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IGNORED NO MORE: WITHIN-PERSON VARIABILITY ENABLES BETTER UNDERSTANDING OF TRAINING TRANSFER

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The empirical findings from training transfer research rest on a rather static view of the transfer phenomenon, ignoring potential within-person change in transfer over time. This study investigates within-person variability in mastery goal orientation together with variability over time in the application of newly acquired knowledge and skills to the job context. Data from longitudinal surveys of trainees voluntarily attending statistical workshops revealed that trainees varied significantly in 2 characteristics of transfer trajectory: (a) initial attempts to transfer and (b) subsequent rate of change in transfer. Two affective learning outcomes showed differential relationships with transfer trajectories: Whereas posttraining self-efficacy predicted initial attempt of transfer, motivation to transfer assessed at the end of training predicted subsequent rate of change in transfer. Furthermore, level and variability of trainees' mastery orientation interacted to influence posttraining self-efficacy and motivation to transfer, and subsequently transfer trajectories. Specifically, a trainee's mastery orientation level had stronger prediction of these outcomes when his/her mastery orientation distribution was less variable across situations. These findings highlight the

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importance of attending to within-person variability in the study of training transfer by (a) considering training transfer as trajectories over time and (b) understanding trainee traits as frequency distributions.

One man's constant is another man's variable.

—Alan Perlis

Employee training and development activities enable organizations to adapt and remain competitive in today's economy (Salas, Tannenbaum, Kraiger, & Smith-Jentsch, 2012). Transfer of training—the extent to which the trainee applies the knowledge and skills acquired from a training environment on the job (Baldwin & Ford, 1988)—is critical for an adequate return on investment of training and development activities (Aguinis & Kraiger, 2009; Salas et al., 2012). Accordingly, researchers have conducted studies to predict and understand transfer of training, culminating in several qualitative and quantitative reviews of training transfer (e.g., Blume, Ford, Baldwin, & Huang, 2010; Burke & Hutchins, 2007; Grossman & Salas, 2011).

The empirical findings rest on a static view of training transfer by focusing on transfer as stable, between person phenomena that are often assessed at one point in time (Blume et al., 2010). Researchers have posited that transfer can vary meaningfully within-person over time (Baldwin & Ford, 1988; Baldwin, Ford, & Blume, 2009), leading to various transfer trajectories for different trainees, with some trainees decreasing their application of trained knowledge and skills over time while others maintaining or enhancing transfer over time. Yet since Baldwin and Ford (1988) articulated the concept of maintenance curves, no empirical studies have tested the idea that transfer varies in different directions across individuals over time.

On the input end of the transfer phenomenon, trait variables such as mastery goal orientation have been found to predict transfer (Baldwin & Ford, 1988; Blume et al., 2010). Traits focus on individuals' average behavioral tendencies (Tellegen, 1991) while treating variability in behaviors across situations as errors (Buss & Craik, 1983; Mischel, 1968). Two individuals may have the same overall level of trait mastery orientation, but one person is more variable across situations than the other (e.g., experiencing lower mastery orientation in situations involving high time pressure, competing tasks, uncertain immediate application, etc.). As a result, for some individuals the average level is less descriptive of their mastery orientation as it is more context dependent (see Baumeister & Tice, 1988). As within-person variability on a trait domain represents an important individual difference in personality (Baird, Le, & Lucas, 2006; Fleeson, 2001; Fleeson & Jayawickreme, 2015), ignoring variability of

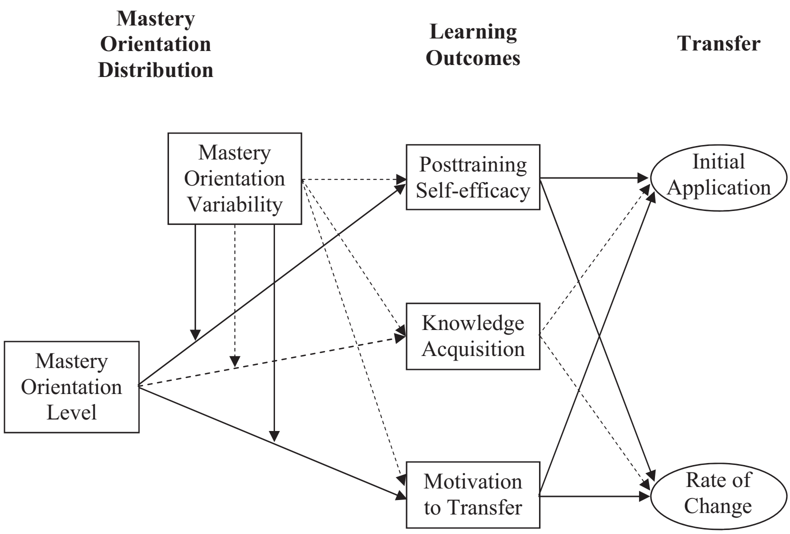

Figure 1: **Summary of the Current Investigation.**

Note. A dashed line indicates an effect is not hypothesized (i.e., serving as an exploratory or a control variable). Although not included in the figure, opportunity to perform is modeled as a time-varying covariate for transfer measure at each time point.

a trait domain limits researchers' ability to predict transfer with greater precision. To better appreciate the dynamic learner's role in the transfer process, both the level and variability of a trait domain must be considered (Ford & Oswald, 2003).

This paper addresses gaps in training transfer research by attending to the within-person dynamics in both transfer outcomes and trainee characteristics. First and foremost, we contribute to the transfer literature by examining the application of trained skills as an intraindividual process that unfolds over time (see Ployhart & Hakel, 1998), separating the initial level of application, and the subsequent change in transfer behavior (see Figure 1). We further model affective learning outcomes as key predictors of transfer curves, assessing the roles of posttraining self-efficacy and motivation to transfer in predicting interindividual difference on initial application and rate of change (see right side of Figure 1). Second, we contribute to the study of trainee characteristics by extending the measurement technique for assessing within-person variability from the personality literature (Edwards & Woehr, 2007; Fleisher, Woehr, Edwards, & Cullen, 2011). Specifically, we examine mastery goal orientation as a trait domain that exerts broad influence on training transfer (Wilson, Huang, & Kraiger, 2013) and argue that the level and variability of a trainee's mastery orientation distribution (see Fleeson, 2001; Fleeson & Jayawickreme, 2015) can interact to affect learning outcomes and subsequent transfer (see left side of Figure 1). Modeling within-person variation on both predictor and criterion constructs as between-person variables, we answer recent calls to better understand trainee motivational mechanisms and to consider time as a key contextual variable (Salas & Kozlowski, 2010).

Transfer of Training

Researchers have proposed several dimensions where transfer may vary. Barnett and Ceci (2002) discussed the contextual similarity underlying near versus far transfer. For example, transferring with temporal proximity (e.g., a day after training) and physical similarity (e.g., comparable room configuration between training and work environments) to the training environment would be considered near transfer, while transferring to a more distant future and a more distinct work environment would be considered far transfer. Yelon and Ford (1999) proposed that the skills being transferred can be considered either closed or open, with closed skills transfer focusing on skill reproduction whereas open skills transfer focusing on using principles to guide the appropriate use of trained skills. Blume et al. (2010) noted that transfer can be examined as the application of trained skills (i.e., use) and/or as the degree of success in applying trained skills (i.e., effectiveness). These advances provide researchers with conceptual lenses to differentiate and understand training transfer across jobs, training programs, and individuals.

Transfer can also vary *in amount* of use within the same individual over time.[1] Transfer consists of two interrelated components: generalization and maintenance (Baldwin & Ford, 1988). Generalization involves the application of knowledge and skills learned from the training setting to different settings, people, and situations, whereas maintenance pertains to the extent to which trainees manage to retain the knowledge and skills and apply these to the job over time (Baldwin & Ford, 1988; Blume et al., 2010). Baldwin and Ford (1988) suggest that after initial attempts of generalization, individuals may have different patterns of application and different forms of maintenance curves over time. Rather than assuming a stable output after training, transfer can be investigated as a change process that unfolds over time, and the variation of each trainee's application patterns and maintenance curves may be accounted for, in part, by trainee characteristics (Baldwin & Ford, 1988).

[1]This focus on within-person variance is distinct from the comparison of variance in training outcomes between groups of trainees that received different interventions (Schurig, Arthur, Day, & Woehr, 2013).

The need to attend to within-person change can be illustrated by research in the job performance literature, where scholars have advanced theory on performance variability and change (e.g., Day, Sin, & Chen, 2004; Lang & Bliese, 2009; Ployhart & Hakel, 1998; Thoresen, Bradley, Bliese, & Thoresen, 2004). For instance, Ployhart and Hakel (1998) revealed that new hires' sales performance trajectories resembled a "learning curve," such that sales performance increased over time yet with decreasing acceleration and that selection instruments differentially predicted interindividual difference on performance change parameters. Such research has advanced understanding on how individuals adapt to changes in the external task environment (Jundt, Shoss, & Huang, 2014). Similarly, examining within-person change in the training context can advance our understanding of how, when, and in what contexts individuals transfer training.

We situate the current investigation of transfer trajectories in voluntary, open skills training programs, focusing on application rather than effectiveness of trained knowledge and skills. Four considerations lie behind this research focus. First, the need to understand application of training content is accentuated in open skills training. With the heightened focus on adaptability at work (Huang, Ryan, Zabel, & Palmer, 2014; Ilgen & Pulakos, 1999), more jobs rely on open rather than closed skills. Adaptive expertise (Kozlowski et al., 2001; Bell & Kozlowski, 2008) requires posttraining application and practice (e.g., Weissbein, Huang, Ford, & Schmidt, 2011) to further develop and refine in order to become proficient.

