ABSTRACT

BEARD, MADISON WHITE. Correlates of Engineer Job Performance: A Meta-Analysis. (Under the direction of Dr. Mark Wilson).

The purpose of the current research study is to begin to organize and summarize the existing literature on the correlates of engineer job performance. This meta-analysis includes comprehensive search of the literature related to engineer performance, a systematic coding and categorization of that literature into a proposed model. The research culminates with a meta-analytic summary of the relationships in the proposed model of the literature. Organizing and summarizing the literature helps to illustrate the current needs of this stream of research and foster greater interest in the performance of some of the most productive members of the American workforce, Engineers.

Correlates of Engineer Job Performance: A Meta-Analysis

by
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DEDICATION

This work is dedicated to my family. Thank you for your love and support through the years in my pursuit of knowledge. You truly are the best village. My loving husband Shannon encouraged me to follow my dreams, and my boys Jackson and Ezra, challenged me to follow all of my dreams simultaneously.

BIOGRAPHY

Industrial and Organizational Psychology allows for the data-driven study of workers in the workplace. My research highlights the importance of STEM workers (specifically engineers) and investigates how to better predict the job performance of this population. I am also interested in employee engagement, work life balance, stress and coping, and personality in the management of teams. My goal is to make a positive impact in the lives of workers by selecting the right people for the job, and making their time at work more productive by limiting obstacles to worker competence, autonomy, and relatedness (Deci & Ryan, 2000).

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INTRODUCTION

Correlates of Engineer Job Performance: A Meta-Analysis

Many economists believe that STEM (science, technology, engineering, math) occupations drive competitiveness and innovation. A study by the US Department of Commerce in 2011 highlighted that in the past decade, growth in STEM jobs was three times the job growth in non-STEM jobs (Langdon, McKittrick, Beede, Beethika & Doms, 2011). Crucial to the sustained growth and stability offered to the US economy by the STEM industries is the ability to successfully train STEM workers, select them for appropriate jobs, and have them perform well in these jobs. Considering the importance of engineers to economic growth, the current Industrial and Organizational Psychological literature has surprisingly little research predicting the job performance of these professionals. Of the literature that addresses this issue; no meta-analysis has yet been performed. This study is an initial step to provide direction for research in selection and performance of engineers. Following Huffcutt's (2004) steps for meta-analytic research we must identify all relevant literature assessing the selection and performance of engineers, identify inclusion criteria, organize literature into a comprehensive model, and then meta-analyze the current literature in order to more clearly describe current relationships and direct future research. The goal of the current research is to summarize the state of the literature assessing engineer performance by modeling and meta-analyzing the data.

First, inclusion criteria for the literature search were identified. All studies with an engineer population, relevant predictor variables, and some sort of performance/outcome variables are included in the comprehensive literature review (*Table* 1). Included studies also specified all relevant statistics, or the statistics were provided by the researchers upon

request. All studies that met the criteria were included and coded regardless of the year of publication; the earliest study included was Laycock and Hutcheon in 1939. Keller (2011) conducted interesting research on scientists and engineers but did not report the engineering sample separate from the scientist sample. In such cases, attempts were made to contact the researcher in order to include this data in the meta-analysis. Unfortunately, Keller did not respond to numerous requests for his data.

The literature search for the current study began with a basic digital database search for existing research publications including the term engineer, and one of the following: job performance, success, selection, performance, skill, ability, attitude, or personality. The total number of studies identified during the comprehensive search process was 122. Most of these studies did not meet inclusion criteria. Included articles in the literature review (N=26) measured performance of a specifically stated engineering sample. Studies that were not an engineering sample, did not have a performance outcome, were not empirical, or did not report necessary correlations were not included in the literature review and resulting model of the literature. If a study was published before 1980 and did not report the necessary meta-analytic correlations, no attempt was made to contact the researcher for inclusion in the meta-analysis. A cutoff date of 1980 was set with the assumption that most data for research published after 1980 would be digitalized, and the researchers would be available to contact. A comprehensive model of existing research was formed (*Figure 1*) by categorizing the predictors of performance studies by the included articles (summarized in *Table 1*).

The model categories were formed around common predictors of performance and moderators studied by multiple researchers. To be clear, the literature model (*Figure 1*) includes all relevant relationships identified by the inclusion criteria and subsequent literature

search; all relationships possible within this model will be meta-analyzed. The proposed model of the literature (*Figure 1*) has four predictor categories: general mental ability, specific abilities, personality factors, and attitudes. There were also four categories of performance outcomes common within existing literature: test performance, supervisor judgment rating of performance, number of patents or publications, and tenure/retention. The two moderators that met the qualifications for categorization in the model were sub-field of engineer, and work context (school vs. job performance, and team vs. individual performance). A review of the literature follows describing the categorization of predictors and performance for the comprehensive model of the literature (*Figure 1*).

There is a well-known link between general mental ability (GMA) and performance on almost any task (Schmidt & Hunter, 2004). This relationship is one of the most heavily researched in the existing engineer performance literature. Most researchers found a moderately strong correlation between GMA and the engineer's performance on tests (Berdie & Sutter, 1950; Cohen, 1946; Huang & Fang, 2013; Laycock & Hutcheon, 1939; Pierson & Jex, 1951). Many of these studies assessed test performance of engineers in engineering college. Researchers found a less impressive, but still substantial positive correlation between GMA and supervisor judgment ratings of performance on the job (Bertua, Anderson & Salgado, 2005; Lee, 1988). One question the proposed meta-analysis will attempt to address is does specific context matter? Does the relationship between GMA and supervisor rating of job performance significantly differ when job complexity is assessed as a moderator (Bertua, Anderson & Salgado, 2005)? None of the researchers using GMA as a predictor of engineer performance assessed the correlation of GMA to patents/publications or tenure/retention.

