lowy, A. (1986). Managerial Learning: First Notes from an Unstudied Frontier. *Group & Organization Management, 11*, 169–202.

Kirwan, C., & Birchall, D. (2006). Transfer of learning from management development programmes: testing the

Holton model. *International Journal of Training and Development, 10*, 252–268.
Kozlowski, S. W. J., Gully, S. M., Brown, K. G., Salas, E., Smith, E. M., & Nason, E. R. (2001). Effects of training goals and goal orientation traits on multidimensional training outcomes and performance adaptability. *Organizational Behavior and Human Decision Processes, 85*, 1–31.
LePine, J. A., LePine, M. A., & Jackson, C. L. (2004). Challenge and Hindrance Stress: Relationships With Exhaustion, Motivation to Learn, and Learning Performance. *Journal of Applied Psychology, 89*, 883–891.
Lievens, F., Harris, M. M., Van Keer, E., & Bisqueret, C. (2003). Predicting cross-cultural training performance: The validity of personality, cognitive ability, and dimensions measured by an assessment center and a behavior description interview. *Journal of Applied Psychology, 88*, 476–489.
Lim, D. H., & Morris, M. L. (2006). Influence of trainee characteristics, instructional satisfaction, and organizational climate on perceived learning and training transfer. *Human Resource Development Quarterly, 17*, 85–115.
Loh, V., Andrews, S., Griffin, B., & Hesketh, B. (2007, April). *Individual differences in error management training: Not everyone learns from their mistakes*. Paper presented at the annual meeting of the Society for Industrial and Organizational Psychology, New York.
Lorenzet, S. J., Salas, E., & Tannenbaum, S. I. (2005). Benefiting from mistakes: The impact of guided errors on learning, performance, and self-efficacy. *Human Resource Development Quarterly, 16*, 301–322.
Machin, M. A., & Fogarty, G. J. (2003). Perceptions of Training-Related Factors and Personal Variables as Predictors of Transfer Implementation Intentions. *Journal of Business and Psychology, 18*, 51–71.
Madera, J. (2006, April). *Effects of training utility perceptions and organizational support on transfer*. Paper presented at the annual meeting of the Society for Industrial and Organizational Psychology, Dallas, TX.
Martineau, J. W. (1996). A contextual examination of the effectiveness of a supervisory skills training program. *Dissertation Abstracts International, 56*, 5207.
Martocchio, J. J. (1992). Microcomputer usage as an opportunity: The influence of context in employee training. *Personnel Psychology, 45*, 529–552.
Martocchio, J. J. (1994). Effects of conceptions of ability on anxiety, self-efficacy, and learning in training. *Journal of Applied Psychology, 79*, 819–825.
Martocchio, J. J., & Dulebohn, J. (1994). Performance feedback effects in training: The role of perceived controllability. *Personnel Psychology, 47*, 357–373.
Martocchio, J. J., & Judge, T. A. (1997). Relationship between conscientiousness and learning in employee training: Mediating influences of self-deception and self-efficacy. *Journal of Applied Psychology, 82*, 764–773.
Martocchio, J. J., & Webster, J. (1992). Effects of feedback and cognitive playfulness on performance in microcomputer software training. *Personnel Psychology, 45*, 553–578.
Massman, A. J. (2009). *Breaking the cycle of remedial training: The effects of gain and loss-framed messaging on training motivation and performance.* (Unpublished master's thesis), Michigan State University, East Lansing, MI.
Mathieu, J. E., Tannenbaum, S. I., & Salas, E. (1992). Influences of individual and situational characteristics on measures of training effectiveness. *Academy of Management Journal, 35*, 828–847.
Melchers, K. G., Lienhardt, N., Von Aarburg, M., & Kleinmann, M. (2011). Is more structure really better? A comparison of frame-of-reference training and descriptively anchored rating scales to improve interviewers' rating quality. *Personnel Psychology, 64*, 53–87.
Munoz, K. F. (2006). *Practice-based continuing education in healthcare: A comparison of learning outcomes between direct and indirect training interventions.* (Unpublished doctoral dissertation), Northern Illinois University, DeKalb, IL.
Myers, S. D. (1998). The role of person, outcome, environmental, and learning variables in training effectiveness. *Dissertation Abstracts International, 59*, 0238.
Naquin, S. S., & Holton, E. F. (2002). The effects of personality, affectivity, and work commitment on motivation to improve work through learning. *Human Resource Development Quarterly, 13*, 357–376.
Oakes, D. W., Ferris, G. R., Martocchio, J. J., Buckley, M. R., & Broach, D. (2001). Cognitive ability and personality predictors of training program skill acquisition and job performance. *Journal of Business and Psychology, 15*, 523–548.
Orvis, K. A., Brusso, R. C., Wasserman, M. E., & Fisher, S. L. (2010). E-nabled for E-Learning? The Moderating Role of Personality in Determining the Optimal Degree of Learner Control in an E-Learning Environment. *Human Performance, 24*, 60–78.
Petkova, Z. (2011). Optimizing training effectiveness: The role of regulatory fit. *Dissertation Abstracts International, 73*, 1652.
Poteet, M. L. (1997). The training transfer process: An examination of the role of individual, motivational, and work environmental factors. *Dissertation Abstracts International, 57*, 6633.
Quiñones, M. A. (1995). Pretraining context effects: Training assignment as feedback. *Journal of Applied Psychology, 80*, 226–238.
Quiñones, M. A., Ford, J. K., Sego, D. J., & Smith, E. M. (1995). The effects of individual and transfer environment

characteristics on the opportunity to perform trained tasks. *Training Research Journal, 1*, 29–48.

