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Review Article

Specific Cognitive Abilities at Work

A Brief Summary From Two Perspectives

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Abstract. Recent findings suggest that the role of specific cognitive abilities in predicting work-related criteria may be critical and may add to the widely demonstrated importance of general mental ability. To summarize and organize these findings, the current paper puts forward two perspectives on the role of specific cognitive abilities in predicting work-related outcomes. Similarities and discrepancies of these perspectives are outlined together with suggestions for boundary conditions of the dominance of general versus specific cognitive abilities. Finally, avenues for future research within and across the two perspectives are discussed.

Keywords: intelligence, general mental ability, specific cognitive abilities, job performance

The pivotal role of general mental ability (hereinafter also referred to as intelligence) for work-related outcomes and beyond is largely undisputed (e.g., Gottfredson, 2002). The same has long been true for the discussion on the additional role of specific cognitive abilities. So, in 1991, Ree and Earles concluded that "not much more than *g*" was necessary to predict performance criteria at work. This claim was echoed a decade later by Viswesvaran and Ones (2002): "All authors [. . .] agree that there is not much more validity to be gained from specific abilities than *g*" (p. 216). However, another decade later a shift in perspectives is underway with the emergence of new findings that challenge and differentiate this contention (Goertz, Hülsheger, & Maier, 2014; Krumm, Lipnevich, Schmidt-Atzert, & Bühner, 2012; Lang, Kersting, Hülsheger, & Lang, 2010; Shea, Lubinski, & Benbow, 2001; Stanhope & Surface, 2014; Webb, Lubinski, & Benbow, 2007; Ziegler, Dietl, Danay, Vogel, & Bühner, 2011).

The current paper seeks to review and organize recent findings, with an emphasis on distinguishing two different classes of cognitive abilities: *components* of intelligence and *sources* of intelligence. In particular, we outline different implications that stem from findings of these two approaches for research and practice. In doing so, we acknowledge but not re-iterate what has been said on the *general versus specific debate* by comprehensive reviews that exist on the topic (e.g., Judge & Kammeyer-Mueller, 2012; Lubinski, 2004).

Components of Intelligence

The vast majority of empirical studies and reviews on the incremental contribution of specific cognitive abilities beyond general mental ability in predicting work-related outcomes define specific abilities in terms of *components* of intelligence (cf. Viswesvaran & Ones, 2002). The assumption is that intelligence can be described in terms of an underlying structure of lower order components, that is, specific cognitive abilities (also referred to as narrow cognitive abilities). So, the spectrum of specific cognitive abilities considered in models of intelligence aggregates to general mental ability. In other words, these approaches consider specific cognitive abilities as descriptive elements of a hierarchically organized intelligence construct. It thus follows that for definitions of specific cognitive abilities – if understood as components of intelligence – readers are best referred to hierarchical models of intelligence (e.g., Carroll, 1993; McGrew, 2009). The most frequently used specific cognitive abilities in studies on their predictive validity can best be drawn from recent meta-analyses (e.g., Goertz et al., 2014) and include reasoning, numerical facility, verbal comprehension, and spatial ability.

Empirical studies on the role of specific cognitive abilities in predicting both job (e.g., Ree, Earles, & Teachout, 1994) and training performance (e.g., Lievens, 2004; Ree & Earles, 1991) are usually concerned with their incremental contribution above and beyond general mental ability. Hence, the underlying question is: Do specific cognitive abilities carry unique variance, that is, variance unaccounted for by general mental ability, which is predictive of work-related criteria? The consensual answer to this question, however, as provided by studies and reviews on this topic is that no incremental contribution should be expected from specific cognitive abilities (Viswesvaran & Ones, 2002). Implications of this conclusion include using aggregate scores of general mental ability and disregarding specific cognitive abilities in requirement analyses and assessment.