Many different types of specific abilities were of interest to researchers addressing the performance of engineers (for a comprehensive list of predictors *see Table 1*). Those assessing test performance as an outcome chose predictive specific abilities such as math ability (Berdie & Sutter, 1950; Huang & Fang, 2013; Pierson & Jex, 1951), mechanical aptitude (Laycock & Hutcheon, 1939; Pierson & Jex, 1951), and English ability (Pierson & Jex, 1951). Researchers assessing supervisory ratings of job performance as an outcome chose specific abilities such as communication (Lee, 1988; Lee, 1994), decision making ability (Lee, 1988), creativity (Kirkpatrick, 1956), job knowledge (Kirkpatrick, 1956), and mechanical comprehension (Kirkpatrick, 1956). Deng, Doll and Cao (2008) assessed the correlation between absorptive capacity and information technology (IT) ability on task productivity and task innovation. They define absorptive capacity as "a person's ability to recognize the value of new information, assimilate it, and apply it to commercial ends" (Deng, Doll, & Cao, 2008, p. 75). They found a significant relationship between absorptive capacity and performance outcomes. Perhaps more interestingly, a strong positive relationship between IT ability and task productivity suggesting the importance of IT as a specific ability for engineers. Kirkpatrick found that sub-field moderated the relationship between certain specific abilities and supervisor judgment rating of performance. The current meta-analysis will look more specifically at the potential for moderation of sub-field on the relationship between specific abilities and different types of performance. None of the researchers using specific abilities as predictors of engineer performance assessed the correlation of specific abilities to tenure/retention.

Researchers interested in the correlation between personality and performance of engineers mainly focused on the Big Five factors (IPIP) of personality including openness,

conscientiousness, extroversion, agreeableness, and neuroticism. Researchers correlated these commonly assessed personality traits with test performance (Yueh, Chang & Liang, 2013), and an earlier version of these traits (the Bernreuter Personality Inventory) with test performance (Laycock & Hutcheon, 1939). Many more researchers were interested in the correlation between the IPIP and supervisory judgment ratings of job performance (Acuña, Gómez, & Juristo, 2009; Keller, 2011; O'Neill & Allen, 2011). Moscoso and Iglesias (2009) assessed the importance of the big five personality factors in tenure of engineers. They found that conscientiousness and agreeableness had the highest correlations with retention of engineers in the field. An overwhelming majority of the researchers assessing personality as a predictor of performance found support for conscientiousness correlating positively with performance (on graded tests and on the job), and the negative correlation between neuroticism and performance on the job.

Other aspects of personality that were of interest to researchers in relation to supervisory judgment ratings were self-esteem (Keller, 2011) and generalized locus of control (Keller, 2011). Unfortunately Keller did not separate his sample of engineers and scientists, and could not be contacted, so this data will not be included in the meta-analysis. The meta-analysis will attempt to address the importance of job context (team versus individual assessment of performance) in the relationship between personality factors and supervisory judgment ratings of performance. Another moderator of interest that will be addressed in the meta-analysis is the potential moderating effect of sub-field in the personality and performance relationship of engineers.

Engineer attitudes was the only predictor category that was studied in relationship to all four of the outcome variables in the proposed model, probably because it is the most

broad of the categories. Researchers interested in the outcome of test performance looked at the relationship between self-efficacy (Cross & Vick, 2001; Yueh, Chang & Liang, 2013) and the Bernreuter Personality Inventory factors (Laycock & Hutcheon, 1939) on test performance in engineering schools. Researchers interested in the correlation between engineer attitudes and supervisory judgment ratings addressed job satisfaction (Acuña, Gómez, & Juristo, 2009; Keller, 1997; Mossholder, Bedeian, Niebuhr, & Wesolowski, 1994), organizational commitment (Keller, 1997), and effort and motivation (Kirkpatrick, 1956). Researchers interested in numerical outcomes such as patents and publications chose attitude predictors such as leader positivity (Avey, Avolio & Luthans, 2011), job satisfaction, job involvement, and organizational commitment (Keller, 1997). Researchers interested in tenure/retention outcomes chose self-efficacy (Cross & Vick, 2001), role conflict, job involvement, job satisfaction, organizational commitment, and career satisfaction (Igbaria & Siegel, 1992) as correlates. We know worker attitudes are important correlates of performance in the general population, but we do not know how strong these correlates are in an engineering sample. The proposed meta-analysis will identify common attitude correlates of each performance outcome and meta-analyze all possible relationships within the proposed model.

The purpose of the proposed study is to organize, describe, and analyze existing literature on the correlation between selection measures and performance outcomes in the field of engineering. The meta-analysis of this data will help to clarify our understanding of what we already know about engineer performance and where future research efforts should be focused.

The present research will address the following research questions:

1. What literature exists assessing the performance of engineers?

2. What is the best way to model the existing literature assessing the performance of engineers?

3. Which relationships within the model have enough data to be meta-analyzed?

4. What does the meta-analysis tell us about selection measures in correlation with performance outcomes of engineers?

More specifically, the following research questions address each arrow in the model of existing literature (*Figure 1*) that meta-analysis will attempt to answer: Based on existing research, how strong is the correlation between GMA and test performance? How strong is the correlation between GMA and supervisor judgment ratings; does context (team vs. individual, school vs. job setting) moderate this relationship? Based on existing research how strongly do specific abilities correlate with test performance; does context moderate this relationship? How strong is the correlation between specific abilities and supervisor judgment ratings; does sub-field moderate this relationship? How strong is the correlation between specific abilities and number of patents/publications? Based on existing research how well do personality factors correlate with test performance? How strong is the correlation between personality factors and supervisor judgment ratings; does sub-field or work context moderate this relationship? How strong is the correlation between personality factors and tenure/retention? Based on existing research how well do certain attitudes correlate with test performance, supervisor judgment ratings, patents/publications, and tenure/retention?

Method

The methodology of the present meta-analysis follows the five main steps proposed by Huffcutt (2004). First, clearly specify the relationship being studied. Second, conduct a thorough search for research studies that have analyzed the specified relationship. Include published research, dissertations, tech reports from companies, and new or unpublished research. Then, create a list of criteria (or standards) that the studies located must meet before they are included in the meta-analysis. Next, at least two persons should code the included studies for information needed from the research; mainly *r* correlation and *d* difference of independent groups. Finally, a mathematical summary of the findings of the meta-analysis should be calculated (mean of the test statistic values; then the variability with moderators) (Huffcutt, 2004). Each of the five steps will be discussed in detail.

Step 1. Specify Relationship

This study is interested in the correlates of performance in specifically stated engineering samples. The samples of engineers were mainly categorized as engineers working in their field (on the job) or engineers within an engineering program in a University setting (engineering students).

