# Using Quantitative and Mixed Research Methods in Marketing: A Meta-Analytic Approach

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**Abstract:** The problem of the inconsistent results of empirical studies is a reality in any research field. Literature provides the meta-analysis approach as a solution that responds to the challenge of evaluating, combining, comparing and synthesizing the accumulation of results to a typical, common and representative value of a particular research topic. In this paper, through meta-analysis, we aim to respond to a double challenge within the marketing scientific research field. We analyze the mixed method applicability level in relation to quantitative methods by evaluating the differences among the empirical results of the studies whose aim concerns the same research topic, namely *customer behavior*. Based on a set of well-defined criteria, we have selected 20 studies published in two journals from the American Marketing Association database. The search has been limited to a number of keywords included in the title of these papers: *consumer, behavior* and *customer*. The results obtained following the quantitative review of the specialized literature specific to consumer behavior analysis suggest that the *type of method* is a significant determinant of the existing differences among the primary studies' empirical results.

**Keywords:** Literature review; empirical results; consumer behavior

**JEL Classification:** A10; M30

## 1. Introduction

Methodological studies may have several objectives, such as the assessment of methods used in a particular field or a particular science, the development of new research methods, testing new methodological instruments etc. In such research, the approach is generally a theoretical one, but there are also empirical studies.

When it comes to empirical studies, the qualitative methods are more appropriate and easier to apply. In order to perform a quantitative study from a methodological perspective, the specialized literature suggests at least two possibilities. The first one requires a strict approach, following some methodological steps that lead to a well defined result type. In this case, we are speaking of meta-analysis. A second possibility involves a multidimensional statistical study on a set of variables defined on the basis of a sample of studies published in scientific journals, in a particular

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research field. The variables are developed according to a set of methodological aims, such as: the identification of method types used in these studies, the existing correlations between methods and research topics, the types of assumptions and the obtained results etc. Bass (1995) suggests four approaches in order to develop an empirical generalization: traditional literature review, meta-analysis, content analysis and clustering, seeking out irregularities by examining different data sets.

In order to perform this study, we have chosen to conduct a *meta-analysis*. In time, the meta-analysis has become a dominant method for the review of scientific literature (Aguinis et al., 2011), allowing the examination of a research field and determining the degree at which a particular outcome has been replicated successfully in various studies (Eden, 2002). Despite the fact that the development of this method has not been without criticism, presenting certain limits (for example, it only refers to the results of studies on a particular research topic), meta-analysis has become the quantitative analysis technique of reviewing the empirical results obtained from studies carried out in a specific research field.

The fundamental aim of our study is to verify if the empirical results of economic studies differ significantly in terms of the type of method applied, namely quantitative or mixed (qualitative and quantitative). However, according to the meta-analysis methodology, we have considered the domain of *marketing* as research field and the *consumer (customer) behavior* as research topic. The customer behavior is one of the key insights of marketing scientific study, which is always evolving and characterized by constant change. Thus, understanding how consumers think and make decisions can provide researchers with the knowledge they need to develop effective marketing models of communication that influence people to purchase goods and services (for more details about the main models of marketing communication, see the study of Oancea (2015)).

The paper is structured as it follows. The ensuing section deals with the fundamental aspects of meta-analysis, enabling a clear understanding of the concept, as well as its applicability in Economics. The third section deals with a brief presentation of methodological steps of meta-analysis. The fourth section of this paper presents an empirical study that analyzes a relatively reduced sample of studies published in two AMA (American Marketing Association) journals. The paper ends with concluding remarks, directions for future research and references.

## 2. Meta-Analysis in Economics

Meta-analysis is a concept coined by Gene Glass in order to define „the analysis of analyses". The author states that meta-analysis refers *to the statistical analysis of a large collection of results from individual studies, for the purpose of integrating their findings. It connotes a rigorous alternative to the casual, narrative discussions of* *research studies which typify our attempts to make sense of the rapidly expanding research literature* (Glass, 1976, p. 3).

In comparison to other reviewing methods (narrative analysis, for example), meta-analysis can be distinguished by imposing the assessment of the association level between the studies features and their results by means of effect size indices. Thus, from a methodological point of view, meta-analysis can be defined as a quantitative statistical procedure (Glass, 1976), which involves estimating the global effect size of a set of primary studies on the basis of their individual effect sizes (Field, 2001).

Throughout the history of scientific research, various forms of meta-analyses can be distinguished. Starting from the comparison of different astronomy results, in the $18^{th}$ and the $19^{th}$ centuries (Gauss and Laplace), followed by a quantitative analysis of the results selected from a series of planned studies in medical research (Pearson, 1904; Fisher, 1935; Cochran, 1937) and then in social sciences (Glass, 1976; Rosenthal, 1984), finally reaching the formalized quantitative synthesized technique of a large amount of results from almost any scientific research field. Over the past two decades, in economics there have been many „crisis” proclamations (Blaug, 1980, pp. 253-264). The Keynesian followers, monetarists and classical economists are not able to engage themselves in a constructive dialogue (Klamer, 1985). Moreover, the methodology and the “orthodox” language of micro-economists make the communication with the behavioral economists impossible (Frantz, 1985; Leibenstein, 1985; Stanley, 1986). In this context, the current literature, no matter how well performed, raises the question of whether it is reasonable to establish a consensus or to identify a clear and uncontroversial pattern of developing economic knowledge.

Literature reviews are essential instruments in summarizing economic theories and identifying unsolved research problems. However, they are dominated by a high level of subjectivity. Researchers often make unjustified choices regarding the reviewed studies, the importance given to certain results of these studies, their interpretation and the selection of determinants explaining the differences between these results. In this context, the questions about the legitimacy of the conclusions formulated on the basis of economic literature review are inevitable. Why is there a so high variation level in the empirical results of economic research? Why do economic researchers obtain different results when analyzing the same phenomenon? Does the reason lie in the choice of statistical methods or is the result of a pattern specification error?

The aim of approaching meta-analysis does not intend to limit the examination of specialized literature to mere speculations, concluded on the basis of economic empirical studies. By using meta-analysis, these assumptions may be tested in the same manner in which any economic phenomenon is empirically assessed. Although it is relatively new in the circle of economists, meta-analysis has developed quickly and continues to gain acceptance among research economists (for an overview of the state of meta-analysis in economics, see Figure 1 in the paper of Koning, 2002). In this matter, Stanley and Jarrell (1989) had an important contribution. Their remarks had a major impact in approaching the meta-analysis methodology (particularly, meta-regression) to assess economic empirical results. Meta-analysis has also become important in finance, marketing and management research. The important place reserved to meta-analytical studies in scientific journals shows an increased interest for this method in marketing, especially in strategic or behavioral marketing topics, such as consumer or customer behavior (Zablah et al., 2012; Chang & Taylor, 2016; Pick & Eisend, 2016; Purmehdi et al., 2017), but also in methodological issues (Franke, 2001; Laroche &Soulez, 2012; Eisend, 2015). In fact, nowadays, it is probably difficult to find a research field in which meta-analysis cannot be applied.

