Exploring the Utility of Three Approaches to Validating a Job Analysis Tool

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Abstract

Building on prior research (Meyer, Foster, & Anderson, 2006), the present study examined the utility of three approaches to validate the Performance Improvement Characteristics (PIC; Hogan & Rybicki, 1998). The PIC is a job analysis instrument used to assess personal characteristics important to successful job performance. Hogan Personality Inventory (HPI; Hogan & Hogan, 1995) data in seven archival studies were weighted/modified in three different ways according to PIC profiles generated from the same jobs as well as other jobs and then correlated with overall performance. Meta-analytic evidence revealed that of the three different approaches (*partial-weighting, full-weighting, and profile similarity*), the *profile similarity* approach was the best at differentiating jobs and predicting performance, thereby evidencing predictive validity of the PIC.

Exploring the Utility of Three Approaches to Validating a Job Analysis Tool

Neither the *Uniform Guidelines on Employee Selection Procedures* (Equal Employment Opportunity Commission, 1978; hereafter "*Uniform Guidelines*") nor *The Principles for the Validation and Use of Personnel Selection Procedures* (Society for Industrial and Organizational Psychology, 2003; hereafter "*Principles*") include stringent standards for the validation of personality-based job analysis tools. However, job analysis tools are often used to determine which selection instruments will predict job performance and serve, therefore, as the cornerstone of many validity studies. Therefore, it is important to demonstrate the validity of job analysis procedures in identifying the selection instruments that should be used for making personnel decisions. The present study explores three different approaches to validating job analysis tools, and identifies the merits and shortcomings of each.

To control for variability between different job analysis methods, each validation approach was investigated using the same instrument: the Performance Improvement Characteristics inventory (PIC: Hogan & Rybicki, 1998). The PIC is a "worker-oriented job analysis method designed to evaluate personality-related job requirements" (J. Hogan & Rybicki, 1998). The PIC is used to identifyidentifies the personal characteristics necessary to perform a job, in contrast to many job analysis tools that are used to identify task and/or behaviorally related job characteristics (e.g., PAQ; McCormick, Jeanneret, & Mecham, 1972). The PIC's structure was derived directly from the Hogan Personality Inventory (hereafter "HPI"; add in Hogan and Hogan, 1995 – the manual). The HPI is a rigorously studied and validated measure of normal personality used by many organizations as a selection and/or development tool. It has been modeled after the Five Factor Model of personality (Goldberg, 1990) and contains seven scales (see Table 1) which are mirrored by the PIC. Therefore, the PIC provides seamless translation of job analysis results into recommendations for which HPI scales to employ in selection systems.

The PIC identifies the personal characteristics needed to execute successfully the requirements of a job and the degree to which possession of these personal characteristics improves job performance (J. Hogan & Rybicki, 1998). The PIC is completed by Subject Matter Experts (e.g., incumbents, supervisors; hereafter "SMEs"). The result is a profile that identifies the personality characteristics most critical to successful job performance. If the PIC is able to identify the required personal characteristics of a job, then we should see variability in the makeup of the PIC profiles across jobs.

In practice, the PIC assists in understanding the requirements of a given job and which personality dimensions may be the best predictors of performance. The PIC is not used as a predictor itself. However, the PIC results are used to help identify which HPI scales should be used for the selection battery. In practice, the top three or four PIC scales from a job analysis are considered evidence toward the use of those HPI scales in the selection system. This evidence is combined with other sources of evidence such as meta-analytic results, transportability of validity, synthetic validity, and criterion-related validity to arrive at the final battery of HPI scales to be used.