Step 2. Comprehensive Search

The search for articles to be included in a meta-analysis is arguably the most important key to the validity of the overall meta-analysis. A comprehensive literature search including reviewed articles, references in studies, computerized bibliographic databases, bibliographic reference volumes, relevant journals, conference programs and proceedings was conducted. In addition, authors or experts in the area, and any relevant government agencies (Lipsey & Wilson, 2001) were contacted. The literature search for the current study

began with a basic digital database search for research including the term engineer, and one of the following: job performance, success, selection, performance, skill, ability, or personality. The psychology databases searched for key terms include ProQuest educational journals, PsycINFO, PsycARTICLES, and Web of Science. Engineering research databases searched include IEEE Xplore, INSPEC, ACM Digital Library, Derwent innovations index, and Business source complete. The online database Google Scholar was also utilized.

The articles were then snowballed for the references cited for each study, and the search expanded. Snowballing is a literature search technique that upon identification of an appropriate study through a traditional search, the researcher then attempts to locate the reference articles from the already identified study. These articles may be different than those available through a traditional database search. After the preliminary search was completed, a team of five research assistants performed a parallel search to make sure all relevant studies were gathered by repeating the database search and snowballing processes.

Step 3. Using Inclusion Criteria

The total number of studies identified during the comprehensive search process was 122. Most of these studies were not included in the comprehensive literature review because they did not meet inclusion criteria. Included articles in the literature review (N=26) had to measure either school or on-the-job performance of a specifically stated engineering sample. Studies that did not have a performance outcome (n=48), were not an engineering sample (n=28), were not empirical (n=14), or did not report correlations necessary (and were from 1980 or earlier) were not included in the literature review and subsequent model of the literature (n=6). The cutoff date of 1980 was chosen because the researchers believe it would

be reasonably difficult to track down the appropriate correlational data of the studies published before this date.

Step 4. Coding and Analysis

A preliminary coding of all included articles was conducted by the primary researcher. In an attempt to identify mediator and moderator variables, all studies were coded for common study inclusion criteria points in order to determine if those items had influence on the studies. These criteria included the following: key variables, operationalization of variables, population (size, type, age, gender, and tenure), organization industry, timeframe, and publication type (Lipsey & Wilson, 2001).

To ensure accuracy of coding information, all study procedures including coding and computation of the test statistic values were independently recorded by another researcher. Disagreements about coding and computation were discussed and resolved by consensus. No disagreements occurred through this process.

Coding of the research articles include the test statistics *r* correlation and *d* difference of independent groups. This is important to create a mathematical summary of the findings of the meta-analysis including the mean of the test statistic values, and the variability with moderators (Huffcutt, 2004). Many different measures of the same constructs have been utilized within the included studies, and can be combined because they are "linearly equitable" with each other (Hedges & Olkin, 1985). Another way to conceptualize linear equitability is when researchers measuring the same underlying construct use different measures as predictors. In some ways, combining these measures into meta-analysis would help to parcel out measurement error. See *Table 1* for a complete list of operationalizations of constructs in each study included in the literature review.

Two main types of moderators have been assessed by other researchers: sub-field of engineer (Bertua, Anderson, & Salgado, 2005; Kaufman, 1978; Kirkpatrick, 1956; Kozlowski & Hults, 1986; Lee, 1994) and work context variables. One work context variable that has been studied is predicting performance of engineering students versus predicting performance of engineers that are on the job. Other work context moderators that have been studied are job requirements (Lee, 1988) and engineer experience or tenure (Kozlowski & Hults, 1986). Moderators will be analyzed for any effect on the relationship between selection and performance of engineers.

Utilizing this well-established five step meta-analytic procedure put forth by Hunter and Schmidt (1990) should result in informing a theoretical framework for continued research in this important area. Engineers and other highly skilled workers are essential to our current economic climate, one in which research in selection and job performance of these workers will be increasingly valuable.

Results

A bare-bones meta-analysis was performed correcting for as many artifacts as possible including sampling error across studies (Hunter & Schmidt, 2004). The goal of this analysis is to gain a more complete picture of the relationships between predictor and criterion in engineer performance, to better understand the construct-level relationships between what we select for, and how we measure performance. A weighted correlation for each relationship in the meta-analysis model was calculated and is presented in *Table 2*. Within bare-bones analysis, studies are mathematically weighted according to the individual study sample size. None of the included studies were significantly larger than the other

studies within the meta-analysis, so the weighted means presented are the best way to attempt to correct for sampling error.

From the 26 included articles in the study, 12 correlational relationships addressed GMA and performance outcomes of Engineers (k = 12, n = 2,207). Nine of those relationships assessed GMA as a correlate of test performance, two assessed the correlation of GMA and supervisory ratings of performance, and only one relationship reported a correlation between GMA and tenure/retention (see *Table 2*). No study reported correlations between GMA and engineers producing patents or publications.

Within the included studies, 86 relationships were coded reporting a correlation between a specific ability and a performance outcome (k = 86, n = 10,565). Seventeen of those relationships assessed specific abilities as correlates of test performance, 65 assessed the correlation of specific abilities and supervisory ratings of performance, 4 reported a correlation between a specific ability and patents/publications (see *Table 2*). No study reported correlations between a specific ability and tenure or retention in the engineer population.

Forty-five correlations were reported between personality traits and performance outcomes (k = 45, n = 7,073). Ten of those relationships assessed personality traits as correlates of test performance, 28 assessed the correlation of personality traits and supervisory ratings of performance, and 7 assessed the correlation of personality traits with measures of tenure or retention (see *Table 2*). No study reported correlations between personality traits and patents or publications in the engineer population.

Sixty correlations were found reporting a correlation between an attitude and performance outcome (k = 60, n = 8,600). Eleven of those relationships assessed attitudes as

correlates of test performance, 24 assessed the correlation of attitudes and supervisory ratings of job performance, 12 assessed the correlation between attitudes and patents/publications, and 13 assessed the correlation of attitudes with measures of tenure/retention (see *Table 2*).

Meta-Analysis

Two meta-analytic calculations were performed on GMA predictors of test performance. Both intelligence tests (k = 3, n = 365, r =0.45) and GPA (k = 6, n = 1,029, r =0.43) were significantly positively correlated with test performance in the engineering population (see *Table 3*).

Five significant main effects of specific abilities and performance outcomes were calculated. Math (k = 3, n = 617, r =0.56) and mechanical aptitude (k = 5, n = 984, r =0.32) were both significantly positively correlated with test performance outcomes of the engineering population. Engineering ability (k = 15, n = 754, r =0.11), creativity (k = 4, n = 1,070, r =0.35), and communication (k = 29, n = 1,217, r =0.04) were all significantly positively correlated with supervisor ratings of performance.