## 3. Meta-analysis Methodology

In time, meta-analysis has known many methodological approaches, but the most comprehensive are those proposed by Glass et al. (1981), Hunter and Schmidt (1981) and Hunter et al. (1982). Starting from these approaches, the emphasis further falls on developing a meta-analysis methodological scheme (Figure 1) that can respond to the aim of our research. According to specialized literature, the main methodological steps are planning and conducting the meta-analysis, with corresponding sub-steps for each of them.

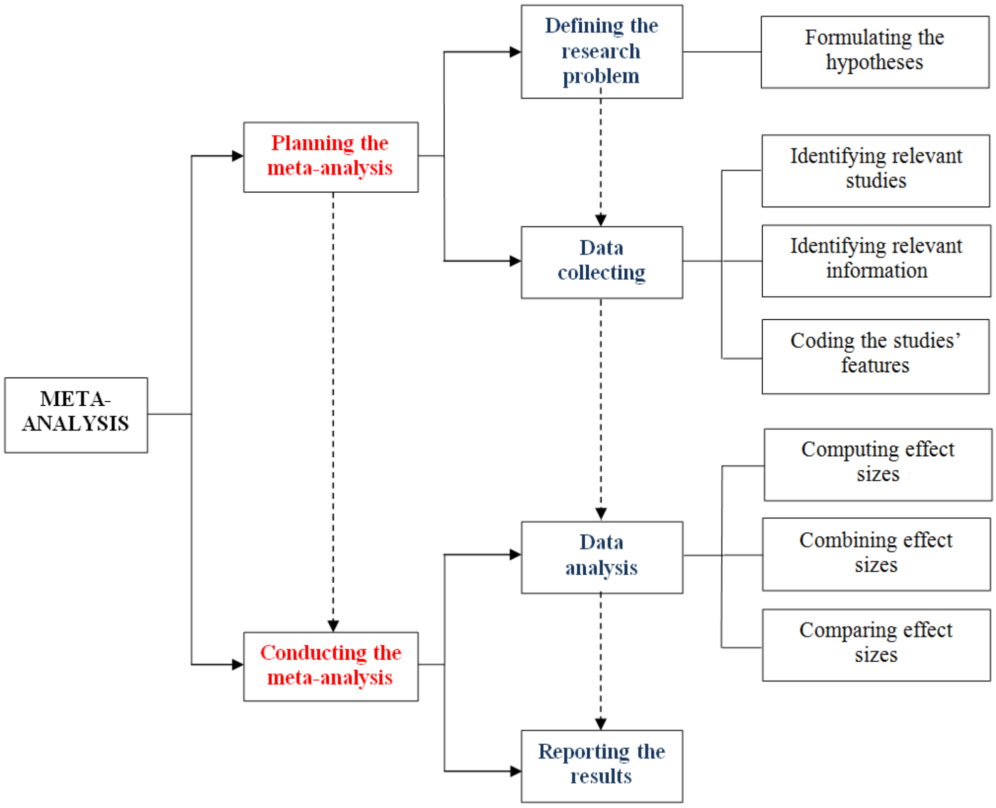


**Figure 1. The methodological steps of meta-analysis**

### 3.1. Planning the Meta-analysis

The first step involves the establishing of the meta-analysis main objective and formulating the research hypotheses, obtaining the sample of analyzed primary studies, identifying the relevant information and coding the features of these studies.

#### 1st Step: Defining the research problem

As any other scientific approach, the meta-analysis starts with the defining of the research problem step[1]. This step requires identifying the research topic, precisely defining the objective, formulating the research questions that should be answered, and the a priori hypotheses, choosing the meta-analytical approach and defining the features of the primary studies.

[1] see (Hedges et al., 1989; Mullen, 1989; Cooper, 1998; Card, 2012).

**2nd Step: Data collecting**

The next step is the actual collection of data in order to obtain the sample. In this regard, the study identification methods and the relevant information from these studies, as well as the possible ways of coding the information should be considered.

To *identify the studies* that respond to the former research questions, an important step in meta-analysis is to determine which type of studies will be included, specifying a series of inclusion or exclusion criteria (Card, 2012). These criteria refer to features that define the statistical population, study design, type of publication etc. The selection of primary studies can be performed either by considering certain keywords that identify the research topic or by searching for relevant references cited in some of these studies. The collection of relevant information for meta-analysis is conducted according to the research goals and the design of the analyzed studies (descriptive studies, experimental studies etc.). In this stage, it is important to define the research problem from at least four points of view: variables used in study; sampling procedure; used statistical methods; obtained statistical results.

Coding the information is very important in establishing and computing the effect sizes, based on which the quantitative analysis of primary studies' results will be possible. Card (2012) provides some examples that require coding the information based on the type of meta-analysis.

### 3.2. Conducting the Meta-analysis

The second fundamental phase of meta-analysis methodology consists in conducting the actual quantitative analysis, which implies two other steps. The first one targets the analysis of data presented in papers from the primary analysis. The second one refers to the actual reporting results of the meta-analysis that is treated in this paper not as a separate section, but as a part of the other steps.

**3rd Step: Data analysis**

On one hand, data analysis involves computing the effect size for each primary study included in meta-analysis and, on the other hand, the analysis of these effect sizes by means of some specific models.

*a. Computing the effect sizes*

The effect size is the most important information extracted from the studies included in a meta-analysis. Therefore, computing this indicator from the data resulting from the studies' original analysis requires special attention. The most commonly used indices for representing the effect sizes are: $r$ (*Pearson correlation coefficient*), $g$ (an indicator of *standardized mean difference*), and $o$ (*odds ratio*). In this regard, several important aspects have to be considered. First, there are different ways of computing the effect sizes, depending on the available information or data reported in primary studies: inferential statistics, descriptive statistics, and information regarding the level of statistical significance. Secondly, if necessary, the comparison and transformation methods among these three indices should be considered.