It is not possible to correlate PIC results with performance in an effort to validate the PIC, as it is only a job analysis tool that asks SMEs to respond in accordance with what the job requires rather than an assessment of their own personality. Instead, we must interject the PIC into the HPI-performance relationship to determine its validity. For the current study, we assess three different approaches to accomplish this: *profile similarity, full-weighting,* and *partial-weighting* (later discussed in detail). When the HPI results for a given job are weighted based on the PIC profile from its own job analysis, the HPI should be predictive of performance. Further, the HPI should be *more* predictive of performance when weighted according to its own PIC profile than when weighted according to the PIC profile of another job; provided the two jobs differ in terms of the personal characteristics required to successfully perform. For example, bus driver performance should be better predicted by a battery of HPI scales selected based on the results of a bus driver job analysis than would a battery of HPI scales selected based on an accountant job analysis. The prior point requires further clarification. It is not our contention that each job will have a PIC profile that is completely unique and unlike any other. To the contrary, we assert that it is certainly possible to have two jobs that have disparate tasks and responsibilities yet require many of the same personal characteristics. Even further, we acknowledge that there should be a pattern across many jobs in which certain personal characteristics maintain their predictive power. Just as prior meta-analytic research has revealed that the Big Five Factors of Conscientiousness, Emotional Stability, and Agreeableness tend to predict performance across jobs (e.g., Barrick & Mount, 1991; Tett, Jackson, & Rothstein, 1991), we should also expect that the corresponding PIC scales of Prudence, Adjustment, and Interpersonal Sensitivity be commonly rated as important for successful performance. In fact, Hogan and Holland (2003) demonstrated meta-analytically that those three scales on the HPI do tend to predict performance (ρ = .36, .43, and .34, respectively).

The first of the three validation approaches, *profile similarity*, employs a metric of similarity between predictor (HPI) scores and PIC scores, sometimes referred to as a *profile correlation index* (PCI: Timmerman, 1996). This approach is similar to that used by others to assess fit (e.g., Caldwell and O'Reilly, 1990). For this approach, the results of the PIC analysis are correlated with each incumbent's HPI scores to determine the extent to which an individual's

HPI profile is congruent to the PIC profile for the job. The resultant correlation is then correlated with performance. As previously mentioned, the PIC is designed to assess the degree to which *successful* performance is associated with the various characteristics. Therefore, the extent to which an individual's profile (HPI) is related to this model profile of successful performance (PIC) should be predictive of that individual's success. Second, if the PIC does an adequate job of differentiating between jobs, there should be a stronger relationship between the PIC and performance when the PIC data from the target job is used than when PIC data from a different job is used.

Hypothesis 1a: Across multiple jobs, profile correlation indices (PCI) will be positively and significantly related to performance.

Hypothesis 1b: PCI's will have a stronger positive relationship with performance when based on its relevant job analysis information than when based on a different job's job analysis information.

The second approach, *full-weighting*, utilizes an algorithm to weight all predictor scales according to their relative importance as identified by the PIC. Specifically, the percentage of total possible for each PIC scale is calculated. Then, each individual's HPI scores are multiplied by these PIC percentages to arrive at weighted scale scores. The seven weighted predictor (HPI) scales were then summed and correlated with performance. This approach is similar to the one used by Arthur, Doverspike, and Barret (1996), in which job analysis information was used to weight various predictors for the purpose of creating a validated selection battery. As each HPI scale has been modified by PIC data intended to profile successful performance, the weighted sum should be correlated with performance. Further, it should be better predictive of performance when the weights are derived from its relative job analysis information (PIC) than from a different job.

Hypothesis 2a: Across multiple jobs, full-weighted predictors will be positively and significantly related to performance.

Hypothesis 2b: Full-weighted predictors will have a stronger positive relationship with performance when based on its relevant job analysis information than when based on a different job's job analysis information

The third approach, *partial-weighting*, was first used by Meyer, Foster, and Anderson (2006), in which a different algorithm is used that more closely mimics practice by weighting only the top three scales (based on PIC results) and eliminating the remaining scales, thereby negating their contribution to the overall predictor score. In practice, multiple HPI scales may be recommended for first-level screening cuts. Therefore, a weighting scheme was created that approximates common practice. Within each study (job), the PIC scales were rank-ordered based on the importance ratings provided by the PIC (percent of total possible). The highest ranked PIC scale was given a weight of "3", the second highest a "2", and the third highest a "1". The remaining four PIC scales were weighted by "0", thereby eliminating them from the subsequent analyses. The included scales are then summed and correlated with performance. Using this approach in the current study will provide a test of its generalizability to a new sample of jobs. Based on the positive results in Meyer, Foster, and Anderson (2006), we expect to find similar results in the present study.

Hypothesis 3a: Across multiple jobs, partially-weighted predictors will be positively and significantly related to performance.

