An Examination of Conflicting Findings Between Job Satisfaction and Absenteeism: A Meta Analysis

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AN EXAMINATION OF CONFLICTING FINDINGS ON THE RELATIONSHIP BETWEEN JOB SATISFACTION AND ABSENTEEISM: A META-ANALYSIS

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This study, which applied meta-analytic procedures, found a significant negative relationship between certain facets of job satisfaction and absenteeism. Findings suggest that sampling errors, scale inadequacies, and the use of different measures of job satisfaction and absence are the reasons for inconsistencies in previous empirical research that examined the relationship between job satisfaction and absenteeism.

Much organizational research has focused on a hypothesized relationship between job satisfaction and work-related employee behaviors (Locke, 1976). Although researchers have largely discredited the once popular notion of a positive relationship between satisfaction and productivity, they have generally thought job satisfaction to be inversely related to absenteeism (Brayfield & Crockett, 1955; Herzberg, Mausner, Peterson, & Capwell, 1957; Johns, 1978; Muchinsky, 1977; Porter & Steers, 1973; Vroom, 1964; Waters & Roach, 1971, 1973). A frequent explanation for this inverse relationship is a hedonistic calculus: employees will withdraw, or be absent, from a work situation that is painful and dissatisfying.

In recent years scholars have questioned the nature of this relationship. Nicholson, Brown, and Chadwick-Jones (1976), Ilgen and Hollenback (1977), and Chadwick-Jones, Nicholson, and Brown (1982) reported finding only a weak relationship, at best, between job satisfaction and absenteeism. Indeed, after reviewing the inconsistent research findings of studies dealing with the relationship between these two variables, and conducting their own absenteeism study, Nicholson and colleagues concluded that the theory that an undesirable work situation causes absenteeism has little empirical support.

An alternative hypothesis advanced by Steers and Rhodes (1978), Cheloha and Farr (1980), and Clegg (1983) is that the relationship between job satisfaction and employee absenteeism is not direct. Instead, they suggested that biographical and situational variables, such as job involvement, moderate it.

Given the conflicting theories and inconsistent empirical evidence, we question the viability of withdrawal theory as an explanation of employee absenteeism. However, such a morass of mixed results is a fertile area in which to employ a relatively new methodology called meta-analysis (Hunter,
Schmidt, & Jackson, 1982), a form of data synthesis that provides a systematic procedure for quantitatively combining the results of existing empirical studies. Researchers have always combined or synthesized such results, but in most cases have employed no formal methodology in the process. Consequently, the validity and reliability of these idiosyncratic efforts are questionable (Pillemer & Light, 1980).

The job satisfaction and absenteeism literature contains such unsystematic reviews that it is not surprising that they provide different interpretations of the relationship between these two variables. For instance, Muchinsky (1977) concluded that a relationship between job satisfaction and absenteeism does exist; Nicholson and colleagues (1976) concluded that such a relationship does not exist; and Steers and Rhodes (1978) suggested that undiscovered moderator variables may cause the mixed findings. Given these conflicting results, a formal, systematic review of this empirical literature has two purposes: (1) to determine if job satisfaction and absenteeism are negatively related, and (2) to identify variables that may moderate this relationship.

METHODOLOGY

Meta-analysis

There are four generally accepted strategies for formal data synthesis: (1) conducting a combined significance test from summary statistics; (2) computing an average effect size; (3) investigating interactions between study attributes and outcomes; and (4) comparing similarly labeled treatments (Pillemer & Light, 1980). The present study uses the second method, determination of an average effect size, as described by Hunter and colleagues (1982). This technique, suited for use with correlational data, has been applied by Fisher and Gitelson (1983) in a recent review of the role conflict and ambiguity literature.