*Pearson' correlation coefficient* measures the association between two continuous variables (symbolized by $r$), between a dichotomous variable and a contionuous one (symbolized by $r_{pb}$) or between two dichotomous variables (symbolized by $\phi$). Pearson's coefficient is considered a useful and easily interpretable indicator of effect size. However, in many meta-analysis, $r$ is converted before the effect sizes should be combined or compared among studies[1] The most common transformation of $r$ is the one developed by Fisher, which is obtained based on the relationship:

$$Z_r = \frac{1}{2} ln\left(\frac{1+r}{1-r}\right),$$

where: $r$ is the correlation coefficient between the two variables; $Z_r$ represents the Fisher transformation of $r$ indicator.

Knowing the sample size ($n$) within each primary study, the estimated standard error corresponding to $Z_r$ has the following expression:

$$s_{Z_r} = 1/\sqrt{n-3},$$

which shows that, as the sample size increases, the error standard decreases.

The indices family of standardized mean difference represents the difference magnitude between the means of two groups as a function of groups' standard deviations. Therefore, it can be considered that these effect sizes express the association of a dichotomous variable (as grouping factor) and a continuous variable. The specialized literature presents three standardized mean difference indices (Rosenthal, 1994; Grissom and Kim, 2005): *Hedges' coefficient ($g$)*, *Cohen's coefficient ($d$)* and *Glass's coefficient ($g_{Glass}$)*. The most widely used is the coefficient of Hedges, which is computed via the following formula:

$$g = \bar{x}_1 - \bar{x}_2/s'_{pooled},$$

where $\bar{x}_1$ and $\bar{x}_2$ are the means of the first and the second group, respectively; $s'_{pooled}$ is the pooled estimate of the population standard deviation.

Odds ratio, denoted as $o$ or symbolized often by $OR$, represents a useful indicator of the effect size in the case of association between two dichotomous variables. The formula of computing $o$ within a primary data set is:

$$o = n_{00}n_{11}/n_{01}n_{10},$$

[1] for details, see (Hedges & Olkin, 1985, pp. 226-228; Schulze, 2004, pp. 21-28).

where $n_{00}$, $n_{01}$, $n_{10}$, $n_{11}$ are the number of observations corresponding to the association between each two categories of the two variables.

The equations for computing the three indices of effect sizes, based on the data reported in primary studies, are presented in Table 1 (Annex 1). It should be also noted that the value of one coefficient can be obtained from the other two indices (Card, 2012).

*b. Combining the effect sizes*

Following the meta-analytical process, the stage of effect size analysis by means of several types of models is considered. In this context, the specialized literature clearly differentiates between fixed-effect and random-effect models. The fixed-effects model takes into account the estimation error of each effect size in relation to an overall effect, considered unique for all studies. Unlike the former model, the random-effects model considers the estimation error of each study in relation to the other ones.

Considering the aim of this paper, we discuss only the fixed-effects model. The estimation of this model requires several steps, described in the table below.

**Table 2. Steps of fixed-effects model**

| Steps | Observation |
|---|---|
| Computing the standard error of the effect size estimate from study *i* | denoted as $s_{ES_i}$, it differs depending on the effect size indices |
| Evaluating the precision of effect size estimate | $w_i = 1/s^2_{ES_i}$ |
| Computing the weighted mean effect size | $\overline{ES} = \frac{\sum_{i=1}^{m}(w_i ES_i)}{\sum_{i=1}^{m} w_i}$ |
| Computing the standard error of the mean effect size | $s_{\overline{ES}} = \sqrt{1/\sum w_i}$ |
| Testing the statistical significance of the mean effect size | $Z = \overline{ES}/s_{\overline{ES}}$ |
| Computing the lower- and upper-bound effect sizes for confidence intervals | lower limit: $ES_{LI} = \overline{ES} - z_{\alpha/2} s_{\overline{ES}}$<br>upper limit: $ES_{LS} = \overline{ES} + z_{\alpha/2} s_{\overline{ES}}$ |
| Testing the heterogeneity among effect sizes | $Q = \sum (w_i (ES_i - \overline{ES})^2) \Leftrightarrow$<br>$Q = \sum (w_i ES_i^2) - \frac{(\sum (w_i ES_i))^2}{\sum w_i}$ |

The $Q$ statistics is distributed as $\chi^2$ with $(m-1)$ degrees of freedom, and the decision concerning the null hypothesis is taken based on the comparison of the calculated value with the theoretical one. Thus, if $Q$ statistics exceeds the critical value of $\chi^2$, the null hypothesis of homogeneity is rejected. In other words, the effect sizes are heterogeneous, meaning that there are significant differences among the analyzed primary studies.

*c. Comparing the effect sizes*

If the meta-analysis shows a significant heterogeneity of effect sizes among studies, the analysis is continued with determining the source of heterogeneity step, by means of the moderator analysis (Baron & Kenny, 1986; Little et al., 2007). This type of analysis aims to explain the variation in effect sizes using the studies' coded features as independent variables. More specifically, the moderator analysis within a meta-analysis determines whether the association between two variables (represented by the effect size) varies significantly depending on a potential moderator (defined by the characteristics of primary studies).

Within a meta-analysis, the moderators of effect sizes can be either categorical variables (for example, the type of method used in primary studies) or continuous variables (for example, the average age). A simultaneous analysis of these moderators is also possible by using the meta-regression procedure.

The logic of assessing the impact of a categorical moderator in meta-analysis is similar to the procedure used for the analysis of variance (ANOVA) in primary studies. While the ANOVA procedure allows dividing the total variability between groups and within groups (defined by a certain group factor), the moderator analysis partitions the overall heterogeneity among effect sizes of studies into between- and within-groups of studies' heterogeneity (Hedges, 1982; Lipsey & Wilson, 2001, pp. 120-121). In other words, approaching the ANOVA procedure in a meta-analysis involves testing the influence of a categorical moderator that acts at two or more levels on the effect size.

In table 3 are listed the steps of evaluating a categorical moderator in meta-analysis.

**Table 3. Steps of moderator analysis**

| **Steps** | **Statistics** | **Degrees of freedom** |
|---|---|---|
| Rule of partitioning the total heterogeneity | $Q_{total} = Q_{between} + Q_{within}$ | |
| Total heterogeneity | $Q_{total} = \sum(w_i ES_i^2) - \frac{(\sum(w_i ES_i))^2}{\sum w_i}$ | $df_{total} = m - 1$ |
| Group heterogeneity | $Q_{group} = \sum(w_i(ES_i - \overline{ES}_k)^2)$ | $df_k = m_k - 1$ |
| Within group heterogeneity | $Q_{within} = \sum_{k=1}^{m} Q_{group}$ | $df_{within} = m - k$ |
| Between groups heterogeneity | $Q_{between} = Q_{total} - Q_{within}$ | $df_{between} = k - 1$ |

The statistical significance of between groups heterogeneity is evaluated by comparing the calculated test value ($Q_{between}$) with a critical value ($\chi^2$) relative to ($k-1$) degrees of freedom and a chosen level of statistical significance ($\alpha$).