Hypothesis 3b: Partially-weighted predictors will have a stronger positive relationship with performance when based on its relevant job analysis information than when based on a different job's job analysis information.

When considering which of the three approaches will be most effective in predicting performance and/or differentiating jobs, we have little reason to make a priori hypotheses. Considering that the *partial-weighting* approach only utilizes the top three scales, which more closely approximates practice, and it has been supported in past research (Meyer, Foster, & Anderson, 2006), we expect it to demonstrate similar utility. However, how this approach will compare to the other, previously untested approaches, is unclear.

Method

Measures

Performance Improvement Characteristics. The PIC contains 48 items, from which come the seven scales outlined in Table 1. SMEs rate each item on a Likert-type scale ranging from “0” (does not improve performance) to “3” (substantially improves performance). Scale scores are then computed by: (1) summing the item responses within each scale, (2) averaging the scores for each scale across raters (SMEs), and (3) converting the average scale scores to a percentage based on the total possible score for each scale.

The PIC has proven to be a reliable job analysis tool. Results reported in the manual (J. Hogan & Rybicki, 1998) indicate that PIC scales’ internal consistency reliability estimates range between .76 (Adjustment) and .87 (Interpersonal Sensitivity); average internal consistency is .83. Test-retest reliability, estimated over a 1-month interval, ranges between .60 (Learning Approach) and .84 (Inquisitive); the average test-retest reliability is .71. A copy of the PIC appears in Appendix B.

Hogan Personality Inventory. The HPI was the first measure of normal personality developed explicitly to assess the Five Factor Model in occupational settings. The HPI has been extensively researched across multiple industries and applications (Axford, 1998; Hogan & Holland, 2003). It contains 206 true-false items which are broken down into seven scales (Table 1). Scale scores are computed by summing the item responses within each scale and then converting the scale scores to a percentile using a national normative database of over 150,000 working adults and job applicants from a variety of organizations including healthcare, military services, transportation, protective services, retail, manufacturing, and hospitality.

The HPI has also proven to be a reliable and valid measure of personality. The average alpha for scales is .80 and test-retest reliabilities range from .74 to .86. Meta-analyses of HPI scales indicate that the estimated true validities for the HPI scales for predicting aligned job performance components are: Adjustment (.43), Ambition (.35), Interpersonal Sensitivity (.34), Prudence (.36), Inquisitive (.34), and Learning Approach (.25) (Hogan & Holland, 2003).

Performance. The criteria used for this study was overall performance. Although the specific method (scale and range) by which overall performance was measured varied between studies, each contained either a single item of overall performance or several items across which an index of overall performance was derived. For all of the seven studies included, overall performance was measured subjectively via supervisor ratings.

Inclusion Criteria

The Hogan Archive was searched to identify prior criterion validation studies that could be used in these analyses. Before conducting the search, criteria had to be established to determine what constituted a qualifying study. The first criterion was that it was a single-job study, or at least that the data was parsed out for each job so that the inclusion of one job but not the others was possible. The next criterion was that the study must have accompanying job analysis (PIC) data. The third criterion was that the sample size was greater than 30 participants. Fourth, the criterion variable must be a measure overall performance. The fourth criterion for the selection of a study was that it was sufficiently different from the jobs of the studies previously included, so that there would be diversity in scope and requirements. The goal was to have representation from a wide variety of occupations, with a minimum of five total studies. The final criterion was that none of the included studies were used in the research by Meyer, Foster, and Anderson (2006), so that the generalizability of the *partial-weighting* approach could be tested. A comprehensive search yielded seven studies (total N = 749) that satisfied all of the established criteria. To test that the selected studies were sufficiently different from one another, their PIC profiles were charted and examined (Figure 1). In addition, a MANOVA was conducted, using all seven PIC scales as dependent variables. Results indicate that there was a significant difference in the linear combination of the PIC scales between the included studies (Pillai's Trace = .991, p = .00, η^2 = .165). Therefore, we can assert that the jobs are sufficiently different from one another.