Second, application of newly acquired knowledge and skills is a necessary condition for effective transfer performance. As Blume et al. (2010) suggested, although trainees are more in control of applying new knowledge and skills, whether they are effective in their transfer attempts may depend on factors outside of their control. As we are interested in explicating posttraining motivation mechanisms as antecedents to transfer trajectories, understanding application is an important intermediate outcome. This notion is consistent with Blume et al.'s (2010) finding that trainee motivation shares a stronger relationship with application than with effectiveness. Third, examining application rather than effectiveness reflects a practical temporal consideration. That is, we expect application to exhibit more rapid changes than effectiveness, which as a distal outcome may take longer to show changes over time.

Finally, we submit that the focus on application does not automatically preclude discussion of effectiveness, as the two aspects of transfer are interrelated over time. For example, repeated application provides practice that leads to greater effectiveness in the long run, whereas early effectiveness may trigger further application at a later time. We will return to the differentiation between application and effectiveness in the discussion section.

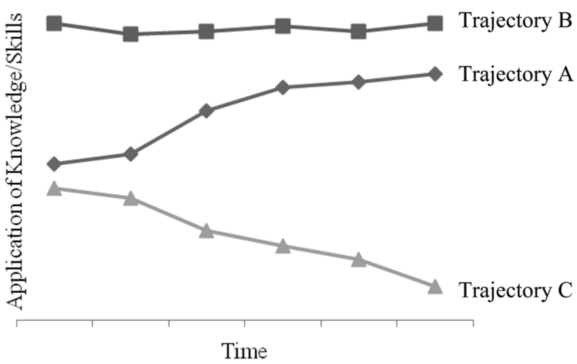

Figure 2: **Hypothetical Transfer Trajectories Over Time.**

We expect time to influence transfer differently across individuals and provide three hypothetical trajectories in Figure 2 as examples. That is, some trainees may identify more opportunities (situations and persons) to apply trained knowledge and skills as time elapses after training (Trajectory A), some may remain quite stable over time (Trajectory B), and others may decrease their application of skills over time (Trajectory C). It is important to note that two parameters can be used to capture linear changes across trainees: (a) *the level of transfer* at any given point in time (e.g., initial level) and (b) *the rate of change* over time. Of these two parameters, the level of transfer (across individuals) has received extensive research coverage (see Blume et al., 2010), but a lacuna looms large in the literature regarding the interindividual difference on the rate of intraindividual change in transfer over time.

We hasten to note that the examples in Figure 2 represent a simplistic depiction of changes in transfer over time. In some situations, changes may be curvilinear (see Baldwin & Ford, 1988 for possible curvilinear examples). For example, after receiving training on a software program that replaces an outdated one, an employee may implement the new skills in a gradual fashion by finishing existing projects on the old program and starting new projects on the new one. As the employee closes out existing projects and starts new ones, the use of the new program continues to increase, but the speed of increase is decreasing and eventually plateauing at a high level after he/she completes all old projects. The trajectory for this employee thus resembles a negative accelerating curve. In fact, unforeseen changes at work may introduce more bends and discontinuous changes that require more parameters to capture (see Lang & Bliese, 2009, e.g., change patterns). Nevertheless, by using the initial level and the rate of change, we can achieve a parsimonious account of *linear changes* over time in the present study context.

Next, we discuss three perspectives that suggest individual trajectories of transfer application may differ meaningfully. First, changes in transfer trajectories can reflect trainees' self-regulated behavior after training. Self-regulation pertains to processes that enable goal attainment and maintenance (Vancouver & Day, 2005). Upon completion of the training program, trainees may set goals regarding desired level of transfer behavior. The posttraining period allows trainees time and opportunity to attain their desired states and, if discrepancies exist, adjust their goal states or behaviors accordingly. Thus, some trainees may recognize that their application of training content falls short of their initial expectations and thus increase their transfer behavior, whereas other trainees may be discouraged from further application by initial setbacks, and thus adjust their goal states downward, resulting in decreasing application over time.

Second, differential transfer trajectories are consistent with the spiral theory of performance (Lindsley, Brass, & Thomas, 1995), which define performance spirals as consecutive increases or decreases in efficacy and performance (also see Chen, Ployhart, Thomas, Anderson, & Bliese, 2011). In the transfer process, trainees' early application of training content may bring about new awareness and understanding of opportunities to transfer, thus leading to increase in application over time (i.e., positive spirals). In contrast, a gradual decreasing trend in application may signal failed attempts to generalize learning to the work context.

Finally, applying the newly acquired open skills to a job context requires the trainee to recognize the difference between the training context and the transfer context, and adapt their behaviors accordingly. For example, the trainees may proactively identify resources and support from their work environment to handle a challenging transfer task. Echoing studies observing individual difference in adaptive performance trajectories (see Baard, Rench, & Kozlowski, 2014), transfer trajectories will likely differ across individuals.

Taken together, we draw from self-regulation, performance spiral, and performance adaptation perspectives to argue that individuals will have different initial attempt levels and different rates of change in transfer application. Investigating the change of application over time can afford a closer look at the transfer process, potentially offering an explanation for the variation of transfer findings across studies (see Blume et al., 2010).Thus, we hypothesize:

Hypothesis 1: Trainees will differ significantly on (a) initial attempt and (b) rate of change in application of trained knowledge and skills.

Affective Learning Outcomes as Predictors of Transfer Trajectories

In their seminal work, Kraiger, Ford, and Salas (1993) developed a three-dimensional taxonomy of *learning outcomes*, which includes cognitive, skill-based, and affective outcomes. Affective learning outcomes, which include posttraining self-efficacy and motivation to transfer, represent "indicators of learning" (Kraiger et al., 1993, p. 319). Specifically, posttraining self-efficacy pertains to subjective evaluation of one's capabilities to execute a specific activity (Bandura, 1997) at the end of the training, whereas posttraining motivation to transfer refers to the degree to which trainees are motivated to attempt and apply the newly acquired knowledge and skills on to the job upon completion of the training (Noe, 1986).

We focus on affective rather than cognitive and skill-based learning outcomes considering this study context. Research has indicated that when trainees do not perceive external pressure to maximize their transfer, affective learning outcomes (i.e., motivation to transfer and to a less extent posttraining self-efficacy) are more important predictors of transfer than cognitive and skill-based outcomes (Huang, Blume, Ford, & Baldwin, 2015). This study context, which is characterized by open skills training, voluntary enrollment, autonomous work environment, and a focus on application of training content, makes affective learning outcomes important drivers for transfer application.

Posttraining self-efficacy level has been shown to predict training transfer in a number of studies (e.g., Ford, Smith, Weissbein, Gully, & Salas, 1998; Kozlowski et al., 2001). Self-efficacy reflects one's self-percepts of *capabilities* with regard to specific tasks (e.g., Meyer & Gellatly, 1988; Wood & Bandura, 1989), and such self-percepts represent a proximal precursor to cognition, motivation, and emotions (Bandura, 1977, 1982). Colquitt, LePine, and Noe (2000) demonstrated pretraining self-efficacy as one of the antecedents to motivation to learn, while Sitzmann and Ely (2011) identified self-efficacy as a key mechanism having a moderate to strong effect on self-regulated learning. Huang et al. (2015) found that having high confidence in setting transfer goals on relevant tasks can galvanize trainees into attempting the new knowledge and skills early on and may further lead trainees to increase application over time. Thus, we predict that:

> *Hypothesis 2*: Posttraining self-efficacy will positively predict (a) initial attempt and (b) rate of change in application of trained knowledge and skills.

At the between-individual level, consistent with work motivation theory that established the motivation-action sequence (e.g., Kanfer, 1990;

Mitchell & Daniels, 2003), motivation to transfer has been proposed as a proximal precursor to transfer behavior (Beier & Kanfer, 2010; Gegenfurtner, Veermans, Festner, & Gruber, 2009). With the current focus on transfer trajectories, motivation to transfer can impact both the initial attempt and rate of change in transfer. Upon completion of the training program, trainees who are motivated to transfer are more likely to seek out opportunities to apply the newly acquired knowledge and skills at work (Ford, Quiñones, Sego, & Sorra, 1992) will exert more effort when transferring and will persist in transfer attempts despite initial obstacles. Indeed, motivated trainees may increase their levels of transfer applications over time as they become more adept at identifying transfer opportunities and become more confident in their ability to apply trained knowledge and skills and thus become more proficient in the work domain. In contrast, trainees who have low motivation to transfer will likely succumb to the gradual reduction in application of trained knowledge and skills over time. Therefore, we predict that:

> *Hypothesis 3*: Posttraining motivation to transfer will positively predict (a) initial attempt and (b) rate of change in application of trained knowledge and skills.

Although the current investigation is focused on affective learning outcomes as antecedents to transfer trajectories, we also explore the role of cognitive learning outcomes. Research shows that posttraining declarative knowledge is positively associated with the level of training transfer (Blume et al., 2010). In the current transfer context characterized by how much trainees "will transfer" rather than "can transfer," declarative knowledge may have a weaker impact relative to affective learning outcomes (see Huang et al., 2015). It is unclear whether declarative knowledge will influence the rate of change in transfer over time. Thus, we include declarative knowledge as a potential antecedent in the model in an exploratory fashion.