## 4. Meta-analysis of Effect Sizes in Consumer Behavior

The empirical study of this paper involves illustrating the steps of the meta-analysis process using a set of primary studies, which have as research topic the consumer behavior.

The research approach follows closely the methodological scheme discussed in the previous section (see Figure 1).

### 4.1. Formulating the Problem

The main research objective is to identify the factors that explain the differences between the empirical results of studies on a specific marketing research topic. Starting with the question "Is the heterogeneity of the results explained by the characteristics of primary studies?", we formulated the principal research hypothesis: the result heterogeneity of primary studies is explained by several categorical moderators.

In order to test this assumption, we have used meta-analysis on a set of primary studies, analyzing the association between a dependent variable that defines the consumer behavior and an independent variable that indicates a consumer behavior determinant. At this point of the analysis, it is important to mention that the approach of a meta-analysis requires the evaluation of the effect size within each primary study included in the sample. In our research, the effect size is the correlation between the two type of variable mentioned above.

Based on the main research hypothesis, we formulate a secondary one: the study groups defined by the categorical moderator – the type of method used, namely the quantitative or mixed analysis methods – differ significantly with respect to the effect sizes.

### 4.2. Collecting and Coding the Information

**Identifying the relevant studies**

The criteria considered for the selection of the relevant primary studies were: database (AMA - American Marketing Association); journals with the highest impact factor (two journals, Journal of Marketing, with an impact factor of 3.3, and Journal of International Marketing, having an impact factor of 3,9); year of publication (2015-2016); several keywords (*consumer*, *behavior*, *customer*).

Based on these criteria, we have selected 24 papers by identifying in their title at least one of the mentioned keywords, but we have been able to include only 20 in our meta-analysis. The reason for two of them is related to the inaccessibility of the entire paper, and the other two did not provide sufficient data for computing the corresponding effect size. The arguments for defining these criteria used in evaluating and selecting the studies refer to: marketing research field for choosing AMA database, journals with the highest impact factor within the AMA database, study publication year (2015-2016) to highlight a more current state of research, and keywords that reflect the topic of interest for our research, namely the *consumer behavior*.

**Selecting the relevant information**

The relevant pieces of information have been selected from primary studies so that the data reported are closely related to the main research goal. To achieve their aims, we have observed that some analyses have been conducted in several stages represented either by different studies, or resulting from one another.

For computing the effect size of each study, we have defined the two variables based on each study research aim and hypotheses (dependent variable reflecting the consumer behavior and independent variable(s) of interest for the respective study), relevant empirical results for computing the effect sizes, other relevant information (for example, sample size).

**Coding the studies**

The included studies have been coded according to a number of characteristics: sample size (continuous variable); categorical moderator - type of method (dichotomous variable: quantitative and mixed); dependent variable defining the consumer behavior; independent variables reflecting the determinants of consumer behavior.

### 4.3. Data Analysis

In data analysis stage, the emphasis is on choosing the most adequate ways of computing the effect sizes and the methods of testing the influence of categorical moderator on effect sizes.

**Computing the effect sizes**

In order to compute the effect sizes we have considered a number of criteria discussed theoretically in the methodology section and described below, in the context of our meta-analysis.

*a. Type of effect size*

According to the chosen research topic, the effect size is defined by the correlation between the dependent variable reflecting the consumer behavior and the independent variable, considered a determinant of the first one.

*b. Indicator for representing the effect sizes*

Among the three indices most frequently used in meta-analyses, we have chosen Pearson's correlation coefficient due to its high level of applicability in primary studies, but also because this coefficient can be computed based on a variety of data reported in these studies: results of descriptive statistics, results of statistical tests, frequencies (for identifying the size samples of the tested groups). Even though this coefficient is relatively easy to obtain, we have also considered that certain information from the studies requires computing other types of indices, such as the standardized mean differences or the odds ratio. For the studies that included control and experimental groups in their analysis, we have used the Hedges' coefficient, and for those studies analyzing two dichotomous variables, for which the available data allowed us to construct only a contingency table, we have chosen to compute the odds ratio.

*c. Transformation between indices*

Considering the latter remark, the results of computing the effect size by means of Hedges' coefficient and odds ratio were converted to Pearson's correlation coefficient.

*d. Multiple effect sizes from a single primary study*

In order to verify the independence assumption in the meta-analysis dataset, we have paid special attention to those studies providing multiple effect sizes. In this respect, we have taken into consideration two options for handling the non-independence in our dataset and obtaining a single effect size from each study. The first option was to identify the results that were more adequate for the main objective within each study. The alternative option required computing the mean of all effect sizes identified in the same study. Finally, based on those studies that included more analyses performed on different samples and whose results led to the achievement of the research goal, we have computed multiple effect sizes, meaning that these studies were included in our sample for two or more times. In this context, we consider that the independence among effect sizes is not violated.

In table 4 (Annex 2) are listed, in detail, more ways of computing the effect size for each primary study. With the evaluation of the correlation between the two type variables, our analysis continues with combining and comparing the effect sizes. These two steps allow us to test our research hypothesis.

## Fixed-Effects Model

In order to facilitate the analysis approach of the fixed-effects model, the meta-analysis database (table 5) is recommended to include the following variables: sample size $(n)$, effect size $(r)$, Fisher's transformation of effect size $(z_r)$, standard error $\left(s_{z_r}\right)$ and the weight corresponding to each effect size estimates $(w)$, which is determined by means of standard error.

