RESEARCH REPORT

General Mental Ability and Specific Abilities: Their Relative Importance for Extrinsic Career Success

Jonas W. B. Lang
Ghent University and University of Exeter

Harrison J. Kell
Educational Testing Service, Princeton, New Jersey

Recent research on the role of general mental ability (GMA) and specific abilities in work-related outcomes has shown that the results differ depending on the theoretical and conceptual approach that researchers use. While earlier research has typically assumed that GMA causes the specific abilities and has thus used incremental validity analysis, more recent research has explored the implications of treating GMA and specific abilities as equals (differing only in breadth and not subordination) and has used relative importance analysis. In this article, we extend this work to the prediction of extrinsic career success operationalized as pay, income, and the attainment of jobs with high prestige. Results, based on a large national sample, revealed that GMA and specific abilities measured in school were good predictors of job prestige measured after 11 years, pay measured after 11 years, and income 51 years later toward the end of the participants' work lives. With 1 exception, GMA was a dominant predictor in incremental validity analyses. However, in relative importance analyses, the majority of the explained variance was explained by specific abilities, and GMA was not more important than single specific abilities in relative importance analyses. Visuospatial, verbal, and mathematical abilities all had substantial variance shares and were also more important than GMA in some of the analyses. Implications for the interpretation of cognitive ability data and facilitating people's success in their careers are discussed.

Keywords: cognitive abilities, intelligence, income, success, longitudinal

Supplemental materials: http://dx.doi.org/10.1037/apl0000472.supp

General mental ability (GMA) is one of the most frequently used predictors in psychological science, historically and currently

Jonas W. B. Lang, Department of Human Resource Management and Organizational Psychology, Ghent University, and Business School, University of Exeter; Harrison J. Kell, Academic to Career Research Center, Research and Development, Educational Testing Service, Princeton, New Jersey.

Correspondence concerning this article should be addressed to Jonas W. B. Lang, Department of Human Resource Management and Organizational Psychology, Ghent University, Henri Dunantlaan 2, 9000 Ghent, Belgium or Harrison J. Kell, Academic to Career Research Center, Research and Development, Educational Testing Service, Princeton, NJ 08541. E-mail: jonas.lang@ugent.be or hkell@ets.org

(Mackintosh, 2011), that captures ability across a broad set of cognitive tasks. Recently, researchers have extended inquiry into the applied value of GMA by systematically examining the degree to which it predicts extrinsic career success such as pay and occupational prestige (Strenze, 2015). Although literature concerning intelligence and career success includes a large-scale study (Judge, Klinger, & Simon, 2010) and a meta-analysis (Ng, Eby, Sorensen, & Feldman, 2005), it is less extensive than existing research linking cognitive ability to job performance (Schmidt & Hunter, 1998), counterproductive behavior (Gonzalez-Mulé, Mount, & Oh, 2014), or leadership (Judge, Colbert, & Ilies, 2004).

A recurring and important theme in the literature concerning the prediction of work-related outcome criteria is the status of GMA in comparison to specific abilities from a set of content-homogenous tests (e.g., mathematical, verbal; Ryan & Ployhart, 2014; Schmitt, 2014). Over the past 30 years many studies have shown that specific abilities contribute little incremental validity to predicting some work criteria like job performance and performance in training once GMA is accounted for (i.e., it is entered in the first step of a hierarchical regression or simultaneously with GMA, see, e.g., Brown, Le, & Schmidt, 2006; Ree & Carretta, 2002). However, recent research has shown that the value of specific abilities vis-à-vis GMA considerably depends on theoretical assumptions

(Kell & Lang, 2017; Lang & Bliese, 2012; Lang, Kersting, Hül-sheger, & Lang, 2010; Stanhope & Surface, 2014). Specifically, it has been argued that it is theoretically justifiable to enter GMA in hierarchical regressions prior to specific abilities only if GMA is treated as a cause of variance in those abilities. However, there are alternative contemporary models of cognitive abilities that fit the data equally well and do not specify a causal relationship between GMA and specific abilities (e.g., Gustafsson, 2002; Kovacs & Conway, 2016; Van der Maas et al., 2006). When the association between GMA, specific abilities, and work outcomes is examined in accordance with these latter models, it is inappropriate to conduct incremental validity analyses. Instead, the *relative importance* of GMA and specific abilities for predicting work criteria is of interest.

In this article, we draw on earlier work on the role of cognitive abilities in career success and extend this work by systematically examining GMA and specific abilities as predictors of extrinsic career success (early career pay, late-career income, and occupational prestige). In so doing, we draw on both cognitive ability theories that assume a causal relationship between GMA and specific abilities and theories that explicitly do not assume such a relationship. Our objective in examining these phenomena is two-fold.

First, we seek to further clarify the consequences of different cognitive ability theories for conclusions regarding the role of GMA and specific abilities in important work-related outcome criteria. By examining career success we contribute understanding of the long-term influence of specific abilities, complementing prior work that focused on assessments of performance (Ryan & Ployhart, 2014; Sackett & Lievens, 2008; Schmitt, 2014). It is reasonable to assume that people who are (objectively) successful in their careers exhibit better job performance in the long-run than those who are less successful—but the few studies that have examined the association between job performance and career progression (Carmeli, Shalom, & Weisberg, 2007; Van Scotter, Motowidlo, & Cross, 2000) have found that the association is not strong. Consequently, examining the relationship between cognitive abilities and career success is not redundant with looking at the association between abilities and performance.

Our second objective is to uncover ability antecedents that can be identified relatively early in people's lives and that may drive successful careers. This second objective has potentially important consequences for detecting, developing, and selecting talent at an early stage, given that individuals' rank-ordering vis-à-vis their cognitive abilities tends to be relatively stable over time (Deary, Pattie, & Starr, 2013). It also has important implications for assisting policymakers in developing educational environments and early interventions that are specifically targeted to enhance abilities implicated in success.

Theoretical Background

Conceptualizing Careers

We situate our investigation in several prevailing approaches to conceptualizing individuals' careers. We briefly review these perspectives below.

Objective career success. Objective (or extrinsic) career success is typically defined as accomplishments that individuals achieve through their work and that can objectively verified or observed by others (Ng et al., 2005). The most common extrinsic career success criteria are pay, income, and the achievement of occupational status/prestige. While pay represents the economic compensation that individuals receive for their work and income individuals' overall financial success (Peters, 1992), occupational prestige or status captures the social standing or the way society overall views an occupation (Hauser & Warren, 1997). Although these criteria are related, the correlation in most samples is typically only moderate (Judge, Higgins, Thoresen, & Barrick, 1999; Weaver, 1977). The discrepancy between prestige and pay/income results from the fact that some high-prestige occupations in many societies are state servants that receive a fixed salary; individuals may forego the possibility of making extraordinary amounts of money and choose these jobs (e.g., judge) based on their high prestige and relative stability. Additionally, some other high-paying jobs require advanced degrees and/or extreme levels of technical skill that are relatively rare for the population at large to possess and, consequently, the general public remains largely unaware of many of these jobs (e.g., oil and gas diver); an occupation cannot be prestigious if few people are aware that it exists. Finally, it is possible that individuals do not manage their financial assets well so that their job-related pay differs from income, particularly late in life.

