



University of Colorado  
Boulder

# Human-Robot Interaction

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## **Experimental Design Fundamentals**

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Previously...

# Methodology

Research strategies

- Field

- Experimental

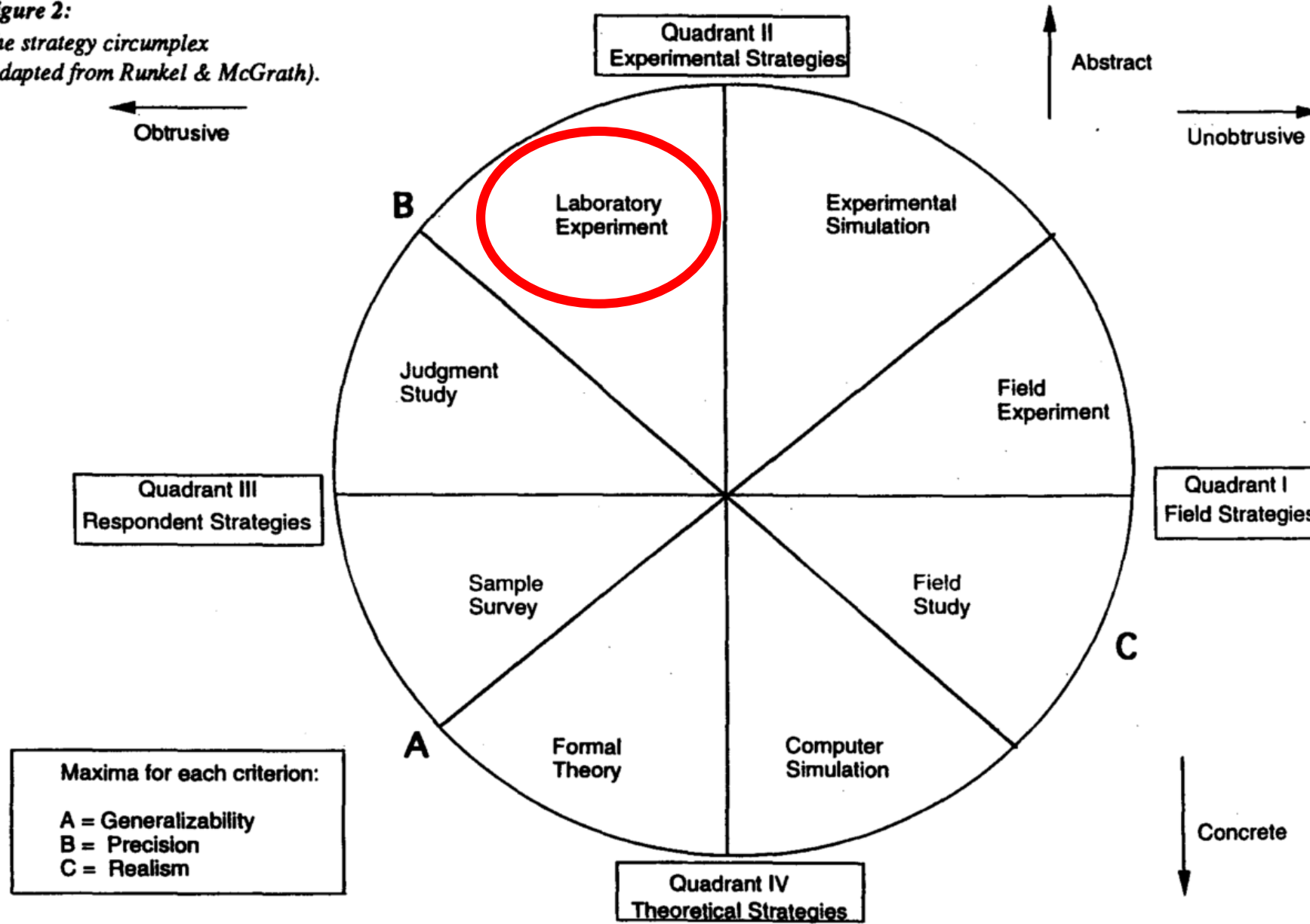
- Respondent

- Theoretical

Nascent, Intermediate, and Mature research

Examples of poor fit

**Figure 2:**  
*The strategy circumplex*  
(adapted from Runkel & McGrath).



# Fundamentals of Experimental Design

What is a **hypothesis**?

# Hypothesis

hypothesis | hī'päθəsis |

*noun* ( pl. **-ses** | -,sēz | )

a supposition or proposed explanation made on the basis of limited evidence as a starting point for further investigation : professional astronomers attacked him for popularizing an unconfirmed hypothesis.

- *Philosophy* a proposition made as a basis for reasoning, without any assumption of its truth.

ORIGIN late 16th cent.: via late Latin from Greek **hupothesis** 'foundation,' from **hupo** 'under' + **thesis** 'placing.'

# Hypothesis

A statement of the predicted or expected relationship between at least 2 variables

- A provisional answer to a research question

- Has to define the variables involved

- Has to define a relationship

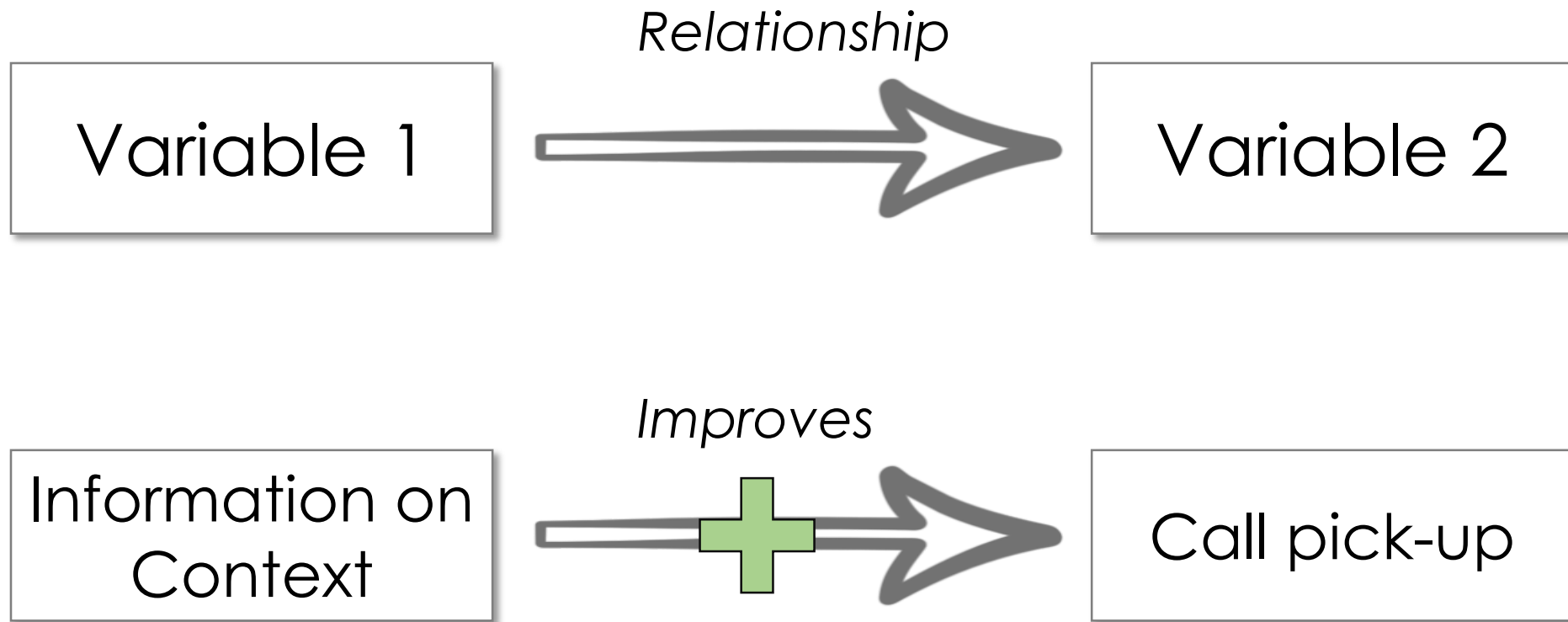
Example:

