The use of effect size in veterinary medicine

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ABSTRACT

Effect size is a statistical index that measures the magnitude of the effect generated by the variable of interest in a study, in a sense, reflecting the practical or clinical value of the study in addition to the statistical results. In recent years, it has become preferable to report the effect size expressing practical significance in addition to the statistical significance expressed by the p-value in hypothesis tests in scientific research, and even it has been required by some scientific journals. By reporting the effect size, it is possible to use it in statistical power analysis, to compare the results of the studies, and to determine the amount of the effect in the study. In this study, by mentioning the concept of effect size, the main effect size indices used according to research types are introduced. In addition, the calculation methods of the effect size indices commonly used for continuous and categorical outcome variables were given and interpreted with scenarios from the field of veterinary medicine. In conclusion, in order to be able to interpret the results of a study in clinical or practical terms, to present the analyzed data in more detail than the p-value, and to ensure its use in power analysis, it was suggested that researchers report effect size in their studies.

ÖZ

Etki büyüklüğü, bir çalışmada ilgilenilen değişkenin meydana getirdiği etkinin büyüklüğünü ölçen, ancak bu anlamba bir çalışmının istatistiksel sonuçlarını ifade etmek için olası pratik veya klinik anlamda olabilecek bir değerdir. Bu sayede bilimsel araştırmalarada hipotez testlerinde p değerini ifade eden istatistiksel değerlerin, p değeriyle bu algıları yaratma ve klinik anlamda değerlendirilmesini sağlar. Bu çalışmada etki büyüklüğünün kavramını en başından bahsetmek, araştırmacıların çalışmalarda etki büyüklüğünü raporlaması önerilmiştir. Ayrıca, sürekli ve kategorik değişkenlerin etki büyüklüğünün raporlanmasına yönelik çalışmaların değerlendirilmesi ve bu raporlamaların klinik anlamda değerlendirilmesi önemlidir. Bu çalışmada etki büyüklüğünün kavramını en başından bahsetmek, araştırmacıların çalışmalarda etki büyüklüğünü raporlaması önerilmiştir.
Psychological Association (APA) have made it mandatory to report effect sizes and confidence intervals in their publishing guidance (11). In summary, hypothesis tests provide information only about the probability of confirming the null hypothesis of observed data, as mentioned above. This information, used as the p-value, forces the researcher to make a dichotomous decision in the form of rejecting or not being able to reject the null hypothesis (12). In order to go beyond this process, additional values such as statistical power, effect size, and confidence interval should be evaluated (13).

1. What is effect size?

The effect size is the statistical value showing the deviation level between the results obtained from the sample and the expectations defined in the null hypothesis (14). Effect size is also defined as a statistical index that measures the magnitude of the effect created by the variable of interest in a study and, in a sense, reflects the practical or clinical value of the study in addition to the statistical results.

Including the effect size while reporting the research results generally serves three main purposes;

- The first of these is the use of the effect size in the statistical power analysis to calculate the sample size at the beginning of the study. Effect size is an important part of statistical power analysis. Although not applied consciously, the effect size contributes to a good experiment design (12). In other words, during the power analysis, the required sample size is chosen on purpose, taking into account the importance of the effect between the phenomena of interest, the sensitivity of the tools used to detect this effect, and the research design (13).

- The second purpose of using effect size is to allow comparison between studies answering the same hypothesis. These studies may have been done using different test statistics, different sample sizes, and designs. Therefore, effect size, which is a standardized index that eliminates different features between studies, is needed in order to compare study results (13).

- Reporting the effect size also makes it possible to interpret the magnitude of effect determined in the studies. In addition to making comparative interpretations of different studies, it is also possible to classify a single effect size as small, medium, large effect size as determined by Cohen. Cohen states that the cut-off values he gives for the interpretation of the effect level will be useful in new areas where there are not many studies. That is, when an effect is observed in a study, it is functional if there are no studies that can be compared to understand its magnitude (14). The classification of some effect size indices of most common used statistical tests are given in Table 1 (14, 15)

2. The calculation and interpretation of effect size

Just as there are different hypothesis tests used for different research designs in inferential statistics, effect size calculations also vary according to the structure of the variables. It is possible to evaluate the frequently used effect size indices under two main titles: those used for continuous outcomes and dichotomous outcomes.

| Test                | Classification |
|---------------------|----------------|
| t-Test              | Small | Medium | Large |
| Variance analysis   | 0.20  | 0.50   | 0.80  |
| f^2                 | 0.10  | 0.25   | 0.40  |
| Regression analysis | 0.02  | 0.15   | 0.35  |
| Contingency tables (2x2) | 1.5  | 2      | 3     |
| Risk ratio (RR)     | 2     | 3      | 4     |
| Contingency tables  | 0.10  | 0.30   | 0.50  |
| Contingency tables  | 0.20  | 0.50   | 0.80  |
| Correlation         | ±0.20 | ±0.50  | ±0.80 |
| Variance analysis/ Regression analysis | 0.04 | 0.25 | 0.64 |
2.1. Effect size indices for continuous outcomes

In the research design where the means of the two independent groups are compared, the effect size can be calculated by the mean difference or standardized mean difference.

