Türkiye Klinikleri Biyoistatistik Dergisi
Turkiye Klinikleri Journal of Biostatistics Turkiye Klinikleri J Biostat. 2024;16(3):

ORIGINAL RESEARCH ORİJİNAL ARAŞTIRMA DOI: 10.5336/biostatic.2024-107203

The Effect of Different Effect Size Measures on Mediation Analysis Performance

Farklı Etki Büyüklüğü Ölçülerinin Aracılık Analizi Performansına Etkisi

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ABSTRACT Objective: In mediation analysis, the use of effect size measures is extremely important to understand the strength and direction of the relationship between variables in depth and to determine the importance of the mediating variable effect. In the literature, it is seen that there are few studies comparing the performance of effect size measures for mediation analysis. The aim of this study is to investigate the relationships between continuous variables and to compare the performances of effect size measures for mediation model. **Material and Methods:** In line with the objective of the study, the performance of effect size measures for the mediation model was examined through a simulation study, considering different sample sizes and small, medium, and large effect sizes. The comparison of effect size measures for the mediation model was conducted by examining bias values. **Results:** For the mediation model, it was observed that R^2, as a measure of explained variance, had the least bias across all scenarios considered in the simulation. While mediation ratio measures required a minimum sample size of 500, R^2 as a measure of explained variance exhibited good performance even with smaller sample sizes, such as 100. **Conclusion:** In models involving mediator variables, it is recommended to use alternative effect size measures in research, in addition to a single measure, to comprehensively capture the strength of the relationship between variables.

Keywords: Mediation analysis; mediator variable; effect size; mediation proportion; explained variance

ÖZET Amaç: Aracı değişken içeren modellerde, değişkenler arasındaki ilişkinin gücünü ve yönünü derinlemesine anlamanın yanı sıra aracı değişken etkisinin önemini ortaya koymak için etki büyüklüğü ölçülerine yer verilmesi son derecede önemlidir. Literatürde aracılık analizi için etki büyüklüğü ölçülerinin performanslarının karşılaştırmalı olarak ele alındığı çalışma sayısının az olduğu görülmektedir. Bu çalışmanın amacı, sürekli türdeki değişkenler arasındaki ilişkilerin araştırılması ve aracılık modeli için etki büyüklüğü ölçülerinin performanslarının karşılaştırılmasıdır. **Gereç ve Yöntemler:** Çalışmanın amacı doğrultusunda, farklı örnek genişliklerinde ve küçük, orta, geniş etki büyüklüğü durumlarında aracılık modeli için etki büyüklüğü ölçülerinin performansları bir simülasyon çalışması ile incelenmiştir. Aracılık modeli için etki büyüklüğü ölçülerinin performans karşılaştırması yanlılık değerleri göz önünde bulundurularak yapılmıştır. **Bulgular:** Aracılık modeli için simülasyonda ele alınan tüm senaryolarda R^2 açıklanan varyans ölçülerinin en az yanlılığa sahip olduğu görülmüştür. Aracılık oran ölçüleri için en az 300 örnek genişliği gerekirken, R^2 açıklanan varyans ölçüsünün 100 gibi daha küçük örnek genişliklerinde de iyi bir performansa sahip olduğu görülmüştür. **Sonuç:** Aracı değişkenli modellerde değişkenler arasındaki ilişkinin gücünün daha kapsamlı şekilde ele alınabilmesi için tek bir etki büyüklüğü ölçüsü yerine alternatif ölçülerin de araştırmalarda kullanılması önerilmektedir.

Anahtar kelimeler: Aracılık analizi; aracı değişken; etki büyüklüğü; aracılık oranı; açıklanan varyans

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Peer review under responsibility of Turkiye Klinikleri Journal of Biostatistics.

Received: 02 Dec 2024 ***Received in revised form:*** 16 Dec 2024 ***Accepted:*** 23 Dec 2024 ***Available online:*** 03 Jan 2025