**Question:** How does having information on the context of a caller affect whether the receiver picks up the call?

**Hypothesis:** Receivers will be more likely to pick up a call when they have information of their callers' context than they will be when they do not



# Hypothesis



# Good Hypothesis Formation

**Testable:** The means for manipulating the variables and/or measuring the outcome variable must potentially exist

**Falsifiable:** Must be able to disprove the hypothesis with data

**Parsimonious:** Should be stated in simplest adequate form

**Precise:** Should be specific (operationalized)

**Useful:**

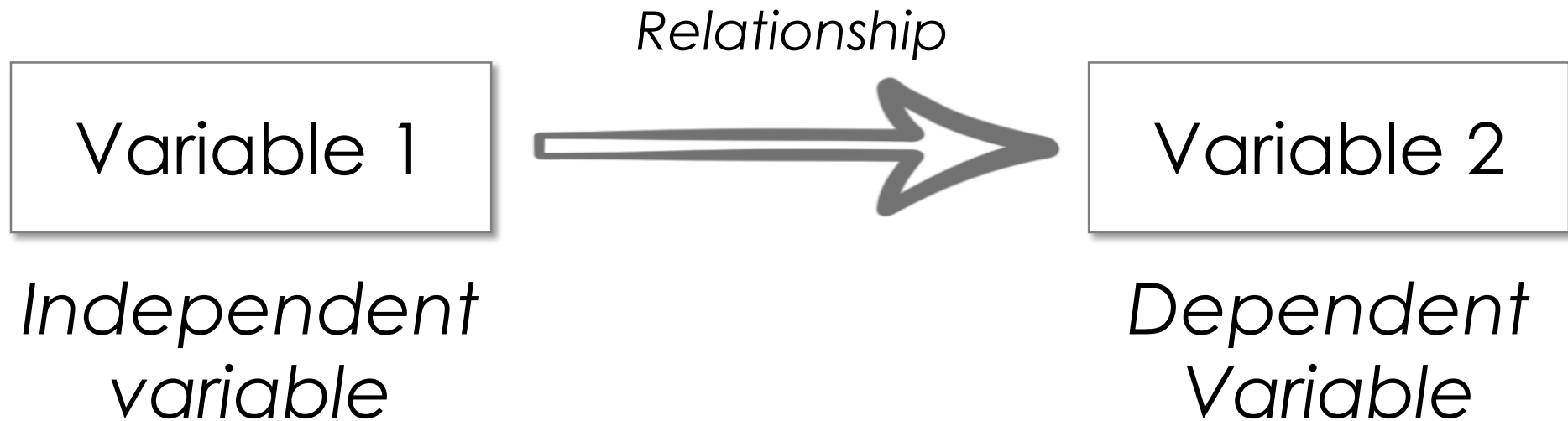
Relate to existing theories and/or “point” toward new theories

Lead to studies beyond the present one (may be hard to determine in advance)

# Variables

Independent variable  
What is manipulated

Dependent variable  
What is measured



# Variables

## Control variables

What is held constant

## Random variables

What is allowed to vary randomly

## Confounding variable

What influences the independent + dependent variable(s)

What is the difference  
between **causality** and  
**correlation**?