The first step in conducting a meta-analysis is compiling empirical studies pertaining to the issue of concern. Ideally, researchers should collect and analyze the results of all studies from the defined population; however, some studies cannot be used because they do not report the statistics necessary for this type of analysis. Fortunately, a complete sampling of the population is not necessary since, as Hunter and colleagues pointed out, meta-analytic procedures are “valid even for ‘convenience’ samples that just happen to lie at hand” (1982:29). If the corrected standard deviation suggests that variation across studies is due to sampling errors, additional studies will not affect the findings. But reliance on a convenience sample always involves some risk—the risk of incorporating bias is of special concern where an investigator may have systematically excluded certain works that others would have added to the population of studies. Thus, although use of a convenience sample will not in and of itself invalidate results of a meta-analysis, a complete review of the relevant literature should be undertaken whenever possible.
The second step involves examining the key statistics—here, the product-moment correlation—across all the studies. Third is calculating an average mean value, weighted by sample size, for the product-moment correlation across all studies to serve as a good estimate of the underlying population value. Use of the population parameter is necessary to eliminate the effect of sampling error from the meta-analysis. Since sampling error cancels out in an average correlation across studies, the best estimate of the mean population correlation is simply the mean of the sample correlations.

Fourth, because sampling error adds to the variance of correlations across studies, analysts must correct the observed sample variance by subtracting the error variance—that is, variance caused by sampling errors. This difference is the variance of population correlations across the studies. The fifth step is correcting the mean and variance of the population values for effects of measurement error and range variation. Reporting error, which includes incorrect computations, typographical errors, and the like, is the only major source of variation left uncorrected. Hunter and colleagues (1982) argued that sampling error is the most prevalent and often the only reason for conflicting findings among empirical studies. Hence, before researchers conducting meta-analysis attempt to find variables that moderate or attenuate a relationship of interest, they must first correct for sampling error. If this correction eliminates all unexplained variance, there is no reason to search for moderator variables. Large differences remaining among studies after correcting for this artifact still only suggest that moderator variables are present; researchers should eliminate other sources of variance, such as errors of measurement, before looking for moderators. If all sources of error that can be corrected have been, and unexplained variance still remains, a search for moderator variables is appropriate. To determine the effect of these variables, a researcher divides the sample of studies into subsets on the basis of suspected moderators and applies meta-analytic procedures separately to each subset. Large mean differences between the subsets and a corresponding reduction in within-subset variation across studies provides evidence supporting a moderator effect. How much of this residual variation is caused by artifacts can then be determined through standard meta-analytic procedures (Hunter et al., 1982).

Sample

A comprehensive review of the job satisfaction and absenteeism literature uncovered 23 studies that reported the information needed for meta-analysis: (1) the product-moment correlation between satisfaction and absenteeism; (2) a sample size for each correlation; and (3) identification of the absence measure—frequency, duration, or both. A listing of these studies appears in Table 1. Since most studies used multiple measures of job satisfaction or absenteeism, we extracted 114 correlation coefficients. Of these, 34

\[1\] Hunter and colleagues (1982) contains a detailed discussion of procedures for meta-analysis.
(29.7 %) indicated a statistically significant (at least \( p < .05 \)) relationship between satisfaction and absenteeism.

Even though meta-analytic formulae assume that correlations are statistically independent, some of the coefficients used in this study lack such independence. In this situation an analyst can either determine an average correlation for each study to use in meta-analysis, or violate the assumption of independence. After considering the advantages and disadvantages of each procedure (cf. Hunter et al., 1982), we elected to treat each correlation as an independent estimate of the relationship between job satisfaction and absenteeism. By so doing, we underestimated the size of the sampling error our sample of studies contains.

This was, in essence, a somewhat conservative approach to this type of analysis, in the sense that its procedures call for subtracting error variance from observed sample variance to show remaining unexplained variance. Thus, underestimating the sampling error means increasing the amount of unexplained variance. If, however, sampling error is as prevalent a problem as Hunter and colleagues (1982) have suggested, meta-analysis would still identify the effects of this artifact on the variance in results across studies despite any underestimation created by using some nonindependent samples.