The moderators of specific abilities and performance outcomes are a little more complicated. Engineering ability as a predictor of supervisor ratings of job performance for highly analytical jobs (k = 7, n = 370, r = 0.08) has less of an impact than engineering ability in jobs considered low analytical (k = 7, n = 293, r = 0.15). Communication, operationalized as the number of communications per day, was a significantly correlated with supervisor ratings of job performance when moderated by sub-field. The direction of the correlation was negative with engineers involved in drafting (k = 4, n = 44, r = -0.34), and positive with those performing testing and analyses (k = 4, n = 120, r = 0.07), programming (k = 4, n = 100, r = 0.01), and production (k = 4, n = 64, r = 0.09) (see *Table 4*). The interesting statistics

calculated with the sub-field moderation of R&D and design engineers suggested another unaccounted for moderator of the relationship between communication and job performance. This will be addressed in the section for moderator analyses.

Three significant main effects of personality traits and performance outcomes were calculated. Self-esteem was significantly positively correlated with test performance (k = 3, n = 394, r = 0.14) of the engineering population. Conscientiousness (k = 5, n = 740, r = 0.40), and integrity (k = 4, n = 226, r = 0.33) were significantly positively correlated to supervisory ratings of job performance. In a team context, openness (k = 3, n = 358, r =0.90), conscientiousness (k = 5, n = 487, r = 0.29), and agreeableness (k = 3, n = 358, r = 0.17) are significantly positively correlated with supervisory ratings of job performance within the engineering population (see *Table 5*).

Because of the wide variety of attitudes studied in relation to performance outcomes, only one main effect could be calculated from this meta-analysis. Feelings of autonomy within the workplace were significantly positively correlated with supervisor judgement ratings of performance (k = 8, n = 543, r = 0.27). This relationship is even stronger for engineers involved in research and development (k = 3, n = 191, r = 0.41) suggesting moderation by sub-field (see *Table 6*).

Moderator Analysis

The meta-analysis of the specific ability of communication (average number of communications per day) and supervisor ratings of job performance produced a wide confidence interval suggesting some other form of moderation was at work (see *Table 4*). Communication in the studies was recorded as number of communications per day with different groups of people: supervisor, team, inter-department, extra-department, and people

outside the organization. Surprisingly, when number of communications was moderated by inter-organizational communication (k = 15, n = 679, r = -0.06) and extra-organizational communication per day (k = 14, n = 538, r = 0.08) the relationship with supervisory ratings of job performance becomes a bit clearer. The more contacts an engineer has during the day with people they work with is correlated with lower supervisor ratings of job performance. However, if they have many more extra-organizational communications per day, this behavior is correlated with higher supervisor ratings of job performance (see *Table 7*).

Discussion

The purpose of the present study is to organize and analyze existing literature on the relationship between selection measures and performance outcomes in the field of engineering. Several of the relationships outlined in the model of existing literature (*Figure 1*) had enough data to be meta-analyzed.

The meta-analysis illustrated a strong positive correlation between GMA and test performance within the engineering population. A correlation we see throughout the literature, and expressly researched in Barrick and Mount's (1991) meta-analysis of GMA and job performance. More recent research studied GMA as a predictor of training outcomes (test outcomes) and suggested a significant moderation by occupation; the higher the job complexity the stronger the correlation (Bertua, Anderson, & Salgado, 2005). Bertua et al. (2004) assessed the relationship between GMA and test performance moderated by occupation in a broad sense. They did not look within the engineering population to detect the nuances of this correlation. This research begins to build the case that engineers, because of the high complexity of most engineering roles, are measurably different in terms of how strong GMA predicts test performance outcomes. The present meta-analysis illuminates the

lack of research in how GMA relates to supervisor judgment ratings of engineers. No research has addressed the potential moderators of GMA and performance within this population (see *Table 2*).

Specific abilities of math and mechanical aptitude are positively correlated with test performance of engineers within a university setting. Creativity is a strong correlate with supervisor ratings of job performance within the engineering population. Engineering ability (operationalized by scores on engineering tests) were significant correlates with supervisory ratings of job performance, but not as significant as was expected. Job complexity significantly moderated this relationship. The less analytical the job, the stronger the correlation between engineering skill and supervisor ratings of job performance. In other words, engineers in less analytically challenging jobs are rated as high performing by their supervisors. However, a pair of correlations suggests the relationship between engineering ability and supervisor ratings of job performance has a negative relationship in a team context. The better the engineer tests on paper, the worse they perform on the job, within a team setting. We were unable to address the relationship between specific abilities and patents/publications, or tenure/retention outcomes as there were not enough studies to meta-analyze. A more rigorous analysis of how sub-field and job contexts moderate these relationships is warranted (see *Table 4*).

Self-esteem was the only personality trait with enough data to meta-analyze in relation to test performance. Conscientiousness and integrity both had a strong positive correlation with supervisor ratings of job performance in line with the existing literature on these traits (Ones, Viswesvaran, & Schmidt, 1993). However, the impact of conscientiousness decreases in a team setting. Witt, Burke, Barrick and Mount (2002)

suggest that in team settings, it may be more important to look at the intra-individual interaction of conscientiousness and agreeableness. They found that when conscientiousness was high, but agreeableness of the same individual was low, there was a negative impact on performance within a team context. Maybe some of the variance in personality predicting performance could be accounted for by hierarchical linear modeling for interactions of intra-individual personality traits.

Openness was very strongly correlated with supervisor ratings of job performance in a team context; a relationship supported by the literature across occupations (Bell, 2007). Openness seems to have a stronger correlation with team performance and decision making when technological communication was used within team interaction (Colquitt, Hollenbeck, Ilgen, LePine, & Sheppard, 2002). This finding suggests the predictive importance of openness in the highly technological atmospheres in which most engineering teams work. There is also opportunity to look at the moderating impact of occupation or sub-field on these relationships. Agreeableness was also correlated with supervisory ratings of job performance in a team context, a finding in line with existing literature. Not enough research has been completed to assess the relationship of the Big Five and test performance or tenure/retention of engineers. None of the collected studies assessed the relationship between personality factors and patents or publications (see *Table 5*).

