CHAPTER-II
RESEARCH METHODOLOGY
SECTION-I
RELEVANCE AND OBJECTIVES OF THE STUDY

1.1 Relevance of the Study
As we may see that past reviews are also not free from limitations like:-
- The past studies relating to job satisfaction-job performance relationship are reviewed and results are synthesized by foreign authors only and there is no such analysis in India.
- Indian studies are not included in these meta-analytic reviews; these reviews are based on foreign studies only.
- These authors did not analyze some moderators like sex, age, autonomy, citizenship, job status, type of the job and type of sector of the studies, etc. which are found during review of the studies.
- Change is the law of nature and some most important changes are made in industrial organizations like:-
  i) Change in job status- temporary or jobs on contract basis are most popular than permanent jobs.
  ii) Complexities of jobs- jobs now become more complexes than earlier jobs.
  iii) Changes in the composition of employees- traditionally men were more involved in the jobs but now women have come forward to do the jobs.
  iv) New issues have come in human resource practices like employees are treated now as an asset than a resource of production.
  v) Change in the corporations- services corporations are now more dominating in India than manufacturing corporations.

Level of job satisfaction may be high or low due to these changes, which in turn may affect the level of job performance.

1.2 Objectives of the Study
1) To find out the magnitude of relationship between job satisfaction and job performance.
2) To find out the moderator variables and their affects on the relationship between job satisfaction and job performance.

3) To compare results produced by Hunter, Schmidt and Jackson (1982); Hedges and Olkin (1985); and Davar (2004) approach.

4) To compare the results of present study with the past researches on meta-analysis of job satisfaction and job performance.

SECTION-II
RESEARCH HYPOTHESIS AND RESEARCH METHODOLOGY

2.1 Research Hypothesis

H$_{01}$: there is no significant relationship between job satisfaction and job performance.

H$_{11}$: there is significant relationship between job satisfaction and job performance.

H$_{02}$: there is no significant difference among the correlation coefficients across studies.

H$_{12}$: there is significant difference among the correlation coefficients across studies.

H$_{03}$: there is no significant difference between the estimates of mean correlations of two moderator based sub-groups (male vs. female employees).

H$_{13}$: there is significant difference between the estimates of mean correlations of two moderator based sub-groups (male vs. female employees).

H$_{04}$: there is no significant difference between the estimates of mean correlations of two moderator based sub-groups (young vs. old employees).

H$_{14}$: there is significant difference between the estimates of mean correlations of two moderator based sub-groups (young vs. old employees).

H$_{05}$: there is no significant difference between the estimates of mean correlations of two moderator based sub-groups (Manager/Professionals vs. Non-Managers).

H$_{15}$: there is significant difference between the estimates of mean correlations of two moderator based sub-groups (Manager/Professionals vs. Non-Managers).

H$_{06}$: there is no significant difference between the estimates of mean correlations of two moderator based sub-groups (Indian Studies vs. Foreign Studies).

H$_{16}$: there is significant difference between the estimates of mean correlations of two moderator based sub-groups (Indian Studies vs. Foreign Studies).
H_{07}: there is no significant difference between the estimates of mean correlations of two moderator based sub-groups (Permanent Jobs vs. Temporary Jobs).

H_{17}: there is significant difference between the estimates of mean correlations of two moderator based sub-groups (Permanent Jobs vs. Temporary Jobs).

H_{08}: there is no significant difference between the estimates of mean correlations of two moderator based sub-groups (Complex Jobs vs. Non-Complex Jobs).

H_{18}: there is significant difference between the estimates of mean correlations of two moderator based sub-groups (Complex Jobs vs. Non-Complex Jobs).

H_{09}: there is no significant difference between the estimates of mean correlations of two moderator based sub-groups (High Autonomy vs. Low Autonomy).

H_{19}: there is significant difference between the estimates of mean correlations of two moderator based sub-groups (High Autonomy vs. Low Autonomy).

H_{010}: there is no significant difference between the estimates of mean correlations of two moderator based sub-groups (Self Administered Questionnaire vs. Existing Scales of job satisfaction).

H_{110}: there is significant difference between the estimates of mean correlations of two moderator based sub-groups (Self Administered Questionnaire vs. Existing Scales of job satisfaction).

H_{011}: there is no significant difference between the estimates of mean correlations of two moderator based sub-groups (Self Administered Questionnaire vs. Existing Scales of job performance).

H_{111}: there is significant difference between the estimates of mean correlations of two moderator based sub-groups (Self Administered Questionnaire vs. Existing Scales of job performance).