**Table 5. Computation elements for fixed-effects model**

| No. | Size sample $(n)$ | Effect size $(r)$ | Fisher's transformation $\left(Z_r = \frac{1}{2} ln\left(\frac{1+r}{1-r}\right)\right)$ | Standard error $\left(s_{Z_r} = \frac{1}{\sqrt{(n-3)}}\right)$ | Weight $\left(w = 1/s^2_{Z_r}\right)$ | Weight of effect size $(w * Z_r)$ | $(w * Z_r^2)$ |
|---|---|---|---|---|---|---|---|
| 1 | 100 | 0.02 | 0.02 | 0.10 | 97 | 1.94 | 0.04 |
| 2 | 372 | 0.09 | 0.09 | 0.05 | 369 | 33.30 | 2.99 |
| 3 | 49 | 0.29 | 0.30 | 0.15 | 46 | 13.73 | 3.87 |
| 4 | 85 | 0.27 | 0.28 | 0.11 | 82 | 22.70 | 5.98 |
| 5 | 53729 | 0.11 | 0.11 | 0.00 | 53726 | 5933.87 | 650.08 |
| 6 | 5000 | 0.22 | 0.22 | 0.01 | 4997 | 1117.61 | 241.85 |
| 7 | 1213 | 0.52 | 0.58 | 0.03 | 1210 | 697.37 | 327.18 |
| 8 | 14384 | 0.02 | 0.02 | 0.01 | 14381 | 287.66 | 5.75 |
| 9 | 1346 | -0.31 | -0.32 | 0.03 | 1343 | -430.49 | 129.06 |
| 10 | 3196 | 0.20 | 0.20 | 0.02 | 3193 | 647.33 | 127.72 |
| 11 | 803 | -0.43 | -0.46 | 0.04 | 800 | -367.92 | 147.92 |
| 12 | 824 | 0.03 | 0.03 | 0.03 | 821 | 24.64 | 0.74 |
| 13 | 1180 | 0.29 | 0.30 | 0.03 | 1177 | 351.41 | 98.99 |
| 14 | 1703 | 0.31 | 0.32 | 0.02 | 1700 | 544.93 | 163.37 |
| 15 | 885 | 0.18 | 0.18 | 0.03 | 882 | 160.51 | 28.58 |
| 16 | 484 | 0.47 | 0.51 | 0.05 | 481 | 245.34 | 106.25 |
| 17 | 773262 | 0.31 | 0.32 | 0.00 | 773259 | 247864.6 | 74310.2 |
| 18 | 838 | -0.01 | -0.01 | 0.03 | 835 | -8.35 | 0.08 |
| 19 | 1309 | 0.61 | 0.71 | 0.03 | 1306 | 925.85 | 485.96 |
| 20 | 411 | 0.37 | 0.39 | 0.05 | 408 | 158.48 | 55.86 |
| 21 | 405 | 0.26 | 0.27 | 0.05 | 402 | 106.98 | 27.18 |
| 22 | 5425 | 0.67 | 0.81 | 0.01 | 5422 | 4395.85 | 2433.94 |
| 23 | 204 | 0.18 | 0.18 | 0.07 | 201 | 36.58 | 6.51 |
| 24 | 30000 | 0.17 | 0.17 | 0.01 | 29997 | 5149.48 | 866.91 |
| $\sum$ | - | - | - | - | **897135** | **267913.4** | **80227** |

*Source: Author's computations of selected data from primary studies using Excel*

Considering all these elements indispensable for the comparison of effect sizes among studies, our analysis continues with the steps imposed by the approach of fixed-effects model. The sequence of these steps and their corresponding results are listed in Table 6.

Summarizing the results from Table 6, it is found that the mean effect size defined by the correlation between the two variables (consumer behavior and its various determinants) is significantly different from zero, falling within the confidence interval (0.281; 0.282). Nevertheless, we have observed that the value of $Q$ statistics exceeds the critical value of $\chi^2$, leading us to reject the null hypothesis of homogeneity and to conclude that there is a significant heterogeneity among the studies around the mean effect size. Our findings highlight the importance of explaining this heterogeneity by means of moderator analysis.

**Table 6. Fixed-effects model results**

| **Steps** | **Obtained results** |
|---|---|
| Weighted mean effect size | $\bar{Z}_r = \frac{267913.4}{897135} = 0.29 \Rightarrow \bar{r} = \frac{e^{\bar{Z}_r} - 1}{e^{\bar{Z}_r} + 1} = \frac{e^{0.29} - 1}{e^{0.29} + 1} = 0.28$ |
| Standard error of the mean effect size | $s_{\overline{ES}} = \sqrt{1/897135} = 0.001$ |
| Statistical significance test of the mean effect size | $Z = 0.29/0.001 = 290$ |
| Confidence interval of effect size | $(LI)ES_{Z_r} = 0.288 \Rightarrow (LI)ES_r = \frac{e^{0.288} - 1}{e^{0.288} + 1} = 0.281$ <br> $(LS)ES_{Z_r} = 0.290 \Rightarrow (LS)ES_r = \frac{e^{0.290} - 1}{e^{0.290} + 1} = 0.282$ |
| Heterogeneity test of effect size | $Q = 86852.45 - \frac{(267913.4)^2}{897135} = 6844.86$ <br> $Q = 6844.86 > \chi^2_{\alpha;m-1} = \chi^2_{0.05;23} = 35.17$ |

*Source: Author's computations of selected data from primary studies using Excel*

## Moderator Analysis

In accordance with the paper main objective and the results obtained until this stage, the research hypothesis is justified in the context of our meta-analysis. Considering the type of used data, we have performed the ANOVA analysis that allows us to evaluate the impact of the potential moderator, type of method, on effect sizes, namely the correlation between consumer behavior and its determinants.

To illustrate the analysis of the variance procedure in our meta-analysis, we have covered each step of obtaining the necessary elements, insisting on the result interpretation. All of these data are listed in Tables 7 and 8.

**Table 7. Computation elements for moderator analysis**

| No. | Size sample $(n)$ | Effect size$(r)$ | Fisher's transformation $(Z_r)$ | Standard error $(s_{Z_r})$ | Weight $(w)$ | Weight of effect size $(w * Z_r)$ | $(w * Z_r^2)$ |
|---|---|---|---|---|---|---|---|
| Type of method: quantitative $(m_1 = 19)$ | | | | | | | |
| 1 | 100 | 0.02 | 0.02 | 0.1 | 97 | 1.94 | 0.04 |
| 2 | 49 | 0.29 | 0.3 | 0.15 | 46 | 13.73 | 3.87 |
| 3 | 53729 | 0.11 | 0.11 | 0 | 53726 | 5933.87 | 650.08 |
| 4 | 5000 | 0.22 | 0.22 | 0.01 | 4997 | 1117.61 | 241.85 |
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| 8 | 3196 | 0.2 | 0.2 | 0.02 | 3193 | 647.33 | 127.72 |
| 9 | 803 | -0.43 | -0.46 | 0.04 | 800 | -367.92 | 147.92 |
| 10 | 1703 | 0.31 | 0.32 | 0.02 | 1700 | 544.93 | 163.37 |
| 11 | 885 | 0.18 | 0.18 | 0.03 | 882 | 160.51 | 28.58 |
| 12 | 773262 | 0.31 | 0.32 | 0 | 773259 | 247864.6 | 74310.2 |
| 13 | 411 | 0.37 | 0.39 | 0.05 | 408 | 158.48 | 55.86 |
| 14 | 405 | 0.26 | 0.27 | 0.05 | 402 | 106.98 | 27.18 |
| 15 | 5425 | 0.67 | 0.81 | 0.01 | 5422 | 4395.85 | 2433.94 |
| 16 | 204 | 0.18 | 0.18 | 0.07 | 201 | 36.58 | 6.51 |
| 17 | 30000 | 0.17 | 0.17 | 0.01 | 29997 | 5149.48 | 866.91 |
| 18 | 372 | 0.09 | 0.09 | 0.05 | 369 | 33.3 | 2.99 |
| 19 | 824 | 0.03 | 0.03 | 0.03 | 821 | 24.64 | 0.74 |
| | | | | Sum within group | **893254** | **266376.5** | **79529.75** |
| Type of method: mixed $(m_2 = 5)$ | | | | | | | |
| 20 | 85 | 0.27 | 0.28 | 0.11 | 82 | 22.7 | 5.98 |
| 21 | 1180 | 0.29 | 0.3 | 0.03 | 1177 | 351.41 | 98.99 |
| 22 | 484 | 0.47 | 0.51 | 0.05 | 481 | 245.34 | 106.25 |
| 23 | 838 | -0.01 | -0.01 | 0.03 | 835 | -8.35 | 0.08 |
| 24 | 1309 | 0.61 | 0.71 | 0.03 | 1306 | 925.85 | 485.96 |
| | | | | Sum within group | **3881** | **1536.95** | **697.26** |
| | | | **Total sum of the two groups** | | **897135** | **267913.4** | **80227** |