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This conclusion, however, is challenged by recent meta-analytical evidence showing that specific cognitive abilities serve as additional or even more important predictors than general mental ability (Goertz et al., 2014; Lang et al., 2010; Ziegler et al., 2011). For instance, Goertz et al. revealed substantial correlations between specific cognitive abilities and training success that were comparable in strength to those usually obtained for general mental ability. Applying relative importance analysis, Lang et al. found some specific cognitive abilities to be more important for job performance than general mental ability. Finally, Ziegler et al. examined the incremental validity of specific cognitive ability in predicting training performance and found that several specific abilities were able to explain incremental variance in different training performance domains. While meta-analytic evidence thus far is based on German samples only, other primary studies with non-German samples further speak to a shift in paradigm (e.g., Mount, Oh, & Burns, 2008; Stanhope & Surface, 2014; Webb et al., 2007). This is not to say that *all* recent studies reveal evidence demonstrating that specific cognitive abilities predict work-related outcomes beyond general mental ability (e.g., Brown, Le, & Schmidt, 2006; Lievens, 2004). However, the changing picture calls for further research on moderators of the incremental contribution of specific cognitive abilities or boundary conditions of the dominant role of general mental ability.

A straightforward but rarely mentioned way of deriving moderating conditions of the incremental contribution of specific cognitive abilities is to apply the Brunswik (1956) lens model. The lens model can be used to identify necessary conditions for the convergence of a prediction with a criterion. A basic assumption in this model is that several cues, which are more or less indicative of the criterion, are used for the prediction. Specifically, convergence (coined "achievement" in the lens model) is assumed to be a function of (a) the validity of the cues, that is, the extent to which the cues are indeed indicative of the criterion; (b) the utilization of the cues, that is, the extent to which the prediction makes use of these cues; and (c) the symmetry of cue usage in prediction and criterion (termed "matching" in the lens model). Transferring this logic to the current topic, general mental ability is assumed to be a good predictor of job-related outcomes if (a) the underlying specific cognitive abilities (cues) are in fact indicative of the criterion; (b) the underlying specific abilities are good representations of general mental ability construct; and (c) the specific cognitive abilities' weights in predicting the criterion and representing general mental ability are symmetrical. On the other hand, a specific cognitive ability will most likely emerge as an incremental predictor if this ability is highly predictive of the criterion (in other words, the criterion must be domain specific) but not strongly weighted in the general mental ability aggregate (in other words, *g*-saturation of this ability must be low). Described in more practical terms, the contribution of this specific ability may be blurred by other abilities that are only marginally predictive of the criterion. In terms of the lens model the aforementioned constellation (domain specific criterion with its predictor showing low *g*-saturation) will cause asymmetry. Such asymmetry will lead to a low correlation between general mental ability and the criterion and in turn increase chances of the specific cognitive ability to contribute incrementally. An example of such a constellation is presented in Figure 1. We thus posit that – ceteris paribus (e.g., range restriction, reliability of measures, see Carretta & Ree, 2000) – domain specifity of the criterion and *g*-saturation of the specific cognitive ability are moderators of the dominance of broad versus narrow cognitive abilities. Initial support is provided by Mount et al. (2008) who found that perceptual speed, an ability with low *g*-saturation (cf. Carroll, 1993), was an incremental predictor of rather specific criteria (performance and rule compliance of warehouse workers who had to quickly find and sort goods). Future research might incorporate these moderators as well as a lens model approach in investigating the relative contribution of general versus specific cognitive abilities.

The slight overrepresentation of studies on training as compared to job performance criteria showing an incremental contribution of specific abilities (Goertz et al., 2014; Stanhope & Surface, 2014; Webb et al., 2007; Ziegler et al., 2011) may also be explained by higher domain specifity of training criteria. Individuals are typically trained in a specific domain – for instance, foreign language (Stanhope & Surface, 2014) or chemical and pharmaceutical knowledge (Ziegler et al., 2011), whereas job performance criteria cut across a variety of domains (e.g., Rotundo & Sackett, 2002). Thus, the use of training versus job performance criteria may also moderate the dominance of broad versus specific cognitive abilities, which may be traced back to the higher domain specifity of training.