The studies our research examined measured job satisfaction with several different instruments. Six studies used the Job Descriptive Index (JDI); two used the 20-item short form of the Minnesota Satisfaction Questionnaire (MSQ), and one study employed the complete version of the MSQ; another study used both the JDI and the 20-item MSQ; three studies used the GM Faces scale; two used the Job Diagnostic Survey (JDS); seven studies either did not give the name of their instrument or used a unique scale developed by the investigator (self-developed); finally, one study used both the JDI and the GM scales. We did not collapse the five facets of the JDI into a single scale for purposes of this meta-analysis, but treated each as a different measure of job satisfaction, as Smith, Kendall, and Hulin (1969) suggested. However, when any of the studies examined herein reported a JDI total score, we included this correlation in our analysis.
Absenteeism was measured in two basic ways: in 74 (64.9%) cases, job satisfaction was correlated with absence duration, and in 40 (35.1%) cases, job satisfaction and absence frequency were correlated. Definitions of duration and frequency were fairly consistent among all the studies. Duration referred to total amount of absence expressed in either hours or days, during a specific time period; this interval varied from 11 to 21 months. Frequency denoted the total number of occasions on which employees failed to report for scheduled work; studies reported frequency data for periods ranging from 11 consecutive weeks to 12 months. If an employee were absent for one day, then two days, during a given period of time, the duration would be three days and the frequency would be twice. Although what different organizations count as absences varies, most organizations do not include such events as vacations, holidays, funerals, military duty, educational leave, and jury duty in their calculations.

Sources of the absenteeism data that appeared in sample studies also varied. In 103 (90.3%) cases, employee attendance data came from official company records; in 9 (7.9%) cases, this data came from the employees themselves; and in 2 (1.8%) cases, researchers did not provide the source of this data.

**RESULTS**

The initial analysis of this data was performed on the full set of 114 correlation coefficients. In Table 2, which shows the results of this analysis, column 1 gives the names of the variables of interest, and column 2 contains the mean correlation weighted by sample size. Column 3 provides the number of correlation coefficients included in this analysis, with column 4 indicating the number of statistically significant correlations.

The columns of interest for the meta-analysis are the last five. Column 5, labeled sample variance, contains the total observed variance in the sample correlations. The sixth column, error variance, gives the variance that can be attributed to sampling error. We subtracted error variance from sample variance to determine the remaining unexplained variance (column 7). Column 8 indicates how much of the sample variance is ascribable to problems of measurement reliability. Column 9 reports the results of a chi-square approximation test used to determine the significance, if any, of the unexplained variance (cf. Marascuilo, 1971); this is the same chi-square procedure Fisher and Gitelson (1983) used for a meta-analysis of the role conflict and ambiguity literature. However, the chi-square test used here is not the significance test Hunter and colleagues (1982) used; as those investigators pointed out, their test is so powerful that it may identify unexplained variance of even trivial magnitude as significant, hence, they advised against its use.

According to Hunter and colleagues (1982), correlation coefficients are subject to three sources of error: sampling error, error of measurement, and

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2 As there were differences in sample sizes, we used a weighted correlation to reflect the relatively greater reliability of the larger samples.
### TABLE 2
Results of Analysis of Full Data Set

<table>
<thead>
<tr>
<th>Relationship Investigated</th>
<th>( r )</th>
<th>Number of Correlations</th>
<th>Number of Significant Correlations</th>
<th>Sample Variance</th>
<th>Error Variance</th>
<th>Unexplained Variance</th>
<th>Measurement Variance</th>
<th>Chi-square</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absenteeism with job satisfaction</td>
<td>(-0.146)</td>
<td>114</td>
<td>34</td>
<td>0.01764</td>
<td>0.00578</td>
<td>0.01186</td>
<td>0.00151</td>
<td>357.243*</td>
</tr>
</tbody>
</table>

*\( p < .05 \)