Opportunity to Perform

An important factor that may influence the application of newly acquired skills is opportunity to perform, defined as "the extent to which a trainee is provided with or actively obtains work experiences relevant to the tasks for which he or she was trained" (Ford, Quiñones, Sego, and Sorra, 1992, p. 512). When deprived of opportunities to perform trained skills a trainee may find it difficult to engage in transfer activities (Baldwin & Ford, 1988; Ford et al., 1992). Variation in opportunity to perform across trainees can introduce variation in transfer trajectory. For instance, some trainees may work in environments with opportunity to perform immediately after training, whereas others may anticipate their work objectives to slowly entail more of the trained behaviors over time (Yelon, Ford, & Bhatia, 2014). As a result, the former group is likely to demonstrate higher initial attempt to transfer, whereas the latter group may slowly increase their transfer use over time. Therefore, when assessing the influence of affective learning outcomes on change in transfer, opportunity to perform should be controlled for in the assessment of training transfer. Specifically, we assess opportunity to perform concurrently with transfer over time and position it as a time-varying covariate, thus accounting for potential variability in opportunity over time.

Level and Variability of Mastery Orientation

Mastery orientation[2] captures individuals' tendency to adopt learning-oriented goals to promote their competence (Button, Mathieu, & Zajac, 1996). Focusing on incremental self-improvement through effortful learning and exploration (Fisher & Ford, 1998), trainees with high levels of trait mastery orientation are likely to adopt appropriate learning strategies (Ford et al., 1998), utilize feedback to adjust a course of action, and persist in the face of setbacks and challenges (VandeWalle, Cron, & Slocum, 2001). Indeed, research in training has documented positive, albeit modest, effects of trait mastery orientation on learning (Payne, Youngcourt, & Beaubien, 2007) and transfer (Blume et al., 2010). Nevertheless, we draw from the broader personality literature to illustrate why considering variability in mastery orientation may add valuable information about the trainee for better prediction of training outcomes.

A traditional trait measure focuses on how a person tends to behave in general (Funder, 2001; Tellegen, 1991), capturing his/her *typical behavioral tendency* (Buss & Craik, 1983) across all possible situations. As an example, the Big Five trait term extraversion measures a person's overall propensity to exhibit sociable, assertive, and energetic behaviors across a wide range of contexts and situations that allow for such behaviors. Through the use of a single numeric value, a *trait level* allows for a convenient summary of a person's behavioral tendency, but at the same time, it

[2]Despite early inconsistency in the use of goal orientation to refer to trait and trait-like constructs as well as states (see DeShon & Gillepsie, 2005 for a review), subsequent work by Payne et al. (2007) has clarified the distinction between trait goal orientation (often without the trait designation) as a stable, individual difference characteristic and state goal orientation as transient experience that is bounded by situation or induced by experimental manipulation. Consistent with common practice, we use goal orientation to refer to the trait aspect (per Fleeson & Javawickreme, 2015) and use state goal orientation to refer to momentary experience.

remains an imprecise summary of all possible acts, ignoring the person's *variability*, that is, how he/she may behave differently across situations and contexts (Buss & Craik, 1983; Mischel, 1968). Thus, the assessment that a person is "moderately extraverted" overlooks the possibility that, from a process perspective, a person can be highly extraverted when interacting with friends and family but become much less so when dealing with work situations.

Fleeson's (2001) influential paper has helped reconcile the apparent tension between the trait approach that focuses on stable behavioral tendencies and the process approach that emphasizes deviations from typical behavioral responses. Conceptualizing a trait (e.g., extraversion) as a frequency distribution of trait-relevant states (e.g., extraverted behavior), Fleeson (2001) demonstrated that the average individual has a highly stable distribution of personality states on any particular trait domain. Aside from the central tendency of a distribution that is captured as the level of the person's trait, the variability of the distribution represents a highly stable characteristic of the person's trait (Fleeson, 2001). Addressing the deficiency in traditional trait measures that focus only on trait levels, Fleeson and Jayawickreme (2015) proposed the whole trait theory that describes a *trait* in terms of the level, the variability, and the shape of the person's distribution of states. This integrated view that jointly considers level and variability is becoming more widely accepted (e.g., Church et al., 2012, 2013; Heller, Komar, & Lee, 2007; Judge, Simon, Hurst, & Kelley, 2014) as a framework for understanding traits in relation to state variability.

All else being equal, the level of a person's trait will be more representative of his/her trait domain when the trait distribution is less variable (Baumeister & Tice, 1988; Bem & Allen, 1974). As a result, research has indicated that a prediction based on the trait level will be more accurate for less variable individuals (e.g., Biesanz, West, & Graziano, 1998; Kernis, Grannemann, & Mathis, 1991; Zuckerman et al., 1988). For instance, using a frequency-based measurement approach (see Edwards & Woehr, 2007), Fleisher et al. (2011) demonstrated that the level and the variability of students' conscientiousness interacted to predict their peer evaluation, such that the level of conscientiousness was more positively associated with peer ratings when the variability was lower.

We use the following hypothetical scenario to illustrate the benefit in considering the variability of mastery orientation in the present investigation. Persons A (Figure 3, upper panel) and B (Figure 3, lower panel) have identical trait levels, which are reflected as similar standings on a Likert scale (*M*s = 3.00). However, A's trait mastery orientation is more variable ($SD = 1.63$) than B's ($SD = .90$), such that A's state mastery orientation changes across situations to a greater degree than B's: A's

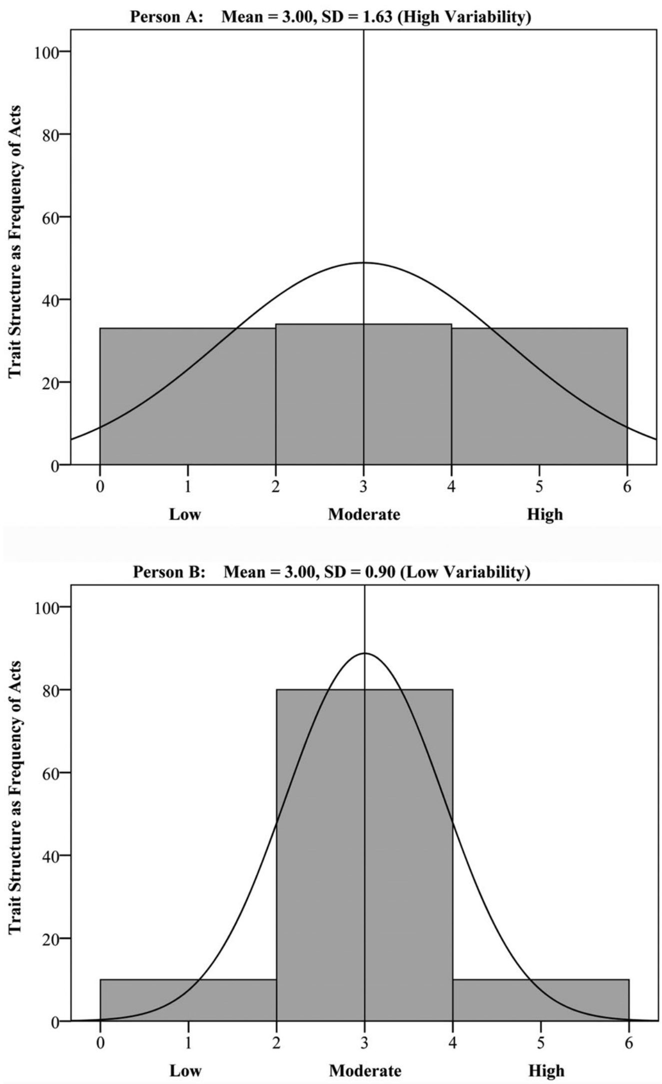

Figure 3: **Hypothetical Trait Shapes With Identical Levels and Different Variability.**

state mastery orientation may be quite high sometimes (e.g., on a new job duty), quite low sometimes (e.g., on a household repair project), and moderate other times (e.g., on a new hobby), whereas B's state mastery orientation stays relatively similar in different contexts or situations. As a result, A's mastery orientation level, compared to B's, provides a less accurate summary of their mastery orientation tendencies and thus is less predictive of relevant outcomes in any given situation.

It is worth noting that researchers have approached the issue of within-individual variability by measuring a trait across different contexts (e.g., at work, at home; Heller, Watson, Komar, Min, & Perunovic, 2007) or roles (e.g., as a friend, as a family member; Baird et al., 2006). This measurement approach allows one to estimate variability in a trait due to contexts or roles, and the resulting *contextualized traits* (Roberts, 2007; Wood & Roberts, 2006) afford more specific assessments of the person's behavioral tendencies (e.g., Heller, Ferris, Brown, & Watson, 2009; Schmit, Ryan, Stierwalt, & Powell, 1995). Parallel in the goal orientation literature, researchers have assessed goal orientation tendencies within a particular context (e.g., at work, VandeWalle, 1997) to remove within-person variability associated with different contexts and yield more precise predictions in that context (DeShon & Gillespie, 2005; Payne et al., 2007). However, even within the same context (e.g., at work), individuals respond to the ebbs and flows of situations with varying states (Huang & Ryan, 2011; Judge et al., 2014). Thus, contextualized goal orientation resembles the traditional trait approach (see Payne et al., 2007) in that it only focuses on the person's average level of state goal orientation within that particular context (as indicated with a single numeric value) while ignoring within-person variability across situations (DeShon & Gillespie, 2005). By jointly considering the level and the variability as critical characteristics of the trainee's mastery orientation distribution, we move away from the traditional trait approach and progress toward the whole trait approach (Fleeson and Jayawickreme, 2015). Consistent with research on the interactive effect of the level and the variability (Edwards & Woehr, 2007; Fleisher et al., 2011), we propose:

Hypothesis 4: Mastery orientation level and variability will interact to predict (a) posttraining self-efficacy and (b) motivation to transfer, such that mastery orientation level will have a more positive effect when mastery orientation variability is lower.