*Source: Author's computations of selected data from primary studies using Excel*

Based on the results from Table 7, we obtain the computing elements of the within-group heterogeneity, thus being able to test if one source of this effect size heterogeneity might be due to the use of the quantitative or mixed methods. The steps are detailed in the table below.

**Table 8. ANOVA results considering the type of method as categorical moderator**

| Steps | Statistics |
|---|---|
| Total heterogeneity | $Q_{total} = 219.42 > \chi^2_{\alpha;m-1} = \chi^2_{0.05;23} = 35.17$ |
| Group heterogeneity | $Q_{group1} = 79529.7 - \frac{(266376.5)^2}{3881} = 93.8 > \chi^2_{\alpha;m_1-1} = \chi^2_{0.05;18} = 28.8$ |
| | $Q_{group2} = 697.26 - \frac{(1536.95)^2}{3881} = 88.59 > \chi^2_{\alpha;m_2-1} = \chi^2_{0.05;4} = 9.49$ |
| Within group heterogeneity | $Q_{within} = 93.86 + 88.59 = 182.45 > \chi^2_{\alpha;m-k} = \chi^2_{0.05;22} = 33.92$ |
| Between groups heterogeneity | $Q_{between} = 219.48 - 182.45 = 36.97 > \chi^2_{\alpha;k-1} = \chi^2_{0.05;1} = 3.84$ |

*Source: Author's computations of selected data from primary studies using Excel*

The findings suggest that there is a significant heterogeneity within the set of primary studies. There is a significant heterogeneity among the studies from the quantitative group, among the studies included in the mixed group and within each of the two groups. Also, the value of $Q_{between}$ is high enough that we can reject the null hypothesis and accept the alternative hypothesis, according to which between the group of quantitative studies and the one of mixed studies, there are significant differences in terms of their effect sizes. In other words, the type of method moderates the association between the customer behavior and its determinants. Therefore, our research hypothesis is validated; meaning that one source of the heterogeneity among studies might be due to the use of a different type of method.

## 5. Concluding Remarks

The problem of inconsistent results of empirical studies is a reality in any scientific research field. Literature provides the meta-analysis approach as a solution because it responds to the challenge of evaluating, combining, comparing and synthesizing the accumulation of results to a typical, common and representative value of a particular research topic.

In this paper, we aimed to respond through meta-analysis to a double challenge within the marketing scientific research field. We analyzed the applicability level of the mixed methods in relation to the quantitative methods by means of evaluating the differences among empirical results obtained in studies with the same research topic. The results obtained from the quantitative review of literature specific to consumer behavior analysis suggest that the type of method is a significant factor explaining the presence of heterogeneity among effect sizes.

Given the complexity and rigors of the meta-analysis methodology, it is inevitable not to reveal certain limits and it is difficult to exceed them at this stage of the research. The major limitation is the small number of studies included in our meta-analysis, especially since we considered a fundamental and wide marketing research topic. Therefore, the research results can be negatively influenced by the small sample size of studies. Another weak point is the exclusion of some important factors in assessing the quality of the results reported in primary studies or other features of these studies. The third limitation concerns the fact that we restricted our analysis to the fixed-effects model. The meta-analysis methodology is very wide, including many other ways of comparing and combining the studies' effect sizes. We highlight, however, that the analysis proposed in this paper represents a basis for the development of our research.

In this regard, the mentioned limits outline at least two other further research directions. The first one is the attempt to identify other moderators explaining the heterogeneity among the empirical results of marketing studies. The second research direction refers to explaining the differences between studies by the simultaneous influence of the potential moderators. Finally, in order to assess the utility of the type of research methods, it is our intention to develop this meta-analytic study by considering several research marketing topics within the same analysis.

This research perspective highlights a possible contribution to the specialized literature by applying the meta-analysis methodology to a general research framework, taking into account that we aim to test a hypothesis regarding a research field, not only a specific research topic.

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## Annex 1. Computing the effect sizes from commonly results reported in primary studies

**Table 1. Computation formula of effect size represented by the three indices**

| | Pearson's correlation coefficient $(\boldsymbol{r})$ | Hedges's coefficient $(\boldsymbol{g})$ | Odds ratio $(\boldsymbol{o})$ |
|---|---|---|---|
| Definitional formula | $\frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{(n-1)s_x s_y}$ | $\frac{\bar{x}_1-\bar{x}_2}{s_{pooled}}$ | $\frac{n_{00}n_{11}}{n_{01}n_{10}}$ |
| Independent *t*-test with unequal group sizes | $\sqrt{\frac{t^2}{t^2+df}}$ | $\frac{t\sqrt{n_1+n_2}}{\sqrt{n_1 n_2}}$ | - |
| Independent *t*-test with equal group sizes | $\sqrt{\frac{t^2}{t^2+df}}$ | $\frac{2t}{\sqrt{n}}$ | - |
| Independent *F*-ratio with unequal group sizes | $\sqrt{\frac{F_{(1,df)}}{F_{(1,df)}+df}}$ | $\sqrt{\frac{F_{(1,df)}+(n_1+n_2)}{n_1 n_2}}$ | - |

