

BINOMIAL EFFECT SIZE DISPLAY

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Binomial Effect Size Display

The Core Definition of BESD

The Binomial Effect Size Display, commonly abbreviated as **BESD**, is a powerful and intuitive statistical method designed to translate the often abstract concept of a correlation coefficient (r^*) into a highly accessible measure of practical difference. At its core, the BESD provides a clear, visual representation of the effectiveness of a treatment or predictor variable by arraying experimental results in terms of success rates. This method assumes that both the predictor variable (e.g., exposure to treatment) and the outcome variable (e.g., successful recovery) have been dichotomized, meaning they are split into two categories, typically of equal size, such as 'High' versus 'Low' or 'Success' versus 'Failure'. This transformation allows researchers and lay audiences alike to grasp the real-world impact of a correlation, even when the underlying statistical values might appear small or negligible.

The fundamental mechanism of the BESD rests on transforming the Pearson product-moment correlation coefficient (r^*) directly into a comparison of success rates between two groups. If a researcher finds a correlation r^* between a treatment and an outcome, the BESD calculates the resulting difference in success rates that would be observed if 100 participants were split equally into two groups (50 receiving the favorable condition and 50 receiving the unfavorable condition). The success rate for the favorable group is calculated as 50% plus half of the correlation coefficient (as a percentage), while the success rate for the unfavorable group is 50% minus half of the correlation coefficient. This simple arithmetic immediately illuminates the magnitude of the effect in terms of tangible outcomes, such as survival rates, improvement rates, or likelihood of achieving a specific behavioral goal.

A key idea driving the BESD is the necessity of communicating statistical findings in a manner that resonates with clinical relevance rather than merely statistical significance. While traditional statistical measures like the coefficient of determination (r^{*2}) might suggest that a correlation of $r^* = 0.30$ accounts for only 9% of the variance, the BESD demonstrates that this correlation corresponds to a 30 percentage point difference in success rates (e.g., 65% vs. 35%). This stark contrast in interpretation helps researchers avoid dismissing seemingly small correlations that hold profound practical implications in fields such as medicine, education, and social policy, where even marginal gains in success rates can affect thousands of lives.

Historical Origins and Development

The Binomial Effect Size Display was introduced in 1982 by renowned psychologists Robert Rosenthal and Donald B. Rubin. Their work emerged from a critical concern regarding the common misinterpretation and undervaluation of correlation coefficients in psychological and social science

research. Rosenthal and Rubin observed that many researchers and reviewers incorrectly minimized the importance of effects simply because the squared correlation coefficient (r^2), which represents the proportion of variance explained, was low. For instance, an r of 0.20, which accounts for only 4% of the variance, was often deemed too weak to warrant further attention, despite potentially representing a clinically meaningful difference.

Rosenthal and Rubin sought a method that could anchor statistical findings to understandable, real-world metrics. They recognized that the human mind is highly attuned to comparing frequencies and rates, especially when outcomes are binary (success/failure). The BESD was explicitly developed to address this communication gap, serving as an educational tool to demonstrate that even modest correlations can yield substantial practical differences when translated into success rates. Their foundational paper argued persuasively that focusing solely on variance explained (r^2) often leads to a severe underestimation of the practical utility of research findings, thereby potentially stalling the implementation of effective interventions.

The historical impetus for the BESD was also tied to the growing field of meta-analysis, which synthesizes findings across multiple studies. When combining results, researchers frequently rely on the correlation coefficient as a standardized measure of effect size. By providing a common metric (the difference in success rates) that remains constant regardless of the original scale of measurement, the BESD facilitated easier comparison and communication of cumulative evidence across disparate research domains, cementing its role as a vital tool for summarizing complex bodies of literature and communicating the collective impact of an intervention.

Practical Application: A Clinical Example

To illustrate the power of the BESD, consider a hypothetical clinical trial investigating a new psychological intervention aimed at reducing test anxiety. Researchers conduct a study and find a correlation of $r = 0.40$ between receiving the new intervention (versus a control condition) and successfully passing a high-stakes exam. While a statistician might note that $r^2 = 0.16$ (meaning 16% of the variance is accounted for), a policymaker or concerned parent might still question the practical significance of this finding. This is where the BESD provides immediate clarity, transforming the correlation into a tangible difference in pass rates.

The application of the BESD begins by conceptually arranging 100 participants into a 2x2 table, assuming the predictor (treatment) and the outcome (passing/failing) are both dichotomized at the median, creating four equal cells. The total sample is divided evenly: 50 participants who received the favorable condition (the new intervention) and 50 who received the unfavorable condition (the control or placebo). Using the formula derived by Rosenthal and Rubin, the success rate for the intervention group is calculated as $50\% + (r/2 * 100)$, and for the control group, $50\% - (r/2 * 100)$.

Step-by-step, the calculation for $r^* = 0.40$ proceeds as follows:

Determine half of the correlation coefficient: $0.40 / 2 = 0.20$ (or 20 percentage points).

Calculate the success rate for the Intervention Group (Favorable): $50\% + 20\% = \mathbf{70\% \text{ success rate}}$.

Calculate the success rate for the Control Group (Unfavorable): $50\% - 20\% = \mathbf{30\% \text{ success rate}}$.