Of the research included, many different attitudes were of interest as correlates of types of performance in the engineering field. The only attitude with enough data to meta-analyze was employee perception of autonomy in correlation with supervisor rating of job performance. This meta-analytic correlation was even stronger in engineers involved in Research and Development. Bailyn (1985) conducted an interesting study distinguishing

between strategic autonomy (freedom over research agenda) and operational autonomy (procedures of the research process). Findings suggested that levels of these two different types of autonomy should not be stable over time and there should be more choice in the levels of each type for R&D performance to thrive. This area is in need of some cohesion and refinement in the correlates of attitude and different types of job performance in engineers (see *Table 6*).

One of the challenges of this research has been to articulate clearly the need for specialized research targeting performance of engineers. Why are engineers unique and how do we define engineering as a profession? Are engineers qualified by job title alone, or do they need to be certified? Are all sub-fields of engineering the same as far as selection and predicting job performance? These are all great questions that deserve further investigation. I believe this study provides a good overview of the numerous holes within this field of research.

Methodological Considerations

Meta-analysis offers a more useful review of existing research than a narrative overview, and has many benefits including the discussion of the characteristics or moderators of existing studies with varying effect sizes (Shadish, Cook, & Campbell, 2002). Meta-analyses are particularly useful in streams of research that have not had a meta-analytic summarization in the past. Founded with the goal of decreasing sampling error, meta-analysis eliminates the effects of sampling error on research findings by averaging them out (Huffcutt, 2004). This process offers a way to unify the findings of many previous studies and to start to more conclusively state relationships between variables (Shadish, Cook, & Campbell, 2002).

Conversely, there are many methodological issues with meta-analysis. There is the common complaint of meta-analysis being subjective; that identifying, coding, and inclusion criteria are hard to replicate. To that, I believe that attempting to organize, analyze, and present the state of the current literature in an objective way is a massive undertaking. One that should be attempted instead of slighted due to fear of subjectivity. Then, there is the file drawer problem; published studies usually report significant correlations, but the studies of the same relationship without significant findings are filed away in a drawer unable to be meta-analyzed (Hunter & Schmidt, 2007). Publishers of scientific articles should be better at recognizing the importance of non-significant results, and making these results centrally available and accessible.

Lastly, correcting for sampling error can only slightly improve the generalizability of results, especially with such a small number of relationships analyzed. In the past, meta-analyses have been criticized in the past for too few studies in a topic area (Hunter & Schmidt, 1990). Some authors have even claimed that meta-analyses should include several hundred studies to be valid (Arthur, Winston, & Huffcutt, 2001). However, the number of studies included in meta-analyses does not bear on the appropriateness of the statistical technique (Mullen, 1989). Meta-analysis techniques can be applied when there are as few as two or three relevant studies (Hunter, Schmidt & Jackson, 1982; Lipsey & Wilson, 2001; Mullen, 1989). The number of studies will vary depending on the topic chosen and how many studies have been published on the topic, with higher numbers in more established lines of research. Most meta-analysis guidelines suggest that including all relevant studies is more important than the number of studies included. The key is to have a wide and comprehensive search that decreases effects of sampling error, with the largest threat to

validity being that included and excluded (or uncollected) studies will systematically differ (Cooper, 1984; Mullen, 1989). In a 1990 estimate by Hunter and Schmidt, most meta-analyses include a range of 5-80 studies. The current meta-analysis, with 26 included studies, is firmly within the average range.

Implications and Future Directions

Engineers, and other STEM workers, are the future of the US economy. The closer researchers get to being able to predict the unique performance of sub-fields of engineers within nuanced job context, the more productive our selected engineers will be. This study has provided a summarized cornerstone of literature for selection innovation research in the field of engineering, highlighting the immense gaps in the current literature, and providing evidence that engineer selection should be including GMA, specific abilities, personality, and attitudes to provide incremental validity that correlates with measures of performance. At this time the correlations illustrated by the current meta-analysis do not in and of themselves make a case for prediction of performance; more research should be directed in an attempt to add predictive validity.

The next step should be to create a valid classification of sub-fields within engineering, and more broadly, occupations as a whole. Accounting for the moderating effects of occupational group using meta-analysis is a nightmare, because researchers are not classifying occupational groups in the same way. Within the engineering literature, the most common classification was looking at R&D engineers separate from the rest of the engineers in the population. This is not enough. There are more useful ways of determining the type of work engineers are performing, and subsequently, the types of workers that should be selected to perform this work.

Finally, more data in the field needs to be collected. Companies should add assessments of personality traits and attitudes so that patterns affecting performance may be ascertained. Researchers should make the case to engineering companies that collecting more data relative to employee performance provides useful tools for predicting future employee success. Engineers typically pride themselves on analytical thought, and data driven decision making. The case for extending those data driven decisions into the recruitment and selection process should not be difficult. Forward thinking companies like Google and Amazon have already begun utilization of these powerful selection tools to select employees in hopes of better performance outcomes of their highly skilled workers.

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Table 1 Summary of Existing Research

Author	Year	IV Construct	IV Operationalization	DV Construct	DV Operationalization
Huang & Fang	2013	Ability	GPA	Test Performance	Final Grade
		Math and Science Ability	GPA	Test Performance	Final Grade
		Dynamics Ability	Exam Scores	Test Performance	Final Grade
Yueh, Chang & Liang	2013	Openness to Experience	BFMM	Test Performance	GPA
		Conscientiousness	BFMM	Test Performance	GPA
		Generative Cognition	Hsu et al. (2013)	Test Performance	GPA
		Self-Efficacy	Hsu et al. (2013)	Test Performance	GPA
Avey, Avolio & Luthans	2011	Complexity	Experimental Condition	Problem solving	Solution quantity
		Leader Positivity	Experimental Condition	Problem solving	Solution quantity
Keller	2011	Self-Esteem	Rosenberg (1965)	Job Performance	Supervisor Ratings
		LOC (internal)	Rosenberg (1965)	Job Performance	Supervisor Ratings
		Need for clarity	Rosenberg (1965)	Job Performance	Supervisor Ratings
		Innovative orientation	KAI	Job Performance	Supervisor Ratings
O'Neill & Allen	2011	Openness	IPIP	Team Performance	Supervisor Team Rating
		Conscientiousness	IPIP	Team Performance	Supervisor Team Rating
		Extraversion	IPIP	Team Performance	Supervisor Team Rating
		Agreeableness	IPIP	Team Performance	Supervisor Team Rating
		Neuroticism	IPIP	Team Performance	Supervisor Team Rating
		Conscientiousness Comp.	JPI-R and PRF	Team Performance	Supervisor Team Rating