Human capital perspective. There are multiple conceptualizations of how individuals go about succeeding in their careers. For this investigation we adopt the human capital view (Becker, 1964), which is generally oriented toward the perspective that individuals have competencies or attributes (e.g., abilities, knowledge, skills) and that individuals are rewarded throughout their careers to the extent that they mobilize these competencies in the service of organizational and/or societal success. Individuals who possess and better mobilize these internal resources are more likely to be rewarded in their organizations and across their careers—such as by being promoted more quickly, earning greater pay, and possessing jobs that hold higher societal prestige value.

Human capital attributes can be conceptualized in multiple ways (Melamed, 1996). First, they differ in their generality, with some attributes (e.g., cognitive skills, personality traits) being considered highly general—given they are applicable to a very wide variety of jobs—and some being considered highly specific (e.g., knowledge of an individual organization's policies and procedures), as they are applicable to only a small number of jobs. We treat general mental ability as a variety of general human capital but we also consider specific cognitive abilities to constitute a type of general human capital; specific abilities are not as widely applicable as general cognitive ability but many (e.g., quantitative, verbal, visuospatial skills) are relevant to a very wide variety of jobs (Hunt & Madhyastha, 2012; Kyllonen, Anguiano Carrasco, & Kell, 2017).

Second, human capital attributes differ in their ease of malleability, with relatively easily modifiable attributes and attributes relatively difficult to modify (Baruch & Bozionelos, 2010). Individuals' rank-ordering on cognitive abilities tends to be highly stable over even very long periods of time (Deary et al., 2013) and, accordingly, retain their predictive value for practical criteria over extended periods (Judge et al., 1999). Moreover, although these abilities can be modified through life experience, education, and intentional interventions (Protzko, Aronson, & Blair, 2013; Ritchie

& Tucker-Drob, 2018), they are nonetheless difficult to alter and the effects of interventions tend to fade if they are not maintained (Protzko, 2015).

The Status of GMA and Specific Abilities

Table 1 provides an overview of major ideas about the status of general and specific abilities. Most relevant for the present study is that these conceptualizations make different assumptions about the causal priority of general and specific abilities. Two-factor theory and the higher-order model assume that GMA has a causal effect on specific abilities. In contrast, the nested-factors and the hierarchies of factor solutions models make no assumption about the causal relations among general and specific abilities. Finally, the bonds and the mutualism models put general and specific abilities on a continuum from specific to general and assume that the causal order is from specific elements (bonds or ecosystems) to general abilities—the opposite of the two-factor and higher-order theories. A conceptual problem of intelligence research is the fact that it is not easy to make a decision about which of the existing conceptualizations best captures the true underlying nature of the data; many of the models (e.g., bonds, mutualism) fit the data equally well (Bartholomew, Allerhand, & Deary, 2013; Van der Maas et al., 2006), with some (e.g., higher-order, nested-factors) capable of being statistically transformed into the other (Murray & Johnson, 2013). While even strong proponents of GMA (e.g., Eysenck, 1997; Jensen, 1987) have stated that data from outside the realm of factor analysis will be the ultimate arbiter of the scientific status of the nature of cognitive abilities, neuroscientific (Deary, Penke, & Johnson, 2010), historical (Flynn, 2007), and longitudinal data (McArdle, Hamagami, Meredith, & Bradway, 2000) offer contradictory accounts of the primacy of general and specific abilities.

Incremental Validity and Relative Importance

A frequently used research strategy in the existing literature on general and specific abilities in outcome criteria is to use incremental validity analyses that enter GMA as the predictor in a first step (e.g., Brown et al., 2006; Ree & Carretta, 2002). In the second step, the specific abilities are then added to examine the variance that these abilities explain after controlling for GMA. This research strategy is in line with the theoretical ideas of both two-factor theory and the higher-order model and is consistent with the recommendation that variables that are assumed to have causal priority are entered first in hierarchical regressions (Cohen, Cohen, West, & Aiken, 2003). As a result of the assumption that GMA precedes the specific abilities, all variance that GMA shares with the specific abilities is attributed to GMA. Research using this research strategy has frequently found that specific abilities do not explain much additional variance beyond GMA. Incremental validity analyses are frequently insightful when the focus is on the pragmatic improvement of an existing prediction system (LeBreton, Hargis, Griepentrog, Oswald, & Ployhart, 2007). However, a problem with cognitive ability research using incremental validity analyses is that incremental validity estimates are only meaningful when the assumption that GMA causes the shared variance between itself and specific abilities is actually correct. Considering the issues in testing this assumption in fundamental re-

search, definitive conclusions as to the relationship between general and specific abilities are lacking. Applied researchers often still face the need to understand the role both types of ability play when predicting outcomes. Therefore, it may frequently be informative to study the role of GMA and specific abilities in relevant outcome criteria without making preliminary assumptions about their causal ordering, in addition to studying incremental validity. There are two approaches that allow researchers to do so.

The first approach is to estimate a nested factors model using structural equation modeling software and to then link the latent nested factors directly to the outcome criterion (Gustafsson & Balke, 1993; Reeve, 2004). A limitation of this approach is that it requires that the research makes the assumption that GMA and the specific abilities are orthogonal in the model, thereby distributing shared variance between GMA and the specific abilities.

The second approach is to use regression techniques that do not require preliminary assumptions about the causal order of correlated predictors. Methodological research suggests that the most suitable technique for comparing the magnitude of the relationship between different predictors and outcome criteria is relative importance analysis (Braun, Converse, & Oswald, 2019; Budescu, 1993; Johnson & LeBreton, 2004; LeBreton et al., 2007; LeBreton, Ployhart, & Ladd, 2004). Relative importance is typically defined as "the contribution a variable makes to the prediction of a criterion variable by itself and in combination with other predictor variables" (Tonidandel & LeBreton, 2011, p. 2). Modern relative importance analysis techniques produce a rank order of correlated predictors and distribute the overall R^2 among the predictors. Relative importance statistics thus provide direct insights into the role that a particular predictor has in an outcome criterion without the assumption of a causal order. These characteristics are major advantages over other regression metrics like semipartial correlations, partial correlations, or beta weights that describe the effect of a predictor on an outcome variable after controlling for another predictor, and that do not provide a rank order or distribute the overall R^2.

Linking General Ability and Specific Abilities With Extrinsic Career Success

Research on the role of specific abilities in career success has typically emphasized the role of GMA, and existing studies have consequently focused on GMA. These existing studies include a relatively small meta-analysis (Ng et al., 2005) that found moderate effects of GMA on pay and job prestige, and a study with a large sample that found similar effects (Judge et al., 2010). In line with this earlier research, we hypothesized that GMA would predict extrinsic career success criteria (early career pay, end-career income, and job prestige in this study).

Hypothesis 1: GMA predicts extrinsic career success criteria.

In extending earlier research on extrinsic career success, we studied the role of specific abilities in GMA using both an incremental validity perspective and a relative importance analysis approach. Analogous to research on job performance, we assumed that specific abilities would not have much incremental validity (Brown et al., 2006; Ree & Carretta, 2002).