Predictor Weighting

Each of the outlined approaches above was applied to the predictor data for each of the seven included jobs. For each job, the incumbents' predictor data was weighted/modified via each of the three approaches in accordance with its derivative job analysis (PIC) and also the job analysis data from the other six jobs. Therefore, in a single study, a single person's data included the results of the three weighting approaches for each of the seven jobs (including its referent job); yielding a total of twenty-one variables that could be correlated with performance. For each of the three approaches, when correlations were made between performance and the variables weighted with the derivative PIC data, the resultant correlations were considered *aligned* correlations. When correlated with data from a different job, the resultant correlations were considered *misaligned* correlations.

Meta-Analyses

Two meta-analyses were computed for each of the three weighting approaches for the present study in accordance with the procedures outline in Hunter and Schmidt (2004). Corrections for unreliability in the criterion were made using the commonly-accepted value of .508, as all performance criteria were single-rater subjective performance appraisals (Rothstein, 1990). The first meta-analysis for each approach consisted of the seven *aligned* correlations. In other words, it consisted of the seven correlations (one per job/study) between the results of the weighting approach when applied to their derivative jobs and overall performance. The second meta-analysis consisted of seven *misaligned* correlations. Although there was actually a total of forty-two such correlations for each approach, only one correlation within each study (job) was taken (in order to maintain congruence in the number correlations used in each meta-analysis). Had we included more than one of the *misaligned* correlations per study, it would have created a study bias via an overrepresentation of data from the same sample. The one correlation was chosen at random for each study by using a random number table.

Results

To provide a reference point against which to compare the utility of each of the approaches, within each study we correlated the HPI scales with performance. Next, the three strongest correlations in each study were combined via the Nunnally (1978) equation, resulting in values ranging from .11 to .39. We then averaged the seven combined correlations into one average correlation. The result of these calculations was .27, which gives us a comparison point for our weighting approaches, and also evidences that the HPI was generally predictive of performance across these seven included jobs without any modifications to the predictor data.

The meta-analytic results are presented in Tables 2 through 4. As indicated by the results in Table 2, Hypothesis 1a was supported; Profile Correlation Indexes were predictive of performance ($\rho = .21$). Hypothesis 1b was partially supported; the *aligned* correlations ($\rho = .21$) for the PCI approach were greater than the *misaligned* correlations ($\rho = .01$). In general, the PCI approach did differentiate between jobs. However, there was a slight overlap of .01 between the two confidence intervals, indicating that the two values were not statistically significantly different at the 90% confidence level.

Hypothesis 2a was supported; performance was predicted by the *full-weighted* predictors ($\rho = .12$), and the 90% confidence interval did not include .00. However, the magnitude of the estimated parameter is not substantial. Hypothesis 2b was not supported; there was substantial overlap in the confidence intervals between *aligned* and *misaligned* correlations, indicating that this approach was not effective in differentiating jobs.

Hypothesis 3a was fully supported; performance was significantly predicted by the *partial-weighted* predictors ($\rho = .21$), consistent with results from Meyer, Foster, and Anderson (2006). Hypothesis 3b was not supported; the confidence intervals of the *aligned* and *misaligned* correlations overlapped each other by .05. Therefore, the *partial-weighted* approach did not effectively differentiate jobs.

Discussion

The present study investigated three approaches to validating a structured, worker-oriented job analysis instrument. Results indicated that the *profile similarity* approach was most effective at predicting job performance and differentiating jobs. These results are somewhat surprising. Inherent in the approach, each of the PIC/HPI correlations were somewhat unstable, as they were based on an "*n*" of 7 (seven scales of the PIC and HPI). When this approach has been used in the past, PCI's have been based on a greater number of items/scales (e.g., Timmerman, 1996). Nonetheless, it appears that this small number of points from which the correlations were derived was enough to compare the relative rank-ordering of the scales for each person. Although this approach worked well for the PIC and HPI, we recognize that it was readily applicable to the PIC and HPI because they are conceptually linked – possessing seven commensurate scales. For another job analysis instrument that does not so readily map onto a predictor, this approach may be inappropriate.

