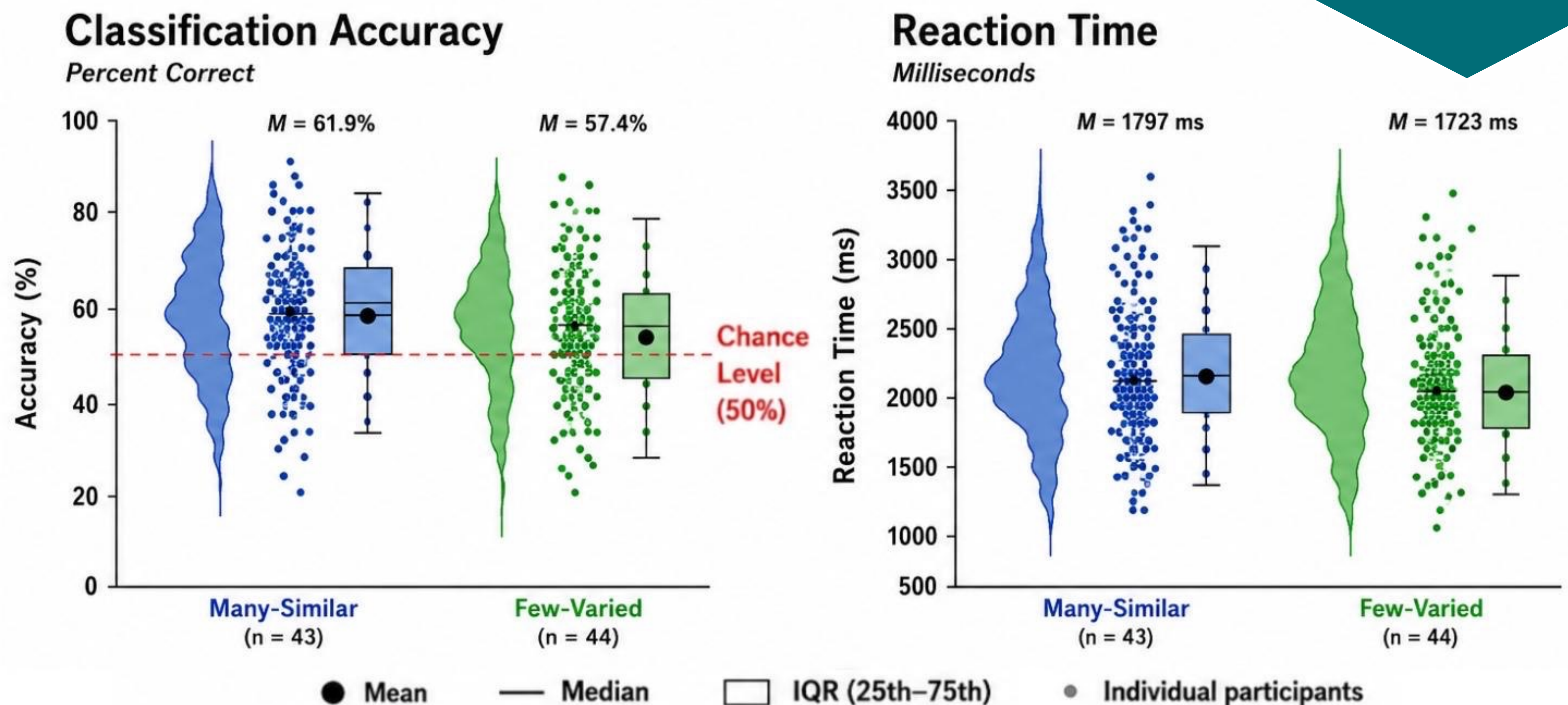




Less Is More?

How Variability Impacts Visual Category Learning

IS LESS MORE? OR IS LESS... JUST AS MUCH?