In clinical research, one of the primary aims of researchers is to identify the variables that are effective in diagnosing diseases, test whether there is a relationship between these variables, and if there is, analyze the structure of this relationship.[1] Besides dependent and independent variables emphasized in studies, there are also variables referred to as "mediators." Mediator variables are third variables that act as a bridge between dependent and independent variables. In mediation models, it is assumed that the independent variable causes the mediator variable, and the mediator variable causes the outcome variable.[2] Mediation analysis is used to model and accurately interpret the causal relationships between dependent, independent, and mediator variables.[3] Various effect size measures have been developed to better understand the strength and direction of the relationships between variables in mediation analysis and to determine the importance of the mediator variable effect.[4,5] The mediation ratio, a commonly used effect size measure, represents the proportion of the mediation effect that occurs through the mediator variable within the total or direct effect (DE).[6] Additionally, there are effect size measures obtained from regression R^2 values, which indicate the proportion of variance explained by the mediator variable in the outcome variable.[7] High mediation ratios and R^2 values indicate that the mediator variable plays a significant role in the relationship between the independent variable and the outcome variable. In summary, effect size measures for mediation are extremely important in interpreting the results of mediation analysis and determining the practical significance of the mediation effect. The aim of this study is to investigate the relationships between continuous variables and compare the performance of effect size measures for the mediation model.

MATERIAL AND METHODS

SIMPLE MEDIATION MODEL AND MEDIATION ANALYSIS

In the simple mediation model, in addition to an X variable, which is known as the independent variable, and a Y variable, which expresses the outcome, there is also an M mediator variable. In the mediation model, the mediator variable M is included in the model as an outcome variable when it is affected by the independent variable X and as an independent variable when it affects the variable Y.[8] Mediation analysis examines the underlying mechanism that explains the observed relationship between the agent and the outcome, as well as the relationship between the mediator and the outcome.[9] In mediation models, it is assumed that the X causes the M, which in turn causes the Y. The relationships within the model must be causal, and the M mediator variable must causally position between X and Y. If the M mediator variable does not causally position between X and Y, it cannot mediate the effect of X on Y. In other words, mediation refers to a sequence such as X → M → Y. In essence, mediation analysis is a statistical method that aims to determine how an independent variable affects the outcome variable.[10,11]

In Figure 1, path c represents the total effect (TE) connecting X and Y, path c' represents the DE, path b represents the effect of the independent variable X on the outcome variable Y through the mediator variable M, and path α represents the effect of the independent variable X on the mediator variable M. In this case, the direct and indirect effects (IE) are obtained from the following two linear equations:

$$M = i_M + aX + e_M \quad (1)$$

$$Y = i_Y + c'X + bM + e_Y \quad (2)$$

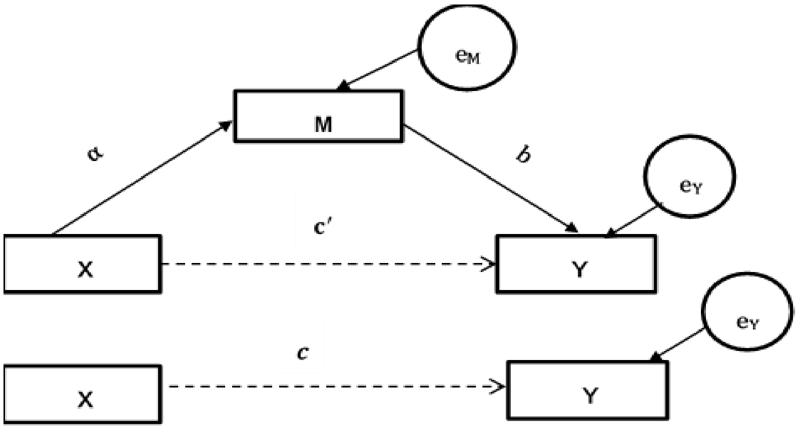

FIGURE 1: Simple mediation model.

EFFECT SIZE MEASURES IN MEDIATION ANALYSIS

Although the importance of effect size measures in both psychology and other fields has been emphasized by many researchers, it is seen that effect size measures for mediation models have been addressed in very few studies.[12] In mediation models, the IE, which represents mediation, is obtained from the product of two regression coefficients and therefore cannot be addressed within the framework of existing effect size criteria. Hence, there is a need for alternative effect size measures to be used in mediation models.[13]

RATIO MEASURES

The mediation ratio is a frequently utilized effect size measure for mediation. The types of mediation ratios, which are the ratio of the IE to the TE or the ratio of the IE to the DE, are also known in studies as the "proportion mediated" or "relative IE." Mediation ratio measures are divided into two categories based on the TE and DE ratios.[14]

PROPORTION MEDIATED (P_M)