On a more technical side, the statistical approach seems to moderate results on the dominance of broad versus narrow cognitive abilities. Lang et al. (2010) argued that the widely used hierarchical regression approach with general mental ability being entered first into the regression is characterized by the underlying assumption of all shared variance between specific and general mental ability being attributed to general mental ability (see Spearman, 1904). Employing a nested factors model, however, results in shared variance between general and specific mental abilities being attributed to general mental ability, specific mental abilities, or both. When Lang et al. used a statistical method that accounted for the nested factors assumption, results showed that some specific abilities were more important predictors of job performance than general mental ability. We thus posit that researchers' underlying model (Spearman vs. nested factors) will moderate the dominance of general over specific cognitive abilities.

The above list of moderators is by no means exhaustive but rather intends to add to what has been debated so far (cf. Judge & Kammeyer-Mueller, 2012; Lubinski, 2004). In light of the changing empirical picture of general versus specific cognitive abilities' relevance in the work context, we would like to stimulate more research on moderating conditions. Specifically, meta-analyses targeting such moderating conditions may be a viable step toward more clarification. Furthermore, requirement analyses may be developed that adopt the lens model logic and thus may

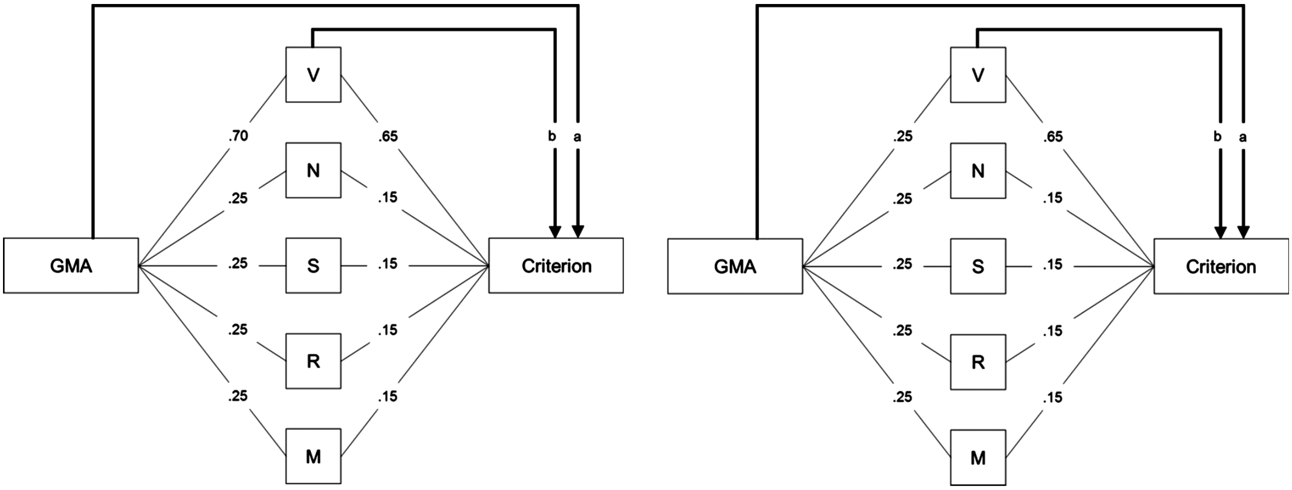

Figure 1. Two hypothetical examples illustrating the Brunswik lens model logic applied to general and specific abilities predicting a criterion (high vs. low *g*-saturation of V). In both examples, a domain specific criterion (strong weight of V on the criterion) is predicted by general mental ability and a specific cognitive ability. As a result of the symmetry of weights in the example on the left (i.e., V has a strong *g*-saturation in this example), the predictive validity of general mental ability (a) will be high, whereas the incremental contribution of the specific cognitive ability (b) will be low. The asymmetry of weights as presented in the example on the right will result in a lower predictive validity of general mental ability, the specific ability will be able to explain incremental variance in the criterion. V = verbal comprehension; N = numerical ability; S = spatial ability; R = reasoning; M = memory; GMA = general mental ability.

be able to filter out the relative merits of specific versus general cognitive abilities in predicting job and training performance.