Table 1
Conceptualizations of General Mental Ability (GMA) and Specific Abilities

Conceptualization	Main publication(s)	Core idea	Status of GMA and specific abilities
Two-factor theory	Spearman (1904)	GMA is a mental energy and causal entity that is responsible for the positive manifold (correlations between ability tests/common factor from a diverse group of ability tests). Spearman also granted there was an element of performance on each cognitive test that was not caused by GMA (he used the letter *g* for GMA) and that this element was specific to each test (specific abilities).	Causal effect of GMA on (manifest) specific abilities
Bonds model	Bartholomew, Deary, and Lawn (2009), Thomson (1916)	Posits that the mind is made up of many hypothetical units ("bonds") and that each cognitive task samples a subset of these bonds, with the correlation between two tests depending on the degree to which they share the same bonds. Individuals may differ in the number of bonds they possess, explaining individual differences in what *appears* to be a general mental ability.	Bottom-up effect of specific abilities on GMA
Higher-order model	Spearman (1939), Thurstone (1947)	GMA is responsible for the positive manifold among broad content-aligned specific ability factors.	Causal effect of GMA on (latent) specific abilities
Nested-factors/bifactor model	Gustafsson and Balke (1993), Holzinger and Swineford (1937), Humphreys (1981)	GMA and specific abilities differ in their breadth of influence but are not subordinate to each other, and independently explain variance in cognitive tasks.	No causal effect of GMA on specific abilities; shared variance distributed through orthogonalization
Mutualism model	Van der Maas et al. (2006, 2017)	Cognitive processes reciprocally interact during development and in so doing positively influence each other, leading to the emergence of the positive manifold.	Bottom-up effect of specific abilities on GMA
Hierarchies of factor solutions	Goldberg (2006), Lang, Kersting, and Beauducel (2016), Zuckerman, Kuhlman, and Camac (1988)	The approach correlates factor scores across different exploratory factor analysis solutions (1-factor, 2-factor, 3-factor, 4-factor, etc.), and is largely a descriptive approach with no assumptions on causality.	No causal relation between GMA and specific abilities; correlations between abilities at different levels of the hierarchy

Hypothesis 2: In incremental validity analyses entering GMA first, GMA accounts for the majority of the explained variance in extrinsic career success criteria.

However, given that incremental validity analyses make the somewhat problematic assumption that GMA is the source of all shared variance between GMA and the specific abilities, we expected different findings in the context of relative importance analyses that do not make this assumption. We specifically expected that specific abilities would account for the majority of the explained variance in extrinsic career success criteria and that single specific abilities would be equally important in extrinsic career success criteria as GMA. These expectations were based on two theoretical rationales. First, we based these expectations on the conceptualizations in Table 1 (bonds model, nested-factors/bifactor model, mutualism model, and hierarchies of factor solutions conceptualization) that suggest that GMA is not the causal source of the positive manifold. When shared variance is not necessarily caused by GMA, it is reasonable to assume that specific abilities may emerge as relatively important predictors in real-world settings under the condition that the criterion requires these specific abilities. Second, we based our expectations on the importance of specific abilities on earlier theoretical and empirical work arguing that job-related outcomes like career success actually require

specific abilities (Schneider & Newman, 2015; Wai, Lubinski, & Benbow, 2009). Our theoretical expectations were also in line with earlier research on other outcomes like job performance and training criteria suggesting that GMA is not always the single most important predictor in relative importance analyses (Kell & Lang, 2017; Lang et al., 2010; Stanhope & Surface, 2014).

Hypothesis 3: In relative importance analyses including GMA and specific abilities, specific abilities account for the majority of the explained variance in extrinsic career success criteria.

Hypothesis 4: In relative importance analyses, single specific abilities are equally or even more important in extrinsic career success criteria than GMA.

One potential implication of studying the role of specific abilities in relevant outcome criteria is the fact that specific abilities provide more insight into why individuals obtain jobs with higher income and prestige (and, perhaps, *why* these jobs pay more and have higher prestige). Although more than three specific abilities exist (see, e.g., the models in Table 1), we focus our hypotheses on visuospatial, verbal, and mathematical abilities, as three core content abilities (Guttman, 1954; Guttman & Levy, 1991; Lubinski, 2000; Wilhelm, 2005). One idea in the literature is that visuospatial abilities are particularly relevant for success in jobs in science,

engineering, technology, and mathematics (STEM; Kell, Lubinski, Benbow, & Steiger, 2013; Lubinski, 2010; Wai et al., 2009) that are now and historically in demand and are on average high-paying (Koncz, 2016; Vilorio, 2014). These jobs require employees to work with spatial representations when they, for instance, read diagrams, interpret graphs, visualize molecules, comprehend cross-sections in biological images or geology plots, or imagine distances and sometimes very high velocities (Uttal & Cohen, 2012). Visuospatial abilities are also important for complex math, which frequently requires an understanding of three-dimensional spatial representations. Visuospatial ability thus forms a valued resource that can generate economic progress (National Science Board, 2015).

Hypothesis 5: Visuospatial ability is a relatively important predictor of pay and income.

In contrast to high pay and income that can frequently be achieved with technical or science skills, a common characteristic of jobs with high job prestige is that achieving success requires a lot of verbal communication and high levels of education. Examples include university professors in some disciplines, judges, or civil servants. Jobs that require less verbal skills frequently have comparatively lower job prestige (Gottfredson & Brown, 1978; Smith & Son, 2014). For instance, engineers have typically lower job prestige than judges, and technicians and electricians typically earn salaries comparable to teachers but have lower job prestige (e.g., U.S. Census Bureau, 1976, p. 383). An earlier meta-analytic study has already suggested that verbal abilities may be a primary driver behind the cognitive ability-job performance relationship by documenting high relative importance of verbal abilities in general job performance (Lang et al., 2010). This finding is also in line with the observation that some short general mental ability tests that are used successfully and frequently in practice are primarily measuring verbal abilities (e.g., Miller Analogies Test, Wonderlic Personnel Test).

Hypothesis 6: Verbal ability is a relatively important predictor of job prestige.

We finally also included a specific hypothesis about mathematical ability. Mathematical ability features prominently in selection tests and mathematical abilities are also frequently required as entry level abilities in order to get into academic careers. For instance, economists typically need to pass difficult econometrics courses. Mathematical abilities, as might be expected, also play a critical role in obtaining and advancing in STEM occupations (Kell et al., 2013; Makel, Kell, Lubinski, Putallaz, & Benbow, 2016; Wai et al., 2009).

Hypothesis 7: Mathematical ability is a relatively important predictor of extrinsic career success criteria.

Method

To conduct our investigation we used data from three time points of Project TALENT, a 1960 national longitudinal study from the United States including approximately 5% of the high school students in Grades 9 to 12 (Flanagan et al., 1961). The initial main data collection occurred in 1960. The original participants were followed up several times and the dataset is frequently used in I–O psychology research (e.g., Austin & Hanisch, 1990; Sackett, Kuncel, Arneson, Cooper, & Waters, 2009). In this study, we focused on extrinsic career success criteria from the 1971–1974 follow-up

($n = 84,831$ for pay, and $n = 15,810$ for job prestige), and the 2011–2012 reconnect study (data on income from $n = 1,796$ participants) that has to our knowledge not been used in research projects on cognitive abilities so far.