The mediation ratio is expressed as the percentage change in regression coefficients when a mediator variable is included in the model.[6,14,15] In a simple mediation model with a single mediator variable, the effect of the mediator variable M on the outcome variable is the IE, which is the product of the α and b coefficients. The mediation ratio (P_M) is obtained by dividing the IE (αb) by the TE (c=αb+c'), as expressed in Equation 3.

$$P_M=\frac{IE}{TE}=\frac{\alpha b}{\alpha b+c'} \quad (3)$$

RATIO MEDIATED (R_M)

The ratio of the IE to the DE is another way to assess the magnitude of the mediation effect. For a simple mediation model with a single mediator variable, the mediation ratio (RM) is expressed with Equation 4.

$$R_M=\frac{IE}{DE}=\frac{\alpha b}{c'} \quad (4)$$

EXPLAINED VARIANCE (R^2)

There are some limitations for the P_M and R_M which used as an effect size measures.[17] When the size of the DE is zero, meaning there is full mediation, it is unclear how ratio measures should be interpreted. Additionally, in the inconsistent mediator models where the signs of the DE and IE are opposite, interpreting ratio measures becomes complex.[18] Because opposite-signed DE and IE reduce the TE, leading to ratio measures exceeding 1. Furthermore, ratio measures do not perform well with small sample sizes (n<500).[19] As an alternative to ratio measures for mediation models, different R^2 measures can be used. These measures partition the amount of change in the dependent variable into the parts that explained and unexplained by the DE.[20] Unlike ratio measures, R^2 measures are not affected by sample size and perform well even with small sample sizes. Two different R^2 measures proposed by MacKinnon (2008) are expressed with the following equations:

$$R^2_{\text{Mediation 1}} = r^2_{YM} - (R^2_{Y.MX} - r^2_{YX}) \quad (5)$$

$$R^2_{\text{Mediation 2}} = (r^2_{MX})(r^2_{YM.X}) \quad (6)$$

APPLICATION

SIMULATION STUDY

This study employed a methodological design. The data sets were created by generating X, M, and Y variables based on specified c', α, b population parameters. In the first step of the simulation, the X was generated from a normal distribution with a mean of zero and a variance of one ($X \sim N(0,1)$). Then, the M and Y variables were generated according to the equations $M = i_M + aX + e_M$ and $Y = i_Y + c'X + bM + e_Y$, using the population parameters of α, b, and c' corresponding to Cohen's small, medium, and large effect sizes.[21] The error terms of the model were also generated from a normal distribution ($\varepsilon_i \sim N(0,1)$). In mediation analyses, it is recommended to work with large sample sizes and not to have a sample size less than 300, and if possible, to work with a sample size of over 500.[22] Considering this information, sample sizes were determined as 100, 300, 500, 700, and 1000, with data sets generated using all effect size combinations (neutral effect=0, small effect=0.14, medium effect=0.39, large effect=0.59) for α, b, and c' coefficients, repeated 1000 times for each sample size.

Simulation Scenarios:

c′	**α**	**b**
0.14	0.14	0.14
0.39	0.39	0.39
0.59	0.59	0.59
0	0.14	0.14
0	0.39	0.39
0	0.59	0.59

The mediated ratio measures, R^2 variance explanation coefficients, and bias values of the models were calculated from the data sets. All operations in the simulation were performed using R version 4.1.3 (2022-03-10). In addition to functions such as “rnorm,” “cbind,” “as.data.frame,” and “write.csv2” etc. used in the generation of variables, functions “med.fit,” “out.fit,” and “med.out” from the “Mediation” package were used for mediation analysis of the obtained data sets.[23]

RESULTS

Table 1 presents the simulation results for P_M, R_M, R^2_{MED1} and R^2_{MED2} values when the c', α, and b coefficients have small (0.14), medium (0.39), and large (0.59) effect sizes, respectively, and the sample sizes are 100, 300, 500, 700, and 1000.

TABLE 1: Model results for small, medium, and large effect sizes of c', α, and b coefficients.