# Relationships

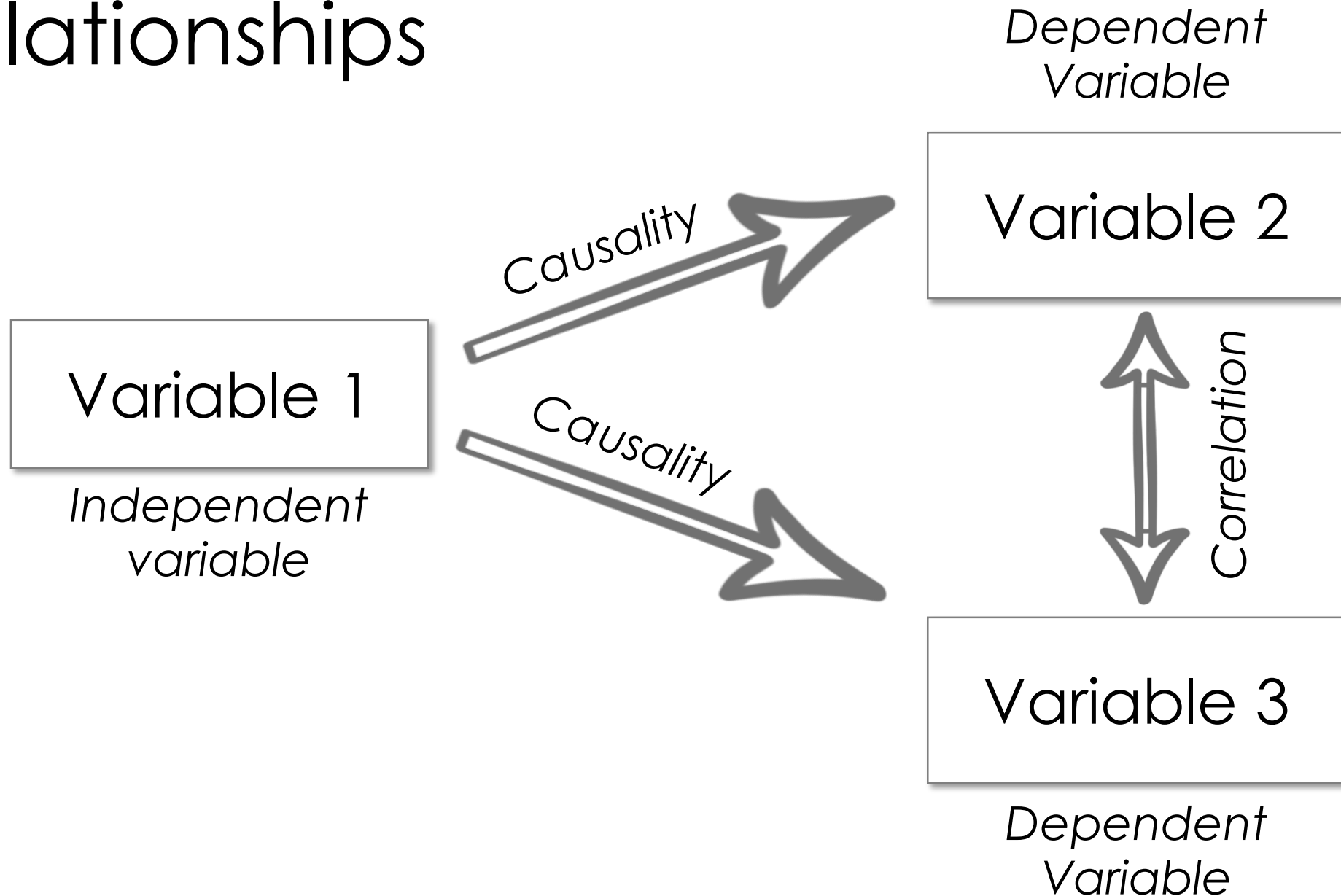
## Causal

One variable depends on and is affected by the other

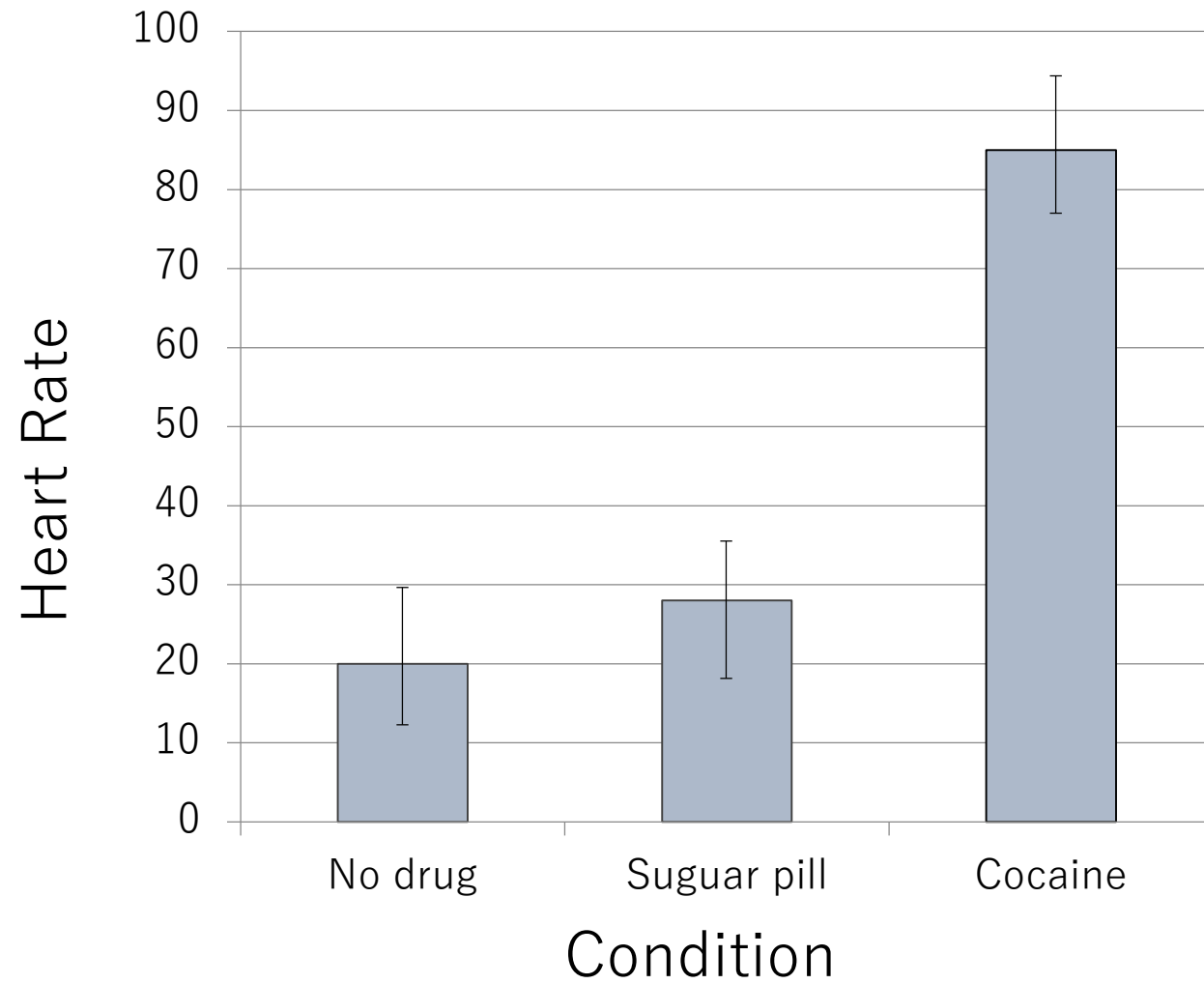
## Correlational

Two variables are affected by a third variable in the same direction

# Relationships

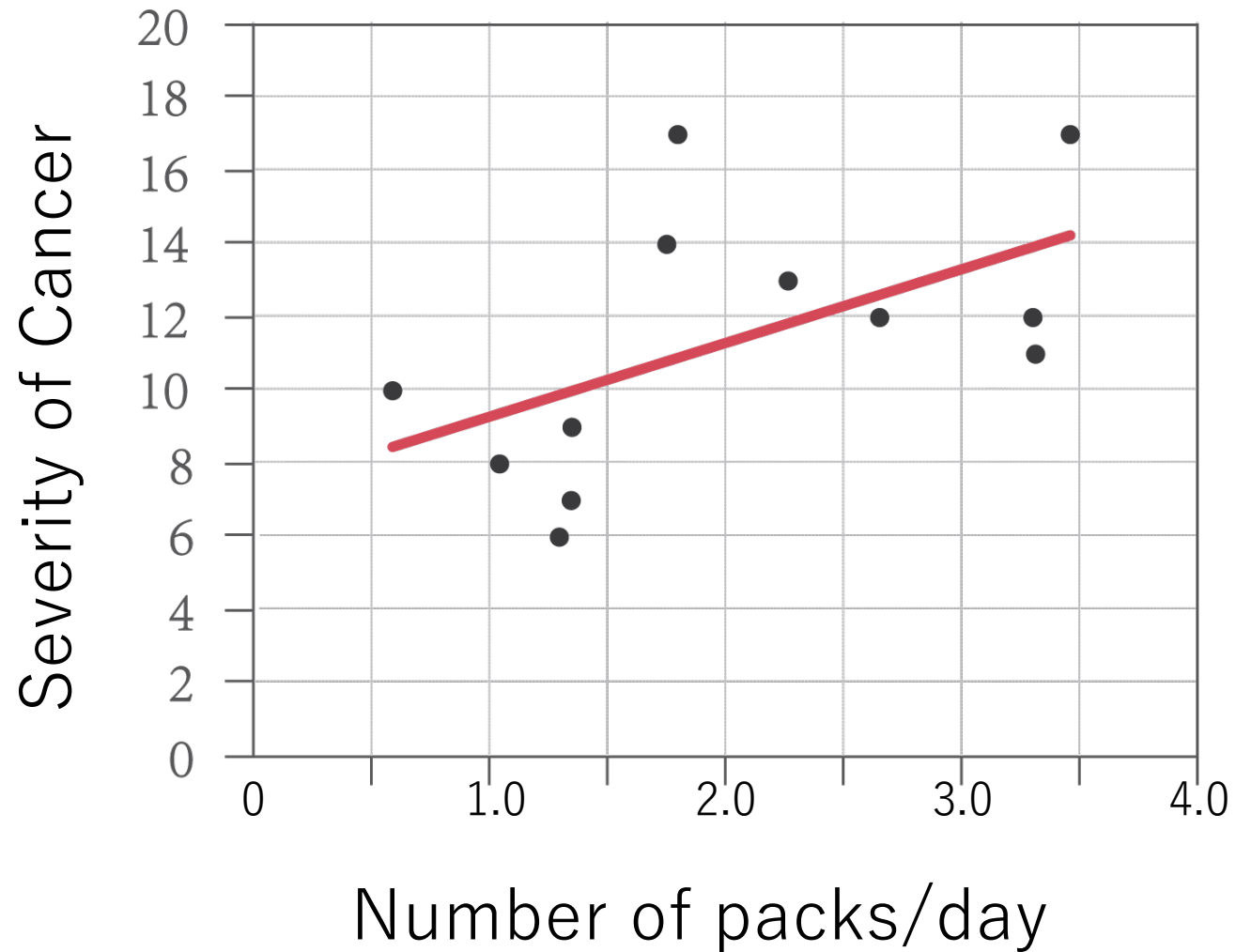


# Causal





# Correlational



# How do we calculate correlation?

Different ways (different interpretations of meaning of *correlation*)

Commonly: correlation = do two variables have a linear (or close to linear) relationship?

To determine, calculate Pearson's correlation coefficient  $r$

$r = +1$  indicates a perfect positive linear fit

$r = 0$  indicates no linear dependency

$r = -1$  indicates a perfect negative linear fit

Often we care more about the coefficient of determination ( $r^2$ ) – we will discuss more later

$$\frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2}}$$

# Determining Causality

## Fundamental Problem of Causal Inference

It is impossible to directly observe causal effects

Is the relationship conceptually valid?

Can you rule out reverse causality?

E.g., Windmill rotation causes wind

Is the relationship temporally correct as effects cannot precede causes?

Can you remove or control for potential confounding variables?

Can you rule out correlation by coincidence?

Use large sample sizes

Perform cross validation

Are your findings repeatable?

How important is causality?

Correlational models can often provide useful predictions

Questions?