Finally, Hypotheses 2, 3, and 4 suggest that posttraining self-efficacy and motivation to transfer can serve as key mechanisms linking the variability in mastery orientation distribution and variability in transfer behavior. This is consistent with research that has established mastery orientation as a proximal predictor of motivation and distal antecedent to transfer (e.g., Colquitt & Simmering, 1998; Ford et al., 1998). At the end of a training program, confidence about performing the newly trained behavior, the particular goals trainees adopt, the level of commitment they have toward those goals, and the amount of effort they intend to expend regarding transfer may be the linkage between the distal mastery orientation domain (in particular, level × variability interaction) and transfer trajectories. A trainee having a high level and low variability on mastery orientation will likely be efficacious and motivated to transfer, and subsequently transfer more on initial attempt and increasingly more afterward.

Hypothesis 5: Posttraining self-efficacy and motivation to transfer will mediate the impact of mastery orientation's level × variability interaction on (a) initial attempt to transfer and (b) rate of change in transfer.

Method

Procedure and Participants

Participants were recruited from statistical workshops at a large public midwestern university in the United States. The workshops provided introductions to statistical techniques and covered operation skills in statistical packages such as R, SPSS, and STATA. The content of a workshop started with knowledge in the form of statistical foundation of a technique or method, followed by skills in applying the statistical knowledge in sample analyses. The workshops varied in length, with four workshops lasting 3 hours and four lasting 6 hours. Registration to the workshops was voluntary and open to faculty, research staff, and graduate students of the university. Trainees were contacted about the research study after they signed up for a workshop. They were informed that (a) the research study was independent from the workshop; (b) their participation in the study was voluntary; and (c) their decision to participate in the study would not impact the regular workshop experience. Upon giving their consent, trainees filled out a questionnaire containing mastery orientation and demographic information. At the end of each workshop, participants filled out a short posttraining assessment that included knowledge acquisition, self-efficacy, and motivation to transfer.

Transfer was assessed once a week for 6 weeks after training. We measured transfer as the *use* (Blume et al., 2010; also see "behavior on the job," Salas, Weaver, & Shuffler, 2012) of the statistical knowledge and skills in the research context. On the same follow-up surveys, we also assessed opportunity to perform. Specifically, a link to the first follow-up survey was sent via email on the eighth day after training, asking participants to report their levels of transfer (see measures below) as well as opportunity to perform over the past 7-day period. The next five surveys, identical to the first follow-up survey, were spaced exactly 7 days apart.

To ensure accurate recall, each follow-up survey was accessible for only 24 hours.

A total of 160 individuals initially consented to participate. Of those, 109 (66%) completed the workshops and subsequently participated in the assessment of learning outcomes immediately after training. The final sample was primarily female (64%) and White (48%), with an average age of 32 ($SD = 9$). Most participants were doctoral (69%) and master's (17%) students, followed by 6% faculty members and 5% postdoctoral research fellows. The number of trainees who responded to the follow-up surveys varied, ranging from 79 to 93, with a total of 105 trainees responding to at least one follow-up survey. Upon completion of the study, participants received $20 gift cards delivered through email. Participants were also informed that a summary of the study's findings would be available upon request after the completion of the research study.

Mastery Orientation Measure

We adapted VandeWalle's (1997) five-item scale to assess mastery orientation. To capture both the typical level and the variability of a trainee's mastery orientation distribution, we utilized the frequency-based measurement approach in personality measurement (Edwards & Woehr, 2007; Fleisher et al., 2011), which is premised on findings that individuals can accurately recall and estimate behavioral frequencies (e.g., Kane & Woehr, 2006; Woehr & Miller, 1997). Given the stem of an item, such as "I enjoy challenging and difficult tasks where I'll learn new skills," trainees were asked to recall their behavior at work as a researcher over the past 6 months and to report the percentage of time each of the following three response categories was descriptive of their behavior. The response categories include: *% very inaccurate*; *% neither inaccurate nor accurate*; and *% very accurate*. In other words, trainees indicated the percentage of times their state mastery orientation was high, moderate, or low, as described by the behavioral statement in each item stem, across a wide range of situations. Trainees were reminded to use a total of 100% across the three response categories, with the sum of percentages they reported automatically computed and displayed on the survey web page. For example, a hypothetical respondent may report that the item describes her very inaccurately 25% of the time, neither inaccurately nor accurately 35% of the time, and very accurately 40% of the time.

The frequency-based measurement approach resulted in a distribution of behavioral tendency on mastery orientation for each individual, enabling the estimation of the level (i.e., mean) and the variability (i.e., standard deviation) of the individual's mastery orientation distribution at work. We assigned a weight to each response category (1 = *very inaccurate*; 3 = *neither inaccurate nor accurate*; 5 = *very accurate*) so that the resulting mastery orientation level would be comparable to a five-point Likert scale (Edwards & Woehr, 2007). In the example item response above, the hypothetical respondent receives a level of 3.30 (i.e., [25 × 1 + 35 × 3 + 40 × 5]/100) and a variability of 1.59 (i.e.,

$$\sqrt{[25 \times (1 - 3.3)^2 + 35 \times (3 - 3.3)^2 + 40 \times (5 - 3.3)^2]/99} \qquad (1)$$

We averaged the levels reported across the five items to indicate trainees' mastery orientation level (Cronbach's $\alpha = .93$). Similarly, we obtained the variability on each item and averaged it to arrive at trainees' mastery orientation variability ($\alpha = .94$).

Learning Outcomes and Transfer Measures

We utilized validated measures to assess affective learning outcomes and transfer. To make the items more appropriate for this study context (i.e., researchers participating in statistical workshops), we modified the items from their original training/transfer contexts. Responses to motivation to transfer, posttraining self-efficacy, transfer, and opportunity to perform were made on a five-point Likert scale (1 = *strongly disagree*; 5 = *strongly agree*).

Posttraining self-efficacy. We measured posttraining self-efficacy with five items ($\alpha = .91$) adapted from Ford et al. (1998). A sample item is "I am confident in my understanding of [. . .] analysis."

Motivation to transfer. We assessed motivation to transfer with six items ($\alpha = .89$) adapted from Bell and Ford (2007) and Warr, Allan, and Birdi (1999). An example item is "I feel very committed to apply what I have learned to my research."

Declarative knowledge. We assessed posttraining declarative knowledge with quizzes in the form of true/false and multiple choice items at the end of the posttraining assessment. The content of the quizzes was directly based on materials provided by the instructor of each workshop. Scores were standardized within workshop and then expressed as T scores ($M = 50$, $SD = 10$).

Transfer. We adapted the scale from Tesluk, Farr, Mathieu, and Vance (1995) to assess transfer in the current context. The current scale included five items for the six follow-up surveys (α ranged from .80 to .90) that tapped the extent to which trainees used the newly acquired knowledge and skills in different research contexts in the preceding 7 days. An example item is "I used the knowledge and skills presented in the workshop to help understand research reports."

Opportunity to perform. Considering the need to keep the weekly follow-up surveys short, we wrote two items (α ranged from .69 to .86) to assess the overall perception of opportunity, as opposed to specific dimensions (cf. Ford et al., 1992). A sample item is "I did not see any opportunities to use the knowledge and skills presented in the workshop in my research activities" (reverse scored).

Results

As the affective learning outcomes' variables were adapted for this study, we conducted confirmatory factor analysis to ensure the structure of the scales conformed to the a priori measurement model. First, a two-factor solution provided good fit to trainees' responses on motivation to transfer and self-efficacy, $\chi^2(43) = 65.35$, $p = .02$, $N = 109$, comparative fit index (CFI) = .97, Tucker-Lewis index (TLI) = .96, root mean square error of approximation (RMSEA) = .069. In contrast, an alternative single-factor solution provided poor fit to the data, $\chi^2(44) = 341.11$, $p < .001$, $N = 109$, CFI = .57, TLI = .47, RMSEA = .249, $\Delta\chi^2(1) = 275.76$, $p < .001$. Thus, the confirmatory factor analysis indicated that motivation and self-efficacy scales were indeed distinct. Further, the observed correlation between these two variables ($r = .36$, $p < .001$) suggests that they are only moderately correlated.