Between-Group Comparison: Accuracy (DV) Many-Similar vs. Few-Varied

Independent-samples *t*-test $t(85) = 1.53, p = .130$
Mean difference = 4.5%, 95% CI [-1.3%, 10.3%]
Cohen's $d = 0.33$ (small)

Between-Group Comparison: Reaction Time (DV) Many-Similar vs. Few-Varied

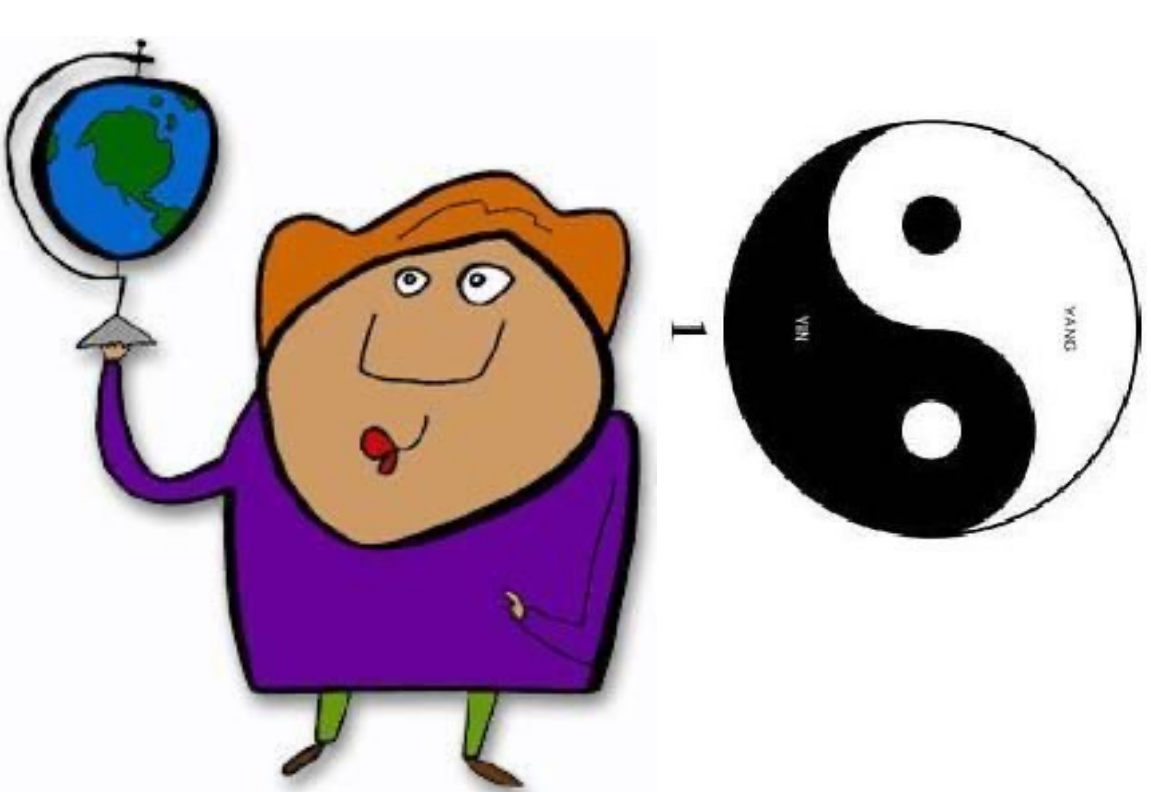
Independent-samples *t*-test $t(85) = 0.86, p = .393$
Mean difference = 74 ms, 95% CI [-95 ms, 243 ms]
Cohen's $d = 0.19$ (negligible)

Accuracy was online slightly numerically higher in Many-Similar than Few-Varied, and Reaction Time was numerically slower. However neither difference was found statistically significant.

PARADIGM

We compared two training strategies: **many similar** versus **few highly variable** training examples. Participants in the **Few-Varied** condition will show **higher or same classification accuracy** for novel test images than participants in the **Many-Similar** condition.

STIMULI MATERIAL



Sample images of the different categories:
Few varied vs many similar

THEORETICAL BACKGROUND

Does variability promote generalization better than pure quantity?