# Experimental Design

# Research Designs

Correlational research

Quasi-experimental research

True Experimental research

# Correlational Design

For studies examining the relationships between variables such as personality traits, work habits, gender, etc., the hypothesis is a specific statement about relationships

When we observe an increase in X, then we will also observe an increase (or decrease) in Y

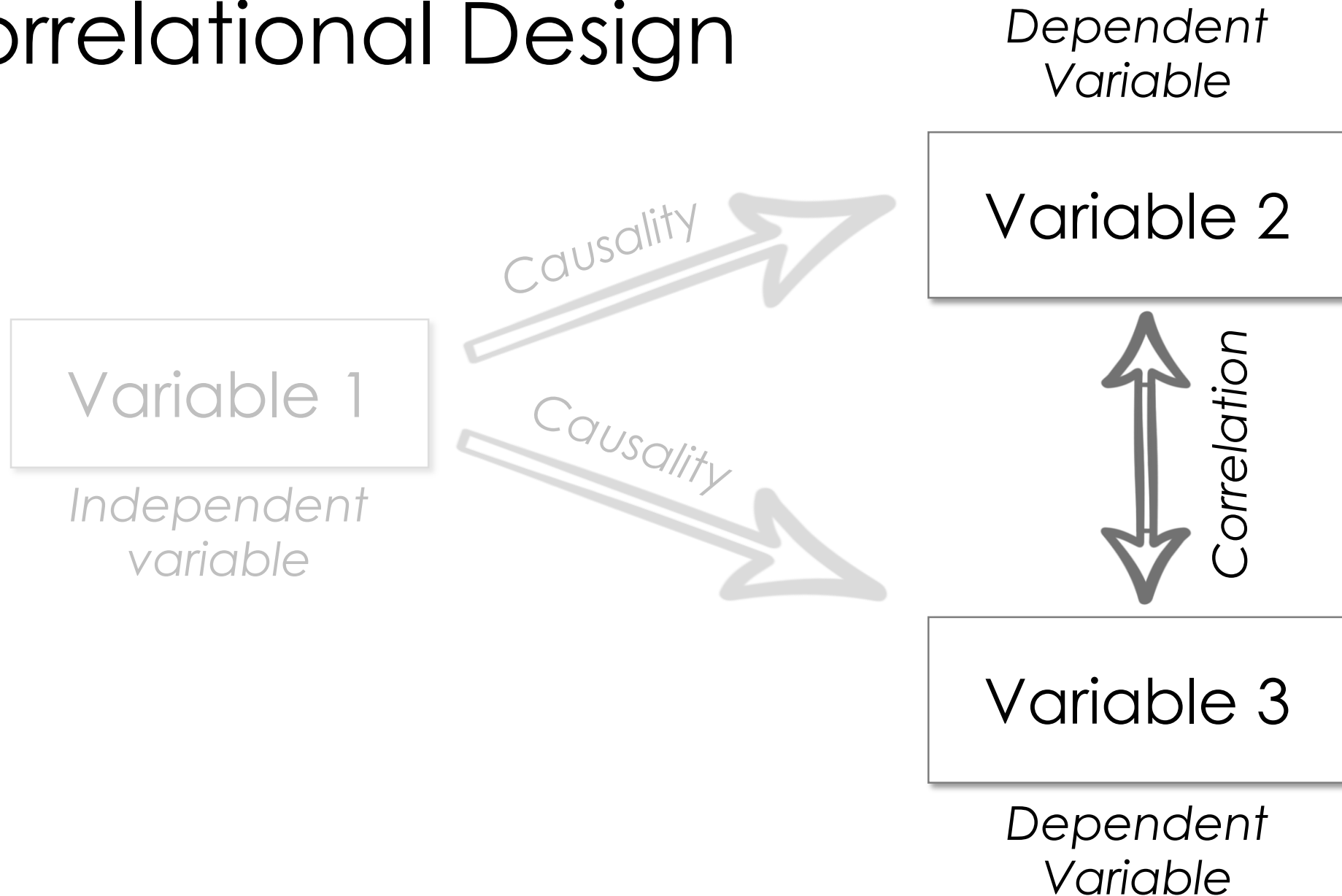
Example questions:

Is there a relationship between smoking and lung cancer?

Is there a relationship between anxiety and test-taking performance?

Correlation does NOT imply causation

# Correlational Design





# Quasi-experimental Design

Used when randomization is impossible and/or impractical

Separate participants based on some characteristic

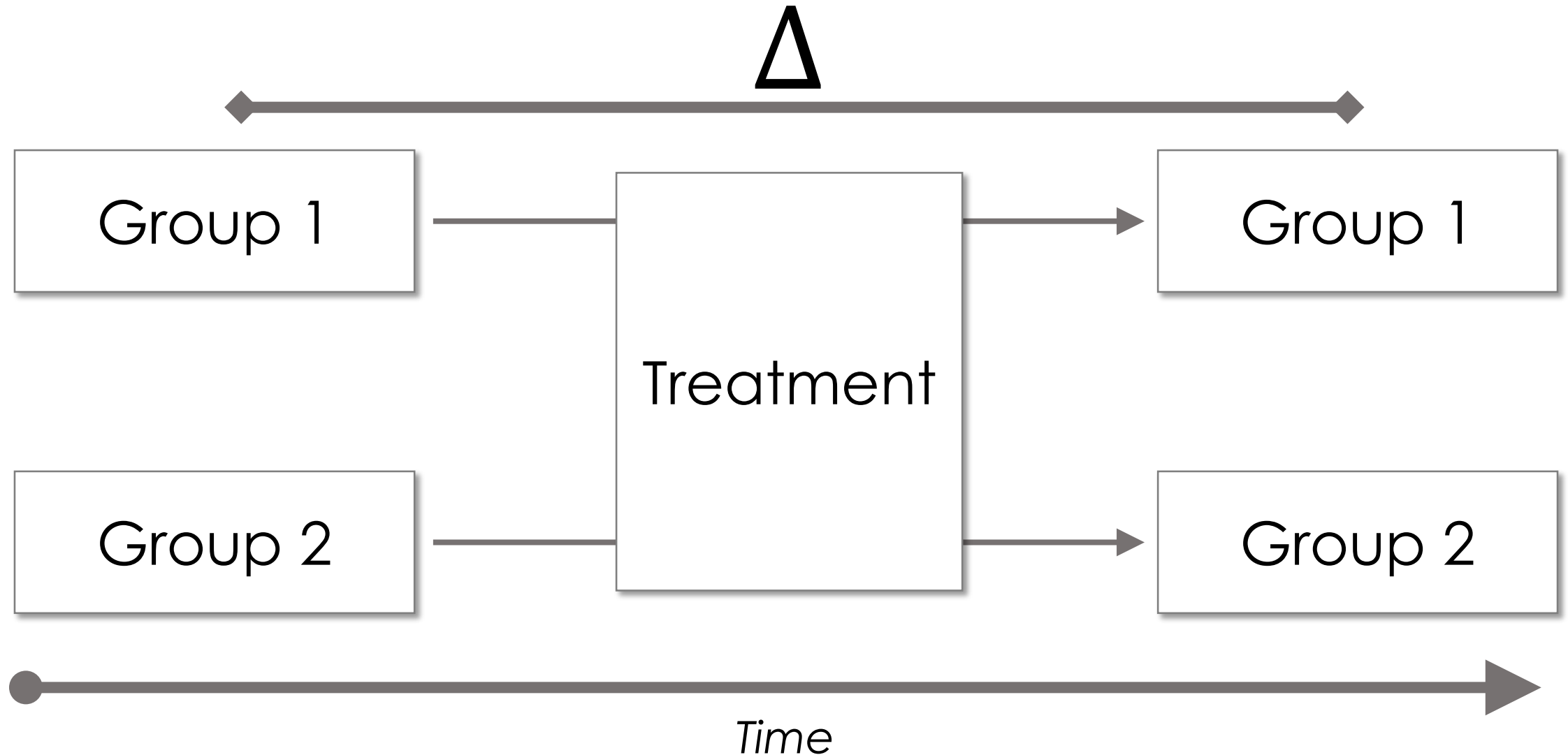
- No random assignment

- E.g., Gender, occupation, verbal ability (VSAT)

Example questions

- Do people with high verbal ability learn new languages faster?