Table 1 presents descriptive statistics and intercorrelations for observed variables. As expected, mastery orientation level was positively associated with posttraining self-efficacy and motivation to transfer, which were both significantly related to average transfer (*r*s = .43 and .31, *p*s < .01). In addition, a strong correlation was identified between mastery orientation level and variability ($r = -.89$). In the frequency-based measurement approach, the amount of variability tends to decrease as the level approaches either end of the scale (i.e., 1 or 5 on the current scale). Thus, this strong correlation was likely due to a ceiling effect on mastery orientation level ($M = 4.26$ out of the possible maximum of 5.00, $SD = .59$), which was to be expected in the present sample of advanced degree researchers. Note that overlap of such a magnitude between variables does not automatically preclude theoretically driven investigations due to redundancy (see Antonakis & House, 2014; Bing, Whanger, Davison, & Vanhook, 2004 for two examples). Whether variability contributed additional information about a trainee's mastery orientation domain beyond its level alone depends on the unique variance associated with the level × variability interaction. Given the high correlation, however, we recognized that the level × variability interaction would be highly correlated with the

TABLE 1
Descriptive Statistics and Intercorrelations for Study Variables

	1	2	3	4	5	6	7	8	9	10	11	12
1. Motivation to transfer	*.89*											
2. Posttraining self-efficacy	$.28^{**}$	*.91*										
3. Declarative knowledge	−.05	.04	–									
4. Mastery orientation	$.26^{**}$	$.22^{*}$	−.03	*.93*								
5. *SD* mastery orientation	$-.22^{*}$	$-.21^{*}$	.04	−.89	*.94*							
6. Average Transfer	$.40^{***}$	$.32^{***}$	−.01	.18	−.15	–						
7. Transfer T1	$.34^{***}$	$.23^{*}$	.08	.13	−.07	$.62^{***}$	*.80*					
8. Transfer T2	$.27^{**}$	$.27^{*}$	.09	.20	−.19	$.87^{***}$	$.38^{***}$	*.86*				
9. Transfer T3	$.32^{**}$	$.24^{*}$	−.14	.03	−.06	$.85^{***}$	$.31^{**}$	$.74^{***}$	*.86*			
10. Transfer T4	$.40^{***}$	$.24^{*}$	−.11	.12	−.14	$.92^{***}$	$.41^{***}$	$.77^{***}$	$.79^{***}$	*.89*		
11. Transfer T5	$.41^{***}$	$.21^{*}$	−.11	.20	−.17	$.90^{***}$	$.44^{***}$	$.73^{***}$	$.72^{***}$	$.81^{***}$	*.90*	
12. Transfer T6	$.47^{***}$	$.31^{**}$	−.07	.18	−.13	$.90^{***}$	$.39^{***}$	$.75^{***}$	$.72^{***}$	$.85^{***}$	$.84^{***}$	*.90*
13. Opportunity week 1	$.48^{***}$	.11	−.08	.07	−.05	$.39^{***}$	$.54^{***}$	$.29^{**}$	$.28^{*}$	$.29^{*}$	$.37^{***}$	$.34^{**}$
14. Opportunity week 2	$.39^{***}$	.10	.13	.13	−.14	$.51^{***}$	$.37^{***}$	$.59^{***}$	$.40^{***}$	$.42^{***}$	$.28^{*}$	$.41^{***}$
15. Opportunity week 3	$.44^{***}$	.13	−.12	.04	−.05	$.53^{***}$	$.30^{**}$	$.45^{***}$	$.63^{***}$	$.44^{***}$	$.38^{***}$	$.45^{***}$
16. Opportunity week 4	$.44^{***}$	.16	−.05	.03	−.06	$.64^{***}$	$.39^{***}$	$.50^{***}$	$.58^{***}$	$.68^{***}$	$.50^{***}$	$.62^{***}$
17. Opportunity week 5	$.49^{***}$	.15	.15	.00	.05	$.54^{***}$	$.43^{***}$	$.36^{**}$	$.45^{***}$	$.45^{***}$	$.55^{***}$	$.52^{***}$
18. Opportunity week 6	$.43^{***}$	.06	.06	.12	−.12	$.60^{***}$	$.37^{***}$	$.55^{***}$	$.46^{***}$	$.58^{***}$	$.52^{***}$	$.63^{***}$
M	3.92	3.37	50.00	4.26	.92	2.85	2.75	2.78	2.88	2.79	2.76	2.76
SD	.74	.76	10.00	.59	.56	.77	.82	.89	.88	.94	.98	.95

(*Continued*)

TABLE 1 (Continued)

	13	14	15	16	17	18
13. Opportunity week 1	*.76*					
14. Opportunity week 2	.42***	*.69*				
15. Opportunity week 3	.41***	.53***	*.76*			
16. Opportunity week 4	.45***	.56***	.69***	*.86*		
17. Opportunity week 5	.44***	.41***	.60***	.67***	*.85*	
18. Opportunity week 6	.44***	.62***	.64***	.75***	.67***	*.79*
M	3.37	3.18	3.32	3.19	3.15	3.12
SD	1.12	1.04	1.09	1.13	1.15	1.12

Note. $N = 105$–109, except for correlations involving variables 7–18, where $N_{T1} = 93$, $N_{T2} = 89$, $N_{T3} = 88$, $N_{T4} = 79$, $N_{T5} = 88$, and $N_{T6} = 84$. Average transfer = transfer averaged across six weeks. All tests are two tailed. Cronbach's alphas are presented along the diagonal.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

quadratic term for the level (Cortina, 1993; Ganzach, 1998) and thus conducted additional analysis (see below) to rule out level's curvilinear effects on either motivation to transfer or posttraining self-efficacy.

Given there was sporadic missing data in the transfer measures over the 6-week period, we examined its pattern using Little's (1998) missing completely at random (MCAR) test, which tests against the null hypothesis that data are missing completely at random. Little's MCAR test revealed a nonsignificant result: $\chi^2(82) = 99.41$, $p = .09$, $N = 109$. Therefore, the evidence suggested that the missingness in transfer measures was random. In light of the result of the missing data analysis, we subsequently modeled transfer measures with maximum likelihood estimator in MPlus 6.11 (Muthén & Muthén, 2011), which deals with missing data by utilizing all available data to estimate models with full information maximum likelihood.

Next, we examined the measurement invariance of transfer measures over the 6-week period, which is a prerequisite for subsequent analysis using latent growth modeling (LGM) (Chan, 1998). Specifically, we assessed both configural and metric invariance. In this study, configural invariance pertained to the appropriateness of a single-factor solution for transfer items measured in each week, while metric invariance entailed that the same item would have the same loading on its latent factor across weeks. In light of the modest sample size, we evaluated measurement invariance (a) between the first week and any subsequent week and (b) between each pair of adjacent weeks. Given the longitudinal nature of the data, we also included a first-order autoregressive structure to model correlated within-person errors (see Bliese & Ployhart, 2002). The measurement invariance results, presented in Table 2, indicated that each configural invariance model received reasonable fit to the data. More importantly, the addition of metric invariance constraints in each metric invariance model did not result in significantly worse fit to the data, supporting the metric invariance of the current measurement. Therefore, the measurement invariance tests satisfied the assumption for conducting LGM.

Hypothesis 1 stated that trainees would vary in (a) the initial level of transfer and (b) rate of change in transfer over time. We utilized LGM in Mplus to evaluate this hypothesis. Specifically, we modeled the unconditional LGM (see Bollen & Curran, 2006) with a latent intercept and a latent slope to capture the covariation in observed transfer over the 6 weeks, while also allowing for heterogeneous error structure and first-order autoregression between adjacent observations (Bliese & Ployhart, 2002). We specified a linear change by fixing factor loadings to 1s on the latent intercept term and to 0 through 5 for the 6 weeks on the latent slope term (see Figure 4). The unconditional model yielded good fit to the data ($\chi^2(11) = 17.63$, $p = .09$, $N = 105$, CFI = .98, TLI = .98,

TABLE 2
Fit Indices from Measurement Invariance Tests

Weeks evaluated	Invariance	χ^2	*df*	*p*	CFI	TLI	RMSEA	$\Delta\chi^2$	*p* for $\Delta\chi^2$
Weeks 1 and 2	Configural	33.97	29	.24	.99	.98	.041		
	Metric	34.03	33	.42	1.00	1.00	.018	.06	>.10
Weeks 2 and 3	Configural	58.56	29	.00	.94	.91	.101		
	Metric	59.23	33	.00	.95	.93	.090	.67	>.10
Weeks 3 and 4	Configural	50.96	29	.01	.96	.94	.090		
	Metric	55.17	33	.01	.96	.95	.085	4.21	>.10
Weeks 4 and 5	Configural	52.36	29	.01	.96	.94	.093		
	Metric	59.17	33	.00	.96	.94	.092	6.80	>.10
Weeks 5 and 6	Configural	46.12	29	.02	.98	.96	.081		
	Metric	52.27	33	.02	.97	.96	.080	6.15	>.10
Weeks 1 and 3	Configural	56.03	29	.00	.93	.89	.096		
	Metric	57.55	33	.01	.94	.92	.085	1.52	>.10
Weeks 1 and 4	Configural	33.91	29	.24	.99	.98	.042		
	Metric	37.63	33	.27	.99	.98	.038	3.72	>.10
Weeks 1 and 5	Configural	21.87	29	.83	1.00	1.03	.000		
	Metric	22.79	33	.91	1.00	1.03	.000	.92	>.10
Weeks 1 and 6	Configural	51.40	29	.01	.95	.92	.088		
	Metric	55.69	33	.01	.95	.93	.083	4.30	>.10

RMSEA = .076). To examine whether the pattern of change was curvilinear, we tested a nested model with a quadratic growth term. The addition of the quadratic growth term did not significantly improve the fit to the data ($\chi^2(7) = 10.95, p = .14, N = 105$, CFI = .99, TLI = .98, RMSEA = .073; $\Delta\chi^2(4) = 6.68, p = .15$). Thus, we proceeded with the more parsimonious growth model with an intercept term and a linear slope term.

In the unconditional LGM, the mean of the latent intercept indicated the initial level of transfer at week 1 ($M_{\text{intercept}} = 2.84$), while the mean of the latent slope indicated the average change of transfer from one week to another ($M_{\text{slope}} = -.01$, $p = .62$). Thus, trainees' transfer *on average* did not significantly change from one week to another. More importantly, significant variation was observed on both the intercept ($S^2{}_{\text{intercept}} = .39$, $p < .001$) and slope terms ($S^2{}_{\text{slope}} = .02$, $p = .04$). Therefore, supporting Hypothesis 1, the results indicate that trainees varied significantly on both the initial level and the rate of change on transfer. Despite being significant, the variance of the slope terms appeared somewhat small. For descriptive purposes, we examined individual slope factor scores, which ranged from $-.34$ to .27. For trainees with negative transfer trajectories ($n = 47$), the mean slope was $-.09$, indicating an average weekly reduction of .09 unit on the five-point transfer scale over the 6-week period. In contrast, for trainees with positive transfer trajectories ($n = 58$), the mean slope was .06, indicating a weekly average increase of .06 unit on the transfer scale.