Acuña, Gómez & Juristo	2009	Neuroticism	NEO FFI test	eam Performance	Supervisor Team Rating
		Extraversion	NEO FFI test	Team Performance	Supervisor Team Rating
		Openness	NEO FFI test	Team Performance	Supervisor Team Rating
		Agreeableness	NEO FFI test	Team Performance	Supervisor Team Rating
		Conscientiousness	NEO FFI test	Team Performance	Supervisor Team Rating
		Social Conflict	GCQ & ICQ	Team Performance	Supervisor Team Rating
		Task Conflict	GCQ & ICQ	Team Performance	Supervisor Team Rating
		Cohesion	GCQ & ICQ	Team Performance	Supervisor Team Rating
		Autonomy	Molleman's Q	Team Performance	Supervisor Team Rating
		Interdependency	van der Veft et al. Q	Team Performance	Supervisor Team Rating
		Satisfaction	Gladstein's Q	Team Performance	Supervisor Team Rating
Moscoso & Iglesias	2009	Openness	IP/5F	Job Experience	Tenure
		Conscientiousness	IP/5F	Job Experience	Tenure
		Extroversion	IP/5F	Job Experience	Tenure
		Agreeableness	IP/5F	Job Experience	Tenure
		Emotional Stability (Neuroticism)	IP/5F	Job Experience	Tenure
Volmer & Sonnentag	2009	Expert Ability	Supervisor rating	Team Performance	Supervisor Ratings
		Team Ability	Supervisor rating	Team Performance	Supervisor Ratings
		Expert Ability	Felfe (2006)	Team Performance	Supervisor Ratings
		Team Ability	Felfe (2006)	Team Performance	Supervisor Ratings

Deng, Doll & Cao	2008	Absorptive Capacity	Igbaria et al. Q	Task Innovation	Doll & Torkzadeh (1998)
		Absorptive Capacity	Igbaria et al. Q	Task Productivity	Doll & Torkzadeh (1998)
		Absorptive Capacity	Igbaria et al. Q	IT use	Doll & Torkzadeh (1998)
		IT Ability	Doll & Torkzadeh, 1998	Task Innovation	Doll & Torkzadeh (1998)
		IT Ability	Doll & Torkzadeh, 1998	Task Productivity	Doll & Torkzadeh
Matzler, Renzl, Muller, Herting & Mooradian	2008	Agreeableness	NEO FFI	Knowledge sharing	Blackler (1995)
		Conscientiousness	NEO FFI	Knowledge sharing	Blackler (1995)
		Openness	NEO FFI	Knowledge sharing	Blackler (1995)
Bertua, Anderson & Salgado	2005	GMA	Meta-analysis	Job Performance	(Meta-analysis)
Becker	2005	Integrity	SJT	Positive Relationships	Supervisor ratings
		Integrity	SJT	Career Potential	Supervisor ratings
		Integrity	SJT	Leadership	Supervisor ratings
		Integrity	SJT	In-role Performance	Supervisor ratings
		Integrity	SJT	Overall Performance	
Cross & Vick	2001	Self-efficacy	Self-report	Test Performance	GPA
		Thoughts of transferring	Self-report	Test Performance	GPA
		Second year retention	Enrolled the second year	Test Performance	GPA
		Self-efficacy	Self-report	Retention	2nd year Enrollment
		Thoughts of transferring	Self-report	Retention	2nd year Enrollment
Keller	1997	Job Involvement	Lodahl & Kejener (1965)	Job Performance	Supervisor Rating
		Organizational Commitment	Porter et al.'s (1974) OCQ	Job Performance	Supervisor Rating

(Keller)	1997	Job Satisfaction	MSQ	Job Performance	Supervisor Rating
		Job Involvement	Lodahl & Kejener (1965)	Patents	Number of Patents
		Org. Commitment	Porter et al.'s (1974) OCQ	Patents	Number of Patents
		Job Satisfaction	MSQ	Patents	Number of Patents
		Job Involvement	Lodahl & Kejener (1965)	Publications	Number of Publications
		Org. Commitment	Porter et al.'s (1974) OCQ	Publications	Number of Publications
		Job Satisfaction	MSQ	Publications	Number of Publications
Lee	1994	Task-related communication	Avg. contacts/day	Job Performance	Supervisor Ratings
		Communication	Avg. group member contacts	Job Performance	Supervisor Ratings
		Communication	Avg. contacts other groups	Job Performance	Supervisor Ratings
		Communication	Avg. contact other ppl in org.	Job Performance	Supervisor Ratings
		Communication	Avg. number of external contacts	Job Performance	Supervisor Ratings
Mossholder, Bedeian, Niebuhr & Wesolowski	1994	Dyadic duration (months)	Months reporting to supervisor	Job Performance	Supervisor Ratings
		Organizational Commitment	Tenure with Organization	Job Performance	Supervisor Ratings
		Job Experience	Tenure with Position	Job Performance	Supervisor Ratings
		Satisfaction with supervision	JDI (Smith et al., 1969)	Job Performance	Supervisor Ratings
		Satisfaction with work	JDI (Smith et al., 1969)	Job Performance	Supervisor Ratings
		Satisfaction with promotions	JDI (Smith et al., 1969)	Job Performance	Supervisor Ratings
		Satisfaction w/ coworkers	JDI (Smith et al., 1969)	Job Performance	Supervisor Ratings