H_{012}: there is no significant difference between the estimates of mean correlations of two moderator based sub-groups (Job Facets Satisfaction vs. Overall Job Satisfaction).

H_{112}: there is significant difference between the estimates of mean correlations of two moderator based sub-groups (Job Facets Satisfaction vs. Overall Job Satisfaction).

H_{013}: there is no significant difference between the estimates of mean correlations of two moderator based sub-groups (Published Studies vs. Unpublished Studies).
H\textsubscript{113}: there is significant difference between the estimates of mean correlations of two moderator based sub-groups (Published Studies vs. Unpublished Studies).

H\textsubscript{014}: there is no significant difference between the estimates of mean correlations of two moderator based sub-groups (Manufacturing Sector vs. Service Sector).

H\textsubscript{114}: there is significant difference between the estimates of mean correlations of two moderator based sub-groups (Manufacturing Sector vs. Service Sector).

2.2 Research Methodology

Meta-analytic techniques are used to analyze & synthesize the results of 100 collected individual studies. Glass and colleagues (e.g., Glass, 1976; 1977; Smith & Glass, 1977; McGaw & Glass, 1980; and Smith, Glass & Miller, 1980) coined the term meta-analysis & introduced the procedures of meta-analysis. Glass 1976 defined Meta Analysis as “The statistical analysis of a large collection of studies results for the purpose of integrating the findings”. Meta analysis is regarded as an accurate and objective way to assimilate research findings in the present era. It is a way to summarize, integrate and interpret selected descriptive statistics (e.g., sample correlations) produced by sample studies. Meta-analysis is a statistical procedure designed to accumulate experimental and correlational results across independent studies. Each strand of a rope contributes to the strength of the rope. But the rope is stronger than any individual strand. Similarly, when a particular finding is obtained repeatedly under a variety of conditions, we are strongly confident that there exists a general principle. The results of small localized individual studies are often insufficient to provide us with confident answers to questions of general importance. Meta-analysis allows us to compare or combine results across a set of similar studies. In the individual study, the units of analysis are the individual observations. In meta-analysis the units of analysis are the results of individual studies. The term meta-analysis means ‘an analysis of analyses’. A particular topic may have been replicated in various ways, using, for example, differently sized samples and conducted in different countries under different environmental, social and economic conditions. Meta-analysis enables a rigorous comparison to be made rather than subjective ‘eyeballing’.

It is being conducted in a variety of disciplines, including medicine, psychology, environmental science, industrial psychology and education. In meta-
analysis, the basic principle is to calculate effect sizes for individual studies, convert them to a common metric, and then combine them to obtain an average effect size. To check the significance of mean effect size, confidence intervals can be constructed around the mean effect size or Z test may be conducted. Johnson, Mullen and Salas (1995) stated that meta-analysis is typically used to address three general issues: Central tendency, Variability and Prediction.

**Central tendency** can be determined through mean effect size, variation on the mean effect size and the significance of this mean effect size.

**Variability** is the difference between effect sizes across studies & can be ascertained by using the test of homogeneity of effect sizes.

**Prediction** means there is need to explain the variability in effect sizes across studies in terms of moderator variables. The variability in effect sizes could be moderated by different facts like studies may be conducted on different age group samples or in different countries etc.

There are many different metrics that can be used to measure effect size: the Pearson product-moment correlation coefficient, $r$; the effect-size index, $d$; as well as odds ratios, risk differences. Of these, the correlation coefficient is used most often (Law et al. 1994) and so is the focus of this study. We took correlation coefficients between job satisfaction and job performance from different studies and analyzed the relationship between these two constructs through different Meta-analytic techniques.

There are different methods of Meta analysis: - Rosenthal and Rubin’s method (1991), Hunter, Schmidt and Jackson (1982), the methods devised by Hedges and colleagues (Hedges & Olkin, 1985; Hedges, 1992; Hedges & Vevea, 1998), Davar (2004). Rosenthal & Rubin have developed a fixed effects model. Hedges & Olkin (1985) have postulated powerful statistical procedures meant for the determination of a common correlation & testing of homogeneity of a set of correlations. For combining correlation coefficients, Hedges et al. and Rosenthal and Rubin (see Rosenthal, 1991) are in agreement about the method used. Hunter et al. (1982) framework is also used to compute true variance i.e. observed variance net of the measurement error, sampling error and range-restriction. Davar (2004) has also given ‘An Improved Version of Hunter et al. (1982) framework. According to Davar (2004) measurement corrected correlation coefficients must be used for valid estimates of
observed variance, sampling error variance and true variance. The computations of these various methods differ.