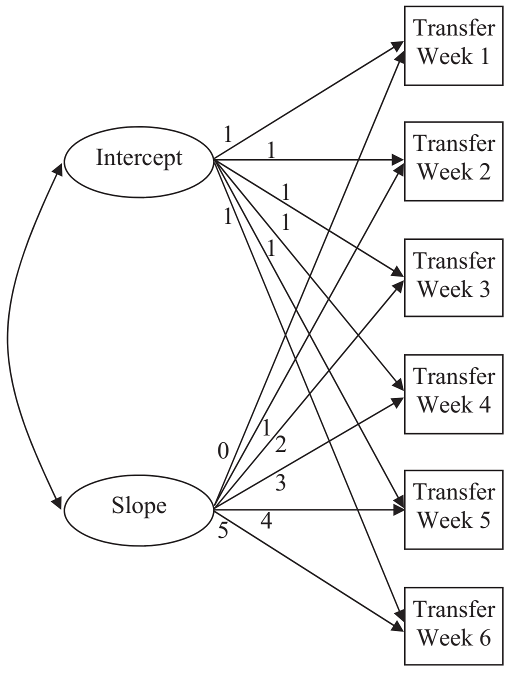

Figure 4: **Unconditional Latent Growth Model.**

Note. Intercept = Initial application; Slope = Rate of change. For simplicity in presentation, autocorrelation between the error terms for adjacent weekly transfer measures are not graphed.

Although not a hypothesized effect, the variance of intercepts and the variance of slopes were not significantly associated in the unconditional model, with a factor correlation of .15, $p = .60$, indicating that the intercept and slope were indeed measured uniquely. This nonsignificant correlation is informative in that the degree to which a trainee increased or decreased his/her use of the training over time did not depend on his/her initial attempt to transfer. From a theoretical standpoint, this finding suggests that research that only examines the level of transfer while ignoring the change in transfer fails to cover the entire theoretical space for the transfer phenomenon.

We proceeded to simultaneously test the study hypotheses using conditional LGM (see Figure 5). In this model, posttraining self-efficacy, motivation to transfer, and knowledge acquisition simultaneously predicted the initial application and the rate of change in transfer. We also modeled opportunity to perform as a time-varying covariate (with a first-order autoregressive structure) that accounted for variance in transfer at each time

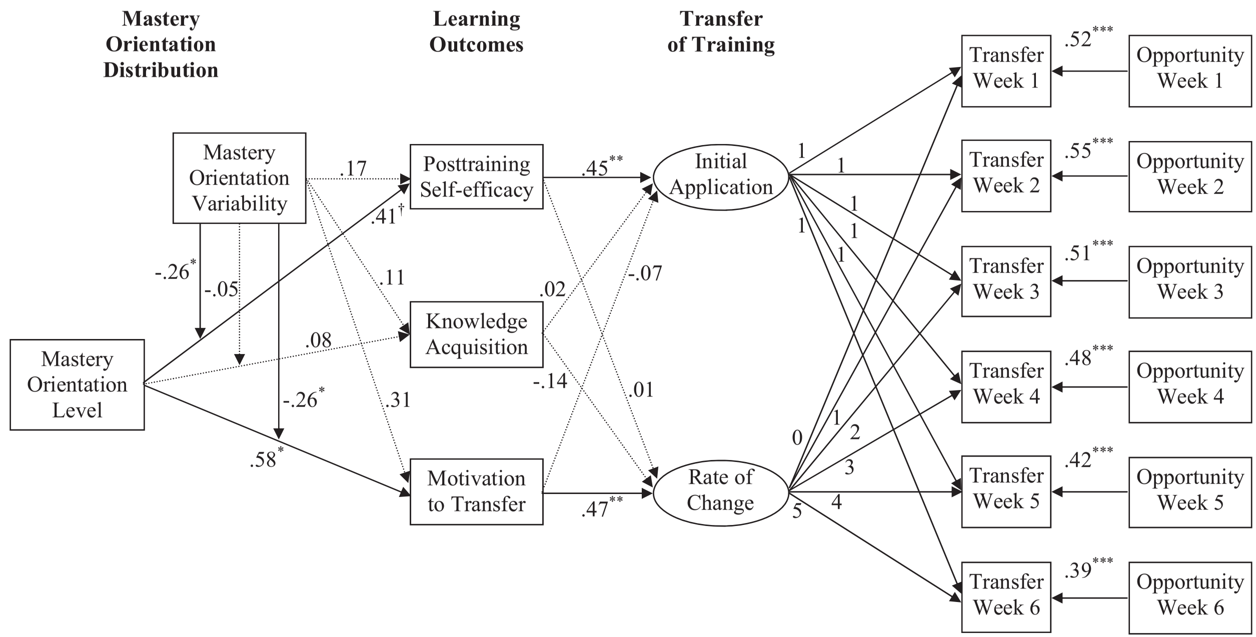

Figure 5: **Standardized Parameter Estimates From Conditional LGM.**

Note. Dotted lines indicate nonsignificant paths. Dummy coded workshops are entered as control variables in the model. For ease of presentation, paths from (a) posttraining self-efficacy and (b) motivation to transfer onto weekly opportunity to perform are not presented.
$^{**}p < .01$. $^{*}p < .05$. $^{\dagger}p < .10$.

point. Considering the potential influence of affective learning outcomes on subsequent opportunity to perform (Ford et al., 1992), we specified posttraining self-efficacy and motivation to transfer as antecedents of weekly opportunity to perform.[3] We also controlled for dummy-coded workshops in the conditional LGM to rule out potential difference across workshops on transfer trajectories. The conditional model provided acceptable fit to the data ($\chi^2(199) = 262.47$, $p = .002$, $N = 105$, CFI = .93, TLI = .90, RMSEA = .056). Controlling for trainee status (i.e., having a PhD or not), and gender did not change the pattern of findings (results available from the first author). We summarize the key path coefficients in Figure 5.

Hypotheses 2 and 3 pertain to the extent to which posttraining self-efficacy and motivation to transfer would predict (a) initial attempt and (b) rate of change in application of trained knowledge and skills. In partial support of Hypothesis 2, posttraining self-efficacy significantly predicted the intercept ($\beta = .45$, $p = .001$, 22% unique variance) but not the slope ($\beta = .01$, $p = .93$, 0% of unique variance). In contrast, motivation to transfer significantly predicted the slope ($\beta = .47$, $p = .002$, 19% of unique variance) but not the intercept ($\beta = -.07$, $p = .60$, 1% of unique variance), thus also providing partial support to Hypothesis 3. As trainees completed the training programs, the degree to which they felt efficacious about the newly acquired knowledge and skills was positively associated with their initial level of transfer at week 1, whereas the degree to which they felt motivated to apply the knowledge and skills in their research activities was positively associated with subsequent increase of transfer over time. It might be worthwhile to note that, if either motivation to transfer or posttraining self-efficacy was removed from the conditional LGM, the pattern of support for Hypotheses 2 and 3 remained the same.

Hypothesis 4 states that mastery orientation's variability will interact with its level to influence (a) posttraining self-efficacy and (b) motivation to transfer. Supporting Hypothesis 4a, mastery orientation variability interacted with its level ($\beta = -.26$, $p = .02$) to qualify level's main effect ($\beta = .41$, $p = .07$) on posttraining self-efficacy. Similarly, the positive effect of mastery orientation level ($\beta = .58$, $p = .01$) was moderated by mastery orientation variability, such that higher variability resulted in a weaker association between level and motivation ($\beta = -.26$, $p = .01$),

[3]To ascertain the relationships between the two affective learning outcomes and weekly opportunity to perform, we evaluated an alternative nested model by constraining to zero the paths from both self-efficacy and motivation to weekly opportunity to perform. This model did not provide adequate fit to the data ($\chi^2(211) = 312.85$, $p < .001$, $N = 105$, CFI = .88, TLI = .86, RMSEA = .069). A model comparison confirmed that this alternative model indeed provided poorer fit ($\Delta\chi^2(12) = 50.38$, $p < .001$). The parameter estimates for the hypothesized effects, however, remained the same with or without these constraints.

TABLE 3

Predicting Learning Outcomes From Mastery Orientation Distribution

	DV = Posttraining self-efficacy						DV = Motivation to transfer					
	Block 1		Block 2		Block 3		Block 1		Block 2		Block 3	
Hypothesized model	*B*	*B*	*B*	β	*B*	β	*B*	β	*B*	β	*B*	β
Intercept	3.36	–	3.36	–	3.14	–	3.92	–	3.92	–	3.71	–
1: Level	.29	.22*	.19	.14	.55	.41†	.33	.26**	.40	.31	.75	.58*
2: Variability	–	–	−.12	−.09	.24	.17	–	–	.07	.05	.43	.32
3: Level × Variability	–	–	–	–	−.73	−.26*	–	–	–	–	−.72	−.26*
ΔR^2	.05*		.00		.05*		.07**		.00		.05*	
	Block 1		Block A				Block 1		Block A			
Alternative model	*B*	*B*	*B*	β			*B*	β	*B*	β		
Intercept	3.36	–	3.22	–			3.92	–	3.83	–		
1: Level	.29	.22*	.40	.31**			.33	.26**	.41	.32**		
2: Level squared	–	–	.39	.19†			–	–	.26	.13		
ΔR^2	.05*		.03†				.07**		.01			

Note. Level = mastery orientation level; Variability = mastery orientation variability. Both level and variability were mean centered. Significance levels omitted on unstandardized coefficients for brevity.