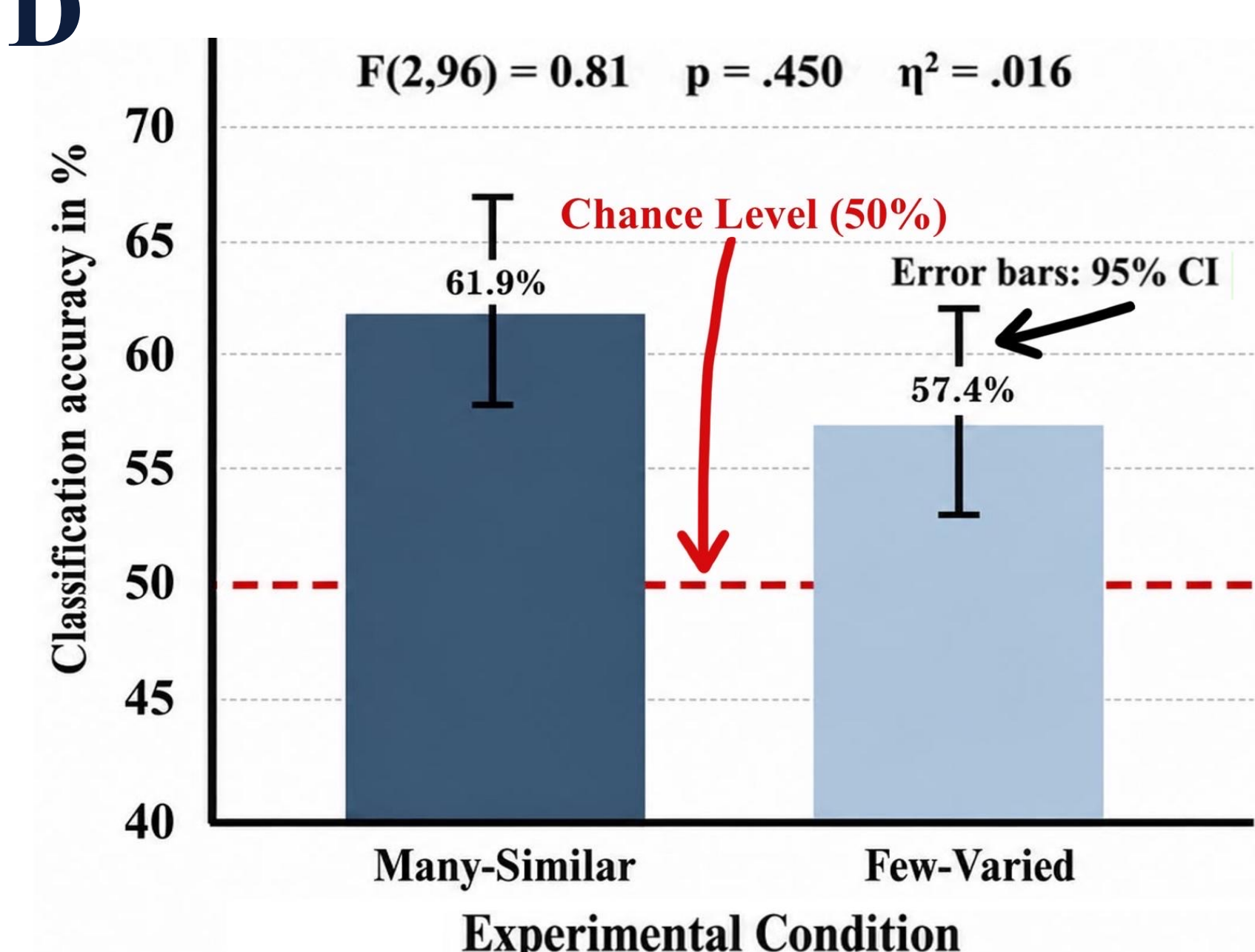
→ Variability as the key to generalization
Raviv et al. (2022)

→ Diverse training promotes invariant reproduction
Manenti et al. (2023)

→ Expected variability improves transfer
Ram et al. (2024)

→ Variable experience shapes later learning
Hosch et al. (2024)

Despite having come to a zero significance finding, we presume our hypothesis still might be worth repeating at a higher scale.



Ground effect proven

All groups at the limit of what is possible - valid finding on task difficulty.

Limits of variability

Variability alone is not enough, contrast and amount of training are decisive.

Replication relevance

Shows need for more realistic training conditions for future studies.