2.1.1. Mean difference

Let us assume that one compares the monthly live weight gains of Angus and Simental cattle in a breeding farm. The mean and standard deviation values of the live weight gain of two breeds are given in Table 2. It is seen that the difference between the means of the two groups, i.e. the effect size, is \( d = 9.03 - 7.46 = 1.57 \). However, it is difficult to comment on the difference between groups based on the pure mean difference. Because this difference is also related to the variation in the dependent variable. If the dependent variable is distributed with a wide variation, the difference of 1.57 units represents a very small effect, while the dependent variable is distributed in a narrow range may infer that the difference of 1.57 units is a significant effect.

2.1.2. Standardized mean difference

If there is a predetermined standard of measurement for the variable of interest, it may be possible to comment on the effect of the difference between the two groups. However, as it is seen in the above example and most studies, generally there is no standard scale for the variable of interest. Therefore, in order to comment on the amount of difference between means, it is necessary to evaluate the means together with the variations of the distributions (16). Accordingly, the effect size of two independent group designs is calculated as in Equation 1.

\[
d = \frac{\bar{x}_1 - \bar{x}_2}{S_{\text{pooled}}}
\]

\[
S_{\text{pooled}} = \sqrt{\frac{(n_1-1)s_1^2 + (n_2-1)s_2^2}{n_1+n_2-2}}
\]

In the formula for the effect size expressed as “Cohen’s \( d \) \( \bar{x} \) refers to the mean, \( S_{\text{pooled}} \) refers to the variance and \( n \) refers to the sample size of each group.

In the example in Table 2, Angus and Simental beef cattle in a farm were intended to be compared in terms of monthly live weight gains. The variance (V) and standard error of d are calculated as in Equations 3 and 4, respectively (17).

\[
V_d = \frac{n_1n_2}{n_1+n_2} + \frac{d^2}{2(n_1+n_2)}
\]

\[
SE_d = \sqrt{V_d}
\]

Herefrom,

\[
S_{\text{pooled}} = \sqrt{\frac{(150 - 1)3.84 + (150 - 1)4.53}{150 + 150 - 2}} = 2.04
\]

\[
d = \frac{9.03 - 7.46}{2.04} = 0.77
\]

Table 2. The measurements of live weight gain of Angus ve Simental cattle

|         | N  | Mean | Standard Deviation | Variance |
|---------|----|------|--------------------|----------|
| Angus   | 150| 9.03 | 1.96               | 3.84     |
| Simental| 150| 7.46 | 2.13               | 4.53     |

When the above formulas are examined, it does not seem difficult to estimate d, if the population parameters are known or it is possible to obtain the data of interest. However, as is frequently encountered today, there may be a new variable that has not been subjected to any experiment, and has no available data. Under these conditions, it is not possible to obtain the required mean difference and standard deviation information for calculating the effect size. For similar cases, Cohen developed the categories of “small”, “medium” and “large” effect size and enabled an approximate interpretation (14). For example, a new nutrition program is aimed to compare, which is thought to affect the milk yield of Holstein breed cows, with the standard nutrition program in terms of milk yield. The effect size was around \( d = 0.2-0.3 \) in expectation of small and the effect size could be around \( d = 0.8-1.00 \) in expectation of large. When the effect of the nutrition program on milk yield is expected to be moderate, the effect size may be about \( d = 0.5 \). If this interpretation is to be generalized, it can be expressed as (14);

\[
d \geq 0.20 \text{ small effect size}
\]

\[
d \geq 0.50 \text{ medium effect size}
\]

\[
d \geq 0.80 \text{ large effect size}
\]

Hedges suggested a degree of freedom correction as in Equation 5 because Cohen’s \( d \) overestimates the effect size when the sample size is small (18).
2.2. Effect size indices for dichotomous outcomes

If both dependent and independent variables are dichotomized, the most frequently used effect sizes are; risk difference, risk ratio, or odds ratio.