$^{**}p < .01$. $^{*}p < .05$. $^{\dagger}p < .10$.

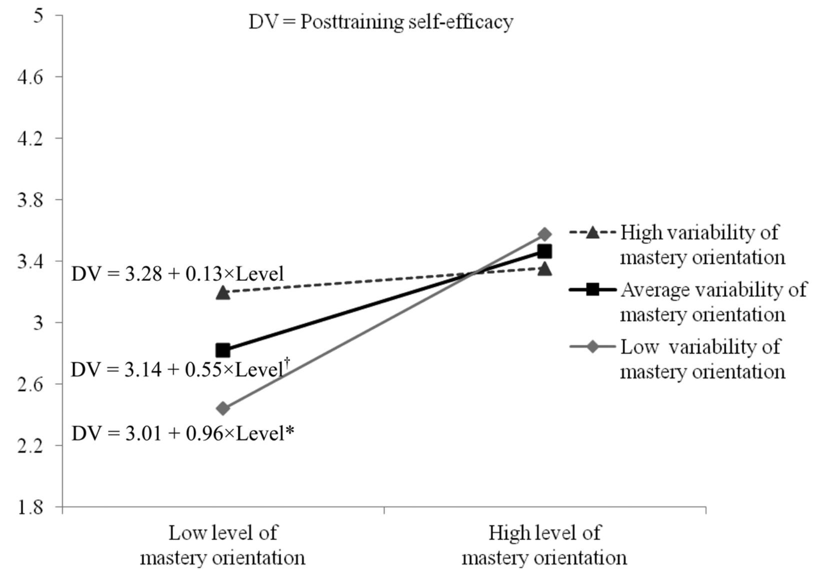

Figure 6: **Interactive Effect of Mastery Orientation Level and Variability on Posttraining Self-Efficacy.**

Note. † $p < .10$. * $p < .05$.

thus providing support for Hypothesis 4b. Together, level, variability, and the level × variability interaction accounted for 10% of variance in post-training self-efficacy and 12% of variance in motivation to transfer.

To fully discern these interaction effects, we performed moderated regression analysis by entering mean-centered level and variability separately before introducing the interaction term. Results reported in Table 3 indicate that mastery orientation level alone (Block 1) accounted for 5% of variance in posttraining self-efficacy and 7% of variance in motivation to transfer, whereas variability (Block 2) did not add to the prediction above and beyond level. The level × variability interaction effect (Block 3) accounted for another 5% of variance in self-efficacy and motivation, respectively. Analysis of simple slopes (see Figure 6) revealed that level had a significant positive effect on self-efficacy when variability was low at 1 SD below the mean ($B = .96$, $\beta = .73$, $p = .03$) but had no effect on motivation when variability was high at 1 SD above the mean ($B = .13$, $\beta = .10$, $p = .63$). Similarly, for the prediction of motivation to transfer (see Figure 7), the simple slope of level was significant when variability was low ($B = 1.15$, $\beta = .90$, $p = .006$) yet nonsignificant when variability was high ($B = .34$, $\beta = .27$, $p = .20$).

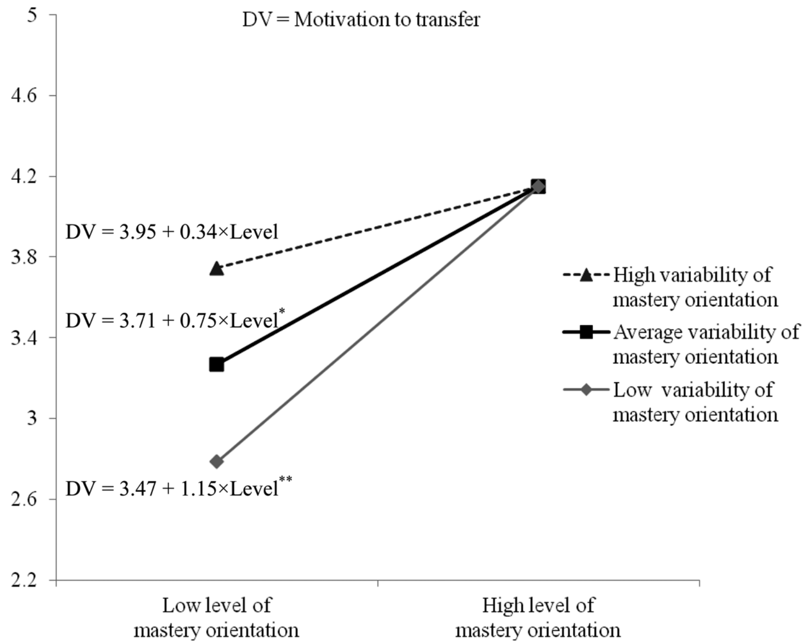

Figure 7: **Interactive Effect of Mastery Orientation Level and Variability on Motivation to Transfer.**

Note. $^{*}p < .05$. $^{**}p < .01$

The strong correlation between level and variability gave rise to the possibility that the level × variability interaction term largely captured the variance in the quadratic term of mastery orientation level. To check against this competing explanation, we examined whether level's quadratic term (i.e., level squared) would provide significant prediction of self-efficacy and motivation beyond level alone. Results from Block A in Table 3 revealed that level's quadratic term did not significantly add to the prediction of self-efficacy or motivation beyond level alone, thus helping rule out this competing explanation.

Finally, Hypothesis 5 states that posttraining self-efficacy and motivation to transfer will mediate the impact of mastery orientation's level × variability interaction on both (a) initial level and (b) rate of change in transfer. The significance of a mediated effect concerned the product term of two paths: (path *a*) the level × variability interaction's effect on one of the affective outcome variables and (path *b*) the effect of the affective outcome variable on either intercept or slope. We only assessed self-efficacy's mediating effect on initial level of transfer and motivation's mediating effect on rate of change in transfer, owing to their respective nonsignificant effects in the results above. Consistent with current practice for mediation analysis (Hayes, 2009; Preacher & Hayes, 2004), we created 10,000 bootstrapped samples in Mplus to obtain the 95% confidence interval (CI) for the *ab* indirect effects. Results indicate that posttraining self-efficacy significantly mediated the level × variability interactive effect on initial attempt at transfer ($\beta = -.11$, 95% CI [−.31, −.01], $p < .05$), while motivation to transfer significantly mediated the level × variability interactive effect on rate of change in transfer ($\beta = -.12$, 95% CI [−.34, −.02], $p < .05$). In addition, motivation to transfer significantly mediated mastery orientation level's main effect on rate of change in transfer ($\beta = .26$, 95% CI [.05, .73], $p < .05$), while self-efficacy marginally mediated mastery orientation level's main effect on initial application ($\beta = .17$, 95% CI [−.01, .50], $p < .10$). Taken together, affective learning outcomes served as an important pathway that explained how trainees' mastery orientation distribution might influence change in application behavior over time.

Discussion

In the context of open skills voluntary training, we demonstrated that trainees varied significantly in terms of initial attempts to apply training content and subsequent changes in application. Variations in trainees' initial attempt were accounted for by posttraining self-efficacy, while variations in their change in transfer application were explained by motivation to transfer. Furthermore, trainees' mastery orientation distribution, including level and level × variability interaction, predicted both posttraining self-efficacy and motivation to transfer, with a significant indirect effect on initial attempts and change in transfer application, respectively.

Theoretical Implications

This study contributes to the training literature by demonstrating within-person variability in transfer behavior over time. In particular, our paper empirically modeled and predicted transfer trajectories, thus making two contributions to the understanding of training transfer as use. First, our study provides evidence that some trainees increase while others decrease the use of trained skills over time. With this finding, we now call for transfer researchers to no longer treat within-person changes on transfer as noise in measurement but rather directly assess changes as an important characteristic of the transfer phenomenon.

Second, we discovered that posttraining self-efficacy significantly predicted the initial level of application whereas motivation to transfer significantly predicted change in transfer application over time. The differential roles of these affective learning outcomes shed light on the nature of transfer (i.e., application) trajectories. It appears that the initial application level is influenced, in part, by capacity and self-evaluation such that trainees who feel efficacious about the newly acquired knowledge and skills make initial efforts to apply training content to the job. On the other hand, only motivation to transfer predicted change in transfer over time. This suggests that change in application is largely motivational in nature, with motivated trainees escalating their application over time while unmotivated trainees' attempts abating over time. This pattern of differential prediction echoes the research on learning performance by Mitchell, Hopper, Daniels, George-Falvy, and James (1994), who demonstrated that self-efficacy better predicted performance during early learning phases, whereas motivational factors better predicted performance during later learning phases.

Another contribution of this paper lies in the enhanced prediction of transfer behavior by assessing the variability of the trainee's mastery orientation distribution, beyond its level alone. Ford and Oswald (2003) made the case that considering within-person variability in traits may enhance prediction of training outcomes. This study represents an initial empirical test of their proposition, resulting in sound support. More importantly, the variability in transfer over time and the variability in mastery orientation were theoretically connected by motivation to transfer, enabling a richer understanding of the trainee's psychological processes.