Igbaria & Siegel	1992	Role Stressors	RA and RC	Retention	Intention to leave
		Role Ambiguity	RA (from Kahn et al. 1964)	Retention	Intention to leave
		Role Conflict	RC (Rizzo et al 1970)	Retention	Intention to leave
		Task Characteristics	JDS (Hackman & Oldham, 1975)	Retention	Intention to leave
		Motivating Potential score	JDS (Hackman & Oldham, 1975)	Retention	Intention to leave
		Challenge	JDS (Hackman & Oldham, 1975)	Retention	Intention to leave
		Job Involvement	Kanungo (1982)	Retention	Intention to leave
		Job Satisfaction	Hackman & Oldham (1975)	Retention	Intention to leave
		Organizational Commitment	OCQ (Porter et al., 1976)	Retention	Intention to leave
		Career Satisfaction	OCQ (Porter et al., 1976)	Retention	Intention to leave
Lee	1988	Understanding job objectives	Supervisor rating	Job Performance	Supervisor Rating
		Creativity and originality	Supervisor rating	Job Performance	Supervisor Rating
		Deal with unstructured tasks	Supervisor rating	Job Performance	Supervisor Rating
		Learn on job	Supervisor rating	Job Performance	Supervisor Rating
		Accomplish difficult assignment	Supervisor rating	Job Performance	Supervisor Rating
		Self-Initiative	Supervisor rating	Job Performance	Supervisor Rating
		Decision making ability	Supervisor rating	Job Performance	Supervisor Rating
		Deliver promises and meet deadlines	Supervisor rating	Job Performance	Supervisor Rating
		Interpersonal relationship	Supervisor rating	Job Performance	Supervisor Rating
		Written communication skills	Supervisor rating	Job Performance	Supervisor Rating

		Oral communication skills	Supervisor rating	Job Performance	Supervisor Rating
(Lee)	1988	Collect and analyze data carefully	Supervisor rating	Job Performance	Supervisor Rating
		Gather relevant design info.	Supervisor rating	Job Performance	Supervisor Rating
		Machine shop and model building	Supervisor rating	Job Performance	Supervisor Rating
		Work with and test machines	Supervisor rating	Job Performance	Supervisor Rating
		Ability	Overall GPA	Job Performance	Supervisor Rating
		Engineering Ability	Major Field GPA	Job Performance	Supervisor Rating
Kozlowski & Hults	1986	Task Complexity	Sum of subscales (A,F, TI, V, TU)	Technical Performance	Farr et al., 1983
		Task Complexity	Sum of subscales (A,F, TI, V, TU)	Technical Performance	Farr et al., 1984
Kaufman	1978	Training	Training performance	Job Performance	Supervisor Rating
Kaufman	1974	Early challenge	Self and Supervisor rating	Job Performance	Supervisor Rating
		Early challenge	Self and Supervisor rating	Publications	Number of publications
		Early challenge	Self and Supervisor rating	Patents	Number of patents
		Early challenge	Self and Supervisor rating	Competence	Inventory of tech. specialties
		Early challenge	Self and Supervisor rating	Diversity	Inventory of tech. specialties

Kirkpatrick	1956	Ability to get along with others	Not reported	Overall Effectiveness	Supervisor Rating
		Creativity	Not reported	Overall Effectiveness	Supervisor Rating
		Effort and Conscientiousness	Not reported	Overall Effectiveness	Supervisor Rating
		Job Knowledge	Not reported	Overall Effectiveness	Supervisor Rating
		Motivation and Drive	Not reported	Overall Effectiveness	Supervisor Rating
		Job Experience	Not reported	Overall Effectiveness	Supervisor Rating
		Mechanical Comprehension Test	Not reported	Overall Effectiveness	Supervisor Rating
		Test of Productive Thinking	Not reported	Overall Effectiveness	Supervisor Rating
Pierson & Jex	1951	English Ability	CGAT	Success in School	Engineering GPA
		Social Studies Ability	CGAT	Success in School	Engineering GPA
		Natural Science Ability	CGAT	Success in School	Engineering GPA
		Math Ability	CGAT	Success in School	Engineering GPA
		GPA	High School Marks	Success in School	Engineering GPA
		General Verbal Ability	Pre-Engineering Inv.	Success in School	Engineering GPA
		Technical Verbal Ability	Pre-Engineering Inv.	Success in School	Engineering GPA
		Scientific Materials Ability	Pre-Engineering Inv.	Success in School	Engineering GPA
		General Math Ability	Pre-Engineering Inv.	Success in School	Engineering GPA
		Mechanical Principles Ability	Pre-Engineering Inv.	Success in School	Engineering GPA
		Spatial Visualization Ability	Pre-Engineering Inv.	Success in School	Engineering GPA
		Modern Society Ability	Pre-Engineering Inv.	Success in School	Engineering GPA

Berdie & Sutter	1950	High School Performance	GPA	School Performance	Test Scores
		High School Performance	High School % rank	School Performance	Test Scores
		GED	GED score	School Performance	Test Scores
		Math Ability	Cooperative Mathematics Test	School Performance	Test Scores
Cohen	1946	GMA	Test battery	School Performance	GPA
		High School Performance	Weighted Grades	School Performance	GPA
Laycock & Hutcheon	1939	Mechanical Aptitude	FRT	School Performance	First Year GPA
		Mechanical Aptitude	CMAT (Models)	School Performance	First Year GPA
		Mechanical Aptitude	CMAT (Diagrams)	School Performance	First Year GPA
		Intelligence	ACPE, 1937 Edition	School Performance	First Year GPA
		Personality	Bernreuter PI	School Performance	First Year GPA
		Neurotic Tendency	Bernreuter PI	School Performance	First Year GPA
		Self-Sufficiency	Bernreuter PI	School Performance	First Year GPA
		Introversion-Extroversion	Bernreuter PI	School Performance	First Year GPA
		Dominance-Submission	Bernreuter PI	School Performance	First Year GPA
		Self-Confidence	Bernreuter PI	School Performance	First Year GPA
		Sociability	Bernreuter PI	School Performance	First Year GPA
		Physical Science Interest	Thurmond Interest Inventory	School Performance	First Year GPA
		High School Performance	Senior year GPA	School Performance	First Year GPA

***Abbreviations used: GCQ- Gross Cohesion Questionnaire; ICQ- Intragroup Conflict Questionnaire; MSQ- Minnesota Satisfaction Questionnaire; A, F, TI, V, TU- Autonomy, Feedback, Task Identity, Variety, Task Uncertainty; CGAT- Cooperative General Achievement Test; FRT- Form Relations Test of the National Institute of Industrial Psychology of Great Britain; CMAT- Cox Mechanical Aptitude Test; ACPE- American Council Psychological Examination.