| | | | |
|---|---|---|---|
| Independent $F$-ratio with equal group sizes | $\sqrt{\frac{F_{(1,df)}}{F_{(1,df)}+df}}$ | $2\sqrt{\frac{F_{(1,df)}}{n}}$ | - |
| Dependent (repeated-measures) $t$-test | $\sqrt{\frac{t^2_{dependent}}{t^2_{dependent}+df}}$ | $\frac{t_{dependent}}{\sqrt{n}}$ | - |
| Dependent (repeated-measures) $F$-ratio | $\sqrt{\frac{F_{repetat(1,df)}}{F_{repetat(1,df)}+df}}$ | $\sqrt{\frac{F_{repetat(1,df)}}{n}}$ | - |
| $2 \times 2$ (1 degree of freedom) contingency $\chi^2$ | $\sqrt{\frac{\chi^2_{(1)}}{n}}$ | $2\sqrt{\frac{\chi^2_{(1)}}{n-\chi^2_{(1)}}}$ | Reconstruct contingency table |
| Probability levels from significance tests | $\frac{Z}{\sqrt{n}}$ | $\frac{2Z}{\sqrt{n}}$ | Reconstruct contingency table |

*Source:* (Card, 2012, p. 97)

## Annex 2. Computing the effect sizes using the relevant data selected from each primary study

**Table 4. Computing the effect sizes using Pearson's correlation coefficient**

| **No.** | **Primary study** | **Size sample ($n$)** | **Information available for computing $r$** | **Different ways of computing $r$** | **Effect size ($r$)** |
|---|---|---|---|---|---|
| 1 | Study 1 | 100 | Correlation coefficients:<br>$r_1 = 0.00$ $(p < 0.01)$<br>$r_2 = 0.04$ $(p < 0.01)$ | $r = (r_1 + r_2)/2 = 0.04/2 = 0.02$ | **0.02** |
| 2 | Study 2 | 372 | Probability level from significance $t$ test:<br>$p < 0.001$ | $p \approx 0.001 \Rightarrow Z = 2.58$<br>$r = Z/\sqrt{n} = 2.58/\sqrt{372} = 0.09$ | **0.09** |
| 3 | Study 3 | 49 | Calculated value of Chi-square test:<br>$\chi^2_{(1)} = 4.18$ $(p < 0.05)$ | $r = \sqrt{\frac{\chi^2_{(1)}}{n}} = \sqrt{\frac{4.18}{49}} = 0.29$ | **0.29** |
| 4 | Study 4 | 85 | Probability level from significance $t$ test:<br>$p = 0.013$ | $p = 0.013 \Rightarrow Z = 2.48$<br>$r = Z/\sqrt{n} = 2.48/\sqrt{85} = 0.27$ | **0.27** |
| 5 | Study 5 | 53729 | Descriptive statistics indicators for:<br>- regained customer group (control group: $n_1 = 39345$):<br>$\bar{x}_1 = 0.27$; $s_1 = 0.44$ | $g = \frac{\bar{x}_1 - \bar{x}_2}{s_{pooled}} = \frac{\bar{x}_1 - \bar{x}_2}{(n_1 s_1 + n_2 s_2)/(n_1 + n_2)}$<br>$g = \frac{0.11}{0.451} = 0.24$ | **0.11** |

<table>
<tr><td></td><td></td><td></td><td>- lost customer group<br>($n_2 = 14384$):<br>$\bar{x}_2 = 0.38$; $s_2 = 0.49$</td><td>$r = \sqrt{\frac{g^2 n_1 n_2}{g^2 n_1 n_2 + (n_1 + n_2) df}} = 0.11$</td><td></td></tr>
<tr><td>6</td><td>Study 5</td><td>5000</td><td>Frequencies table for the association controlled by the offer of regaining (price and service) between variables regaining probability and reason for leaving:<br>- customers who left because of the price:<br>$n_{\cdot 1} = 2330$<br>- customers who left because of the service:<br>$n_{\cdot 2} = 1666$<br>- customers who left because of the price and service:<br>$n_{\cdot 3} = 1004$<br>- regained customers who left because of the price:<br>$n_{11} = 1213$<br>- regained customers who left because of the service: $n_{21} = 711$<br>- regained customers who left because of the price and service:<br>$n_{21} = 228$</td><td>Table of observed frequencies ($n_{observed}$)
<table>
<tr><th rowspan="2">reason of leaving</th><th colspan="2">regaining probability</th><th rowspan="2">Tota l</th></tr>
<tr><td>regained customer s</td><td>lost customer s</td></tr>
<tr><td>price</td><td>1213</td><td>1117</td><td>2330</td></tr>
<tr><td>service</td><td>711</td><td>955</td><td>1666</td></tr>
<tr><td>price and service</td><td>228</td><td>776</td><td>1004</td></tr>
<tr><td>Total</td><td>2152</td><td>2848</td><td>5000</td></tr>
</table>
Table of estimated frequencies ($n_{estimated}$)
<table>
<tr><th rowspan="2">reason of leaving</th><th colspan="2">regaining probability</th><th rowspan="2">Tota l</th></tr>
<tr><td>regained customer s</td><td>lost customer s</td></tr>
<tr><td>price</td><td>1002.83</td><td>1327.17</td><td>2330</td></tr>
<tr><td>service</td><td>717.05</td><td>948.95</td><td>1666</td></tr>
<tr><td>price and service</td><td>432.12</td><td>571.88</td><td>1004</td></tr>
<tr><td>Total</td><td>2152</td><td>2848</td><td>5000</td></tr>
</table>
$X^2 = \sum \frac{(n_{observed} - n_{estimated})^2}{n_{estimated}} = 246.69$<br>
$r = \sqrt{\frac{X^2}{n}} = \sqrt{\frac{246.69}{5000}} = 0.22$</td><td>0.22</td></tr>
<tr><td>7</td><td>Study 5</td><td>1213</td><td>Independent t-test with unequal group sizes:<br>$t = 21.04$</td><td>$r = \sqrt{\frac{t^2}{t^2 + df}} = \sqrt{\frac{21.04^2}{21.04^2 + (1213 - 1)}} = 0.52$</td><td>0.52</td></tr>
<tr><td>8</td><td>Study 5</td><td>14384</td><td>Probability level from significance $t$ test:<br>$p < 0.05$</td><td>$p \approx 0.05 \Rightarrow Z = 1.96$<br>$r = Z/\sqrt{n} = 1.96/\sqrt{14384} = 0.02$</td><td>0.02</td></tr>
<tr><td>9</td><td>Study 6</td><td>1346</td><td>Correlation coefficient:<br>$r = -0.31$ ($p < 0.01$)</td><td>-</td><td>-0.31</td></tr>
</table>