For calculating the mean effect size, three main approaches are used i.e. Hedges et al. (1985) approach, Hunter et al. (1982) approach, and Davar (2004) approach.
Hedges et al. (1985) Approach

Fixed-Effects Model

In this method, correlations are first converted into a standard normal metric (using Fisher’s r-to-Z transformation) before calculating a weighted average of these transformed scores. Fisher’s r-to-Z transformation (and the conversion back to r) is described in equations (1&2) in which \( r_i \) is the correlation coefficient from study \( i \).

\[
\begin{align*}
z_{r_i} &= \frac{1}{2} \log_e \left( \frac{1+r_i}{1-r_i} \right) \quad (1)
\end{align*}
\]

The transformation back to \( r_i \) is simply

\[
r_i = \frac{e^{2z_{r_i}} - 1}{e^{2z_{r_i}} + 1} \quad (2)
\]

The transformed effect sizes are then used to calculate the initial average in which each correlation is weighted by the inverse of the within-study variance of the study from which it came. For correlation coefficients the individual variance is the inverse of the sample size minus three (see Hedges & Olkin, 1985, p. 227 and p. 231).

\[
w_i = \frac{1}{v_i} \quad v_i = \frac{1}{n_i - 3} \quad \text{So,} \quad w_i = n_i - 3
\]

\[
\begin{align*}
\bar{z} &= \frac{\sum w_i z_{r_i}}{\sum w_i} = \frac{\sum(n_i - 3)z_{r_i}}{\sum(n_i - 3)} \quad (3)
\end{align*}
\]

This average is then used to calculate a test of the homogeneity of correlations: The squared difference between each study’s observed transformed \( r \) and the mean transformed \( r \) (from equation 3), weighted by the within-study variance, is used. This gives us the statistic \( Q \) in Equation (4), which has a chi-square distribution with \( k-1 \) degrees of freedom under the null hypothesis of homogenous effect sizes (Hedges & Olkin (1985), Equation 16, p. 235):

\[
Q = \sum(n_i - 3)(z_{r_i} - \bar{z}_{r_i})^2
\]

Random-Effect Model

To calculate the random-effects average correlation, the weights use a variance component that incorporates both between-studies variance and within-study variance used in fixed-effect model. The weighted average in the \( z_r \) metric is (based on Hedges & Vevea, 1998, Equation 12)

\[
\begin{align*}
\bar{z}^* &= \frac{\sum w^*_i z_{r_i}}{\sum w^*_i} \\
\end{align*}
\]

The between-studies variance is denoted by
\( \tau^2 \) and is simply added to the within-study variance. As such the weights for the random-effects model \((w_i^*)\) are (see Hedges & Vevea, 1998, equation 13):

\[
w_i^* = \frac{1}{v_i + m^2} \quad v_i = \frac{1}{n_i - 3} \quad \text{So, } w_i = \left( \frac{1}{n_i - 3} + m^2 \right)^{-1}
\]

Hedges and Vevea (1998) provide equations for estimating the between-study variance based on the weighted sum of squared errors, \(Q\) (see equation 4), the number of studies in the meta-analysis, \(k\), and a constant, \(c\) (see equation 7).

\[
\tau^2 = \frac{Q - (k - 1)c}{c} \tag{6}
\]

The constant, \(c\), is calculated using the weights from the fixed effects model:

\[
c = \sum w_i - \frac{\sum (w_i)^2}{\sum w} \tag{7}
\]

When combining correlation coefficients the weights are just \(n_i - 3\) and the constant, therefore, becomes:

\[
c = \sum (n_i - 3) - \frac{\sum (n_i - 3)^2}{\sum (n_i - 3)} \tag{8}
\]

If, however, the estimate of between-study variance, \(\tau^2\), yields a negative value then it is set at zero (because the variance between-studies cannot be negative). And the estimate of homogeneity of study effect sizes is calculated in the same way as for the fixed-effect model. Finally, the average correlation is then converted back to the \(r\) metric (using equation 2) before being reported (in both fixed and random effect model).