# Quasi-experimental Design



# True Experimental Design

Studies in which variables are manipulated and outcomes measured, the hypothesis is a cause and effect statement

Y will occur, when X is manipulated

## **Examples:**

Students will remember more items from a word list if they learn the list in quiet, rather than in the presence of intense music

Reading speed (words/minute) will change when font size is manipulated, such that reading speed will increase as font size is increased from 4pt to 20pt, but reading speed will decrease as font size is increased above 20pt

# Number of Variables

## Single Variable

- Only one independent variable

- Cannot look at interactions

## Multiple Variables

- Two or more independent variables

- If use **factorial design**, can look at interactions

- Will require more participants (*between design*) or time (*within design*)

# Within vs Between Designs

Comparisons between conditions **within participants**

- Demands time

- Statistical power with smaller number of participants

- Potential for *transfer effects*

Comparisons between conditions **across participants**

- Demands larger sample

- Avoids transfer effects

- Easier to avoid bias

Can also have **mixed design**

- Complicates statistical analysis

# Factorial Design

Suppose we are interested in the effect of both how gaming and computer use affect perception of robots

Ideally: look at all 4 populations in one experiment

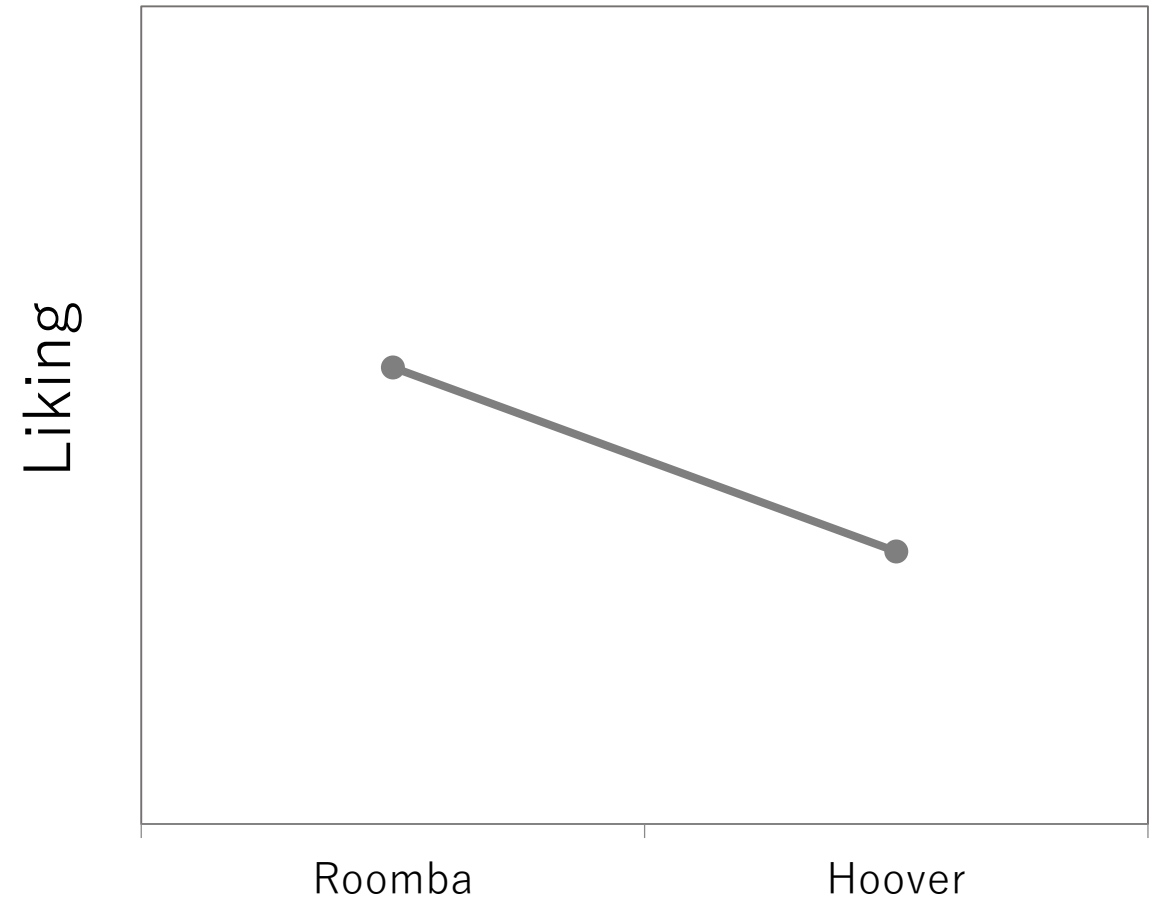
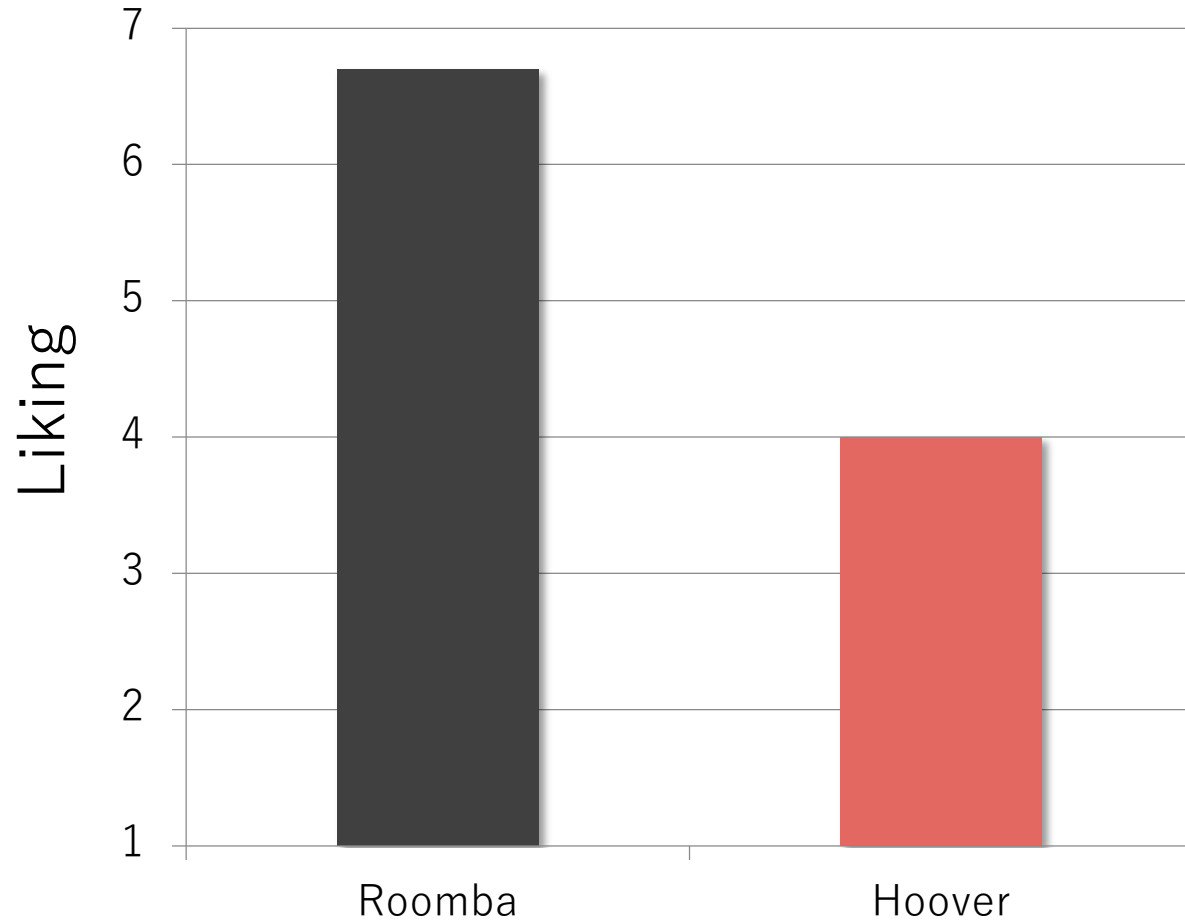
		<b>Factor 1: Computer use</b>	
		<i>Level 1:</i> High computer use	<i>Level 2:</i> Low computer use
<b>Factor 2:</b> Gaming	<i>Level 1:</i> High gaming	Population 1	Population 2
	<i>Level 2:</i> Low gaming	Population 3	Population 4

Why?