The *full-weighting* approach was the least effective of all three approaches; it did not effectively predict performance nor differentiate jobs. The best *post hoc* explanation of this is that the approach is fully compensatory in design, which does not mimic practice very well. As previously stated, all scales are not expected to be predictive of success for each job, but the *full-weighting* approach employs a weighting algorithm that does not inherently provide significant differentiation between the scales. For example, in one of the included jobs the range of PIC scores was 67.15% to 88.71%, which were used as the actual weights in the *full-weighting* approach. Although this was a narrow range, it is not indicative of the range found in all jobs. However, with this particular job, the maximal differentiation in predictor weights was 1.32. In other words, HPI Ambition scores were weighted by 88.71, while HPI Adjustment scores were weighted by 67.15, meaning that, for this job, HPI Ambition scores were given only 1.32 times more weight than HPI Adjustment scores. Therefore, the approach did not provide much differentiation between the more and less important personal characteristics of the job.

Contrary to expectations, the *partial-weighting* approach was not as effective as it was in Meyer, Foster, and Anderson (2006). However, if we examine the differences in the estimated parameters between that study and the current one, we can see that the results were somewhat similar. In the earlier study, the difference between the *aligned* and *misaligned* meta-analyses was .17. In the present study, the difference was .10. When examining the confidence intervals, it appears that there must have been greater variability in the predictor-criterion correlations in the present study than there was in the earlier study. A likely reason for why the *partial-weighting* approach, in this study, was not effective at differentiating jobs is that Learning Approach was a top three scale for six of the seven jobs. Examining the univariate effects of the PIC profile MANOVA reveals that there were no significant differences between the jobs on the Learning Approach scale [F (6, 742) = .806, p = .57]. Therefore, the differentiation process of the *partial-weighting* approach was hampered in the present study because of the consistent importance of Learning Approach across studies. It could be reasoned that the approach would be fruitful with a different sample of jobs with more diverse personal characteristic requirements (as it was in Meyer, Foster, and Anderson, 2006), or with simply a much larger sample of jobs in which these commonalities would likely be overshadowed.

In summary, there are multiple methods that could be investigated to assess the predictive validity of a structured job analysis instrument. As indicated earlier, the *Uniform Guidelines* and the *Principles* are quite vague about validating a job analysis instrument beyond content and face validity. But because much weight is often placed on the results of a job analysis, it is imperative to demonstrate the instrument or process's ability to support a valid battery of predictors. Each of the approaches evaluated in the present study to establish such predictive validity have their strengths and weaknesses. Depending on the type of job analysis instrument used, and the intended predictors, one may be precluded from using one of the multiple approaches.

The meta-analytic results provide evidence for the validity of the PIC in identifying the personal characteristics critical to the successful execution of job requirements. Specifically, the results support the importance of conducting a job analysis and the ability of the PIC to reliably differentiate the personal characteristics required for jobs. Jobs will differ in the extent to which each of the seven scales is important. For example, for some jobs that are more interactive in nature, Extraversion, Sociability, and/or Interpersonal Sensitivity may be integral to successful performance, while the same dimensions could actually detract from performance in other jobs. The current results suggest the PIC is capable of detecting such differences.

The results also suggest that the PIC is instrumental in selecting a battery of HPI scales that best predicts job performance. However, the true instrumentality of the PIC profile is best achieved when its results are used for the job from whence it came. In other words, it cannot be assumed that simply because a selection of HPI scales, based on the recommendations from a PIC profile, is predictive of performance for one job that it will be predictive for another. A thorough job analysis must be conducted for each job to ensure that the appropriate HPI scales are being employed for selection decisions.

Despite the encouraging results, we acknowledge that there may be some limitations to the present study. First, we recognize that due to the stringent criteria we placed on study inclusion and the restriction to the Hogan Archive there was a small number of studies used for the present analyses. Future research may include more studies and with somewhat similar jobs to determine the generalizability of this study's findings. Second, because the meta-analyses were based on zero-order correlations, the assumption is that there are linear relationships between personality and performance. It may be the case that having more of a particular personality dimension helps performance only to a certain point at which it may begin detracting from performance.

Although there are some limitations of the present study, the findings are encouraging and provide a base of validity evidence for a widely used job analysis tool. We hope further research will explore alternative methods for validating job analysis instruments and make attempts to validate other commonly used job analysis tools.