Ramirez, A. E. (2000). Individual, attitudinal, and organizational influences on training effectiveness: A test of Noe's model. *Dissertation Abstracts International, 61*, 1122.

Ree, M. J., Carretta, T. R., & Teachout, M. S. (1995). Role of ability and prior knowledge in complex training performance. *Journal of Applied Psychology, 80*, 721–730.

Richman-Hirsch, W. L. (2001). Posttraining interventions to enhance transfer: The moderating effects of work environments. *Human Resource Development Quarterly, 12*, 105–119.

Richman, W. L. (1999). Examining the effects of post-training interventions on transfer of training. *Dissertation Abstracts International, 59*, 6102.

Ronen, E. (2010). Transfer of e-learning in the workplace: The effects of trainee characteristics and contextual factors. *Dissertation Abstracts International, 70*, 5218.

Rouiller, J. Z., & Goldstein, I. L. (1993). The relationship between organizational transfer climate and positive transfer of training. *Human Resource Development Quarterly, 4*, 377–390.

Rowold, J. (2007). The impact of personality on training-related aspects of motivation: Test of a longitudinal model. *Human Resource Development Quarterly, 18*, 9–31.

Sekowski, G. J. (2003). Evaluating training outcomes: Testing an expanded model of training outcome criteria. *Dissertation Abstracts International, 63*, 6130.

Short, M. A. (1997). *Transfer of training: Examining the relationship of supervisor, peer, and subordinate support on the transfer of leadership behaviors to the work place.* (Unpublished doctoral dissertation), The Ohio State University, Columbus, OH.

Simon, S. J., & Werner, J. M. (1996). Computer training through behavior modeling, self-paced, and instructional approaches: A field experiment. *Journal of Applied Psychology, 81*, 648–659.

Sitzmann, T., & Johnson, S. K. (2012). When is ignorance bliss? The effect of inaccurate self-assessments of knowledge on learning and attrition. *Organizational Behavior and Human Decision Processes, 117*, 192–207.

Smith, E. M. (1997). The effects of individual differences, discovery learning, and metacognition on learning and adaptive transfer. *Dissertation Abstracts International, 57*, 0000.

Sookhai, F., & Budworth, M. H. (2010). The trainee in context: Examining the relationship between self-efficacy and transfer climate for transfer of training. *Human Resource Development Quarterly, 21*, 257–272.

Stevens, C. K., Bavetta, A. G., & Gist, M. E. (1993). Gender differences in the acquisition of salary negotiation skills: The role of goals, self-efficacy, and perceived control. *Journal of Applied Psychology, 78*, 723–735.

Stevens, C. K., & Gist, M. E. (1997). Effects of self-efficacy and goal-orientation training on negotiation skill maintenance: What are the mechanisms? *Personnel Psychology, 50*, 955–978.

Stewart, G. L., Carson, K. P., & Cardy, R. L. (1996). The joint effects of conscientiousness and self-leadership training on employee self-directed behavior in a service setting. *Personnel Psychology, 49*, 143–164.

Sulsky, L. M., & Kline, T. J. B. (2007). Understanding frame-of-reference training success: a social learning theory perspective. *International Journal of Training and Development, 11*, 121–131.

Switzer, K. C., Nagy, M. S., & Mullins, M. E. (2005). The influence of training reputation, managerial support, and self-efficacy on pre-training motivation and perceived training transfer. *Applied Human Resource Management Research, 10*, 21–34.

Tan, J. A., Hall, R. J., & Boyce, C. (2003). The role of employee reactions in predicting training effectiveness. *Human Resource Development Quarterly, 14*, 397–411.

Tannenbaum, S. I., Mathieu, J. E., Salas, E., & Cannon-Bowers, J. A. (1991). Meeting trainees' expectations: The influence of training fulfillment on the development of commitment, self-efficacy, and motivation. *Journal of Applied Psychology, 76*, 759–769.

Tews, M. J., & Tracey, J. B. (2008). An empirical examination of posttraining on-the-job supplements for enhancing the effectiveness of interpersonal skills training. *Personnel Psychology, 61*, 375–401.

Thompson, L. F., Stoughton, J. W., Behrend, T. S., Waton, A. M., & Vignovic, J. A. (2009, April). *The physiological influence of self-efficacy during monitored web-based training.* Paper presented at the annual meeting of the Society for Industrial and Organizational Psychology, New Orleans, LA.