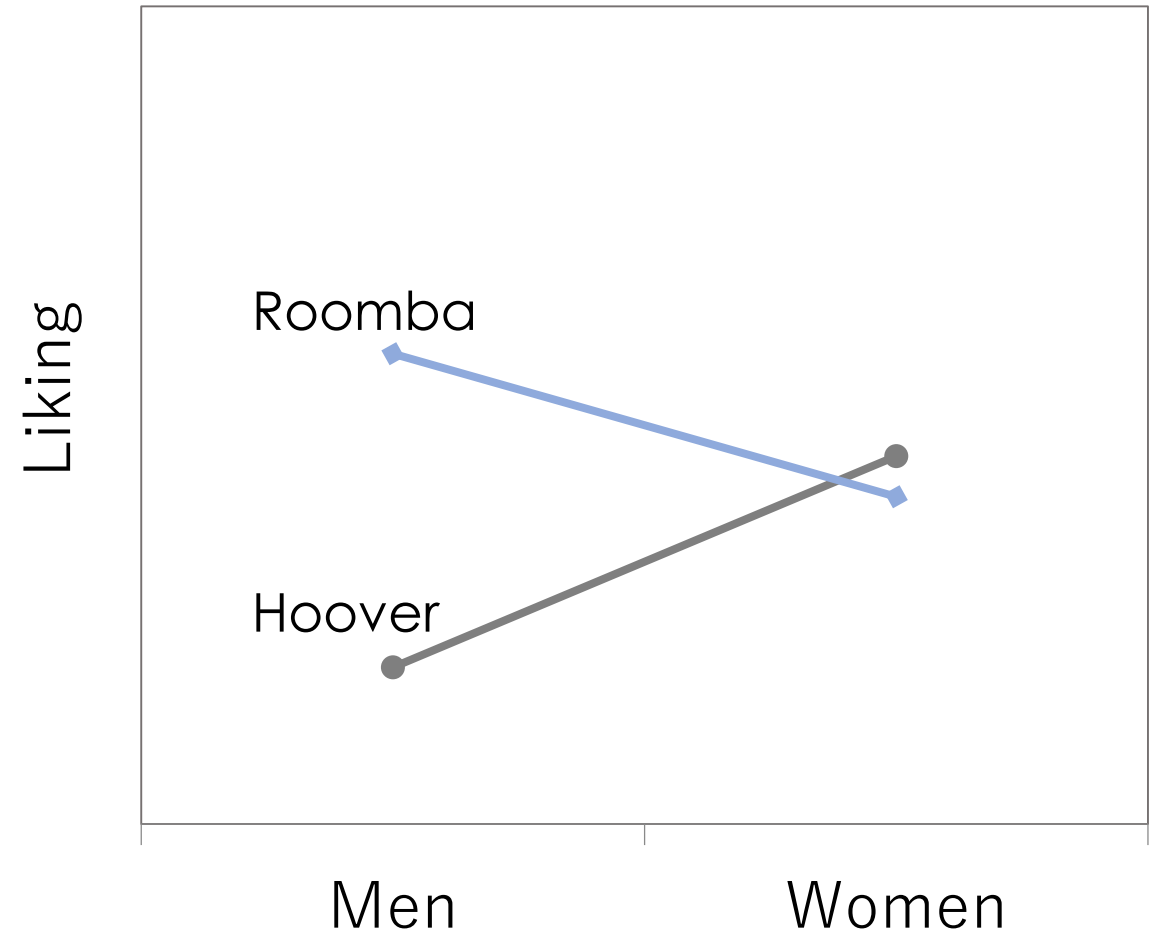
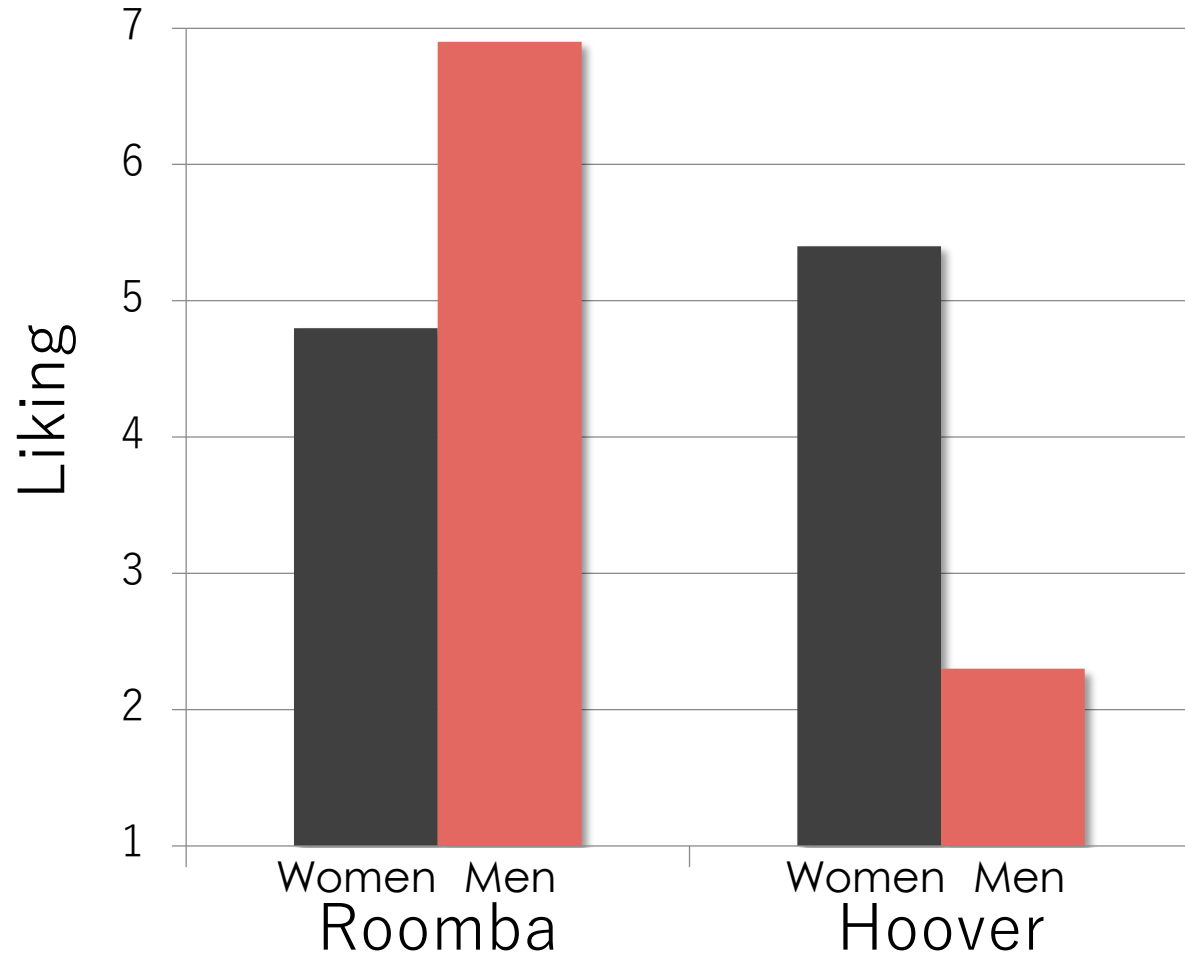
We can learn more

More efficient than doing numerous single-factor experiments

# Main Effects



# Interaction Effects





# Random Sampling

## Random Sampling

- Choosing participants randomly from the entire population

- Allows generalization to the population

- Randomization allows later use of probability theory and gives a solid foundation for statistical analysis

- Avoid bias

  - The first six participants who come to the lab might be highly motivated

## Random Assignment

- Random does not mean haphazard

- One needs to explicitly randomize

  - Random assignment at arrival, counterbalancing, matching

# Counterbalancing

Particularly important to **within** designs

Important because of **transfer effects**

Taking part in earlier trials changes performance in later trials

Examples: learning, fatigue, etc.