### TABLE 3
Results of Analyses with Absence Measures as Moderators

<table>
<thead>
<tr>
<th>Moderator Variables</th>
<th>( r )</th>
<th>Number of Correlations</th>
<th>Number of Significant Correlations(^a)</th>
<th>Sample Variance</th>
<th>Error Variance</th>
<th>Unexplained Variance</th>
<th>Measurement Variance</th>
<th>Chi-square</th>
</tr>
</thead>
<tbody>
<tr>
<td>Duration</td>
<td>(-0.088)</td>
<td>74</td>
<td>10</td>
<td>0.01496</td>
<td>0.01008</td>
<td>0.00488</td>
<td>—</td>
<td>110.984*</td>
</tr>
<tr>
<td>Frequency</td>
<td>(-0.181)</td>
<td>40</td>
<td>23</td>
<td>0.01593</td>
<td>0.00322</td>
<td>0.01271</td>
<td>0.00190</td>
<td>206.481*</td>
</tr>
</tbody>
</table>

*\( p < .05 \)

\(^a\)Note that the number of significant correlations decreased from 34 to 33. One study that used absence duration employed the Job Diagnostic Survey (JDS) to measure job satisfaction. Since meta-analysis requires a minimum of two studies per scale, the JDS results had to be deleted.
range variation. Our analysis corrected the first two sources of error, but there were insufficient data reported in the subject studies to allow for the range variation correction. We found that of the total variance of sample correlations (0.01764, column 5), 32.8 percent (0.00578) was due to sampling error.

Use of three reliability estimates of absence measures provided by Chadwick-Jones, Brown, Nicholson, and Sheppard (1971) and by Waters and Roach (1973), as well as use of the 30 job-satisfaction reliability estimates of Terborg, Lee, Smith, Davis, and Turbin (1982), made corrections for errors of measurement possible. According to Hunter and colleagues (1982), use of unreliable measures will cause the correlation between variables of interest to be systematically lower than the correlation between the true scores. Moreover, a certain amount of sample variance across studies is due to variation in reliability from one study to the next.

Making this reliability correction indicated that 0.00151 (8.6%) of the sample variance was due to reliability problems with the measures of absenteeism or job satisfaction. We also determined that if absenteeism and satisfaction were measured with perfectly reliable instruments, the mean correlation between these variables would be $-0.29$. In this sample, however, the mean correlation was only $-0.15$ (column 2), a depressed figure largely explained by errors of measurement—that is, unreliability.

Even though sampling errors and problems of reliability are the two largest sources of variation among studies (Hunter et al., 1982), corrections for both of these artifacts account for only 41.4 percent of the total variance in the sample correlations. This much unexplained variance would seem to indicate the presence of some variable acting to moderate the relationship between employee absenteeism and job satisfaction. Potential moderators include the different measures of the absence constructs and job satisfaction used. Consequently, we divided the total sample into subgroups on the basis of which absence measure, frequency or duration, a study used. Table 3 provides a summary of the results of this analysis.

When the total collection of studies is subdivided in such a manner, a moderator variable will show itself in two ways: (1) the average correlation will vary from subset to subset, and (2) the average unexplained variance will be lower in the subsets than for the data as a whole (Hunter et al., 1982). Both of these conditions occurred when we formed subsets on the basis of the type of absence measure used. For instance, the mean correlation for the relationship between absence duration and job satisfaction is $-0.088$, and the mean for frequency and satisfaction is over twice as large ($-0.181$). Similarly, when a pooled estimate—a form of average—of the common unexplained variance is calculated from both samples, the resulting unexplained variance of 0.00761 is lower than the unexplained variance (0.01186) for the entire data set. It appears that type of absence measure does moderate the relationship between absenteeism and job satisfaction.

Of course, in the full data set corrections were made for both sampling error and errors of measurement before moderator analysis. However, when
the data were divided into absence duration and frequency subsets, sampling error was the only artifact we could correct. Indeed, only one reliability estimate for the duration measure emerged, and since meta-analysis requires a minimum of two estimates to correct for problems of unreliability, this correction was not possible. Correcting the correlation between job satisfaction and absence frequency for errors of measurement also was impossible, since all estimates of satisfaction scale reliability came from studies that used absence duration as their attendance measure.

Having made the correction for sampling error, we found that the influence of this artifact varied between the frequency and duration subsets. Although sampling error accounted for 67.4 percent of the variance in results of the studies that used absence duration, it is responsible for only 20.2 percent of the variance in the studies that used frequency of absence.