Towler, A., Kraiger, K., Sitzmann, T., Van Overberghe, C., Cruz, J., Ronen, E., & Stewart, D. (2008). The seductive details effect in technology-delivered instruction. *Performance Improvement Quarterly, 21*, 65–86.

Towler, A. J., & Dipboye, R. L. (2001). Effects of trainer expressiveness, organization, and trainee goal orientation on training outcomes. *Journal of Applied Psychology, 86*, 664–673.

Tracey, J. B., & Cardenas, C. G. (1996). Training Effectiveness: an Empirical Examination of Factors Outside the Training Context. *Journal of Hospitality & Tourism Research, 20*, 113–123.

Tracey, J. B., Hinkin, T. R., Tannenbaum, S., & Mathieu, J. E. (2001). The influence of individual characteristics and the work environment on varying levels of training outcomes. *Human Resource Development Quarterly, 12*, 5–23.

Tracey, J. B., Tannenbaum, S. I., & Kavanagh, M. J. (1995). Applying trained skills on the job: The importance of the work environment. *Journal of Applied Psychology, 80*, 239–252.

Tross, S. A., & Maurer, T. J. (2008). The effect of coaching interviewees on subsequent interview performance in structured experience-based interviews. *Journal of Occupational and Organizational Psychology, 81*, 589–605.

Tziner, A., & Falbe, C. M. (1993). Training-Related Variables, Gender and Training Outcomes: A Field Investigation. *International Journal of Psychology, 28*, 203–221.

Tziner, A., Fisher, M., Senior, T., & Weisberg, J. (2007). Effects of trainee characteristics on training effectiveness. *International Journal of Selection and Assessment, 15*, 167–174.

Tziner, A., Haccoun, R. R., & Kadish, A. (1991). Personal and situational characteristics influencing the effectiveness of transfer of training improvement strategies. *Journal of Occupational Psychology, 64*, 167–177.

Vaccaro, J. (2009). *The effect of self-efficacy and goal orientation on transfer of training to the world outside the classroom.* (Unpublished master's thesis), Northern Kentucky University, Highland Heights, KY.

Varela, O. E., Cater, J. J., & Michel, N. (2011). Similarity attraction in learning contexts: An empirical study. *Human Resource Development Quarterly, 22*, 49–68.

Velada, R., Caetano, A., Michel, J. W., Lyons, B. D., & Kavanagh, M. J. (2007). The effects of training design, individual characteristics and work environment on transfer of training. *International Journal of Training and Development, 11*, 282–294.

Warr, P., Allan, C., & Birdi, K. (1999). Predicting three levels of training outcome. *Journal of Occupational and Organizational Psychology, 72*, 351–375.

Watson, A. M. (2011). Cognitive and Motivational Influences on Performance during Training: A Longitudinal Field Study. *Dissertation Abstracts International, 72*, 2425.

Weissbein, D. A. (2000). Improving training effectiveness through motivation: Creating a psychological states intervention. *Dissertation Abstracts International, 61*, 2807.

Wexley, K. N., & Baldwin, T. T. (1986). Posttraining strategies for facilitating positive transfer: An empirical exploration. *Academy of Management Journal, 29*, 503–520.

Wieland Handy, L. A. (2008). *The importance of the work environment variables on the transfer of training.* (Unpublished doctoral dissertation), North Carolina State University, Raleigh, NC.

Yamkovenko, B., & Holton, E. (2010). Toward a theoretical model of dispositional influences on transfer of learning: A test of a structural model. *Human Resource Development Quarterly, 21*, 381–410.

Zayed, M. S. E. (1994). *Work environment factors related to the transfer of training to public organizations in Egypt.* (Unpublished doctoral dissertation), The Ohio State University, Columbus, OH.

Appendix 2

See Table 9.

Table 9 Coding information for studies included in meta-analysis

Study	Transfer	*N*	*r*	rxx	ryy	Comment
Predictor: Conscientiousness						
Chen, Donahue, & Klimoski, 2004	Maximum	27	.11	.82	.73	
Herold, Davis, Fedor, & Parsons, 2002	Maximum	85	.20	.88	NR	
Loh, Andrews, Griffin, & Hesketh, 2007 (conference)	Maximum	104	.10	.90	NR	
Huang, 2012	Maximum	177	−.11	.82	NR	
Tews & Tracey, 2008	Typical	87	.22	.84	.84	
Tziner, Fisher, Senior, & Weisberg, 2007	Typical	130	.40	.86	.88	
Stewart et al. 1996	Typical	80	.27	.94	.90	
Ronen, 2008	Typical	362	.13	.83	.82	SS/SMC
Oakes, Ferris, Martocchio, Buckley, & Broach, 2001	Typical	9,721	.01	.76	NR	Excluded
Predictor: Cognitive ability						
Chen, Donahue, & Klimoski, 2004	Maximum	27	−.05	NR	.73	

