Replicability: Are we finding real effects?



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Studies with smaller sample sizes (i.e. with lower power) are more likely to overestimate the effect size.

Aside on effect sizes and power

- Power: The probability of finding an effect of a particular magnitude ("effect size") given a particular sample size.
 - Power analyses: What is the required sample size to achieve a certain power threshold (usually 0.8) for a given effect size.
 - Underpowered study: Sample size has power less certain threshold.

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 - Underpowered study: Sample size has power less certain threshold.
- In the context of power analyses, effect sizes are usually specified in terms of standardized mean differences

Effect size = <u>Mean(Group 1)</u> - <u>Mean(Group 2)</u> Combined standard deviation

Cohen's estimates: 0.2 - small, 0.5 - average, 0.8 - large

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Caveat:

- Power is calculated based on effect size in original study
 - Effect size could be an overestimate if the original study was underpowered.
 - Might need more power than expected.

Camerer et al (2018) study

- Replicated 21 studies in Nature and Science between 2010 and 2015
 - All studies had experimental vs control comparison with at least one significant result and were run on accessible populations.
 - Replicated one finding from every study.
- Two stage process:
 - Stage 1: 90% power to detect 75% of effect size
 - Stage 2 (if stage 1 doesn't replicate): 90% power to detect 50% of effect size

Statistical significance criterion

- 12 studies (57%) replicated when powered to detect 75% of the effect size
- 2 additional studies replicated when powered to detect 50% of the effect size.

This is a much higher percentage than the 36% in the Reproducibility Project Psychology (RPP) which replicated 100 studies in psychology.

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If we want to use this criterion, base the power analysis on 50% of the effect size.

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 d_{0} : Effect size that would have 33% power with original sample size

 d_{R} : Effect size of the replication.

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One study had a significant effect in the right direction but was too small to have been found by the original study.

Combining data: Meta-analytic estimate

- Combine original effect and replication effect
- 16 studies had significant meta-analytic effect (p < 0.05)
 - Something not significant in the replication but in the same direction as the original can add up and become significant
- More stringent alpha level recommended for meta-analysis. With this the same 13 were significant (p < 0.005)

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Similarly confidence intervals can be plotted (with combined sd). 14 studies fell in the 95% confidence interval

Criticism about NHST approaches

These approaches are useful to think about what a successful replication can tell us. But if we fail to find a significant effect we cannot reason directly about whether or not the effect exists.

Bayes factor

Bayes Factor = P (data | model1) * P(model1)

P (data | model2) * P(model2)

BF < 1: Supports model2

BF > 3 : Substantial evidence for model1

BF > 20 : Strong evidence for model1

Bayes factor

Bayes Factor = $P(data | H_A) * P(H_A)$ $P(data | H_0) * P(H_0)$

BF < 1: Supports model2

BF > 3 : Substantial evidence for model1

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The studies that failed to replicate had Bayes factor < 1 providing evidence for the null hypothesis

Summary

- The effect size in studies particularly those that are underpowered can be exaggerated. So design replication studies such that they have the power to find 50% of the original effect size.
- Different approaches to looking at replication success resulted in the same conclusions.
- Studies that failed to replicate did not show any evidence for the effect.
 These were probably false positives
- People were able to predict which studies would not replicate failure to replicate not due to chance alone.

Replication assumes that there are no systematic differences in the procedures. This is a reasonable assumption to make. But some of our data suggest that there are baseline differences between crowdsourcing platforms.