Despite the correction for sampling error, the amount of unexplained variance in both of the subsets was still statistically significant (column 9 of Table 3). This fact justified a search for other variables perhaps affecting the absence duration-satisfaction and the absence frequency-satisfaction relationships. Given the importance of psychometric adequacy of instruments used to measure job satisfaction in studies like those in our sample, we felt that type of scale could be a potential source of variance. Table 4 provides the results of this analysis.

In column 9 of Table 4, the nonsignificant chi-square values mean that once the effects of error variance—sampling error—have been removed from the sample variance, the remaining unexplained variance is not significant \( (p > .05) \). Therefore, sampling errors can largely explain differences in results among all studies that measure job satisfaction with the Job Descriptive Index (JDI). Our analysis justifies drawing this same conclusion regarding studies that used absence duration as a dependent variable and measured job satisfaction with the GM-Faces scale, as well as those that used absence frequency and the MSQ. Consequently, the weighted mean correlation (column 3 of Table 4) of these 14 sets of studies represents the best estimate of the population value. Since the unexplained variance for studies using either (1) absence duration and the MSQ, (2) absence frequency and the JDS, or (3) absence frequency and self-developed scales is statistically significant, the mean correlations of these groups cannot be interpreted as parameter estimates.

Following Hunter and colleagues (1982) and Fisher and Gitelson (1983), the next step in this analysis was to determine the statistical significance of these population estimates by converting the values in the unexplained variance column to standard deviations. If the mean correlations in column 3 were more than two standard deviations from zero, we considered these correlations significant. It is worth noting that in 9 of 14 (64.3%) instances in which the unexplained variance was nonsignificant, the mean correlations were significantly different from zero. By contrast, the original set of 114 coefficients contained only 34 (29.7%) statistically significant values.
### TABLE 4
Results of Analyses with Satisfaction Measures as Moderators