Scenarios		n=100	n=300	n=500	n=700	n=1000
c'=0.14 α=0.14 b=0.14	P_M (Bias)	0.201 (-0.078)	0.143 (-0.020)	0.136 (-0.013)	0.133 (-0.010)	0.127 (-0.004)
	SD	1.427	0.211	0.126	0.070	0.050
	95% CI	-0.870; 0.771	0.028; 0.889	0.093; 0.377	0.098; 0.185	0.105; 0.164
	R_M (Bias)	0.069 (0.071)	0.163 (-0.023)	0.083 (0.057)	0.154 (-0.014)	0.153 (-0.013)
	SD	4.273	1.353	2.616	0.139	0.071
	95% CI	-0.196; 0.334	0.079; 0.247	-0.079; 0.246	0.146; 0.163	0.149; 0.157
	R^2_{MED1} (Bias)	0.000 (0.000)	0.000 (0.003)	0.000 (0.000)	0.000 (0.000)	0.000 (0.003)
	SD	0.001	0.000	0.000	0.000	0.000
	95% CI	0.000; 0.000	0.000; 0.000	0.000; 0.000	0.000; 0.000	0.000; 0.000
	R^2_{MED2} (Bias)	0.006 (-0.004)	0.006 (-0.002)	0.006 (0.001)	0.006 (0.000)	0.006 (-0.001)
	SD	0.009	0.004	0.003	0.003	0.002
	95% CI	0.005; 0.006	0.006; 0.006	0.006; 0.006	0.006; 0.006	0.006; 0.006
c'=0.39 α=0.39 b=0.39	P_M (Bias)	0.294 (-0.013)	0.280 (0.001)	0.280 (0.001)	0.282 (-0.001)	0.280 (0.001)
	SD	0.119	0.060	0.045	0.040	0.034
	95% CI	0.237; 0.375	0.252; 0.315	0.255; 0.305	0.261; 0.304	0.264; 0.298
	R_M (Bias)	0.472 (-0.082)	0.400 (-0.010)	0.394 (-0.004)	0.398 (-0.008)	0.392 (-0.002)
	SD	0.381	0.152	0.091	0.081	0.068
	95% CI	0.448; 0.496	0.395; 0.414	0.389; 0.400	0.393; 0.403	0.388; 0.397
	R^2_{MED1} (Bias)	0.002 (0.011)	0.001 (0.015)	0.000 (0.021)	0.000 (0.012)	0.000 (0.017)
	SD	0.003	0.001	0.001	0.000	0.000
	95% CI	0.002; 0.002	0.001; 0.001	0.000; 0.000	0.000; 0.000	0.000; 0.000
	R^2_{MED2} (Bias)	0.111 (0.005)	0.111 (-0.006)	0.111 (0.003)	0.112 (-0.027)	0.112 (0.012)
	SD	0.043	0.024	0.019	0.017	0.014
	95% CI	0.108; 0.114	0.109; 0.112	0.11; 0.112	0.111; 0.113	0.111; 0.113
c'=0.59 α=0.59 b=0.59	P_M (Bias)	0.377 (-0.006)	0.370 (0.001)	0.370 (0.001)	0.372 (-0.001)	0.370 (0.001)
	SD	0.091	0.049	0.037	0.033	0.028
	95% CI	0.330; 0.427	0.346; 0.396	0.349; 0.389	0.354; 0.389	0.357; 0.385
	R_M (Bias)	0.644 (-0.054)	0.597 (-0.007)	0.592 (-0.002)	0.597 (-0.007)	0.591 (-0.001)
	SD	0.275	0.128	0.095	0.085	0.072
	95% CI	0.627; 0.661	0.589; 0.605	0.586; 0.598	0.591; 0.602	0.587; 0.596
	R^2_{MED1} (Bias)	0.006 (0.030)	0.003 (0.041)	0.003 (0.028)	0.003 (0.043)	0.003 (0.033)
	SD	0.009	0.003	0.002	0.002	0.002
	95% CI	0.005; 0.006	0.003; 0.004	0.003; 0.003	0.003; 0.003	0.003; 0.003
	R^2_{MED2} (Bias)	0.277 (-0.041)	0.277 (-0.008)	0.277 (-0.025)	0.279 (0.017)	0.279 (-0.021)
	SD	0.061	0.034	0.027	0.024	0.020
	95% CI	0.273; 0.281	0.275; 0.279	0.276; 0.279	0.277; 0.280	0.278; 0.280

When the c', α, and b coefficients each have small effect sizes (0.14), examining the mediation ratio (P_M) values, which represent the ratio of the IE to the TE by sample size, it is observed that the P_M value has the highest bias at a sample size of 100. When the sample size is 500 or larger, P_M values are close to each other, with narrower confidence intervals and closest to the expected P_M mediation ratio (0.123). Examining the mediation ratio (R_M) values, which represent the ratio of the IE to the DE, it is observed that the results closest to the expected R_M mediation ratio (0.140) and, consequently, with the least bias, occur at sample sizes of 700 and 1000. When examining the R^2_{MED1} and R^2_{MED2} values, it is observed that the biases and confidence intervals of the R^2 values are similar across all sample sizes.