Table 2 Summary of Correlations

	Performance Outcome				
Predictor	Test Performance	Supervisor Rating	Patents/Publications	Tenure/Retention	Overall Performance
GMA	9	2		1	k=12, n=2,207
Specific Ability	17	65	4		k=86, n=10,565
Sub-field		19			
Context – team		4			
Personality	10	28		7	k=45, n=7,073
Context – team		18			
Attitudes	11	24	12	13	k=60, n=8,600
Sub-field - R&D		3			
Context – team		6			

k= number of correlations, n=sample size, r= weighted correlation

Table 3 Meta-Analysis of GMA as a Correlate of Performance of Engineers

General Mental Ability Correlated with Performance Outcomes of Engineers

Criterion/Predictor	k	N *tot*	Mean r/r̄	*σr2*	*σe2*	*σp2*	*SDp/σp*	95% Conf. Int. Lower	95% Conf. Int. Upper
Test Performance									
Intelligence Test	3	365	0.45*	0.17	0.01	0.17	0.41	0.42	0.48
GPA	6	1029	0.43*	0.2	0	0.19	0.44	0.46	0.4
Supervisor Rating									
GPA	2	688	0.27						
Patents/Publications									
Tenure/Retention									
GPA	1	125	0.31						

k= number of correlations, n=sample size, r= weighted correlation

Table 4 Meta-Analysis of Specific Ability as a Correlate of Performance of Engineers

Criterion/Predictor	k	n	r̄	*σr2*	*σe2*	*σp2*	*σp*	95% Conf. Int. Lower	95% Conf. Int. Upper
Test Performance									
Math	3	617	0.56*	0.16	0	0.15	0.39	0.54	0.58
Mechanical Aptitude	5	984	0.32*	0.11	0	0.11	0.33	0.31	0.34
Supervisor Rating									
Engineering	15	754	0.11*	0.03	0.02	0.01	0.09	0.1	0.12
Sub-field (Highly Analytical)	7	370	0.08*	0.03	0.02	0	0.04	0.07	0.09
Sub-field (Low Analytical)	7	293	0.15*	0.03	0.02	0.02	0.12	0.14	0.16
Context (Team)	2	81	-0.13						
Creativity	4	1070	0.35*	0.08	0	0.08	0.28	0.34	0.36
Sub-field (R&D)	1	88	0.41						
Communication	29	1217	0.04*	0.03	0.02	0.01	0.09	0.03	0.05
Sub-field (R&D)	4	40	0.06	0.15	0.11	0.04	0.21	-0.03	0.16
Sub-field (Design)	4	144	0.05	7.01	0.03	6.98	2.64	-2.24	2.34
Sub-field (Testing & Analysis)	4	120	0.07*	0.02	0.03	-0.01	0	0.06	0.08
Sub-field (Programming)	4	100	0.01*	0.04	0.04	0	0	0.09	0.11
Sub-field (Drafting)	4	44	-0.34*	0.27	0.08	0.19	0.44	-0.49	-0.18
Sub-field (Production)	4	64	0.09*	0.04	0.07	-0.02	0	0.07	0.11
Mechanical Aptitude	2	244	0.26						
Sub-field (R&D)	1	88	0.28						
Patents/Publications									
IT Ability	2	416	0.62						
Tenure/Retention									

Table 5 Meta-Analysis of Personality as a Correlate of Performance of Engineers

Personality Traits Correlated with Performance Outcomes of Engineers								95% Conf. Int.	
Criterion/Predictor	k	n	r̄	*σr2*	*σe2*	*σp2*	*σp*	Lower	Upper
Test Performance									
Openness	1	435	0.07						
Conscientiousness	1	435	0.26						
Extraversion	2	288	0.03						
Agreeableness	1	114	-0.05						
Neuroticism	1	144	0.06						
Self-Esteem	3	394	0.14*	0.02	0.01	0.02	0.13	0.14	0.15
Supervisor Rating									
Openness - Context (Team)	3	358	0.90*	0.06	0.01	0.05	0.23	0.08	0.1
Conscientiousness	5	740	0.40*	0.09	0	0.08	0.29	0.39	0.41
Conscientiousness - Context (Team)	4	487	0.29*	0.08	0.01	0.07	0.27	0.28	0.3
Extraversion - Context (Team)	2	234	0.22						
Agreeableness - Context (Team)	3	358	0.17*	0.05	0.01	0.04	0.19	0.16	0.17
Neuroticism - Context (Team)	2	234	0.18						
Self-Esteem	1	573	0.29						
Integrity	4	226	0.33*	0.08	0.01	0.06	0.25	0.3	0.35
Patents/Publications									
Tenure/Retention									
Openness	1	80	0.14						
Conscientiousness	1	80	0.01						
Extraversion	1	80	0.01						
Agreeableness	1	80	-0.11						
Neuroticism	1	80	0.05						
Self-Esteem	2	250	0.15						

Table 6 Meta-Analysis of Attitude as a Correlate of Performance of Engineers

Attitudes Correlated with Performance Outcomes of Engineers								95% Conf. Int.	
Criterion/Predictor	k	n	r̄	*σr2*	*σe2*	*σp2*	*σp*	Lower	Upper
Test Performance									
Self-Efficacy	2	560	0.37						
Supervisor Rating									
Job Involvement	1	282	0.23						
Job Satisfaction	2	387	0.13						
Context (Team)	1	105	0.18						
Org. Commitment	1	282	0.06						
Autonomy	8	543	0.27*	0.12	0.01	0.11	0.45	0.24	0.3
Context (Team)	1	105	0.04						
Sub-field (R&D)	3	194	0.41*	0.22	0.01	0.21	0.45	0.35	0.46
Patents/Publications									
Job Involvement	2	564	0.22						
Job Satisfaction	2	564	0.07						
Org. Commitment	2	564	0.06						
Tenure/Retention									
Job Involvement	1	107	-0.16						
Job Satisfaction	1	107	-0.31						
Org. Commitment	1	107	-0.27						
Self-Efficacy	1	125	0.20						

Table 7 Type of Communication Moderation on Supervisor Ratings of Performance

								95% Conf. Int.	
Criterion/Predictor	k	n	$\bar{r}$	*σr2*	*σe2*	*σp2*	*σp*	Lower	Upper
Communication	29	1217	0.04*	0.03	0.02	0.01	0.09	0.03	0.05
Intra-organizational	15	679	-0.06*	0.02	0.02	0	0.02	-0.07	-0.05
Extra-organizational	14	538	0.08*	0.05	0.03	0.02	0.14	0.07	0.1

Figure 1 Comprehensive Model of Literature Review