<table>
<thead>
<tr>
<th>Measures of Absenteeism</th>
<th>Moderator Variables</th>
<th>$r$</th>
<th>Number of Correlations</th>
<th>Number of Significant Correlations</th>
<th>Sample Variance</th>
<th>Error Variance</th>
<th>Unexplained Variance</th>
<th>Chi-square</th>
</tr>
</thead>
<tbody>
<tr>
<td>Duration</td>
<td>JDI work</td>
<td>−0.148*</td>
<td>11</td>
<td>4</td>
<td>0.01541</td>
<td>0.01146</td>
<td>0.00395</td>
<td>14.353</td>
</tr>
<tr>
<td></td>
<td>JDI promotion</td>
<td>−0.072*</td>
<td>11</td>
<td>0</td>
<td>0.00939</td>
<td>0.01186</td>
<td>−0.00247</td>
<td>8.232</td>
</tr>
<tr>
<td></td>
<td>JDI supervision</td>
<td>−0.038*</td>
<td>11</td>
<td>0</td>
<td>0.00767</td>
<td>0.01195</td>
<td>−0.00428</td>
<td>6.855</td>
</tr>
<tr>
<td></td>
<td>JDI coworkers</td>
<td>−0.062</td>
<td>11</td>
<td>1</td>
<td>0.01288</td>
<td>0.01189</td>
<td>0.00099</td>
<td>11.596</td>
</tr>
<tr>
<td></td>
<td>JDI pay</td>
<td>−0.068</td>
<td>11</td>
<td>2</td>
<td>0.01676</td>
<td>0.01187</td>
<td>0.00489</td>
<td>15.854</td>
</tr>
<tr>
<td></td>
<td>JDI total</td>
<td>−0.063</td>
<td>5</td>
<td>1</td>
<td>0.00754</td>
<td>0.00646</td>
<td>0.00108</td>
<td>5.692</td>
</tr>
<tr>
<td></td>
<td>MSQ</td>
<td>−0.176</td>
<td>6</td>
<td>0</td>
<td>0.02259</td>
<td>0.00583</td>
<td>0.01676</td>
<td>24.241**</td>
</tr>
<tr>
<td></td>
<td>GM faces</td>
<td>−0.066</td>
<td>7</td>
<td>2</td>
<td>0.01044</td>
<td>0.00862</td>
<td>0.00162</td>
<td>7.939</td>
</tr>
<tr>
<td>Frequency</td>
<td>JDI work</td>
<td>−0.336*</td>
<td>5</td>
<td>5</td>
<td>0.00160</td>
<td>0.00754</td>
<td>−0.00594</td>
<td>0.992</td>
</tr>
<tr>
<td></td>
<td>JDI promotion</td>
<td>−0.067</td>
<td>3</td>
<td>0</td>
<td>0.01059</td>
<td>0.00804</td>
<td>0.00255</td>
<td>3.827</td>
</tr>
<tr>
<td></td>
<td>JDI supervision</td>
<td>−0.043*</td>
<td>3</td>
<td>0</td>
<td>0.00669</td>
<td>0.00808</td>
<td>−0.00139</td>
<td>2.418</td>
</tr>
<tr>
<td></td>
<td>JDI coworkers</td>
<td>−0.208*</td>
<td>3</td>
<td>3</td>
<td>0.00061</td>
<td>0.00742</td>
<td>−0.00681</td>
<td>0.221</td>
</tr>
<tr>
<td></td>
<td>JDI pay</td>
<td>−0.155*</td>
<td>3</td>
<td>1</td>
<td>0.00323</td>
<td>0.00772</td>
<td>−0.00449</td>
<td>1.168</td>
</tr>
<tr>
<td></td>
<td>JDI total</td>
<td>−0.250*</td>
<td>6</td>
<td>6</td>
<td>0.00717</td>
<td>0.00818</td>
<td>−0.00101</td>
<td>5.148</td>
</tr>
<tr>
<td></td>
<td>MSQ</td>
<td>−0.203*</td>
<td>3</td>
<td>1</td>
<td>0.00296</td>
<td>0.00799</td>
<td>−0.00503</td>
<td>1.172</td>
</tr>
<tr>
<td></td>
<td>JDS</td>
<td>−0.416</td>
<td>2</td>
<td>1</td>
<td>0.00612</td>
<td>0.00104</td>
<td>0.00508</td>
<td>18.091**</td>
</tr>
<tr>
<td></td>
<td>Self-developed</td>
<td>−0.134</td>
<td>11</td>
<td>6</td>
<td>0.00607</td>
<td>0.00148</td>
<td>0.00459</td>
<td>43.245**</td>
</tr>
</tbody>
</table>

*p < .05

**p < .001
Additionally, as column 3 of Table 4 indicates, there are several differences between the subsets in terms of these significant correlations. Indeed, the two subsets agree only in the sense that in both the relationship between absenteeism and the JDI work and JDI supervision scales is significantly different from zero. Not only is the pattern of significant correlations different, but the magnitude of these coefficients also differs. For instance, the correlation between the JDI co-workers scale and absence duration (-0.062) is only about one-third as strong as the correlation between the same scale and absence frequency (-0.208).

**DISCUSSION AND CONCLUSIONS**

There is a long-standing belief that job satisfaction is related to employee absenteeism, as withdrawal theory and the numerous studies that have examined this relationship have indicated. Unfortunately, empirical findings have not been consistent, and as a result, the nature of this relationship is uncertain. The purpose of the present study was to clarify the relationship between job satisfaction and absenteeism, and to determine why such contradictory evidence has arisen.

In light of our meta-analysis, a stronger case for a relationship between job satisfaction and absenteeism emerges than previous research has suggested. Specifically, the strongest associations seem to be between (1) employee absenteeism, measured by both absence frequency and absence duration, and satisfaction with the work itself; (2) absence frequency and satisfaction with co-workers; and (3) absence frequency and overall satisfaction. Of course, this does not imply a causal relationship between job satisfaction and worker absenteeism, as correlational analysis does not allow inference of causality.