Table 9 continued

Study	Transfer	N	r	rxx	ryy	Comment
Fisher & Ford, 1998	Maximum	121	.23	.88	.89	
Holladay & Quinones, 2003	Maximum	82	.12	NR	NR	
Smith, 1996 (dissertation)	Maximum	161	.26	NR	NR	
Bell & Kozlowski, 2008	Maximum	350	.49	.90	NR	
Loh, Andrews, Griffin, & Hesketh, 2007 (conference)	Maximum	104	.38	.67	NR	
Bourgeois (2007) (dissertation)	Maximum	183	.24	NR	NR	
Bell & Kozlowski, 2002	Maximum	277	.39	.84	NR	
Kozlowski, Gully, Brown, Salas, Smith, & Nason, 2001	Maximum	60	.28	NR	NR	
Gorman & Rentsch, 2009	Maximum	73	.12	NR	.78	
Carter & Beier, 2010 (Campbell, 2007 Diss)	Maximum	161	.52	NR	NR	
Watson, 2010	Maximum	511	.28	NR	NR	
Huang, 2012	Maximum	124	.20	NR	NR	
Tews & Tracey, 2008	Typical	87	−.14	NR	.84	
Oakes, Ferris, Martocchio, Buckley, & Broach, 2001	Typical	9,721	.09	NR	NR	Excluded
Predictor: Workplace support						
Tziner, Haccoun, Kadish, 1991	Typical	81	.16	.80	.69	
Bates, Holton & Burnett, 1999	Typical	68	−.09	.64	NR	
Madera, 2006 (conference)	Typical	53	.16	.91	NR	
Brown & de Leon, 2008 (conference)	Typical	176	.08	.69	.90	
Frash, 2004 (dissertation)	Maximum	65	.00	NR	NR	
Poteet, 1996 (dissertation)	Typical	136	.18	.85	.91	
Short, 1997 (dissertation)	Typical	19	.38	.88	.93	
Switzer, Nagy, & Mullins, 2005	Typical	68	.18	.90	.83	
Velada, Caetano, Michel, Lyons, & Kavanagh, 2007	Typical	182	.31	.89	.87	
Axtell, Maitlis, & Yearta, 1996	Typical	45	.35	.84	NR	
Chiaburu & Tekleab, 2005	Typical	71	.20	.91	.84	
Chiaburu, Van Dam, & Hutchins, 2009	Typical	111	.29	.78	.76	
Coyne, 2008	Typical	68	.18	.89	NR	
Goldberg & Perry, 2009	Typical	17	.39	.88	.86	
Tziner & Fable, 1993	Typical	73	.21	.80	.69	
Fitzgerald, 2002	Typical	19	−.14	NR	NR	
Devos, Dumay, Bonami, Bates, & Holton, 2007	Typical	106	.18	.68	.91	
Chiaburu & Marinova, 2005	Typical	186	.48	.67	.82	SS/SMC
Ottoson & Patterson, 2000	Typical	549	.42	NR	NR	SS/SMC
Cromwell & Kolb, 2004	Typical	57	.67	.86	NR	SS/SMC
Brittain, 2000 (dissertation)	Typical	61	.40	.68	NR	SS/SMC
Mohamed, 1994 (dissertation)	Typical	118	.75	NR	NR	SS/SMC
Warr, Allan, & Birdi, 1999	Typical	123	.05	.77	NR	SS/SMC
Borowski, 2000 (dissertation)	Typical	405	.32	NR	NR	SS/SMC
Casper, 2005 (dissertation)	Typical	118	.34	.76	NR	SS/SMC
Awoniyi, Griego, & Morgan, 2002	Typical	276	.11	.91	.89	SS/SMC
Predictor: Declarative knowledge						
Bourgeois (2007) (dissertation)	Maximum	183	.39	NR	NR	
Smith, 1996 (dissertation)	Maximum	161	.28	NR	NR	
Weissbein, 2000 (dissertation)	Maximum	114	.19	NR	NR	
Chen, Thomas, & Wallace, 2005	Maximum	156	.41	NR	.82	
Fisher & Ford, 1998	Maximum	121	.36	.65	.89	
Kozlowski, Gully, Brown, Salas, Smith, & Nason, 2001	Maximum	60	.65	NR	NR	