Makes within-subjects designs difficult to interpret

# Counterbalancing

In within-subjects counterbalancing:

Possible **linear transfer effects**

Is the transfer from the 1<sup>st</sup> position to the 2<sup>nd</sup> position the same as the transfer from the 2<sup>nd</sup> to 3<sup>rd</sup> position?

E.g., sometimes the most important learning happens in 1<sup>st</sup> trials

Always worry about asymmetrical transfer

Does A influence B more than B influences A?

# Counterbalancing

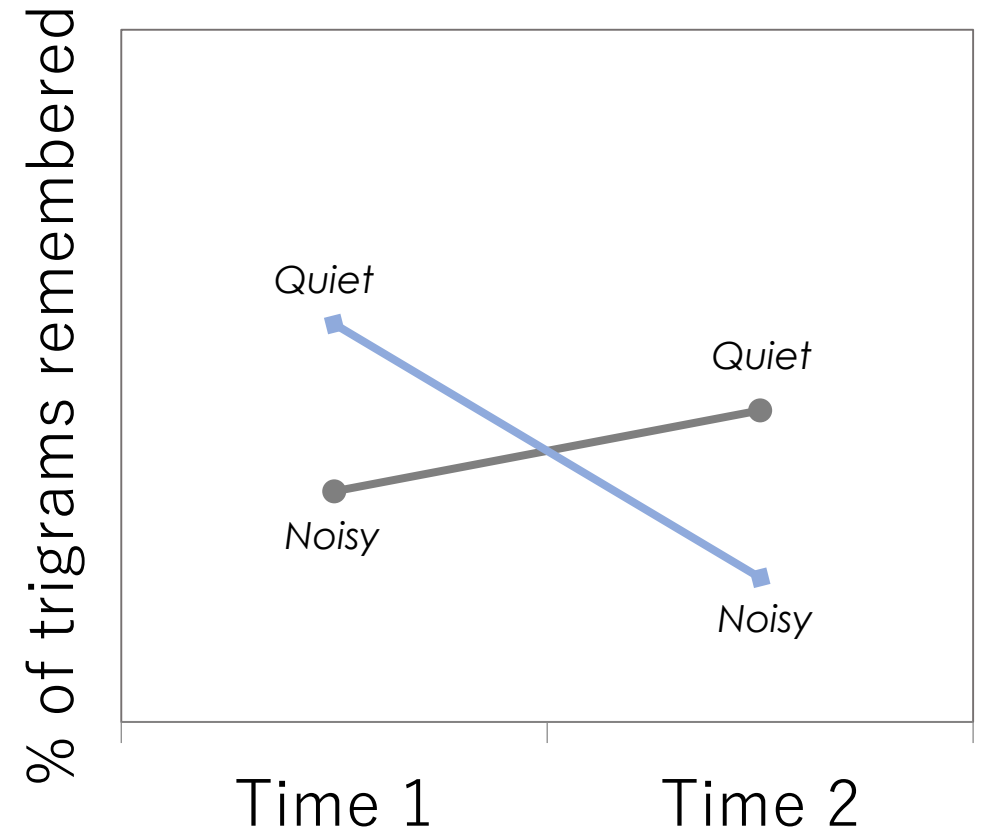
## Asymmetrical transfer

Effect of noise depends on order

People stick with the strategy they pick first

Or mix strategies

Use a between-participants design



# Counterbalancing

## Full counterbalancing

Test all possible orderings:

Group 1:	A	B	C
Group 2:	A	C	B
Group 3:	B	A	C
Group 4:	B	C	A
Group 5:	C	A	B
Group 6:	C	B	A

May be infeasible

# Counterbalancing

## Partial counterbalancing

### Latin Square

Every condition appears in every position equally:

Joe:	A	B	C
Mary:	B	C	A
John:	C	A	B

Transfer effects can still be a problem

Order is preserved (e.g., A always comes before B)

Solution: use a balanced Latin square

# Counterbalancing

## Balanced Latin Square

Depends on even or odd number of conditions

Even:

1, 2, n, 3, n-1, 4, n-2, ... where n = # of conditions

Subsequent rows: add one to the previous, returning to 1 after n rows

Example: 6 conditions:

Subject Group	1 <sup>st</sup> Condition	2 <sup>nd</sup>	3 <sup>rd</sup>	4 <sup>th</sup>	5 <sup>th</sup>	6 <sup>th</sup>
A	1	2	6	3	5	4
B	2	3	1	4	6	5
C	3	4	2	5	1	6
...						

Every condition follows every other condition once

# Counterbalancing

## Balanced Latin Square

Depends on even or odd number of conditions

Odd:

Create two Latin squares

First square: use same method (1, 2, n, 3, n-1, 4, n-2, ... where n = # of conditions)

Second square: mirror image of first square

Example: 5 conditions:

1	2	5	3	4		4	3	5	2	1
2	3	1	4	5		5	4	1	3	2
3	4	2	5	1		1	5	2	4	3
4	5	3	1	2		2	1	3	5	4
5	1	4	2	3		3	2	4	1	5

Every condition follows every other condition twice



# Matching

Try to reduce between-group differences

E.g., rank hearing as Good, Fair, Poor

Unmatched, could get:

Noisy: Poor1, Poor2, Fair1

Quiet: Good1, Good2, Fair2

Matched, get:

Noisy: Poor1, Fair2, Good1

Quiet: Poor2, Fair1, Good2

# Stratification

Supposed that some social measurements will be made in the morning and some in the afternoon

If you anticipate a difference between morning and afternoon measurements:

Ensure that within each period, there are equal numbers of subjects in each treatment group

Take account of the difference between periods in your analysis (e.g., as covariate)

This is sometimes called “blocking”

# Very Bad Design

Week One					Week Two				
M	Tu	W	Th	F	M	Tu	W	Th	F
C	C	C	C	C	T	T	T	T	T
C	C	C	C	C	T	T	T	T	T
C	C	C	C	C	T	T	T	T	T
C	C	C	C	C	T	T	T	T	T

T = treated, C = control, pink = female, blue = male

# Randomized

Week One					Week Two				
M	Tu	W	Th	F	M	Tu	W	Th	F
T	T	T	T	T	C	T	T	C	T
C	T	T	T	T	C	C	C	T	C
C	C	C	T	T	C	C	T	C	C
T	C	C	C	C	C	T	C	T	T