This analysis seems to indicate that use of overly small samples may have obscured the relationship between employee absenteeism and job satisfaction. The less frequent occurrence of significant findings in studies using absence duration suggests that this measure is more sensitive to sample size than is absence frequency. As Table 3 shows, a statistically significant relationship between job satisfaction and duration of absence existed in 10 out 74 studies; significant relationships between satisfaction and frequency of absence occurred in 23 out of 60 studies. Furthermore, as Table 4 shows, absence duration is apparently only related to three of the seven measures of job satisfaction that have nonsignificant unexplained variance, whereas six out of the seven job satisfaction scales having nonsignificant unexplained variance have a negative relationship with absence frequency.

The stronger association between job satisfaction and absence frequency—stronger relative to the association between job satisfaction and absence duration—supports Vroom’s (1964) hypothesis that absence frequency will be more strongly related to job satisfaction than will absence duration. He argued that short term absences of one or two days are more likely to be at an employee’s discretion and are subject to employee abuse. Long term absences,
on the other hand, are more likely to be for reasons outside of employees' control, such as major illness. Because absence frequency measures give more weight to short-term than to long-term absences, and because employees are held less accountable for short absences than for long ones, we would expect absence frequency to capture the type of absenteeism that withdrawal theory predicts. Thus, we might also predict that job satisfaction will be more strongly associated with absence frequency than with absence duration, a finding that supports Smulders' (1980) position that not all measures of absenteeism capture the same phenomenon.

Despite the evidence supporting the significant negative relationship between job satisfaction and absenteeism, certain limitations are inherent in this research. First, we used only individual correlational studies—those that matched absence and job satisfaction scores of individual employees—in this analysis, as these were the only studies that provided the information needed for this type of analysis. Consequently, we left unsampled both criterion or contrasted-group studies, and group correlational studies. Although individual correlational studies tend to be the most methodologically rigorous (Nicholson et al., 1976), questions as to the adequacy of content domain sampling may still arise.

Second, as Fisher and Gitelson (1983) stated, a common argument against the use of only published studies is that unpublished results may have fewer significant findings. As Rosenthal (1979) pointed out, in its most extreme form this argument maintains that journals are filled with the 5 percent of the studies that show Type I errors, while the 95 percent of the studies that show nonsignificant (e.g., p > .05) results are consigned to file drawers. Using Rosenthal's (1978, 1979) method, we determined that 9,928 studies with statistically nonsignificant correlations would have to be found to invalidate our conclusion that job satisfaction and employee absenteeism are negatively related.

Finally, although our research indicates that a negative relationship exists between job satisfaction and absenteeism, especially absence frequency, the correlation is only $-0.15$, which explains slightly over 2 percent of the total variance. However, as noted earlier in this paper, this relationship is stronger than is apparent in the literature. If perfectly reliable instruments were used to measure job satisfaction and absenteeism, the correlation between them would be $-0.29$, which represents almost 9 percent explained variance.

Even though this meta-analytic examination of the research concerning job satisfaction and employee absenteeism offers some support for the traditional notion of a significant negative relationship between these variables, it also raises disturbing questions about research practices in this area. Our analysis indicates that the controversy surrounding the satisfaction-absenteeism relationship may be an artificial one created in large part by the use of insufficient sample sizes and different measures of the phenomena of interest. Controlling for these problems better explains the variance in results among studies. For instance, of the 16 studies using the JDI work scale, 7 reported nonsignificant results, and the other 9 found a statistically significant
relationship. Yet, once we controlled for variance due to sampling error, these different findings could be reconciled. In light of the fact that the entire field of inferential statistics rests on the assumption of correct sampling, the gravity of such poor research techniques is fully evident.

Furthermore, this study indicates that inconsistencies and nonsignificant relationships between variables are not necessarily the result of undiscovered third variable moderators. We considered the effects of moderating variables only after statistical analyses failed to explain a sufficient amount of variance among the studies. This, perhaps, is one of the strongest virtues of meta-analysis—its methodology helps prevent premature searches for moderator influences. Indeed, Hunter and colleagues (1982) argued directly that researchers must correct for statistical artifacts before calling for any moderator analysis. The present study found the inconsistencies among the results of previous inquiries into the relationship between absenteeism and job satisfaction to be accountable to sampling error and use of different measurement instruments.

REFERENCES


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