Table 9 continued

Study	Transfer	*N*	*r*	rxx	ryy	Comment
Lorenzet, Salas, & Tannenbaum, 2005	Maximum	90	.07	NR	.83	
Mathieu, Tannenbaum, Salas, 1992	Maximum	106	.31	.81	.99	
Quinones, 1995	Maximum	69	.59	NR	NR	
Gist & Stevens, 1998	Maximum	121	.13	.70	.89	
Stevens, Bavetta, & Gist, 1993	Maximum	60	.01	.83	NR	
Gist, Stevens, Bavetta, 1991	Maximum	35	−.12	.72	NR	
Gorman & Rentsch, 2009	Maximum	73	.22	.65	.78	
Tross & Maurer, 2008	Maximum	144	.22	NR	.87	
Thompson, Stoughton, Behrend, Watson, & Vignovic, 2009	Maximum	95	.51	NR	.93	
Towler, Kraiger, Sitzmann, van Overberghe, Cruz, Ronen, & Stewart, 2008 (Study 2)	Maximum	77	.43	NR	NR	
Towler, Kraiger, Sitzmann, van Overberghe, Cruz, Ronen, & Stewart, 2008 (Study 1)	Maximum	47	.60	NR	.92	
Bell & Kozlowski, 2002	Maximum	277	.57	NR	NR	
Bell & Kozlowski, 2008	Maximum	350	.54	NR	NR	
Sulsky & Kline, 2007	Maximum	65	−.09	.86	NR	
Huang, 2012	Maximum	177	.31	.74	NR	
Chiaburu, Sawyer, & Thoroughgood, 2009	Typical	37	.18	NR	NR	
Wexley & Baldwin, 1986	Typical	256	.10	NR	.90	
Vaccaro, 2009	Typical	140	.12	NR	.94	
Burke & Baldwin, 1999	Typical	30	−.06	NR	.87	
Essary, 2001 (dissertation)	Typical	183	.07	.88	.93	
Ramirez, 2000 (dissertation)	Typical	110	.30	NR	.75	
Poteet, 1996 (dissertation)	Typical	136	.41	NR	.91	
Myers, 1997 (dissertation)	Typical	111	−.24	NR	.94	
Clasen, 1997 (dissertation)	Typical	93	.06	NR	NR	
Martineau, 1995 (dissertation)	Typical	50	−.18	.94	.97	
Bates, Holton & Burnett, 1999	Typical	70	−.08	NR	NR	
Dierdorff, Surface, & Brown, 2010	Typical	149	.01	.73	NR	
Burke, 1997	Typical	90	.07	NR	.77	
Baldwin, 1992	Typical	72	.06	.86	.90	
Rouiller & Goldstein, 1993	Typical	102	.28	.89	NR	
Fagan, 1998 (dissertation)	Typical	131	−.02	.92	.81	
Warr, Allan, & Birdi, 1999	Typical	123	.16	NR	NR	
Hutchins, 2004 (dissertation)	Typical	36	−.11	NR	.91	
Al-Ammar, 1994 (dissertation)	Typical	121	.04	NR	NR	
Tracey, Tannenbaum, & Kavanagh, 1995	Typical	104	.09	.71	.93	
Chiaburu & Tekleab, 2005	Typical	71	.15	NR	.80	
Tziner, Haccoun, Kadish, 1991	Typical	81	.16	NR	.69	
Tan, Hall, & Boyce, 2003	Typical	15	−.05	NR	NR	
Goldberg & Perry, 2009	Typical	17	−.32	NR	.86	
Sekowski, 2002	Typical	49	.32	.68	.78	
Richman, 1998	Typical	267	.13	.80	.93	
Richman, 1998	Typical	83	−.20	.70	.93	
Richman, 1998	Typical	87	.27	.82	.93	
Richman-Hirsch, 2001	Typical	267	.13	NR	.65	
Tziner, Fisher, Senior, & Weisberg, 2007	Typical	130	.71	NR	.88	Outlier
Zayed, 1994 (dissertation)	Typical	371	.36	NR	.70	Outlier
Predictor: Skill acquisition						
Cruz, 1995 (dissertation)	Maximum	40	.34	NR	NR	