2.2.1. Risk difference

The effect size which expresses the difference between the two proportions \( P_1 \) and \( P_2 \) is shown as

\[
j = P_1 - P_2 \tag{9}\]

But for example, let be \( P_1 = 0.65 \) and \( P_2 = 0.45 \), the effect size is calculated as \( j = 0.20 \); and let be \( P_1 = 0.25 \) and \( P_2 = 0.05 \), the effect size is still calculated as \( j = 0.20 \). This situation shows that the index \( j \) is insufficient to scale equal units. Therefore Cohen developed the index \( h \) in Equation 11, which he obtained with a non-parametric transformation on \( P \) values (14).

\[
\phi = 2 \arcsin \sqrt{P} \tag{10}
\]

\[
h = \phi_1 - \phi_2 \tag{11}
\]

A generalization can be made about the interpretation of the index \( h \) as follows (14):

- \( h \leq 0.20 \): small effect size
- \( h \leq 0.50 \): medium effect size
- \( h \leq 0.80 \): large effect size

2.2.2. Risk ratio

Risk ratio or relative risk (RR) is another effect size index frequently used in cross-sectional or prospective studies (17). It expresses the ratio of the probability of observing the event of interest in two independent samples.

\[
RR = \frac{P_1}{P_2} \tag{12}
\]

\[
SE_{ln(RR)} = \left( \frac{1-P_1}{n_1 P_1} + \frac{1-P_2}{n_2 P_2} \right)^{1/2} \tag{13}
\]

As an illustrative example, let the data of a research design investigating the efficacy of the drug C developed for the treatment of Feline Infectious Peritonitis (FIP) disease seen in cats, compared to placebo, given in Table 3.

According to Table 3, the risk of disease occurrence in cats treated with placebo is calculated as \( P_1 = 40/50 = 0.80 \), while the risk of disease occurrence in cats treated with drug A is calculated as \( P_2 = 5/50 = 0.10 \). Accordingly, the risk ratio is found as \( RR = P_1 / P_2 = 0.80 / 0.10 = 8 \). This result is interpreted as the risk of disease in cats treated with placebo is 8 times higher than in cats treated with drug A. The point to be considered in relative risk is that one of the ratios of interest should belong to the unpreferable situation and the other to the preferred situation (17).

2.2.3. Odds ratio

Odds is defined as the ratio of the probability of occurrence of an event to the probability of non-occurrence. And the odds ratio (OR) is defined as the ratio of the odds of two groups (eg, treatment and placebo groups) whose effects were examined (19). While the risk ratio is an effect size measure used in cross-sectional and prospective studies, the odds ratio can also be used in retrospective research design (17). The observed positive and negative values of the \( X \) and \( Y \) variables are given in Table 4, and the calculation of the odds ratio according to these values in Equation 14 and the calculation of its standard error (SE) in Equation 15 are shown.

\[
OR = \frac{n_{21}n_{22}}{n_{11}n_{12}} \tag{14}
\]

\[
SE_{OR} = \left( \frac{1}{n_{11}} + \frac{1}{n_{12}} + \frac{1}{n_{21}} + \frac{1}{n_{22}} \right)^{1/2} \tag{15}
\]

Odds ratio based on the example in Table 4 is calculated as;

\[
OR = 40 \times 45 / 5 \times 10 = 36
\]

According to this result, it is interpreted that the likelihood of being positive for FIP disease in cats treated with placebo is 36 times more than cats treated with drug A. In other words, cats treated with drug A had 36 times more likelihood of recovery than cats treated with placebo.
CONCLUSION

In this study, we evaluated not only the effect size of calculations that can be used in different research designs but also evaluated how these calculated indexes should be interpreted. Furthermore, Cohen's effect size classification as “small”, “medium” and “large” is also mentioned. Some researchers attribute Cohen's popularity about effect size to this classification system that he brought to the interpretation of effect size (10, 20). However, Vacha-Haase and Thompson argued that the use of this classification system is unreasonable, as it resembles the rigidity in the p < 0.05 system used in the hypothesis testing approach (10). Therefore, it was stated that a specific evaluation should be made for each study without sticking to a classification in the interpretation of the effect size. For example, in a study investigating the effect of smoking on lifetime, even if the effect size is found to be low, this is considered a valuable result. Because first of all, the outcome we are interested in is, the lifetime, clinically very important and it would also be seen that it is approximately similar to the effect size found in previous studies conducted on the same subject. Accordingly, while interpreting the effect size, interpretation should be made by considering both the characteristics of the outcome evaluated in the study and the effect sizes found in previous studies on the same subject.

The recommendations using effect size in addition to p-value aim to overcome the deficiencies of p-value. The most important limitation of the p-value is that it is affected by the sample size. Even though the effect size is zero or very small, p-value would indicate a statistically significant difference, if the sample size is adequately big. Statistically significance depends upon both effect size and sample size, while effect size is independent of sample size. The other limitation of p-value is that it is provided information only about the existence of the effect, not its effect. Thus, reporting only the p-value is not sufficient to fully understand the results (15).

Finally, it should be noted that, even though Cohen's small-medium-large effect size classification seems like it prevents to avoid the inflexibility of the p-value, it can be used as a rough guide in the absence of any preliminary information during the design phase of the research. In addition, researchers should prefer to report effect size to give information about the amount of the effect revealed in the intervention.

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DECLARATIONS

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Not applicable.

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The authors declare that they have no competing interests.

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Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.
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