Students' cognitive abilities were assessed by 17 tests in 1960. A parallel analysis of all cases with not more than one of the 17 test scores missing ($n = 363,607$) suggested the presence of five specific abilities because the first five eigenvalues (6.14, 1.04, 0.69, 0.29, 0.11, 0.02, and −0.02) were higher than simulated eigenvalues (0.32, 0.06, 0.05, 0.04, 0.03, 0.02, and 0.02). A principal axis factor analysis with oblimin rotation indicated that the five factors could be clearly interpreted as verbal ability, coding speed, visuospatial ability, mathematical ability, and short-term memory (STM; see Table 2). We also conducted a one-factor factor analysis and found that the general factor explained 36% of variance (see Table 2). For subsequent analyses, we generated unit-weighted composite scores (Bobko, Roth, & Buster, 2007) by first z-standardizing all variables and then taking the average for each composite.

We studied three extrinsic career success criteria. Early career pay was measured using the participants' self-report in 1971–1974 when most participants had finished college and had a job and indicated what they made annually in an open question ("How much was your pay or other earnings [before deductions] on this job?"). As a measure job prestige, we used the available information on the classification of participants' job in 1971–1974 on the job categories in the *Dictionary of Occupational Titles* (DOT; U.S. Department of Labor, 1970). We then linked this information to available Siegel prestige scores for the participants' jobs published by Gottfredson and Brown (1978). Classification information from Project TALENT was available for 16,883 participants and linking to Prestige scores reduced the sample size to 15,810 because of missing prestige ratings for some jobs. Prestige scores have a theoretical range from 0 to 100 and are based on a series of surveys conducted in the 1960s—and the rank-ordering of prestige ratings has been found to be highly stable over time (Hauser & Warren, 1997; Smith & Son, 2014). Finally, late-career income was measured in the reconnect study in 2011–2012 when the participants ($n = 1,796$) mostly had fully or partly retired so that their income also included income from savings and pensions and was affected by other life decisions. They answered the question "Thinking of all income source of your household, what was your total household income in 2010"? on an scale ranging from $1 = less\ than\ \$10,000$, $2 = \$10,000\ to\ \$49,999$, $3 = \$50,000\ to\ \$99,999$, $4 = \$100,000\ to\ \$149,999$, $5 = \$150,000\ or\ more$.

Analyses

Inverse probability weighting. Because the study is based on a substantive population of high-school students, it was possible to correct for sample attrition. To perform these corrections, we relied on inverse probability weighting (IPW; Seaman & White, 2013; Thoemmes & Ong, 2016; Wooldridge, 2007). IPW includes three steps. The first step includes a logistic regression analysis with the study status at follow-up (attrition yes/no) as the dependent variable and the variables of interest on which the two groups potentially differ as the independent variables (the 1960 ability predictors in our research). In the second step, propensity scores are calculated on

Table 2

Principal-Axis Factor Analyses of the Cognitive Ability Tests in Project TALENT

Cognitive ability test	5-Factor Oblimin-Rotated					1-Factor
	3: Visuospatial	4: Mathematical	1: Verbal	2: Coding speed	5: Short-term memory	
Mechanical reasoning	**.74**	.09	.08	−.04	−.06	.62
Visualization 3d	**.69**	.06	.02	.01	.06	.62
Visualization 2d	**.58**	.02	−.03	.19	.06	.52
Abstract reasoning	**.42**	.09	.25	.01	.13	.72
Intro math	.04	**.89**	−.01	−.01	.03	.78
Advanced math	.07	**.63**	−.01	.02	−.09	.53
Arithmetic computing	−.10	**.42**	.12	.28	.20	.61
Arithmetic reasoning	.17	**.42**	.27	−.08	.09	.77
Reading comprehension	.09	.05	**.74**	−.08	.10	.81
Disguised words	−.02	.00	**.70**	.22	.00	.67
Creativity	.31	.03	**.49**	−.04	.04	.71
Word functions in sentences	−.02	.32	**.43**	−.01	.12	.72
Clerical checking	−.11	.04	.08	**.73**	−.05	.20
Table reading	.05	.05	−.02	**.65**	.03	.28
Object inspection	.26	−.10	−.03	**.61**	.08	.32
Memory for sentences	.04	−.05	−.06	−.01	**.61**	.34
Memory for words	−.07	.09	.18	.00	**.52**	.53
Explained variance (%)	.13	.13	.14	.09	.06	.36

Note. For the five-factor solutions, loadings higher than .40 are printed in bold.

the basis of the logistic regression analysis. In the final and third step, the inverse of the propensity scores (1/PS) is used as sampling weights in the main analysis thereby removing differences between the follow-up samples and the full sample with regard to their mean abilities in 1960. IPW only requires a model for the probability that an individual has complete data—a univariate outcome (Seaman & White, 2013; Thoemmes & Ong, 2016). In contrast, other approaches require more assumptions (e.g., multiple imputation needs a model for the joint distribution of the missing data—a multivariate outcome— given the observed data). In the present study, there was very limited missing data in the initial and follow-up data collections but attrition was substantial making the dataset well suited for IPW.

Attenuation corrections. We corrected all cognitive ability predictors for measurement error using the internal consistencies across the tests included in each ability measure and the Spearman attenuation correction formula, $\rho_{T_x T_y} = \dfrac{\rho_{xy}}{\sqrt{\rho_{xx'}\rho_{yy'}}}$. In the special case of the correlations between the specific ability composites and the general ability composite, we relied on Zimmerman and Williams' (1977) extended attenuation correction formula $\rho_{T_x T_y} = \dfrac{\rho_{xy}-\rho_{E_x E_y}\sqrt{1-\rho_{xx'}}\sqrt{1-\rho_{yy'}}}{\sqrt{\rho_{xx'}\rho_{yy'}}}$ to adjust for the fact that the inclusion of tests in both the specific and the general ability composite results in correlated measurement error, $\rho_{E_x E_y}$. $\rho_{E_x E_y}$ can be estimated using Nunnally and Bernstein's (1994, p. 173) composite correlation formula, $r_{wy} = \dfrac{\overline{R}_{wy}}{\sqrt{\overline{R}_w}\sqrt{\overline{R}_y}}$ when one assumes that measurement errors between independent tests are not correlated and identical measures are correlated with 1.[1]

The income and pay variables in the present study and the DOT job classification on which the prestige score was based were objective criteria. In line with earlier work, we therefore did not

correct for measurement error (e.g., Kuncel, Hezlett, & Ones, 2001).

Incremental validity and relative importance analyses. We ran analyses using the three core specific abilities for which we developed theoretical hypotheses and a GMA composite based on the tests included in these core specific abilities. In the incremental validity analyses, we first entered GMA and then each of the specific abilities and also all specific abilities in the second step. In the relative importance analyses, we used dominance weights because it is the most widely accepted modern approach to relative importance analysis (Braun et al., 2019; Grömping, 2015; LeBreton et al., 2004). We estimated bootstrap confidence intervals for all variance shares using the relaimpo package (Grömping, 2006) and the boot package in the R environment (R Core Team, 2018). In supplementary analyses, we also ran the same analyses with all tests included in Table 2 and all five specific abilities including the two for which we did not develop hypotheses (STM and coding speed).

