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Independent Samples t-test

Use when...

Use this inferential statistical test when you wish to compare two population means, μ_1 and μ_2, and the observations are independent both within groups and between groups. You do not know the population means or population standard deviations (or variances). This a very popular test used most often when you wish to compare two groups in terms of their averages on an interval or ratio scaled variable.

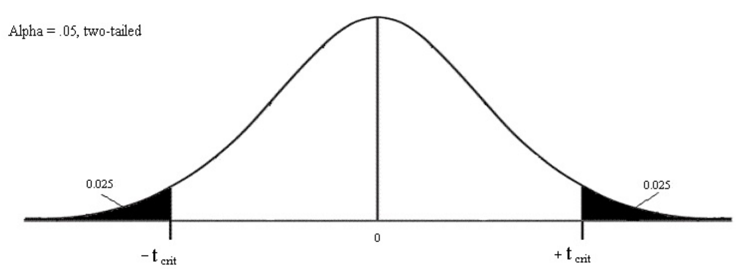
Assumptions

- Random sampling or random assignment to groups
- observations are independent
- $\sigma_1 = \sigma_2$ Population standard deviations (or variances) are homogeneous
- Population distributions are normal
- Variable for which means are computed is continuous
- H_o is true

Hypotheses

H_o: $\mu_1 = \mu_2$
H_A: $\mu_1 > \mu_2$
or $\mu_1 < \mu_2$

Sampling Distribution and Critical Values



The *t* distribution is the sampling distribution from which t_{crit} is determined. The darkened area in the distribution is the "rejection region." When t_{obs} falls in the rejection region, the result is "statistically significant", which means that the null hypothesis is rejected. The t_{crit} value is taken from a table of such values or determined using an online calculator. The shape of the *t* distribution changes depending upon the number of people (observations) in the sampling process. As the sample size grows larger, the distribution approaches a normal curve. For smaller sample sizes, it is somewhat platykurtic. To obtain the correct t_{crit} value, the degrees of freedom value is used. For the independent samples t-test, df = $n_1 + n_2 - 2$.

Formulas (when $\sigma_1 = \sigma_2$. If this assumption is violated, then modified formulas in SPSS must be used)

Observed statistic: $$t_{obs} = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_p^2}{n_1} + \frac{s_p^2}{n_2}}}$$ df = $n_1 + n_2 - 2$

where $$s_p^2 = \frac{(n_1 - 1)(s_1^2) + (n_2 - 1)(s_2^2)}{n_1 + n_2 - 2}$$

Standardized effect size: $$d = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{s_p^2}}$$ Cohen's Conventions: .2 = small, .5 = med, .8 = large

Another very popular effect size index is eta-squared: $$\eta^2 = \frac{t_{obs}^2}{t_{obs}^2 + df}$$

Eta-squared ranges from 0 to 1 and indicates the proportion of overlap between the grouping variable (the IV) and the outcome variable (the DV). It is often reported like "the independent variable explained 15% of the variance in the dependent variable." Cohen's conventions for eta-squared are: .01 small, .06 = medium, .14 = large.

Confidence Interval (written as: $? \le \mu_1 - \mu_2 \le ?$) $$\bar{X}_1 - \bar{X}_2 \pm \left(\left|t_{crit}\right|\right)\left(\sqrt{\frac{s_p^2}{n_1} + \frac{s_p^2}{n_2}}\right)$$

If width of the interval is approximately equal to s_p, then the interval is "middling" precision; if smaller, then "narrow" (precise); if larger, then "wide" (imprecise). Alternatively, you can compare the width of the interval to the possible scale range and judge as narrow, middling, or wide.

APA Style Example

As predicted, results from an independent samples *t* test indicated that individuals diagnosed with schizophrenia ($M = .76$, $SD = .20$, $N = 10$) score higher (i.e., less logically consistent) on the sorting task than college students ($M = .17$, $SD = .13$, $N = 9$), $t(17) = 7.53$, $p < .001$, two-tailed. The difference of .59 scale points is large (scale range: 0 to 1; $d = 3.47$), and the 95% confidence interval around the difference between the estimated population means is relatively precise (.43 to .76).