| | | | | | |
|---|---|---|---|---|---|
| 10 | Study 7 | 3196 | Independent *t*-test with equal group sizes:<br>$t_1 = 2.87$<br>$t_2 = 21.41$ | $r = \sqrt{\frac{t^2}{t^2 + (n-2)}}$<br>$\Rightarrow \begin{cases} r_1 = \sqrt{\frac{2.87^2}{2.87^2 + (3196-2)}} = 0.05 \\ r_2 = \sqrt{\frac{21.41^2}{21.41^2 + (3196-2)}} = 0.35 \end{cases}$<br>$r = (r_1 + r_2)/2 = 0.4/2 = 0.20$ | **0.20** |
| 11 | Study 8 | 803 | Correlation coefficient:<br>$r = -0.43$ ($p < 0.01$) | - | **-0.43** |
| 12 | Study 9 | 824 | Independent *t*-test with equal group sizes:<br>$t_1 = 1.26$ ($p < 0.01$)<br>$t_2 = 0.46$ ($p < 0.01$)<br>$t_3 = 1.02$ ($p < 0.01$) | $g = \frac{2t}{\sqrt{n}} \Rightarrow \begin{cases} g_1 = 2\frac{1.26}{\sqrt{824}} = 0.09 \\ g_2 = 2\frac{0.46}{\sqrt{824}} = 0.03 \\ g_3 = 2\frac{1.02}{\sqrt{824}} = 0.07 \end{cases} \Rightarrow g = \frac{g_1 + g_2 + g_3}{3} = 0.06$<br>$r = \sqrt{\frac{g^2 n_1 n_2}{g^2 n_1 n_2 + (n_1 + n_2) df}} \Rightarrow r = 0.03$<br>$r = \sqrt{\frac{0.06^2 \cdot 412 \cdot 412}{0.06^2 \cdot 412 \cdot 412 + 824 \cdot (824-2)}}$ | **0.03** |
| 13 | Study 10 | 1180 | Independent *F*-test with equal group sizes:<br>$F_{(1,df)} = 4.77$ ($p < 0.05$)<br><br>Correlation coefficient:<br>$r_2 = 0.51$ ($p < 0.001$) | $g = 2\sqrt{\frac{F_{(1,df)}}{n}} = 2\sqrt{\frac{4.77}{1180}} = 0.13$<br>$r_1 = \sqrt{\frac{g^2 n_1 n_2}{g^2 n_1 n_2 + (n_1 + n_2) df}} \Rightarrow$<br>$r_1 = \sqrt{\frac{0.13^2 \cdot 590^2}{0.13^2 \cdot 590^2 + 1180 \cdot 1178}} = 0.07$<br>$r = (r_1 + r_2)/2 = 0.58/2 = 0.29$ | **0.29** |
| 14 | Study 10 | 1703 | Correlation coefficient:<br>$r = 0.31$ ($p < 0.01$) | - | **0.31** |
| 15 | Study 10 | 885 | Correlation coefficient:<br>$r = 0.18$ ($p < 0.01$) | - | **0.18** |
| 16 | Study 11 | 484 | Correlation coefficients:<br>$r_1 = 0.47$ ($p < 0.01$)<br>$r_2 = 0.46$ ($p < 0.01$) | $r = (r_1 + r_2)/2 = 0.93/2 = 0.47$ | **0.47** |
| 17 | Study 12 | 773262 | Correlation coefficient:<br>$r = 0.31$ ($p < 0.01$) | - | **0.31** |
| 18 | Study 13 | 838 | Frequencies table for the association between two dichotomous variables: | Table of observed frequencies ($n_{observed}$)<br>**value-in-use** \| **customer perception of *value-in-use*** \| **Total** | **-0.01** |

<table>
<tr><td></td><td></td><td></td><td>- customer perception concerning the value-in-use solution:<br>$p_1 = 0.07$ (direct)<br>$p_2 = 0.08$ (indirect)<br>- value-in-use:<br>$p_1 = 0.12$ (direct)<br>$p_2 = 0.23$ (indirect)</td><td><table>
<tr><td></td><td>direct</td><td>indirect</td><td></td></tr>
<tr><td>direct</td><td>0.19</td><td>0.20</td><td>0.39</td></tr>
<tr><td>indirect</td><td>0.30</td><td>0.31</td><td>0.61</td></tr>
<tr><td>Total</td><td>0.49</td><td>0.51</td><td>1</td></tr>
</table>
$$o = \frac{p_{00}p_{11}}{p_{01}p_{10}} = \frac{153 \cdot 266}{164 \cdot 255} = 0.97$$
$$r = cos\left(\frac{\pi}{(1 + o^{1/2})}\right)$$
$$= cos\left(\frac{3.14}{(1 + 0.97^{1/2})}\right) = -0.01$$</td><td></td></tr>
<tr><td>19</td><td>Study 14</td><td>1309</td><td>Independent $F$-test with unequal group sizes:<br>$F = 782.64$ ($p < 0.01$)</td><td>$$r = \sqrt{\frac{F_{(1,df)}}{F_{(1,df)} + df}}$$
$$= \sqrt{\frac{782.64}{782.64 + (1309 - 2)}} = 0.61$$</td><td>0.61</td></tr>
<tr><td>20</td><td>Study 15</td><td>411</td><td>Correlation coefficient:<br>$r = 0.37$ ($p < 0.05$)</td><td>-</td><td>0.37</td></tr>
<tr><td>21</td><td>Study 15</td><td>405</td><td>Correlation coefficient:<br>$r = 0.26$ ($p < 0.05$)</td><td>-</td><td>0.26</td></tr>
<tr><td>22</td><td>Study 16</td><td>5425</td><td>Correlation coefficient:<br>$r = 0.67$ ($p < 0.05$)</td><td>-</td><td>0.67</td></tr>
<tr><td>23</td><td>Study 17</td><td>204</td><td>Probability level from significance $t$ test:<br>$p < 0.01$</td><td>$p \approx 0.01 \Rightarrow Z = 2.58$<br>$r = Z/\sqrt{n} = 2.58/\sqrt{204} = 0.18$</td><td>0.18</td></tr>
<tr><td>24</td><td>Study 18</td><td>30000</td><td>Correlation coefficients:<br>$r_1 = 0.176$ ($p < 0.05$)<br>$r_2 = 0.162$ ($p < 0.05$)</td><td>$r = (r_1 + r_2)/2 = 0.338/2 = 0.17$</td><td>0.17</td></tr>
</table>

*Source: Author's computations based on selected data from primary studies*