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Measuring Individual Differences in Content via Changing Person–Context Interaction

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Kanfer's (2009) article took a triumvirate approach to understanding work motivation by describing the relevance of content, context, and change. In this commentary, I suggest integrating these three elements to move the field further yet. Specifically, we need to recognize the fact that the elements are inextricability linked and thus to better understand and develop measures of the content of individuals that matter (i.e., predictive individual differences), we must model how those individual differences are influenced by and influence context. Moreover, we must model how these influences change the context and the individual over time. By model, I am referring to Ilgen and Hulin's (2000) third discipline—computational modeling—as a means to explicitly recognize the dynamics and how they involve both the individual and the environment. Computational modeling is not merely a statistical representation of observed data but a way to conceptually represent the underlying dynamics responsible for the data observed. Without this approach, we will be slow to change our field's understanding of the entire system (i.e., person nested in context).

Although there are many phenomena and issues to be addressed from taking this dynamic, interactionist perspective (Vancouver, 1996, 2008), here I want to talk about an issue near and dear to the individual difference-oriented industrial–organizational (I–O) psychologist. Kanfer broached the topic when she discussed the concept of trait complexes. In that section, she cites Mischel and Shoda (1995), who find that personality traits are not very useful without considering the contexts that are likely to evoke behavioral tendencies. This is more than the simple strong–weak situation concept where we assume that personality will be more predictive in weak situations. Instead, it implies that the personality trait expressed might change as a function of context. For example, Johnny Carson was famous for his ability to make people laugh when on stage but was also notoriously shy at parties. Context mattered, yet it was not the mere presence of people, but the clear roles (and script) associated with Johnny as host as opposed to Johnny as guest that likely mattered. Of course, I am just speculating. Unfortunately, we do not have the theory, instruments, or Mr. Carson to examine the possibility. That is, we do not have a good handle on context-dependent individual differences. This might seem a striking remark given psychology's devotion to deliminating individual differences (Cronbach, 1957), but for so many of the constructs we list, we are largely at a loss when it comes to describing why the differences emerge. Without such knowledge, it is not surprising that we have not examined the moderating role of contexts.

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However, it is more complex than considering Content × Context interactions. We also need to know the *when* of context and content interaction. That is, we need to incorporate the change element. Kanfer described change in terms of a developmental timescale (e.g., age). Although important, much shorter time frames are also likely to matter. For example, I noticed that Johnny Carson could make me laugh much more easily after a hard day of work than an easy one. It is unlikely Johnny knew what I needed but that my previous states influenced my reaction to a current context. Likewise, after a day alone, I notice that I am much more talkative if around others later. These are examples of not only how context matters but also how previous states influence present behaviors. That is, dynamics matter.

Kanfer's concern was for parsimony and she wanted to simplify the content domain by examining clusters of cross-domain trait complexes. It at first appears that I want to add dramatically to the complexity of the individual difference field by seeking to list Content × Context × Order (i.e., change) effects. However, this is not my end game. Rather, I want to advocate a deeper understanding of human behavior and use that understanding to develop new instruments for measuring individual differences, instruments that take advantage of the Context × Content × Order interaction. This might mean more constructs, but it might mean fewer applied in a different way.

Some illustrations of the approach I am advocating can be found in two examples by cognitive psychologists examining clinically relevant individual difference measures. In the first, Busemeyer and Stout (2002) examined a model of the underlying dynamics and processes they believed were involved in performing the Bechara gambling task (also called the Iowa gambling task). In the task, examinees are asked to make 100 choices from four decks of cards. Each deck has a unique payoff structure (i.e., different expected values and levels of risk) that examinees learn *as they interact* with the decks. Task performance, in terms of money earned, has been found to be related to various clinical and behavioral conditions of interest, like Asperger's and substance abuse (Yechiam, Busemeyer, Stout, & Bechara, 2005). However, Busemeyer and Stout believed that different reasons existed for the performance scores, and these differences matter in terms of understanding the specific deficiencies associated with the clinical conditions. Taking an expectancy-valence approach, they suggested that the *rate of learning* the payoffs (i.e., expectancies) regarding the decks, one's relative sensitivity to rewards and punishments *received*, and the consistency of one's responding *given experience*, were all individual difference constructs that could affect performance. They explicitly capitalized on the idea that individuals will interact over time with this gambling context, creating a computational model with three free parameters that represented the individual-difference variables. Then, using observations of each individual's 100 choices and the context those choices created (i.e., payoff feedback), they could estimate values for the three free parameters for each individual. After several studies, summarized in Yechiam et al., they showed how the estimated parameter values discriminated among the different clinical conditions despite the similarities in task performance.

In another example, Wallsten, Pleskac, and Lejuez (2005) examined several computational models of the possible underlying cognitive processes involved in determining behavior on the Balloon Analog Risk Task (BART), another measure of risk-taking behavior used by clinical psychologists. Like the gambling task described above, BART involves repeated measures (i.e., simulating the "pumping up" of many balloons) with feedback. They found a model that fit the data and parameters in that model that matched self-reported risk-taking behavior in real life. I have also developed a model of BART behavior that includes an element focused on learning the contingencies of the task as well as differences related to the goals one might have for the task.

The point of these projects is to reduce superficial behavioral measures to the underlying and possibly generalizable processes related to learning and decision making (Yechiam & Busemeyer, 2008). Moreover, these measures do not rely on self-reports but on direct observations of behavior (albeit behavior on artificial tasks performed in standardized settings). So far these examples have only been applied to clinical, maladaptive behavior. However, I suspect that the task/models are likely to be of more general interest (i.e., useful for predicting work behavior). For example, I–O psychologists might be interested in applying the approach to predict how individuals will approach risk in work contexts, something that the current financial crisis highlights as relevant to organizations.

We might also be interested in other measures, expanding the modeling approaches taken. For example, Steel and König (2006) described behavior related to meeting goals with deadlines. They have a computational model representing their theory that I translated into a process model (i.e., a computational model that can be simulated over time). An important individual-difference parameter in the theory and model is a time sensitivity parameter that is hypothesized to reflect how responsive individuals are to approaching deadlines. This construct might have important implications for predicting how people behave in a variety of settings with a deadline (e.g., work). Indeed, Mitchell and James (2001) and others (e.g., Dalal & Hulin, 2008; Fried & Slowik, 2004) have highlighted the field's need to incorporate temporal issues into our theories and measures of work behavior. Perhaps, other models might prove useful for examining constructs like goal orientations, conscientiousness, and achievement motives.

Indeed, it seems that applied motivational researchers might be able to increase the utility of the dynamic modeling approach to measuring individual differences by applying their knowledge and concepts to measures of behavior over time. In particular, applied motivational researchers have expertise in dynamic interactional processes like those involved in goal choice, planning, and striving (Diefendorff & Lord, 2008; Klein, Austin, & Cooper, 2008). Moreover, the largest gap in predicting individual differences relates to predicting motivation in the work place (i.e., "will do" as opposed to "can do"). With this content held by I–O psychologists, perhaps it is time we made some changes to our approach to predicting behavior in context.

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