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[1] As a minimal example, consider a correlation matrix of seven tests that all correlate .30 with each other. The first three tests measure a specific ability and the goal is to estimate the correlation between this specific ability and GMA (composite of all tests). The internal consistencies of the specific ability and GMA are Cronbach's $\alpha = .5625$ and $\alpha = .75$, respectively. The uncorrected correlation between the two composites estimated using the Nunnally and Bernstein composite correlation formula is .866. Putting these values into the standard Spearman attenuation formula results in the unrealistic corrected correlation of $\rho_{T_x T_y} = \dfrac{\rho_{xy}}{\sqrt{\rho_{xx'}\rho_{yy'}}} = \dfrac{.866}{\sqrt{.5625 \times .75}} = 1.333$. In contrast, using Zimmerman and Williams' (1977) extended attenuation correction formula yields $\rho_{T_x T_y} = \dfrac{\rho_{xy}-\rho_{E_x E_y}\sqrt{1-\rho_{xx'}}\sqrt{1-\rho_{yy'}}}{\sqrt{\rho_{xx'}\rho_{yy'}}} = \dfrac{.866-.832\sqrt{1-.5625}\sqrt{1-.75}}{\sqrt{.5625 \times .75}} = .91$.

Table 3

Uncorrected and Corrected (Behind the Slash) Intercorrelations, Means, and Standard Deviations of the Study Variables

Variable	1	2	3	4	5	6	7
1. Verbal, 1960	—						
2. Mathematical, 1960	.73/.89	—					
3. Visuospatial, 1960	.64/.77	.60/.75	—				
4. General mental ability 1960[a]	.90/.91	.88/.89	.85/.85	—			
5. Pay, 1971–1974	.11/.12	.20/.22	.26/.28	.22/.22	—		
6. Job prestige 1971–1974	.41/.45	.40/.46	.30/.35	.43/.46	.24	—	
7. Income, 2011–2012	.26/.28	.31/.34	.25/.28	.32/.32	.24	.04	—
N	363,607	363,607	363,607	363,607	84,831	15,810	1,796
M	.00[b]	.00[b]	.00[b]	.00	7,266.71/6,760.27	48.49/48.46	2.87/2.80
SD	1.00[b]	1.00[b]	1.00[b]	1.00	6,791.15/6,632.16	14.39/14.46	.97/.95

Note. Correlations after the slash were inverse probability weighted when not based on the full sample and corrected for attenuation. *M*s and *SD*s after the slash were inverse probability weighted.
[a] Composite based on the verbal, mathematical, and visuospatial tests. [b] *z*-standardized.

Results

Table 3 provides means, standard deviations, intercorrelations, and sample sizes for the study variables. As shown in Table 3, the ability composites were positively correlated with the three extrinsic career success criteria. The positive relationship of GMA with all three criteria supports Hypothesis 1.

Table 4 and Figures 1A, 2A, and 3A include results from the incremental validity analyses to study our Hypothesis 2 that specific abilities would not explain much additional variance in extrinsic career success when GMA is entered first in incremental validity analyses (making the assumption that GMA has a causal effects on the specific abilities). The results confirmed these ideas for job prestige in 1971–1974 and income in 2011–2012. For pay in 1971–1974 (see Table 4 and Figure 1A), visuospatial ability explained a considerable amount of incremental variance, and verbal ability also showed sizable incremental validity albeit with

a negative β weight. These findings were somewhat unexpected on the basis of the earlier literature on job performance. A potential explanation is that jobs that require visuospatial abilities like science and technical jobs (e.g., engineer) may pay good wages also early in the participants' careers. In contrast, high prestige jobs (e.g., lawyer) frequently only lead to a high wage after a long education and career. Overall, our findings partly support Hypothesis 2.

We next examined the results for the relative importance analyses shown in Table 5 and Figure 1B, 2B, and 3B to address our Hypotheses 3 to 7. As indicated in Table 4 and the figures, the results show that GMA was not more important than the specific abilities and only explained a comparatively small amount of the overall explained variance. The majority of the explained variance was explained by specific abilities, and these results thus support our Hypotheses 3. The rank orders and confidence intervals also

Table 4

Incremental Validity Analyses Regressing Pay in 1971–1974, Job Prestige in 1971–1974, and Income in 2011–2012 on General Mental Ability and Three Specific Abilities Measured in 1960

Criterion and predictors	R^2	ΔR^2 vs. Step 1	β General mental	β Verbal	β Mathematical	β Visuospatial
Pay, 1971–1974						
Step 1: General mental	.050 [.047, .053]	—	.22 [.22, .23]	—	—	—
Step 2a: Verbal	.082 [.078, .087]	.033 [.030, .035]	.59 [.58, .61]	−.41 [−.43, −.39]	—	—
Step 2b: Mathematical	.051 [.048, .055]	.002 [.001, .002]	.15 [.13, .16]	—	.08 [.07, .10]	—
Step 2c: Visuospatial	.080 [.076, .085]	.030 [.028, .033]	−.05 [−.06, −.04]	—	—	.32 [.31, .34]
Step 2d: All four	.126 [.120, .133]	.077 [.071, .082]	.14 [.14, .15]	−.51 [−.53, −.48]	.29 [.26, .31]	.33 [.32, .35]
Job prestige 1971–1974						
Step 1: General mental	.208 [.195, .221]	—	.46 [.44, .47]	—	—	—
Step 2a: Verbal	.217 [.204, .234]	.009 [.006, .012]	.26 [.22, .29]	.22 [.19, .26]	—	—
Step 2b: Mathematical	.224 [.211, .238]	.016 [.012, .020]	.24 [.21, .27]	—	.25 [.22, .28]	—
Step 2c: Visuospatial	.213 [.201, .226]	.005 [.003, .008]	.57 [.54, .60]	—	—	−.14 [−.17, −11]
Step 2d: All four	.229 [.216, .243]	.021 [.017, .026]	.28 [.26, .29]	.11 [.05, .16]	.20 [.15, .25]	−.11 [−.13, −.08]
Income, 2011–2012						
Step 1: General mental	.105 [.077, .136]	—	.32 [.28, .37]	—	—	—
Step 2a: Verbal	.106 [.078, .138]	.001 [.000, .007]	.39 [.28, .50]	−.07 [−.18, .04]	—	—
Step 2b: Mathematical	.116 [.087, .152]	.012 [.004, .024]	.12 [.02, .22]	—	.23 [.13, .33]	—
Step 2c: Visuospatial	.105 [.078, .137]	.000 [.000, .004]	.30 [.22, .39]	—	—	.02 [−.07, .11]
Step 2d: All four	.123 [.091, .164]	.018 [.006, .041]	.19 [.16, .22]	−.18 [−.34 −.04]	.30 [.16, .44]	.04 [−.04, .12]