The sampling variance of the transformed average correlation is the reciprocal of the sum of weights and the standard error of this average correlation is the square root of this sampling variance. (see Hedges & Vevea, 1998, p. 493)

\[
SE(\bar{z}^*) = \sqrt{\frac{1}{\sum w_i}} \tag{9}
\]

Hedges and Olkin (1985) recommended constructing a confidence interval around the average effect size, which is easily done using the standard error and \(z_{a/2}\) the two-tailed critical value of the normal distribution (which is 1.96 for the most commonly used 95% confidence interval). The upper and lower bounds are calculated by taking the average effect size from equation 5 and adding or subtracting its standard error multiplied by 1.96:

\[
CL_{Upper} = \bar{z}_r^* + 1.96SE(\bar{z}_r^*)
\]
\[
CL_{Lower} = \bar{z}_r^* - 1.96SE(\bar{z}_r^*) \tag{10}
\]
These values are again transformed back to the \( r \) metric using equation 2 before being reported.

**Hunter et al. (1982) approach**

Hunter and Schmidt’s method is thoroughly described by Hunter et al. (1982; 1990). Hunter and Schmidt advocate a single method (a random-effect method) based on their belief that fixed-effects models are inappropriate for real-world data and the type of inferences that researchers usually want to make. The main difference between Hedges et al. (1985; 1998) & Hunter et al. (1982; 1990) is in the use of untransformed effect-size estimates in calculating the weighted mean effect size and the weight used is simply the sample size, \( n_i \) (see Hunter and Schmidt, 1990, p. 100).

\[
\bar{r} = \frac{\sum n_i r_i}{\sum n_i}
\]  

(11)

Hunter et al. (1982; 1990) argue that the variance across sample correlations will be made up of the variance of correlations in the population and the sampling error; therefore, to estimate the variance in population correlations we have to correct the variance in sample correlations by the sampling error. The variance of sample correlations is the frequency weighted average squared error (see Hunter and Schmidt, 1990, p. 100).

\[
\sigma_r^2 = \frac{\sum n_i (r_i - \bar{r})^2}{\sum n_i}
\]  

(12)

The sampling error variance is calculated using the average correlation, \( \bar{r} \), and the average sample size (see Hunter and Schmidt 1990, p. 108):

\[
\sigma_e^2 = \frac{(1 - \bar{r}^2)^2}{\frac{\sum n_i}{k}}
\]  

(13)

Hunter et al. (1982, pp.42-43) propose that the true variance in population correlations across studies can be obtained by deducting the sampling error variance from the observed variance of various correlations:

\[
\sigma_p^2 = \sigma_r^2 - \sigma_e^2
\]  

(14)

Alternatively, Hunter et al. have also recommended \( \chi^2 \) test to test the homogeneity of effect sizes (Hunter and Schmidt, 1990, p. 110-112).

\[
\chi^2 = \frac{\sum (n_i - 1) (r_i - \bar{r})^2}{(1 - \bar{r})^2}
\]  

(15)
To obtain the standard error of mean correlation, simply divide the variance of sample correlations by the number of studies in the meta-analysis, \( k \), and take the square root (see Schmidt & Hunter, 1999):

\[
SE(\bar{r}) = \sqrt{\frac{\sigma_{r^2}}{k}}
\]  

(16)

Confidence intervals can be obtained by using the standard error of mean correlation (see Hunter & Schmidt, 2004).

\[
CL_{Upper} = \bar{r} + 1.96SE(\bar{r})
\]

\[
CL_{Lower} = \bar{r} - 1.96SE(\bar{r})
\]

(17)

**Higgins and Thompson (2002)**

However, \( Q \) test of Hedges et al. (1985) and \( \chi^2 \) test of Hunter et al (1982, 1990) only informs us about the presence versus the absence of heterogeneity, but it does not report on the extent of such heterogeneity. Higgins and Thompson (2002) has been proposed \( I^2 \) index to quantify the degree of heterogeneity in a meta-analysis. The \( I^2 \) index measures the extent of true heterogeneity dividing the difference between the result of the \( Q \) test and its degrees of freedom \((k-1)\) by the \( Q \) value itself, and multiplied by 100.

\[
I^2 = \frac{Q - (k - 1)}{Q} \times 100
\]

The \( I^2 \) index can be interpreted as the percentage of the total variability in a set of effect sizes due to true heterogeneity, that is, to between-studies variability. For example, a meta-analysis with \( I^2 = 0 \) means that all variability in effect size estimates is due to sampling error within studies. On the other hand, a meta-analysis with \( I^2 = 50 \) means that half of the total variability among effect sizes is caused not by sampling error, but by true heterogeneity between studies. Thus, percentages of around 25\% \((I^2 = 25)\), 50\% \((I^2 = 50)\), and 75\% \((I^2 = 75)\) would mean low, medium, and high heterogeneity, respectively.