When the c', α, and b coefficients each have medium effect sizes (0.39), examining the mediation ratio (P_M) values, which represent the ratio of the IE to the TE by sample size, it is observed that the PM value has the highest bias at a sample size of 100. When the sample size is 300 or larger, P_M values are close to each other, with narrower confidence intervals and closest to the expected P_M mediation ratio (0.281). Examining the mediation ratio (R_M) values, which represent the ratio of the IE to the DE, it is observed that the results closest to the expected R_M mediation ratio (0.390) and, consequently, with the least bias, occur at sample sizes of 500 or larger. When examining the R^2_{MED1} and R^2_{MED2} values, it is observed that the biases and confidence intervals of the R^2 values are similar across all sample sizes.

When the c', α, and b coefficients each have large effect sizes (0.59), examining the mediation ratio (P_M) values, which represent the ratio of the IE to the TE by sample size, it is observed that the P_M value has the highest bias at a sample size of 100. When the sample size is 300 or larger, P_M values are close to each other, with narrower confidence intervals and closest to the expected P_M mediation ratio (0.371). Examining the mediation ratio (R_M) values, which represent the ratio of the IE to the DE, it is observed that the results closest to the expected R_M mediation ratio (0.590) and, consequently, with the least bias, occur at sample sizes of 300 or larger. When examining the R^2_{MED1} and R^2_{MED2} values, it is observed that the biases and confidence intervals of the R^2 values are similar across all sample sizes.

Table 2 presents the simulation results for P_M, R_M, R^2_{MED1} and R^2_{MED2} values when the c' coefficient is at a neutral effect (c'=0), and the α and b coefficients are 0.14, 0.39, and 0.59, respectively, with sample sizes of 100, 300, 500, 700, and 1000. When the DE coefficient c' is at a neutral effect (c'=0) and the α and b coefficients each have small effect sizes (0.14), examining the mediation ratio (P_M) values, which represent the ratio of the IE to the TE by sample size, it is observed that the P_M values are closest to the expected value (1.000) at a sample size of 1000.

When examining the R^2_{MED1} and R^2_{MED2} values, it is observed that the biases and confidence intervals of the R^2 values are similar across all sample sizes. When the DE coefficient c' is at a neutral effect (c'=0) and the α and b coefficients each have medium effect sizes (0.39), examining the mediation ratio (P_M) values, which represent the ratio of the IE to the TE by sample size, it is observed that the P_M values are closest to the expected value (1.000) at sample sizes of 700 and 1000. When examining the R^2_{MED1} and R^2_{MED2} values, it is observed that the biases and confidence intervals of the R^2 values are similar across all sample sizes. Finally, when the DE coefficient c' is at a neutral effect (c'=0) and the α and b coefficients each have large effect sizes (0.59), examining the mediation ratio (P_M) values, which represent the ratio of the IE to the TE by sample size, it is observed that the P_M values are closest to the expected value (1.000) at sample sizes of 500 and larger. When examining the R^2_{MED1} and R^2_{MED2} values, it is observed that the biases and confidence intervals of the R^2 values are similar across all sample sizes.

Table 3 presents the minimum sample size required with the least bias for P_M, R_M, and R^2 mediation values obtained when the α, b, and c' coefficients in the mediator variable model have small, medium, and large effect sizes. Accordingly, the minimum sample size required for P_M and R_M mediation ratios, depending on the degree of effect size, is observed to be 300. For R^2 values, the minimum sample size required for all effect sizes is observed to be 100.

TABLE 2: Model results with neutral c' coefficient and small, medium and large effect sizes of α and b coefficients.