Note. The values in parentheses are 95% confidence intervals estimated using weighted nonparametric bootstrapping with 10,000 replicates and the percentile method.
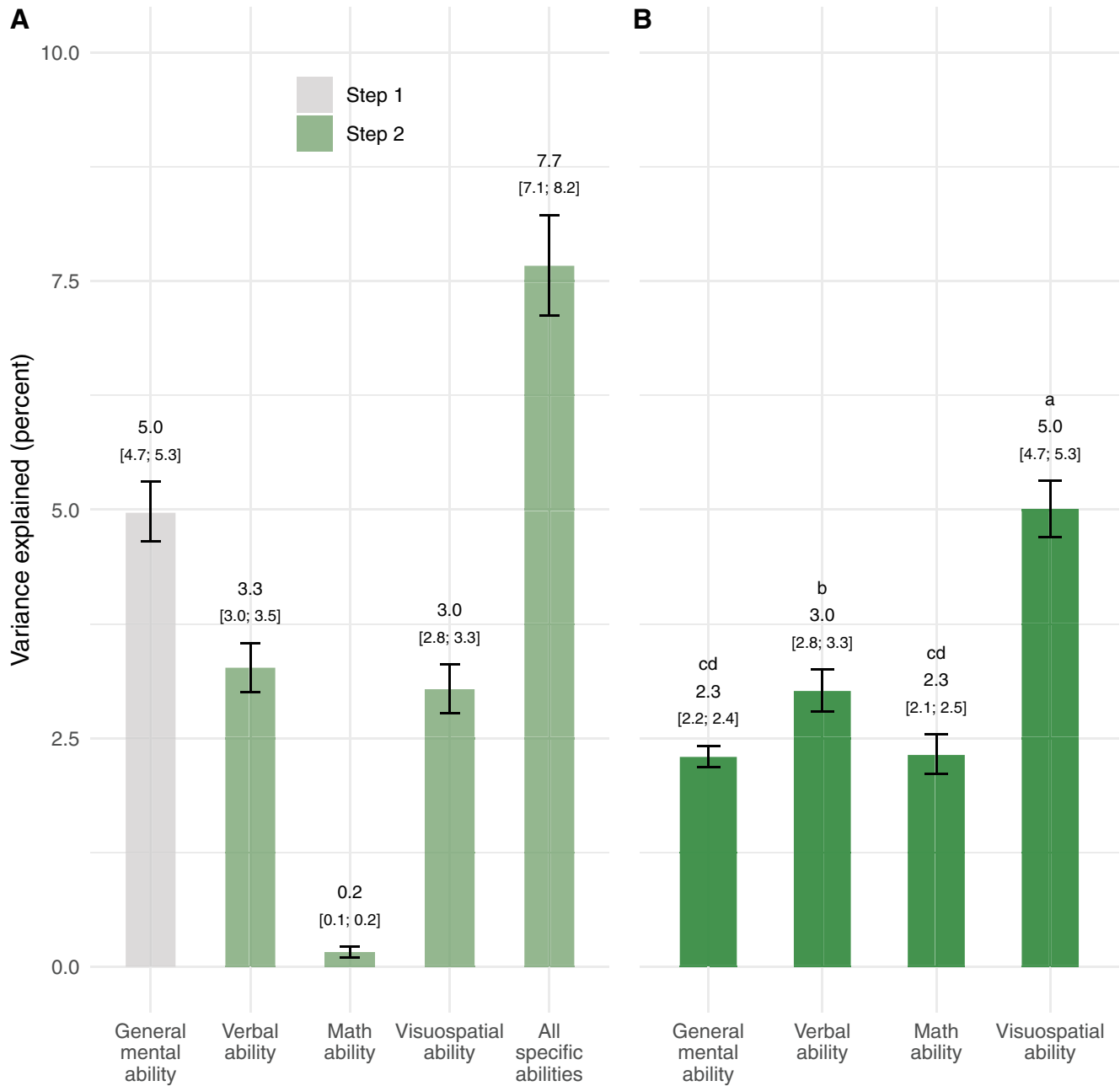
Figure 1. Incremental validity analyses and relative importance analyses regressing pay in 1971–1974 on GMA and specific abilities measured in 1960. Panel A shows an incremental validity analysis. Panel B shows a relative importance analysis. The values in parentheses are 95% confidence intervals estimated using weighted nonparametric bootstrapping with 10,000 replicates and the percentile method. For each weight, the letter(s) above the bar indicates the bootstrapped rank order. Weights with only one letter have a rank order that does not overlap with any other weight (i.e., they substantially differ with a 95% confidence interval from the other weights). Weights that are labeled with more than one letter do not differ from the weights that are labeled with the same letter (the 95% confidence intervals of the difference between the respective two weights overlaps). See the online article for the color version of this figure.

indicate that GMA was not more important than all single specific abilities in any of the relative importance analyses. These results support our Hypothesis 4 suggesting that single specific abilities are equally important as GMA.

We also examined our hypotheses about which specific abilities would be particularly good predictors of the extrinsic job criteria in Project TALENT. As shown in Figure 1B, visuospatial ability had a strong relative weight for pay in 1971–1974 and especially the
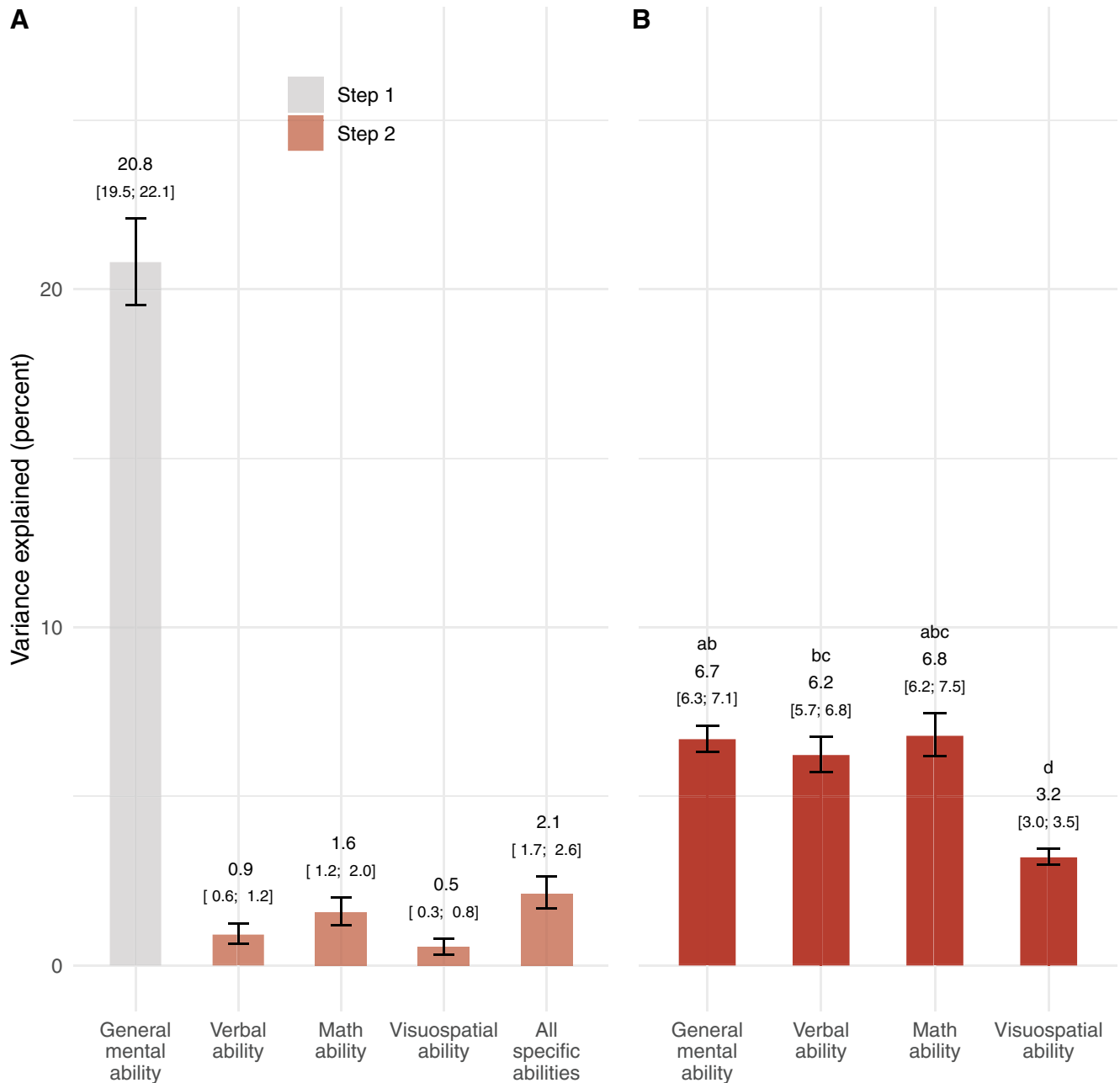
Figure 2. Incremental validity analyses and relative importance analyses regressing job prestige in 1971–1974 on GMA and specific abilities measured in 1960. Panel A shows an incremental validity analysis. Panel B shows a relative importance analysis. The values in parentheses are 95% confidence intervals estimated using weighted nonparametric bootstrapping with 10,000 replicates and the percentile method. For each weight, the letter(s) above the bar indicates the bootstrapped rank order. Weights with only one letter have a rank order that does not overlap with any other weight (i.e., they substantially differ with a 95% confidence interval from the other weights). Weights that are labeled with more than one letter do not differ from the weights that are labeled with the same letter (the 95% confidence intervals of the difference between the respective two weights overlaps). See the online article for the color version of this figure.