Sources of Intelligence

Much less research has been conducted on sources of intelligence and their relative importance in predicting work-related outcomes. We refer to sources of intelligence as abilities reflecting the efficiency or the capacity of the human cognitive system (cf. Schweizer, 2005). Popular concepts are, for example, working memory capacity, mental speed, and facets of attention. Notably, these concepts are not considered descriptive elements but sources of intelligence,[1] in that they provide essential capacities for higher cognitive functioning. For example, the tradition of working memory capacity as a source of higher cognitive functioning maintains that most cognitive tasks cannot be solved "in the blink of an eye." Rather, different pieces of information must be acquired and understood sequentially and retained momentarily to enable combination and integration of information (Schweizer, 2005). Thus, working memory capacity (and other concepts mentioned above) is not *part* of the broader concept of intelligence but a necessary *precondition* or source of higher cognitive functioning. A rich body of research shows that individual differences in such abilities are indeed highly predictive of individual differences in intelligence (e.g., Bühner, Krumm, & Pick, 2005; Carlson & Jensen, 1982; Danthiir, Wilhelm, Schulze, & Roberts, 2005; Kyllonen & Christal, 1990).

Considering specific cognitive abilities as sources rather than descriptive elements of general mental ability shifts the main research goal from explaining incremental variance in work-related outcomes to understanding the underlying cognitive processes. In other words, the focus is not only on identifying unique variance of specific cognitive abilities. Rather, shared variance between general mental ability and specific cognitive abilities, which predicts work-related outcomes, provides us with information about the underlying cognitive process needed to accomplish a task or acquire work-related knowledge.

Several theories describing cognitive processes needed in accomplishing work-related tasks are available. Nijstad and Stroebe (2006), for example, suggested a cognitive model of idea generation (Search for Ideas in Associative Memory, SIAM), which is in the work context often conducted through brain storming in groups. In this model, working memory capacity is considered a crucial limiting factor as it helps remembering own ideas in the context of an ongoing discussion (see Mojzisch, Krumm, & Schultze, 2014). The role of working memory for foreign language learning, as another example, has also been highlighted by several authors (e.g., Papagno, Valentine, & Baddeley, 1991). Similarly, Ackerman (1988) presented a theory of three levels of task-related skill acquisition, in which he assumed that application of initially learned

[1] Please note that some concepts (e.g., mental speed) are considered as sources of intelligence and are part of hierarchical models of intelligence.

principles will be limited by individuals' speediness in applying the principles to the task at hand, or, to summarize, by their mental speed.

Although many researchers acknowledge the relevance of sources of intelligence, empirical investigations in work-related contexts are rare. The available evidence is largely limited to educational settings. For instance, several authors confirmed the relevance of working memory for performance at school (e.g., Krumm, Ziegler, & Bühner, 2008), at university (D'Amico & Guarnera, 2005; Gropper & Tannock, 2009; Krumm et al., 2012), and for foreign language acquisition (e.g., Ellis & Beaton, 1993; Masoura & Gathercole, 1999; Palladino & Cornoldi, 2004). Similarly, mental speed has been shown to predict performance in the educational context (e.g., Carlson & Jensen, 1982; Luo, Thompson, & Detterman, 2003; Rindermann & Neubauer, 2004; Rohde & Thompson, 2007).