Table 9 continued

Study	Transfer	*N*	*r*	rxx	ryy	Comment
Foster & Macan, 2002	Maximum	116	.40	NR	NR	
Bell & Kozlowski, 2002	Maximum	277	.72	NR	NR	
Chen, Thomas, & Wallace, 2005	Maximum	156	.62	.81	.82	
Ford, Smith, Weissbein, Gully, & Salas, 1998	Maximum	93	.60	NR	NR	
Keith & Frese, 2004	Maximum	55	.63	.87	.87	
Huang, 2012	Maximum	177	.30	.70	NR	
Baldwin, 1992	Typical	72	−.22	.94	.90	
Martineau, 1995 (dissertation)	Typical	50	.42	.81	.97	
Myers, 1997 (dissertation)	Typical	111	.04	.88	.94	
Cruz, 1995 (dissertation)	Typical	40	.34	NR	NR	
Dierdorff, Surface, & Brown, 2010	Typical	149	.10	NR	NR	
Predictor: Posttraining self-efficacy						
Bell & Kozlowski, 2008	Maximum	350	.29	.92	NR	
Ford, Smith, Weissbein, Gully, & Salas, 1998	Maximum	93	.39	.90	NR	
Kozlowski, Gully, Brown, Salas, Smith, & Nason, 2001	Maximum	60	.45	.95	NR	
Smith, 1996 (dissertation)	Maximum	161	.10	.85	NR	
Chen, Thomas, & Wallace, 2005	Maximum	156	.30	.65	.82	
Gist, Stevens, Bavetta, 1991	Maximum	35	.22	.93	NR	
Stevens, Bavetta, & Gist, 1993	Maximum	60	.51	.95	NR	
Essary, 2001 (dissertation)	Typical	183	−.03	.95	.93	
Holladay, Anderson, Gilbert, & Turner, 2008 (conference)	Typical	42	−.08	NR	NR	
Poteet, 1996 (dissertation)	Typical	136	.16	.90	.91	
Tews & Tracey, 2008	Typical	87	.20	.79	.84	
Guardiola, 2000 (Dissertation)	Typical	109	−.01	.83	NR	
Brown & de Leon, 2008 (conference	Typical	176	.10	.96	.90	
Fagan, 1998 (dissertation)	Typical	131	.03	.94	.81	
Madera, 2006 (conference)	Typical	61	.10	.78	NR	
Tross & Maurer, 2008	Maximum	144	.22	.88	.87	
Carter & Bier, 2010 (Campbell 2007)	Maximum	161	.23	.81	NR	
Huang, 2012	Maximum	177	.13	.91	NR	
Budworth & Sookhai, 2009	Typical	29	.45	NR	.62	
Brown & Warren, 2009	Typical	51	.09	.89	.89	
Coyne, 2008	Typical	66	.13	.76	NR	
Dierdorff, Surface, & Brown, 2010	Typical	149	.13	.92	NR	
Richman, 1998	Typical	267	.08	.91	.93	
Richman, 1998	Typical	83	.21	.91	.93	
Richman, 1998	Typical	87	.41	.91	.93	
Devos, Dumay, Bonami, Bates, & Holton, 2007	Typical	106	.26	.77	.91	
Petkova, 2011	Typical	172	.54	.79	.90	
Brown, 2005	Typical	51	.29	.89	NR	
Ameel, 1992 (dissertation)	Typical	53	.77	NR	NR	SS/SMC
Brown, 2005	Typical	51	.42	.90	.78	SS/SMC
Hutchins, 2004 (dissertation)	Typical	36	.38	.85	.91	SS/SMC
Predictor: Motivation to transfer						
Bell & Ford, 2007	Maximum	113	.10	.96	.87	
Frash, 2004 (dissertation)	Maximum	65	−.12	NR	NR	
Tross & Maurer, 2008	Maximum	144	−.02	.78	.87	
Melchers, Lienhardt, Aarburg, & Kleinmann, 2011	Maximum	199	−.11	NR	.70	

Table 9 continued

Study	Transfer	*N*	*r*	rxx	ryy	Comment
Huang, 2012	Maximum	177	.06	.88	NR	
Axtell, Maitlis, & Yearta, 1996	Typical	27	.30	.84	NR	
Bates, Holton & Burnett, 1999	Typical	68	−.08	.89	NR	
Burke, 1997	Typical	90	.05	.84	.77	
Martineau, 1995 (dissertation)	Typical	50	.37	.76	.97	
Myers, 1997 (dissertation)	Typical	111	−.02	.89	.94	
Poteet, 1996 (dissertation)	Typical	136	.12	.93	.91	
Ramirez, 2000 (dissertation)	Typical	110	.10	.90	.75	
Stevens & Gist, 1997	Typical	53	.24	.88	NR	
Tziner, Haccoun, Kadish, 1991	Typical	81	.24	.65	.69	
Warr, Allan, & Birdi, 1999	Typical	123	.09	.79	NR	
Coyne, 2008	Typical	70	−.01	.78	NR	
Wieland, 2008	Typical	115	.42	.78	.74	
Sekowski, 2002	Typical	49	.12	.94	.78	
Richman, 1998	Typical	267	.05	.94	.93	
Richman, 1998	Typical	83	.22	.94	.93	
Richman, 1998	Typical	87	.08	.94	.93	
Fitzgerald, 2002	Typical	19	.40	.83	NR	
Devos, Dumay, Bonami, Bates, & Holton, 2007	Typical	106	.43	.85	.91	
Petkova, 2011	Typical	172	.63	.92	.90	
Casper, 2005 (dissertation)	Typical	118	.39	.85	NR	SS/SMC
Naowaruttanavanit, 2002 (dissertation)	Typical	623	.33	.83	.90	SS/SMC
Borowski, 2000 (dissertation)	Typical	405	.64	NR	NR	SS/SMC

SS/SMC same source and same measurement context, *NR* not reported

References

Aguinis, H., & Kraiger, K. (2009). Benefits of training and development for individuals and teams, organizations, and society. *Annual Review of Psychology, 60*, 451–474.

Alliger, G. M., Tannenbaum, S. I., Bennett, W., Jr, Traver, H., & Shotland, A. (1997). A meta-analysis of the relations among training criteria. *Personnel Psychology, 50*, 341–358.

Arthur, W., Jr, Bennett, W., Jr, Edens, P. S., & Bell, S. T. (2003). Effectiveness of training in organizations: A meta-analysis of design and evaluation features. *Journal of Applied Psychology, 88*, 234–245.

Baldwin, T. T. (1992). Effects of alternative modeling strategies on outcomes of interpersonalskill training. *Journal of Applied Psychology, 77*, 147–154.

Baldwin, T. T., & Ford, J. K. (1988). Transfer of training: A review and directions for future research. *Personnel Psychology, 41*, 63–105.