Scenarios		n=100	n=300	n=500	n=700	n=1000
c′=0 α=0.14 b=0.14	**P_M (Bias)**	0.201 (-0.078)	0.143 (-0.020)	0.136 (-0.013)	0.133 (-0.010)	0.127 (-0.004)
	SD	1.427	0.211	0.126	0.070	0.050
	95% CI	-0.870; 0.771	0.028; 0.889	0.093; 0.377	0.098; 0.185	0.105; 0.164
	R^2_{MED1} (Bias)	0.000 (0.000)	0.000 (0.003)	0.000 (0.000)	0.000 (0.000)	0.000 (0.003)
	SD	0.001	0.000	0.000	0.000	0.000
	95% CI	0.000; 0.000	0.000; 0.000	0.000; 0.000	0.000; 0.000	0.000; 0.000
	R^2_{MED2} (Bias)	0.006 (-0.004)	0.006 (-0.002)	0.006 (0.001)	0.006 (0.000)	0.006 (-0.001)
	SD	0.009	0.004	0.003	0.003	0.002
	95% CI	0.005; 0.006	0.006; 0.006	0.006; 0.006	0.006; 0.006	0.006; 0.006
c′=0 α=0.39 b=0.39	**P_M (Bias)**	5.964 (-4.964)	1.174 (-0.174)	1.377 (-0.377)	1.104 (-0.104)	1.038 (-0.038)
	SD	179.526	4.682	5.709	0.525	0.265
	95% CI	-8.357; 4.474	-0.372; 2.616	0.611; 2.381	1.722; 32.696	0.934; 1.356
	R^2_{MED1} (Bias)	0.001 (0.003)	0.000 (0.010)	0.000 (0.019)	0.000 (0.014)	0.000 (0.019)
	SD	0.002	0.001	0.000	0.000	0.000
	95% CI	0.001; 0.002	0.000; 0.001	0.000; 0.000	0.000; 0.000	0.000; 0.000
	R^2_{MED2} (Bias)	0.019 (-0.017)	0.020 (0.021)	0.020 (0.006)	0.020 (-0.017)	0.020 (0.014)
	SD	0.028	0.016	0.012	0.011	0.009
	95% CI	0.017; 0.021	0.019; 0.021	0.019; 0.020	0.019; 0.020	0.020; 0.021
c′=0 α=0.59 b=0.59	**P_M (Bias)**	1.137 (-0.137)	1.029 (-0.029)	1.018 (-0.018)	1.016 (-0.016)	1.003 (-0.003)
	SD	1.265	0.224	0.165	0.139	0.109
	95% CI	-1.150; 2.188	0.950; 1.214	0.947; 1.127	0.955; 1.102	0.955; 1.074
	R^2_{MED1} (Bias)	0.003 (0.085)	0.001 (0.077)	0.001 (0.063)	0.001 (0.060)	0.001 (0.063)
	SD	0.005	0.002	0.001	0.001	0.001
	95% CI	0.003; 0.004	0.001; 0.002	0.001; 0.001	0.001; 0.001	0.001; 0.001
	R^2_{MED2} (Bias)	0.081 (-0.006)	0.082 (0.003)	0.082 (0.003)	0.082 (0.003)	0.083 (0.002)
	SD	0.051	0.030	0.024	0.021	0.016
	95% CI	0.078; 0.084	0.080; 0.084	0.080; 0.083	0.081; 0.084	0.082; 0.084

TABLE 3: The minimum sample size required for ratio measures and explained variance values.

Scenarios	P_M	R_M	R^2_{MED1}	R^2_{MED2}
c′=0.14, α=0.14, b=0.14	500	700	100	100
c′=0.14, α=0.14, b=0.39	500	700	100	100
c′=0.14, α=0.14, b=0.59	500	700	100	100
c′=0.14, α=0.39, b=0.14	500	700	100	100
c′=0.14, α=0.39, b=0.39	500	700	100	100
c′=0.14, α=0.39, b=0.59	500	700	100	100
c′=0.14, α=0.59, b=0.14	500	700	100	100
c′=0.14, α=0.59, b=0.39	500	700	100	100
c′=0.14, α=0.59, b=0.59	500	700	100	100
c′=0.39, α=0.14, b=0.14	300	300	100	100
c′=0.39, α=0.14, b=0.39	300	300	100	100
c′=0.39, α=0.14, b=0.59	300	300	100	100
c′=0.39, α=0.39, b=0.14	300	500	100	100
c′=0.39, α=0.39, b=0.39	300	500	100	100
c′=0.39, α=0.39, b=0.59	300	500	100	100
c′=0.39, α=0.59, b=0.14	300	500	100	100
c′=0.39, α=0.59, b=0.39	300	500	100	100
c′=0.39, α=0.59, b=0.59	300	500	100	100
c′=0.59, α=0.14, b=0.14	300	300	100	100
c′=0.59, α=0.14, b=0.39	300	300	100	100
c′=0.59, α=0.14, b=0.59	300	300	100	100
c′=0.59, α=0.39, b=0.14	300	300	100	100
c′=0.59, α=0.39, b=0.39	300	300	100	100
c′=0.59, α=0.39, b=0.59	300	300	100	100
c′=0.59, α=0.59, b=0.14	300	300	100	100
c′=0.59, α=0.59, b=0.39	300	300	100	100
c′=0.59, α=0.59, b=0.59	300	300	100	100
c′=0, α=0.14, b=0.14	1000	-	100	100
c′=0, α=0.14, b=0.39	1000	-	100	100
c′=0, α=0.14, b=0.59	1000	-	100	100
c′=0, α=0.39, b=0.14	700	-	100	100
c′=0, α=0.39, b=0.39	700	-	100	100
c′=0, α=0.39, b=0.59	700	-	100	100
c′=0, α=0.59, b=0.14	700	-	100	100
c′=0, α=0.59, b=0.39	700	-	100	100
c′=0, α=0.59, b=0.59	500	-	100	100