relative weight for visuospatial ability clearly exceeded the weight for GMA. In contrast, visuospatial abilities were important for income in 2011–2012 (see Figures 3B) but not more important than GMA. Overall, these findings partially support Hypothesis 5

(visuospatial ability is important for pay and income). We next examined the role of verbal ability in job prestige. The results revealed that verbal ability was indeed an important predictor of job prestige and did not substantially differ from GMA in impor-
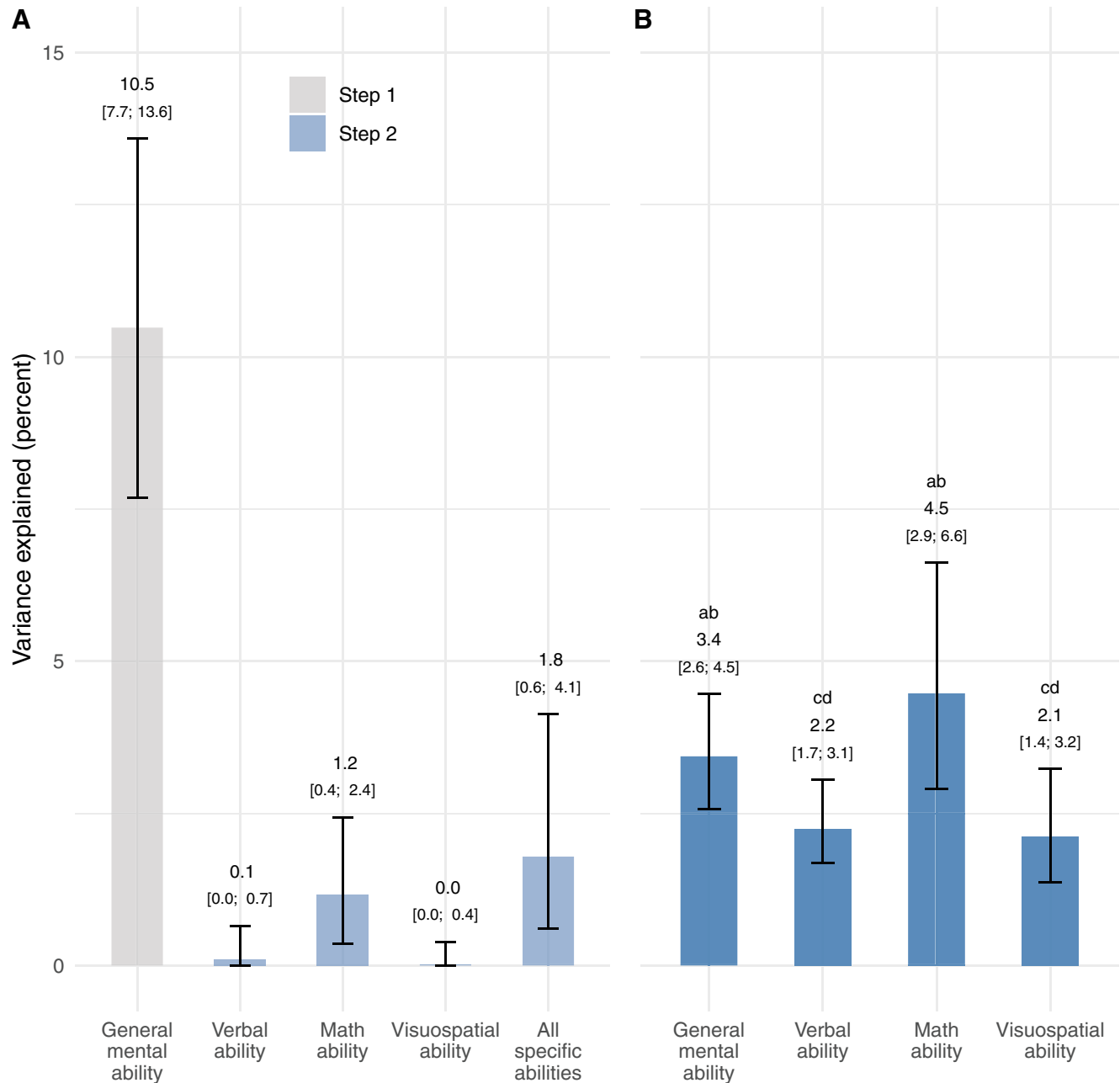
Figure 3. Incremental validity analyses and relative importance analyses regressing income in 2011–2012 on GMA and specific abilities measured in 1960. Panel A shows an incremental validity analysis. Panel B shows a relative importance analysis. The values in parentheses are 95% confidence intervals estimated using weighted nonparametric bootstrapping with 10,000 replicates and the percentile method. For each weight, the letter(s) above the bar indicates the bootstrapped rank order. Weights with only one letter have a rank order that does not overlap with any other weight (i.e., they substantially differ with a 95% confidence interval from the other weights). Weights that are labeled with more than one letter do not differ from the weights that are labeled with the same letter (the 95% confidence intervals of the difference between the respective two weights overlaps). See the online article for the color version of this figure.

tance confirming Hypothesis 6. Finally, we examined the relative importance of mathematical ability. As shown in Figures 1B, 2B, and 3B, mathematical ability was more or equally important as GMA in all analyses and consistently one of the three most important abilities, confirming Hypothesis 7.