Barnes, C. M., & Morgeson, F. P. (2007). Typical performance, maximal performance, and performance variability: Expanding our understanding of how organizations value performance. *Human Performance, 20*, 259–274.

Beal, D. J., Corey, D. M., & Dunlap, W. P. (2002). On the bias of Huffcutt and Arthur's (1995) procedure for identifying outliers in the meta-analysis of correlations. *Journal of Applied Psychology, 87*, 583–589.

Beus, J., & Whitman, D. (2012). The relationship between typical and maximum performance: A meta-analytic examination. *Human Performance, 25*, 355–376.

Blume, B. D., Ford, J. K., Baldwin, T. T., & Huang, J. L. (2010). Transfer of training: A meta-analytic review. *Journal of Management, 36*, 1065–1105.

Bobko, P. (2001). *Correlation and regression: Applications for industrial organizational psychology and management*. Thousand Oaks, CA: Sage.

Burke, L. A., & Hutchins, H. M. (2007). Training transfer: An integrative literature review. *Human Resource Development Review, 6*, 263–296.

Campbell, J. P., McCloy, R. A., Oppler, S. H., & Sager, C. E. (1993). A theory of performance. In N. Schmitt & W. C. Borman (Eds.), *New developments in selection and placement* (pp. 35–70). San Francisco: Jossey-Bass.

Chen, G., & Klimoski, R. J. (2007). Training and development of human resources at work: Is the state of our science strong? *Human Resource Management Review, 17*, 180–190.

Cheng, E. W. L., & Hampson, I. (2008). Transfer of training: A review and new insights. *International Journal of Management Reviews, 10*, 327–341.

Colquitt, J. A., LePine, J. A., & Noe, R. A. (2000). Toward an integrative theory of training motivation: a meta-analytic path analysis of 20 years of research. *Journal of Applied Psychology, 85*, 678–707.

Deadrick, D. L., & Gardner, D. G. (2008). Maximal and typical measures of job performance: An analysis of performance variability over time. *Human Resource Management Review, 18*, 133–145.

DeChurch, L. A., & Mesmer-Magnus, J. R. (2010). The cognitive underpinnings of effective teamwork: A meta-analysis. *Journal of Applied Psychology, 95*, 32–53.

Dubois, C. L. Z., Sackett, P. R., Zedeck, S., & Fogli, L. (1993). Further exploration of typical and maximum performance criteria: Definitional issues, prediction, and white-black differences. *Journal of Applied Psychology, 78*, 205–211.

Ferris, D. L., Brown, D. J., & Heller, D. (2009). Organizational supports and organizational deviance: The mediating role of organization-based self-esteem. *Organizational Behavior and Human Decision Processes, 108*, 279–286.

Ford, J. K., & Oswald, F. L. (2003). Understanding the dynamic learner: Linking personality traits, learning situations, and individual behavior. In M. Barrick & A. M. Ryan (Eds.), *Personality and work* (pp. 229–261). San Francisco: Jossey-Bass.

Gagné, R. M. (1984). Learning outcomes and their effects: Useful categories of human performance. *American Psychologist, 39*, 377–385.

Gegenfurtner, A., Veermans, K., Festner, D., & Gruber, H. (2009). Motivation to transfer training: An integrative literature review. *Human Resource Development Review, 8*, 403–423.

Huang, J. L., Liu, M., & Bowling, N. A. (2014a). Insufficient effort responding: Examining an insidious confound in survey data. *Journal of Applied Psychology*. doi:10.1037/a0038510.

Huang, J. L., Ryan, A. M., Zabel, K. L., & Palmer, A. (2014b). Personality and adaptive performance at work: A meta-analytic investigation. *Journal of Applied Psychology, 99*, 162–179.

Huffcutt, A. I., & Arthur, W. (1995). Development of a new outlier statistic for meta-analytic data. *Journal of Applied Psychology, 80*, 327–334.

Hunter, J. E., & Schmidt, F. L. (2004). *Methods of meta-analysis: Correcting error and bias in research findings* (2nd ed.). Thousand Oaks, CA: Sage.

Ilies, R., Fulmer, I. S., Spitzmuller, M., & Johnson, M. D. (2009). Personality and citizenship behavior: The mediating role of job satisfaction. *Journal of Applied Psychology, 94*, 945–959.

Judge, T. A., & Ilies, R. (2002). Relationship of personality and to performance motivation: A meta-analysis. *Journal of Applied Psychology, 87*, 797–807.

Judge, T. A., Jackson, C., Shaw, J. C., Scott, B. A., & Rich, B. L. (2007). Self-efficacy and work-related performance: The integral role of individual differences. *Journal of Applied Psychology, 92*, 107–127.

Klehe, U.-C., & Anderson, N. (2007a). Working hard and working smart: Motivation and ability during typical and maximum performance. *Journal of Applied Psychology, 92*, 978–992.