DISCUSSION

Mediation analysis methods are used to investigate the underlying mechanism of the observed relationship between cause and effect and to examine how this mechanism relates to a set of intervening variables. Effect size measures are utilized to better understand and interpret the strength and direction of the relationship between variables.[4,24] It is observed that there are few studies in the literature that comparatively examine the performance of effect size measures for mediation analysis.[25] Fairchild and McDaniel, in a study conducted in 2009, noted that while the use of mediation ratios is practical and easy, there are some limitations and disadvantages depending on the sample size.[16,17] MacKinnon and Dwyer, in a study conducted in 1995, stated that the bias of the mediation ratio (PM), which is the ratio of the IE to the TE, is high for small sample sizes (N<500). For the mediation ratio (RM), which is the ratio of the IE to the DE, it was found that the bias decreases with a sample size of at least 1000.[25,26] According to our simulation results in Table 3, when the α, b, and c' coefficients have small effect sizes, the P_M value has the least bias at a sample size of 500, and the R_M value has the least bias at a sample size of 700. When the α, b, and c' coefficients have medium effect sizes, the sample sizes with the least bias for P_M and R_M values are found to be 300 and 500, respectively. When the α, b, and c' coefficients have large effect sizes, the sample size with the least bias for both P_M and R_M values is found to be 300.

In a study conducted by Miočević et al. in 2018, it was reported that when the DE coefficient is zero (c'=0) and the α and b coefficients have small effect sizes, the bias for the P_M value is least at a sample size of 1000.[14] In the simulation results, it was also observed that when the c' coefficient is zero and the α and b coefficients have small effect sizes, the bias for the P_M value is least at a sample size of 1000. Additionally, in combinations where the α and b coefficients have medium and large effect sizes, the bias for the P_M value is least at sample sizes of 700 and 500, respectively.

A study by Preacher et al. in 2011, in parallel to the study by Fairchild et al. in 2009, stated that R^2 explained variance measures should be used in addition to PM and RM mediation ratios.[12,27,28] Indeed, in their study on effect size measures for mediation, Fairchild et al. reported that R^2 mediation values in different sample size and effect size situations are more stable than ratio measures and more appropriate for small sample sizes.[7] According to our simulation results, it was also observed that in cases where effect sizes were small, medium and large, the biases in R^2 mediation values were quite small even with a sample size of 100. In summary, the minimum sample size required for P_M and R_M mediation ratios is found to be 300, and for R^2 values, the minimum sample size required for all effect sizes is found to be 100.

CONCLUSION

In models with mediating variables, the magnitudes of the c', α and b coefficients of the direct and IEs in the model and sample size should be taken into consideration when using ratio measures, and it is recommended that alternative measures be used in the studies instead of a single effect size measure in order to address the strength of the relationship between variables more comprehensively. In addition, for future studies, it is suggested that existing effect size measures should be developed and adapted for models with more than one mediator variable or in cases where the variable structure is not continuous.

Source of Finance

During this study, no financial or spiritual support was received neither from any pharmaceutical company that has a direct connection with the research subject, nor from a company that provides or produces medical instruments and materials which may negatively affect the evaluation process of this study.

Conflict of Interest

No conflicts of interest between the authors and/or family members of the scientific and medical committee members or members of the potential conflicts of interest, counseling, expertise, working conditions, share holding and similar situations in any firm.

Authorship Contributions

All authors contributed equally while this study preparing.

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