We finally ran the supplementary analyses with all five specific abilities including the two specific abilities for which we did not develop hypotheses. As shown in Supplementary Tables S1, S2, and S3, the conclusions regarding our hypotheses did not fundamentally change. However, the variance shares for GMA relative

Table 5

Relative Importance Analyses Regressing Pay in 1971–1974, Job Prestige in 1971–1974, and Income in 2011–2012 on General Mental Ability and Three Specific Abilities Measured in 1960

Criterion and predictors	Dominance weight	Rank	R^2
Pay, 1971–1974			.126 [.120, .133]
General mental	.023 [.022, .024]	cd	
Verbal	.030 [.028, .033]	b	
Mathematical	.023 [.021, .025]	cd	
Visuospatial	.050 [.047, .054]	a	
Job prestige 1971–1974			.229 [.216, .243]
General mental	.067 [.063, .071]	ab	
Verbal	.062 [.057, .068]	bc	
Mathematical	.068 [.062, .075]	abc	
Visuospatial	.032 [.030, .035]	d	
Income, 2011–2012			123 [.091, .164]
General mental	.034 [.025, .044]	ab	
Verbal	.022 [.017, .030]	cd	
Mathematical	.045 [.029, .064]	ab	
Visuospatial	.021 [.014, .033]	cd	

Note. The values in parentheses are 95% confidence intervals estimated using weighted nonparametric bootstrapping with 10,000 replicates and the percentile method. The ranks are bootstrapped ranks. Ranks with only one letter have a rank order that does not overlap with any other weight (i.e., they substantially differ with a 95% confidence interval from the other weights). Weights that are labeled with more than one letter do not differ from the weights that are labeled with the same letter (the 95% confidence intervals of the difference between the respective two weights overlaps).

to the most important specific ability in the relative importance analyses became somewhat smaller (1.7% vs. 5.3%, 6.0% vs. 6.3%, and 1.9% vs. 4.6% for pay in 1971–1974, job prestige in 1971–1974, and income in 2011–2012, respectively) and there were some changes in the exact rank-order of the abilities.

Discussion

We used data from a large longitudinal study that tracked participants from high school until retirement age and examined the role of different abilities in their extrinsic career success (pay, income, and job prestige). This study extends previous research examining the relative importance of GMA and content-aligned specific abilities for predicting job performance (Kell & Lang, 2017; Lang & Bliese, 2012; Lang et al., 2010)—now increasingly recognized in the personnel selection literature (e.g., Hanges, Scherbaum, Goldstein, Ryan, & Yusko, 2012; Ryan & Ployhart, 2014; Schmitt, 2014)—to another research domain. While findings on the role of specific abilities in job performance have potential implications for selection decisions, findings on extrinsic career success are more broadly relevant to individuals' lifelong experiences.

Our results revealed that GMA typically accounted for nearly all of the explained variance in the criterion in incremental validity analyses with specific abilities adding a trivial additional amount of explained variance (However, the results for pay in 1971–1974 are an exception; see Figure 1.) For these same criteria, however, when relative importance analyses were conducted, the majority of the explained variance was explained by specific abilities and GMA was ranked either as equal or below single specific abilities.

The findings for the specific abilities also provided insights into unique characteristics of the extrinsic career success criteria (see Figures 1, 2, and 3).

From a theoretical perspective, this study underscores the important role that different theoretical outlooks and fundamental research about intelligence can play when conducting investigations of even highly practical topics, along with the need to select analytic strategies capable of representing those outlooks methodologically. The field of intelligence is currently in the midst of a vigorous, exciting debate about the nature and structure of the construct(s) that underlie performance on cognitive tests as evidenced by the emergence and reemergence of theories that do not assume that the *g* factor is causal (see Table 1). Many leading cognitive ability researchers are thus open-minded about the status and interpretation of GMA. With this open-mindedness have come explicit calls for more research into the value of specific cognitive abilities (Coyle, 2014) and the view that intelligence includes all cognitive abilities instead of seeing intelligence as a construct that is synonymous with GMA (Carroll, 1997) is increasingly recognized (Beier, Kell, & Lang, 2019; Schneider & Newman, 2015; Stankov, 2017). Open-mindedness about the status of GMA, along with the results of this study and others (e.g., Lang & Bliese, 2012; Lang et al., 2010) that do not show it to be of overwhelming importance, should not be taken as evidence that GMA is *un*important: Findings consistently demonstrate substantial correlations with work-relevant outcomes and, even if the rank-order of a predictor in a relative importance analysis is not Number 1, it can still account for a substantial amount of criterion variance.

This study has several strengths and limitations related to the nature of the Project TALENT data. A strength of the Project TALENT study is the representative nature of the initial sample and the fact that the data extends across essentially the entire professional life of the participants (a 50 year timespan). However, a limitation of the Project TALENT is the fact that the extrinsic career success data were gathered near the beginning and end of participants' careers only. Accordingly, we could not investigate the relationship between intelligence and success during midlife, roughly corresponding to the maintenance (Super, 1957, 1980) or midcareer stage (Lam, Ng, & Feldman, 2012; Melamed, 1996). Future research would benefit from examining the relative importance of abilities at more stages of individuals' careers.

Another limitation is that our investigation was restricted to early career pay, late-career income, and job prestige. These three criterion measures are widely used measures of career success (e.g., Cox & Harquail, 1991; Judge et al., 1999; Lam et al., 2012; Melamed, 1996; Slocum & Cron, 1985; Whitely, Dougherty, & Dreher, 1991). However, these measures capture somewhat distinct aspects of success because high-paying jobs do not always have high prestige and because income captures elements of success beyond simply getting a high-paying job. In future research, it likely makes sense to include additional measures of career success. For instance, measuring salary progression and number of promotions could be of interest in early career stages (Cox & Harquail, 1991), and more detailed questions about the investment strategies of late-career/retired participants may be helpful (e.g., 401(k)s, investments, savings).

Finally, a limitation of this and other longitudinal studies over very long periods of time is their generalizability across time; the

findings of our study may be different had Project TALENT started later. Most notably, we found that visuospatial abilities were especially important for pay early in participants' careers but we did not find a similar effect for pay in retirement. These findings may not hold in future research because the nature of work and skill requirements have changed with the decline of many traditional manufacturing jobs, an increasingly aging workforce, and a broad need for older workers to acquire new, complex skills (Carnevale, Smith, & Strohl, 2013; Charles, Hurst, & Schwartz, 2013; Edgell, 2012).

Practically, this investigation's results provide insight into how developmental experiences (e.g., explicit training interventions, K–12 education) could potentially be designed and altered to facilitate people's success in their careers. Attempts to increase cognitive skills date back over a century (e.g., Binet, 1909; Thorndike & Woodworth, 1901), with the majority of research finding that it is relatively rare (although not impossible; cf. Barnett & Ceci, 2002; Karbach & Kray, 2009) for training to transfer to another domain or broad range of other tasks (De Simoni & von Bastian, 2018; Detterman, 1993). Evidence for near-transfer is much more commonly found (e.g., Melby-Lervåg & Hulme, 2013), however, suggesting that it may be more feasible to train specific cognitive abilities than GMA. Indeed, a recent 60-year longitudinal study showed that education tends to exert positive effects on specific cognitive abilities even while not influencing GMA (Ritchie, Bates, & Deary, 2015). If future research uncovers good evidence that these relationships are of a causal nature, the prospect of enhancing intelligence in order to facilitate workforce success may be brighter when the goal is to train specific cognitive abilities, rather than GMA.

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