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Appendix A

Table 1

HPI and PIC Scale Definitions

Scale Name	Definition
	The degree to which a person seems….
Adjustment	calm and self-accepting
Ambition	self-confident and competitive
Sociability	to need or enjoy social interaction
Interpersonal Sensitivity	perceptive, tactful, and sensitive
Prudence	conscientious and conforming
Inquisitive	creative and interested in problems
Learning Approach	to value learning for its own sake

Figure 1. PIC Profile Comparisons

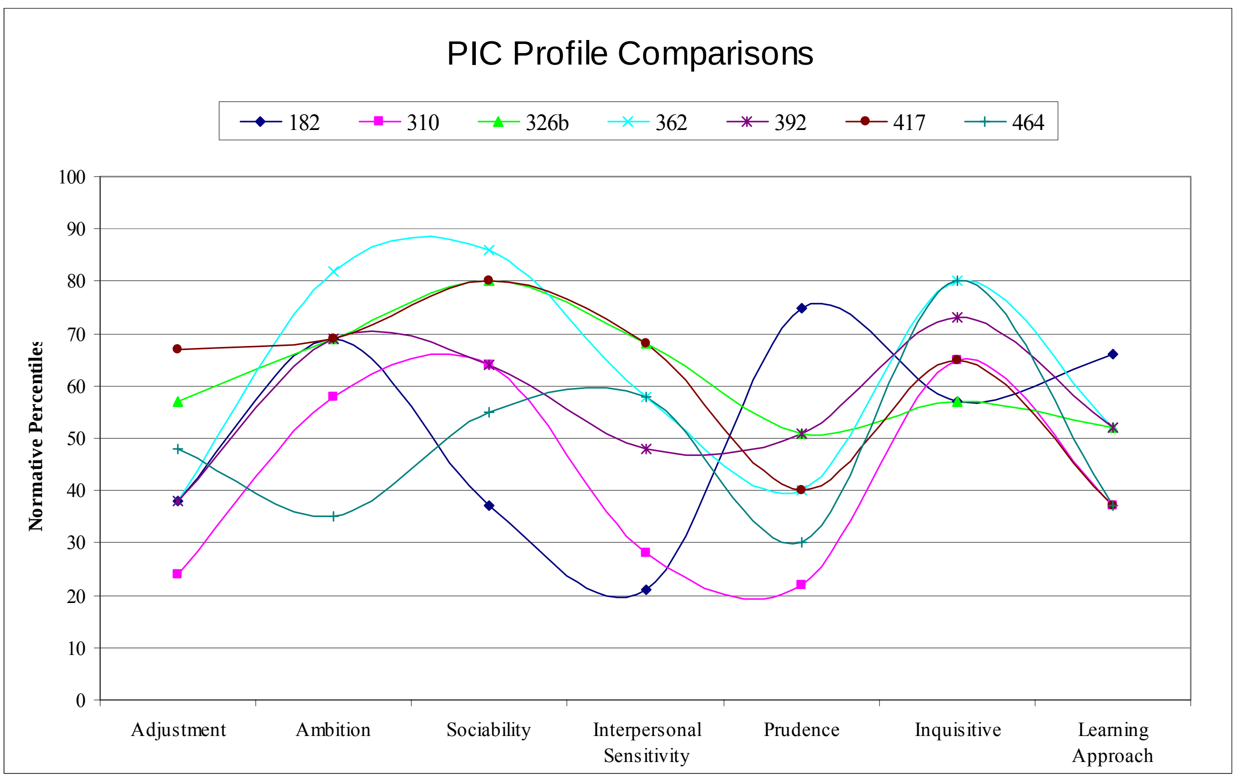

Table 2

Meta-analytic results for the Profile Similarity Approach

Correlation	K	N	r_{sw}	ρ	90% CI Lower	90% CI Upper	% VE
Aligned	7	749	.16	.22	.08	.36	34.13%
Misaligned	7	749	.01	.02	-.05	.09	100%

Note. K = number of studies; N = total sample size; r_{sw} = sample-weighted mean correlation; ρ = corrected estimated population parameter; CI = confidence interval; % VE = percent of variance accounted for by sampling error and statistical artifacts.

Table 3

Meta-analytic results for the Full-Weighting Approach

Correlation	K	N	r_{sw}	ρ	90% CI Lower	90% CI Upper	% VE
Aligned	7	749	.09	.12	.06	.18	100%
Misaligned	7	749	.07	.10	.04	.17	100%

Note. K = number of studies; N = total sample size; r_{sw} = sample-weighted mean correlation; ρ = corrected estimated population parameter; CI = confidence interval; % VE = percent of variance accounted for by sampling error and statistical artifacts.