T = treated, C = control, pink = female, blue = male

# Stratified

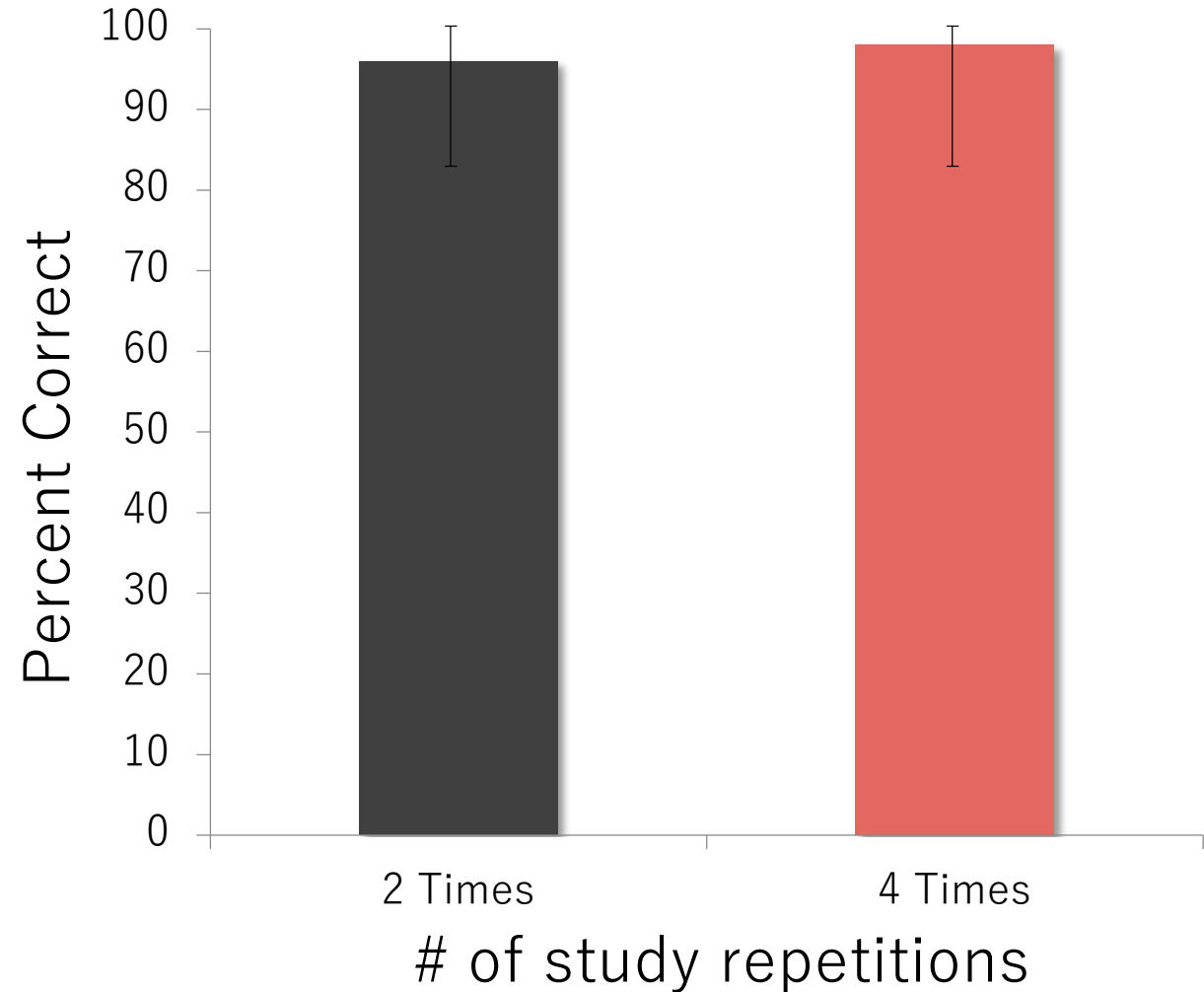
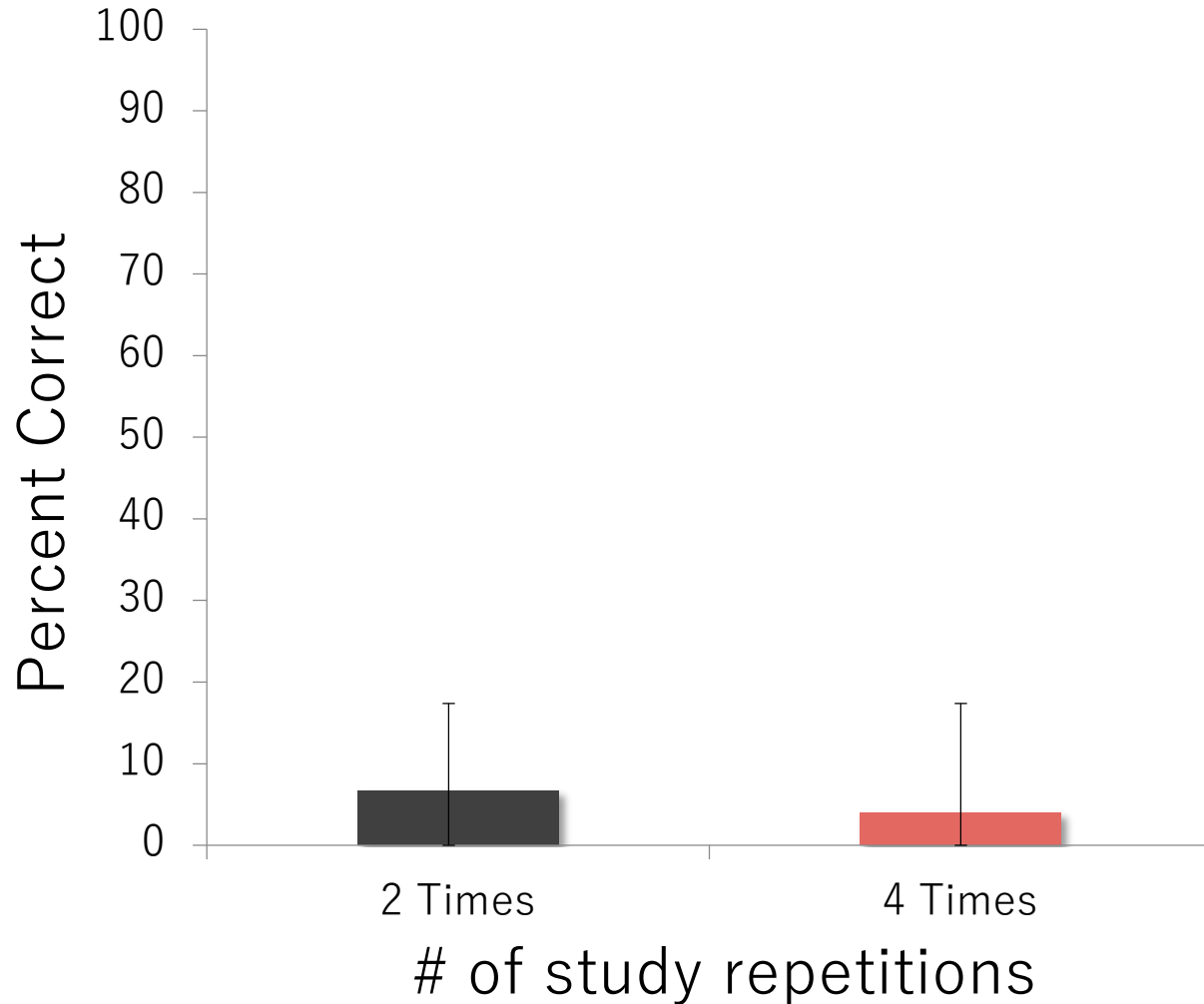
Week One					Week Two				
M	Tu	W	Th	F	M	Tu	W	Th	F
C	T	T	C	T	C	C	T	C	T
T	T	C	C	C	T	T	T	C	C
C	C	T	T	C	C	T	C	T	C
T	C	C	T	T	T	C	C	T	T

T = treated, C = control, pink = female, blue = male

All of these techniques  
make trade-offs between  
validity and practicality

Other considerations

# Floor and Ceiling Effects





# Blinding

Measurements made by people can be influenced by unconscious bias

Ideally, dissections and measurements should be made without knowledge of the treatment applied

Single vs. double-blind designs

Internal controls

It can be useful to use the subjects themselves as their own controls (e.g., measuring the response after vs before treatment)

Increased precision

# Representativeness

Are the subjects you are studying really representative of the population you want to study?

Ideally, your study material is a random sample from the population of interest (true vs quasi experiment)

# Summary:

## Characteristics of Good Experiments

Unbiased

Randomization

Blinding

Wide range of applicability

Deliberate variation

Factorial designs

High precision

Uniform material

Replication

Blocking

Able to estimate uncertainty

Replication

Randomness

Good methodological fit

Simple

Protect against mistakes

Questions?

# Next

## **Reading #5**

Posted on Moodle

Need Pro/Con presenters for **Wednesday 2/20**

## **Assignment 2**

Due **Monday 3/4/19**

See guidelines on Moodle

## **Project**

Interim Presentation/Writeup Due **Monday 3/11**

See guidelines on Moodle

## **Guest Lecture next class (Monday 2/18)**



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# THANKS!

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