Klehe, U.-C., & Anderson, N. (2007b). The moderating influence of personality and culture on motivation in typical versus maximum performance situations. *International Journal of Selection and Assessment, 15*, 250–262.

Klehe, U.-C., & Latham, G. P. (2006). What would you do—Really or ideally? Constructs underlying the behavior description interview and the situational interview predicting typical versus maximum performance. *Human Performance, 19*, 357–382.

Kraiger, K., Ford, J. K., & Salas, E. (1993). Application of cognitive, skill-based, and affective theories of learning outcomes to new methods of training evaluation. *Journal of Applied Psychology, 78*, 311–328.

LeBreton, J. M., Hargis, M. B., Griepentrog, B., Oswald, F. L., & Ployhart, R. E. (2007). A multidimensional approach for evaluating variables in organizational research and practice. *Personnel Psychology, 60*, 475–498.

Lipsey, M. W., & Wilson, D. B. (2001). *Practical meta-analysis*. Thousand Oaks, CA: Sage.

MacKinnon, D. P., Fairchild, A. J., & Fritz, M. S. (2007). Mediation analysis. *Annual Review of Psychology, 58*, 593–614.

MacKinnon, D. P., Lockwood, C. M., & Williams, J. (2004). Confidence limits for the indirect effect: Distribution of the product and resampling methods. *Multivariate Behavioral Research, 39*, 99–128.

Mangos, P. M., Steele-Johnson, D., LaHuis, D., & White, E. D., I. I. I. (2007). A multiple-task measurement framework for assessing maximum-typical performance. *Human Performance, 20*, 241–258.

Marcus, B., Goffin, R. D., Johnston, N. G., & Rothstein, M. G. (2007). Personality and cognitive ability as predictors of typical and maximum managerial performance. *Human Performance, 20*, 275–285.

McCloy, R. A., Campbell, J. P., & Cudeck, R. (1994). A confirmatory test of a model of performance determinants. *Journal of Applied Psychology, 79*, 493–505.

Noe, R. A. (1986). Trainees' attributes and attitudes: Neglected influences on training effectiveness. *Academy of Management Review, 11*, 736–749.

Oakes, D. W., Ferris, G. R., Martocchio, J. J., Buckley, M. R., & Broach, D. (2001). Cognitive ability and personality predictors of training program skill acquisition and job performance. *Journal of Business and Psychology, 15*, 523–548.

Ployhart, R. E., Lim, B.-C., & Chan, K.-Y. (2001). Exploring relations between typical and maximum performance ratings and the five factor model of personality. *Personnel Psychology, 54*, 809–843.

Podsakoff, P. M., MacKenzie, S. M., Lee, J., & Podsakoff, N. P. (2003). Common method variance in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*, 879–903.

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods, 40*, 879–891.

Preacher, K. J., & Selig, J. P. (2012). Advantages of Monte Carlo confidence intervals for indirect effects. *Communication Methods and Measures, 6*, 77–98.

Rouiller, J. Z., & Goldstein, I. L. (1993). The relationship between organizational transfer climate and positive transfer of training. *Human Resource Development Quarterly, 4*, 377–390.

Sackett, P. R., Zedeck, S., & Fogli, L. (1988). Relations between measures of typical and maximum job performance. *Journal of Applied Psychology, 73*, 482–486.

Salas, E., Tannenbaum, S. I., Kraiger, K., & Smith-Jentsch, K. A. (2012). The science of training and development in organizations: What matters in practice. *Psychological Science in the Public Interest, 13*, 74–101.

Selig, J. P., & Preacher, K. J. (2008, June). *Monte Carlo method for assessing mediation: An interactive tool for creating confidence intervals for indirect effects* [Computer software]. Available from http://quantpsy.org/.

Smith-Jentsch, K. A., Salas, E., & Brannick, M. T. (2001). To transfer or not to transfer? Investigating the combined effects of trainee characteristics, team leader support, and team climate. *Journal of Applied Psychology, 86*, 279–292.

Stevens, C. K., & Gist, M. E. (1997). Effects of self-efficacy and goal orientation training on negotiation skill maintenance: What are the mechanisms? *Personnel Psychology, 50*, 955–978.

Tannenbaum, S. I., Mathieu, J. E., Salas, E., & Cannon-Bowers, J. A. (1991). Meeting trainees' expectations: The influence of training fulfillment on the development of commitment, self-efficacy, and motivation. *Journal of Applied Psychology, 76*, 759–769.

Tews, M. J., & Tracey, J. B. (2008). An empirical examination of posttraining on-the-job supplements for enhancing the

effectiveness of interpersonal skills training. *Personnel Psychology, 61*, 375–401.
Viswesvaran, C., & Ones, D. S. (1995). Theory testing: Combining psychometric meta-analysis and structural equations modeling. *Personnel Psychology, 48*, 865–885.
Wilson, A. M. (2001). Mystery shopping: Using deception to measure service performance. *Psychology & Marketing, 18*, 721–734.
Witt, L. A., & Spitzmuller, C. (2007). Person-situation predictors of maximum and typical performance. *Human Performance, 20*, 305–315.