Only few studies have explicitly applied sources of intelligence in the work place (e.g., a search in Web of Science with the words "working memory" and "job performance" as topic resulted in only 31 hits). For example, Higgins, Peterson, Pihl, and Lee (2007) assessed workers' prefrontal cognitive ability (including working memory) and revealed substantial correlations (around .50) with supervisor ratings of job performance. With respect to training criteria, Perlow, Jattuso, and De Wayne Moore (1997) found working memory to be relevant for performance in a complex learning scenario (correlations around .35). Albeit a few additional studies may be mentioned here, we conclude that not much evidence on the relevance of source of intelligence can be presented. However, in light of (a) promising findings in educational settings, (b) available theories on their relevance for work-related tasks, (c) their correlation with other variables that are also relevant at work (e.g., impulsivity or multitasking; Hofmann, Gschwendner, Friese, Wiers, & Schmitt, 2008; König, Bühner, & Mürling, 2005), and (d) the sources' groundedness in the cognitive architecture of the brain, we maintain that their relevance for job performance and training should be further explored. Thereby, we agree with the call to not only improve the prediction of important outcomes but also to undertake more efforts to understand the role of intelligence in our working life (Scherbaum, Goldstein, Yusko, Ryan, & Hanges, 2012).

Conclusions

Although we generally acknowledge that general mental ability is by far the most successful construct in predicting job and training performance (Kuncel, Hezlett, & Ones, 2004; Schmidt & Hunter, 1998), this summary seeks to contribute to a more differentiated picture as to when and why general or specific cognitive abilities are the dominant predictors of work-related outcomes. On the basis of the aforementioned findings and ideas, we would like to make the following calls and thereby add to what has already been discussed along the "general versus specific debate" (Judge & Kammeyer-Mueller, 2012).

Distinguish Components and Sources of Intelligence

As outlined above, predicting work-related outcomes on components versus sources of intelligence goes along with differing underlying rationales. The first approach is concerned with comparing the relative contribution of general and specific cognitive abilities and seeks unique contributions of specific cognitive abilities, for example, to enable improved personnel selection. The second approach, in contrast, treats specific abilities as limiting aspects of higher cognitive functioning and thus assumes that shared variance between specific and general cognitive abilities is useful for understanding cognitive underpinnings of work-related performances.

Embrace Basic Lens Model Assumptions in Research and Practice

Considering the long tradition of the Brunswik (1956) lens model and its recent popularity in personality psychology (e.g., Gosling, Ko, Mannarelli, & Morris, 2002; Hirschmüller, Egloff, Nestler, & Back, 2013), its underrepresentation in the general versus specific debate in the realm of cognitive abilities seems surprising. As mentioned above, it may be used in future research as well as in re-analyses of available data to identify moderators of the dominance of general mental abilities. From a practical point of view, the model may generally be informative in aligning insights from requirement analyses with assessment procedures. That is, cognitive tests may be selected by content and by their factor loadings on a common general mental ability factor and/or weighted accordingly to match results from requirement analyses so that maximum symmetry is achieved.

Meta-Analytically Examine Moderators of the Dominance of General Versus Specific Abilities

Although available meta-analyses usually include job complexity, occupational domain, reliability of predictor and criterion, as well as range restriction, we would like to promote using the aforementioned moderators (symmetry of predictor and criterion as well as domain specificity of the criterion). Also, alternative statistical models may be applied (hierarchical regression vs. relative importance analyses).

In sum, research on personnel selection and assessment may undertake more efforts to better understand and incorporate specific cognitive demands of increasingly specialized work environments. Such efforts are justified in light of an increasingly aging workforce (OECD, 2013) and the lack of skilled workers (at least in some areas; e.g., German Employment Agency, 2013), as they may not only increase predictive validity of assessments but, for instance, also shorten assessment times and costs, improve applicant reactions to cognitive tests (e.g., Anderson, Salgado, & Hülsheger, 2010), and ensure that job relevant specific strengths are not overlooked (for examples on future nobel laureates not classified as gifted in the Terman studies, see Webb et al., 2007).

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