The resulting BESD shows that the intervention group has a 70% success rate, while the control group has only a 30% success rate.

This display immediately reveals that the correlation of 0.40, which might seem small when squared, translates to a massive 40 percentage point difference in the likelihood of a successful outcome. This dramatic visualization clarifies the practical value of the intervention, showing that participants who received the treatment were more than twice as likely to pass the exam compared to those in the control group. This simplicity makes the BESD an invaluable tool for communicating research findings to stakeholders who may lack statistical expertise.

Significance and Impact in Psychological Research

The significance of the BESD lies primarily in its role as a tool for improving the communication and interpretation of effect size within the behavioral sciences. Before its development, a pervasive issue was the tendency to overlook or dismiss research findings that produced statistically significant but seemingly small effects. The BESD effectively reframed this perception by demonstrating that correlations often deemed "weak" possess substantial predictive and clinical utility when viewed through the lens of differential success rates. This shift in perspective has been crucial for ensuring that valuable, if subtle, research findings are not prematurely discarded.

In applied psychology, the BESD has wide-ranging applications, particularly in areas requiring decisions about resource allocation and intervention efficacy. For clinical psychologists, it helps quantify the real benefit of therapeutic approaches. For educational researchers, it clarifies the practical gain achieved by a new pedagogical method. Furthermore, in the context of policy making, the BESD provides legislators and administrators with a compelling, easily digestible metric to justify investment in programs that exhibit a measurable, positive correlation with desired social or health outcomes. It transforms statistical jargon into actionable information about improvement or survival.

The continued impact of the BESD is its enduring contribution to addressing the persistent problem of misunderstanding statistical magnitude. It serves as a pedagogical instrument used in teaching research methods to highlight the difference between statistical significance (whether an effect exists) and practical significance (how important the effect is in the real world). By forcing

researchers to visualize the effect in terms of concrete, binary outcomes, the BESD encourages a more responsible and nuanced interpretation of data, ultimately strengthening the reliability and perceived relevance of psychological science.

Limitations and Criticisms

While the Binomial Effect Size Display offers powerful interpretive advantages, it is not without its limitations and has faced specific criticisms within the quantitative psychology community. One of the primary limitations is the inherent assumption that both the predictor and outcome variables are perfectly dichotomized at their respective medians, creating a 50/50 split in both dimensions. In real-world data, variables are rarely split perfectly at 50% for both the outcome (e.g., success rate might naturally be 80%) and the predictor (e.g., a treatment group might be smaller than a control group). When the base rates deviate significantly from 50%, the BESD can become misleading, as the displayed success rates no longer accurately reflect the true proportions in the population under study.

A significant criticism concerns the fact that the BESD maximizes the apparent magnitude of the effect. By forcing the data into a 50/50 contingency table, it presents the largest possible difference in success rates corresponding to a given r^* . While this is useful for demonstrating the maximum potential impact of the correlation, critics argue that it can sometimes exaggerate the effect size, especially when compared to other metrics like Cohen's d^* or the odds ratio, which are more sensitive to the actual base rates and prevalence of the outcome. Researchers must therefore use the BESD cautiously, ensuring they explicitly communicate that the displayed success rates represent the maximal effect under ideal, balanced conditions, rather than necessarily reflecting the precise rates observed in a natural population.

Finally, the BESD is fundamentally limited to interpreting the Pearson r^* and is designed specifically for binary outcomes. It does not easily translate to more complex statistical models, such as multivariate regressions or analyses involving continuous outcomes, where other statistical power metrics are more appropriate. While it excels at communicating simple bivariate relationships, its utility diminishes rapidly when the research question requires accounting for multiple predictors or complex causal pathways, necessitating a reliance on more traditional measures of variance explained.

Connections to Other Effect Size Metrics

The Binomial Effect Size Display belongs to the broader category of **Effect Size Metrics**, which are quantitative measures of the strength of a phenomenon. It is housed within the subfield of **Quantitative Psychology**, specifically serving as an interpretive tool for classical correlation analysis. Unlike traditional metrics that focus on variance, the BESD focuses on the practical

consequences of that variance. Its utility is best understood in relation to the two major families of effect size: the r^2 family (correlation-based) and the d^2 family (mean difference-based).

The BESD is directly derived from the Pearson correlation coefficient (r), placing it firmly within the r^2 family. It is often contrasted with the coefficient of determination (r^2), which is the primary metric that Rosenthal and Rubin sought to supplement. While r^2 quantifies the proportion of shared variance between two variables, the BESD translates that correlation into a difference in dichotomous outcomes. This translational capability provides a crucial bridge, allowing researchers who think in terms of variance to communicate effectively with audiences who think in terms of success versus failure rates.

In contrast, effect sizes from the d^2 family, such as **Cohen's d** , measure the standardized difference between the means of two groups. While d is excellent for comparing average performance (e.g., the average test score difference between treatment and control groups), it does not inherently communicate success rates without further conversion. Interestingly, the BESD provides a method for easily estimating a correlation coefficient ($r = 2 * (\text{BESD difference}) / 100$), which can then be converted to Cohen's d using established formulas, demonstrating the deep interconnectedness of these standard effect size measures in summarizing the magnitude of psychological phenomena.