Table 4

Meta-analytic results for the Partial-Weighting Approach

Correlation	K	N	r_{sw}	ρ	90% CI Lower	90% CI Upper	% VE
Aligned	7	749	.15	.21	.12	.29	100%
Misaligned	7	749	.08	.11	.05	.17	100%

Note. K = number of studies; N = total sample size; r_{sw} = sample-weighted mean correlation; ρ = corrected estimated population parameter; CI = confidence interval; % VE = percent of variance accounted for by sampling error and statistical artifacts.

Appendix B

JOB CHARACTERISTICS

INSTRUCTIONS

Below is a list of behavioral characteristics. Please rate the extent to which each characteristic would **IMPROVE** the performance of a ____________. Try to work quickly. Do not spend too much time thinking about any single item. Please mark your responses in the bubbles provided.

Does **Not** Improve Performance	**Minimally** Improves Performance	**Moderately** Improves Performance	**Substantially** Improves Performance
0	**1**	**2**	**3**

Would job performance IMPROVE if a___________……?

		Rating
1.	Is steady under pressure	⓪ ① ② ③
2.	Is not easily irritated by others	⓪ ① ② ③
3.	Is relaxed and easy-going	⓪ ① ② ③
4.	Doesn't worry about his/her past mistakes	⓪ ① ② ③
5.	Stays calm in a crisis	⓪ ① ② ③
6.	Rarely loses his/her temper	⓪ ① ② ③
7.	Doesn't complain about problems	⓪ ① ② ③
8.	Trusts others – is not suspicious	⓪ ① ② ③
9.	Gets along well with supervisors and authority figures	⓪ ① ② ③
10.	Takes initiative – solves problems on his/her own	⓪ ① ② ③
11.	Is competitive	⓪ ① ② ③
12.	Is self-confident	⓪ ① ② ③
13.	Is positive	⓪ ① ② ③
14.	Takes charge of situations	⓪ ① ② ③
15.	Has clear career goals	⓪ ① ② ③
16.	Enjoys speaking in front of groups	⓪ ① ② ③
17.	Seems to enjoy social interaction	⓪ ① ② ③
18.	Likes social gatherings	⓪ ① ② ③
19.	Likes meeting strangers	⓪ ① ② ③
20.	Needs variety at work	⓪ ① ② ③
21.	Wants to be the center of attention	⓪ ① ② ③
22.	Is witty and entertaining	⓪ ① ② ③
23.	Is warm and friendly	⓪ ① ② ③
24.	Is tolerant (not critical or judgmental)	⓪ ① ② ③

		Rating
25.	Is kind and considerate	⓪ ① ② ③
26.	Understands others' moods	⓪ ① ② ③
27.	Likes being around other people	⓪ ① ② ③
28.	Is good-natured - not hostile	⓪ ① ② ③
29.	Is self-controlled and conscientious	⓪ ① ② ③
30.	Supports the organization's values	⓪ ① ② ③
31.	Is hard-working	⓪ ① ② ③
32.	Does as good a job as possible	⓪ ① ② ③
33.	Pays attention to feedback	⓪ ① ② ③
34.	Likes predictability at work	⓪ ① ② ③
35.	Rarely deviates from standard procedures	⓪ ① ② ③
36.	Respects authority	⓪ ① ② ③
37.	Is imaginative and open-minded	⓪ ① ② ③
38.	Is interested in science	⓪ ① ② ③
39.	Is curious about how things work	⓪ ① ② ③
40.	Likes excitement	⓪ ① ② ③
41.	Enjoys solving problems and puzzles	⓪ ① ② ③
42.	Generates good ideas and solutions to problems	⓪ ① ② ③
43.	Likes cultural activities	⓪ ① ② ③
44.	Keeps up on advances in their profession	⓪ ① ② ③
45.	Likes to learn new things–enjoys training	⓪ ① ② ③
46.	Is good with numbers	⓪ ① ② ③
47.	Remembers details	⓪ ① ② ③
48.	Reads in order to stay informed	⓪ ① ② ③

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