As per Davar (2004; 2006), Hunter et al. (1982) procedure has various limitations such as the use of weighing based formulae and improper procedure for the removal of effects of measurement error. Their examples end up with a zero true
variance. To obtain a correct estimate of true variance, Davar (2004) suggest major amendments in their procedure and formulas.

Hunter et al. (1982) argue that we can estimate and remove the effect of measurement error on observed variance ($\sigma_r^2$) and sampling variance ($\sigma_e^2$). But Davar (2004) state that measurement error on $\sigma_r^2$ and $\sigma_e^2$ cannot be removed with mathematical formulas. As per Davar (2004), the measurement corrected correlation coefficients must be used for a valid estimate of the sampling error variance as well as observed variance. The individual (observed) correlations could be corrected for measurement error by the classic formula (Hunter et al., 1982, p. 55).

$$r_i = \frac{r_{xy}}{\sqrt{r_{xx} \cdot r_{yy}}}$$

(18)

Where,

- $r_{xy}$ = correlation coefficient between x and y variable of individual studies
- $r_{xx}$ = reliability estimate of the variable x (independent variable)
- $r_{yy}$ = reliability estimate of the variable y (dependent variable)

Davar (2004) does not recommend a weighing of correlation values with the sample-sizes for the computation of common correlation ($\rho$) for a set of studies. As per Davar (2004), an estimate of $\rho$ could be made by simply dividing the sum of individual measurement corrected correlations ($\sum r_i$) by number of studies ($k$):

$$\rho = \frac{\sum r_i}{k}$$

(19)

Davar (2004) stated that Hunter et al. (1982) procedure of the computation of the observed variance results in cumulative weighing. As per Davar (2004) weighing of sample statistics (the correlation coefficient) can produce either magnified or an underestimate of $\sigma_r^2$. Therefore, we must utilize the non-weighted formula for the computation of observed variance. To obtain observed variance, the sum of squared difference of individual measurement corrected correlations from common correlation must be divided by number of studies.

$$\sigma_r^2 = \frac{\sum (r_i - \rho)^2}{k}$$

(20)

Davar (2004) recommends two modifications in Hunter et al. (1982) formula for the computation of the sampling error. One, we should compute the sampling error
variance per study. Two, we must utilize mean correlation \((\rho)\) computed with the help of the measurement-corrected individual correlations coefficients.

The sampling error variance is calculated using mean of the measurement corrected correlations, \((\rho)\), and the number of studies \((k)\).

\[
\sigma_e^2 = \frac{(1-\rho)^2}{k}
\]  

(21)

Davar (2004) has recommended that the true variance in population correlations across studies \((\sigma_p^2)\) can be computed as given by Hunter et al. (1982) procedure.

\[
\sigma_p^2 = \sigma_r^2 - \sigma_e^2
\]  

(22)

If the value of true variance is zero (or close to zero), Davar (2004) conclude that the variation in population correlation coefficients across studies is not significant. But a substantial value of true variance indicates that one or more moderator variables do exist. Davar (2006) find that meta-analytic formulas of \(\chi^2\)-statistic and mean correlation developed by Hunter et al. (1982) do not produce the valid estimates of \(\chi^2\)-statistic and mean correlation. Davar (2006) suggests that the dataset must satisfy certain assumptions before the application of \(\chi^2\)-test of variability. For example, the assumption of large sample-size should be met by each study included in the dataset.

Neter et al. (1988) have advocated t-statistics to test whether there is difference between the correlations across the two moderator-based subgroups. The following equation for t-statistics is given by Neter, Wasserman, & Whitmore, 1988, p. 402:

\[
t = \frac{|\bar{r}_1 - \bar{r}_2|}{\sqrt{\frac{\text{Var}(r_1)}{k} + \frac{\text{Var}(r_2)}{k}}}
\]

Where,

- \(\bar{r}_1\) = mean corrected correlation for each of the moderator-based subgroups;
- \(\bar{r}_2\) = mean corrected correlation for each of the moderator-based subgroup;
- \(\text{Var}(r_1)\) = the variance of set of correlations in subgroup;
- \(\text{Var}(r_2)\) = the variance of set of correlations in subgroup;
- \(k\) = number of studies in the subgroup.
t-distribution has \((2k-2)\) degrees of freedom. The computed t-statistics is compared with the table value, if computed value of \(t\) is greater than the table value, the sub groups differ on account of a proposed moderator.