Transfer application and effectiveness are likely interrelated over time. With the present findings, researchers may begin to propose and examine the shape of transfer effectiveness curves in relation to application trajectories. For instance, although repeated application can lead to increase in effectiveness over time, effective transfer may have a reciprocal effect on application, such that prolonged success breeds the willingness and interest to attempt more application in a variety of tasks. We can illustrate this point through the use of a hypothetical motivated trainee from an open skills statistical training course. During the course, the trainee has the working knowledge surrounding a statistical analysis after having gone through structured instructions and subsequently practiced the analysis with a sample dataset. She now attempts to apply the analytic method to an actual dataset and runs into problems. Given her high motivation to transfer, she persists at the task, possibly enlisting assistance from colleagues or browsing the internet for solutions. As her experience on the topic accumulates, she sees more opportunity to apply the analysis and becomes more proficient in using it. In contrast, with an unmotivated trainee, the initial transfer attempt accompanying the fresh interest from the training may peter out over time, resulting in sporadic application and low transfer effectiveness. Of course, unlike application, effectiveness necessitates *successful use* of trained knowledge and skills. Thus, we do anticipate cognitive predictors such as general mental ability and posttraining declarative knowledge to have stronger influence on transfer effectiveness.

Practical Implications

The discovery of different transfer trajectories across trainees underscores the need for practitioners to take into account the timing of transfer assessment. As some trainees may increase while others decrease transfer over time, measuring transfer at two points in time, such as a few weeks apart, may lead to somewhat different conclusions as to who have transferred as expected and who have not. In the event that only one transfer assessment is possible, practitioners may want to base the timing decision on the goal of the assessment, specifically whether it is serving a formative or evaluative purpose. If the transfer assessment is serving a formative purpose, such as providing input to further improve a training program, then transfer might be assessed earlier so as to create opportunity to act upon the assessment results. If the transfer assessment is serving an evaluative purpose, such as identifying the trainees who achieved the desirable level of effectiveness, then transfer may be measured later so as to allow within-person changes to occur and plateau over time.

At a more practical level, this finding highlights the importance of managing expectations of supervisors and trainees regarding how quickly the benefits of a given training program may be reached. Educating managers regarding transfer trajectories can lead them to be more supportive of training programs that do not show immediate change in employee behavior or that seem to "work only for some people" in the short run. Managers may also start considering when to give additional opportunities to perform and who to give them to over time. Incorporating the notion of trajectories into training programs may help trainees to manage their own expectations. When dealing with limited opportunities to perform early on, trainees may be encouraged to be proactive and to enact incremental changes in transfer application over a longer period of time.

The differential effects of posttraining self-efficacy and motivation on transfer trajectory suggest that, beyond measuring these two affective learning outcomes to identify trainees in need of interventions, training program designers can consider trajectories in decisions to allocate resources (i.e., time, effort, and money), both within training and in promoting transfer. A relative emphasis on enhancing posttraining self-efficacy versus enhancing motivation to transfer might be warranted depending on organizational needs regarding how essential it is that trained knowledge/skill *be* applied quickly. To facilitate early application of trained skills, the training designer may want to provide sufficient practice, feedback, and encouragement during training to ensure trainees feel confident about transfer when they leave the training program. To promote positive changes in transfer in the long run, the training designer may utilize posttraining motivational techniques such as formulating implementation intentions (e.g., Gollwitzer, 1999) or provide follow-up interventions to boost motivation and expand opportunities to transfer.

Recognizing variability in mastery orientation across contexts or situations can lead to changes in training programs and in transfer supports. We can envision tools to help trainees to recognize contextual factors that weaken their mastery orientation and developing strategies for effectively enhancing transfer in those contexts. Research on mindset interventions (Paunesku et al., 2015; Yeager & Walton, 2011) might help in designing effective messaging prior to training as well as for posttraining prompts that might induce mastery orientation in contexts where some trainees seem to adopt a different stance. Enabling learner control of such prompts would allow trainees to tailor their own posttraining transfer supports to best fit their own motivational variability. Note that incorporating mastery orientation inductions into training programs themselves is not a new idea (e.g., Bell & Kozlowski, 2008; Stevens & Gist, 1997); what this study suggests is that as some trainees' mastery orientation may be more variable, greater contextual awareness and targeted interventions might help these trainees achieve better training outcomes.

Limitations and Future Research Directions

Several limitations of this study point to venues for future investigations. First, we relied on self-report for transfer measurement and focused on trainees' use of knowledge and skills. While trainees are arguably in a good position to assess this, additional data from colleagues on observations of use would strengthen the assertions. Although common method variance is unlikely a concern given the current growth modeling approach, the reliance on self-report limited our ability to evaluate the effectiveness of transfer (e.g., Ford et al., 1998). In addition to measuring use as the proximal outcome, future studies may involve informant reports or objective measures administered with a longer time lag after training as distal outcomes.

Second, this study examined changes in transfer application as a result of affective learning outcomes, whereas environmental variables such as workplace support, transfer climate, workload, and constraints may also impact training transfer (Blume et al., 2010; Salas & Cannon-Bowers, 2001). It is possible that factors such as workplace support and transfer climate affect both affective learning outcomes and subsequent transfer, thus leading to overestimating the effects of affective learning outcomes. We did, however, assess opportunity to perform on a weekly basis as a control mechanism. If a trainee had to focus on tasks that had little relevance to the trained knowledge and skills or had to deal with a heavy workload, he/she would likely report lower opportunity to perform, thus allowing us to control for some of the influence from the work environment to mitigate this concern. Meanwhile, it is important to note that the relationship between opportunity to perform and motivation to transfer is likely reciprocal: Perceived opportunity before training may enhance motivation to transfer, whereas high motivation can drive trainees to seek out more opportunities to perform later on. In addition, we should note that we measured weekly opportunity to perform in a general way, assessing trainees' perceived opportunity to use the knowledge and skills acquired from the training. As noted by an anonymous reviewer, opportunity to perform in this study context could come in the form of an objective need to conduct a specific statistical analysis, and it is possible for a participant in this study to not encounter such a need even many weeks after the training. This lack of a need or opportunity might have restricted the observed variability in transfer.

Third, given the typical focus in measuring affective learning outcomes from a training effectiveness perspective (Arthur, Bennett, Edens, & Bell, 2003; Kraiger et al., 1993), we assessed motivation to transfer upon completion of the training programs. However, transfer motivation may be conceptualized as a dynamic construct that changes over time. Indeed, together with changes in transfer motivation, training researchers may include changes in other variables such as perceived needs and challenges to transfer. It is likely that transfer motivation will serve as a dynamic mediator (see Pitariu & Ployhart, 2010) between various trainee perceptions and actual transfer behavior. Extending the current findings to explicate these dynamic relationships can offer a richer understanding of the volitions and decisions surrounding transfer behavior.

Finally, the strong correlation between mastery orientation level and variability—attributable to the overall high level of mastery orientation in the current sample—can lead to questioning the usefulness in assessing variability. Despite our best effort to rule out the competing explanation for the current findings, some concern remains. To further address this concern, we conducted a constructive replication (Lykken, 1968) that specifically examined the mastery orientation level × variability hypothesis (i.e., Hypothesis 4), which received an observed power of .65 for posttraining self-efficacy and .65 for motivation to transfer, respectively, in the study above. In a sample of 107 psychology students enrolled in undergraduate statistical courses, we assessed their trait mastery orientation level and variability, as well as their self-efficacy and motivation to transfer, near the end of a semester. A weaker correlation emerged between mastery orientation level and variability ($r = -.60$, $p < .001$) than was observed in the main study. As expected, qualifying mastery orientation level's respective significant main effects on self-efficacy ($\beta = .25$, $\Delta R^2 = .06$, $p = .01$) and motivation ($\beta = .28$, $\Delta R^2 = .08$, $p = .003$), mastery orientation variability interacted with level to predict self-efficacy ($\beta = -.33$, $\Delta R^2 = .10$, $p < .001$) and motivation to transfer ($\beta = -.29$, $\Delta R^2 = .08$, $p = .003$), and the interactive effects held after accounting for level's curvilinear effects. This replication study (details available from the first author) thus offered additional evidence that mastery orientation level is more predictive of training outcomes when variability is lower.

In terms of the epistemology of psychological constructs, as the opening quote suggests, researchers can make one of two choices: (a) continuing to treat within-person variation on traits and behavioral outcomes as noise in measurement to be ignored in substantive research or (b) assessing within-person variation as an important characteristic of the person's trait or behavior that can enable better understanding of the construct of interest. Although only an initial step in the context of predicting training transfer, this study adds to the weight of evidence in support of the second choice. Indeed, our study complements recent studies on variability of personality captured at the momentary level (e.g., Huang & Ryan, 2011; Judge et al., 2014; Minbashian, Wood, & Beckmann, 2010) and indicates that variability can be assessed globally at the trait level as well (also see Edwards & Woehr, 2007; Fleisher et al., 2011). Together, these findings highlight areas for future investigations. For instance, trait variables of trainee contribute to studies on aptitude–treatment interaction (Snow, 1992; see Gully & Chen, 2010 and Pashler, McDaniel, Rohrer, & Bjork, 2008 for reviews). One form of such interaction is when the treatment directly targets the trait domain (Wilson et al., 2013), as when the use of an intervention to elevate state mastery orientation is more effective for individuals with lower standings on trait mastery orientation (Bell & Kozlowski, 2008). Considering variability leads to the potential to examine a three-way interaction: Trainees who have low level *and* high variability on trait mastery orientation are likely most amenable to such intervention efforts. As another example, researchers may seek to better understand the nature of variability. Variability of a given trait domain might indicate the person's assessment of situational need to adapt (e.g., Maddux, Adam, & Galinsky, 2010), signal an underlying disposition (e.g., Snyder, 1974), or reflect the broader environment the person interacts with (e.g., Huang & Ryan, 2011). Following current findings, many interesting questions await answer.

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