Within-Participants Designs

PSYC204: Experimental Research Methods

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Week 3

Learning Objectives

- Introduction to within-participants designs:
  - characteristics
  - threats to internal validity: environment & time
  - order effects as a confounding variable
- Managing time-related threats and order effects:
  - controlling time
  - switch to between-participants design
  - counterbalancing
- Comparing within- and between-participants designs:
  - advantages of within-participants designs
  - disadvantages of within-participants designs
  - choosing between designs

Within-Participants Designs

Within-Participants Designs

- There are two basic research designs used to obtain groups of scores that are compared in an experiment:
    1. In a **between-participants design**, each group of scores is obtained from a different group of participants
    2. In a **within-participants design**, the different groups of scores are obtained from the same group of participants

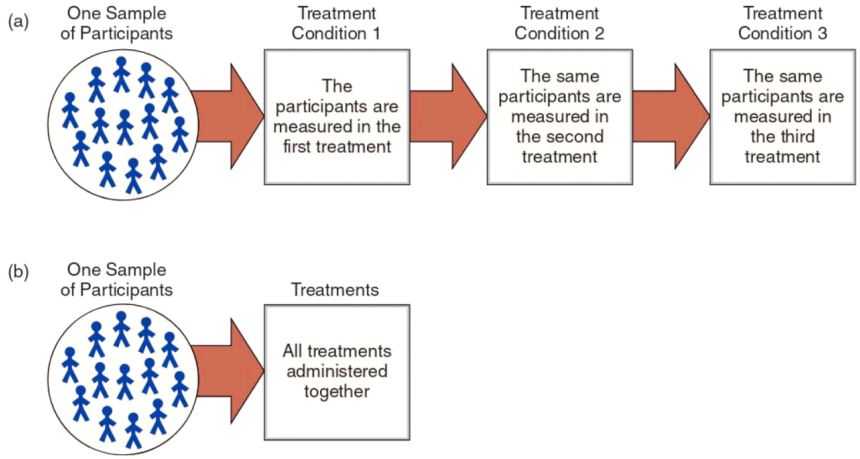
Today:

- Focus on within-participants designs

Within-Participants Designs

- A **within-participants design** uses a single group of participants in each treatment being compared:
  - the same group of individuals participates in every level of the independent variable
  - the ultimate in “equivalent groups”
- Two ways of administering such a design:
  1. different treatment conditions can be administered sequentially, with participants receiving one treatment condition followed by the next
  2. different treatment conditions can be administered all together (in random order)

Two Types of Within-Participants Designs



Threats to Internal Validity of Within-Participants Experiments

- There are two major sources of potential confounding for within-participants designs:
    1. Confounding from *environmental variables*
    2. Confounding from *time-related variables*

Confounding from Environmental Variables

- These are characteristics of the environment that may change systematically from one treatment to the next
- For example, one treatment may always be evaluated in the morning, another in the afternoon
- Any such variable may cause differences in scores from one treatment to another
- This provides a confounding explanation for differences between treatments

Confounding from Time-Related Variables

- During time between each measurement, participants can be influenced by factors other than the treatments being studied
- If these other factors affect participants scores, the internal validity of the study is threatened
- There are five time-related threats to internal validity:
    1. History
    2. Maturation
    3. Instrumentation
    4. Regression toward the mean
    5. Order effects (practice, fatigue, and carry-over effects)

Confounding from Time-Related Variables: History

- **History** refers to environmental events that change over time and may affect scores in one treatment differently than another
- *Validity threat because:* differences between treatment conditions may reflect history instead of the treatments themselves
- For example, a researcher examines attitudes to risk and uncertainty:
  - initial treatment conditions are administered before the COVID-19 crisis, whereas the final treatment is administered during the crisis
  - heightened risk attitudes in the final treatment condition may reflect a treatment effect or history

Confounding from Time-Related Variables: Maturation

- **Maturation** refers to naturally occurring time-related changes in participants occurring during a research study that influence their scores
- *Validity threat because:* changes in performance from one treatment to the next may reflect an effect of the treatment or maturation
- For example, a researcher examines vocabulary size in 3-year olds before and after a vocabulary training intervention (with a 4-week gap apart):
  - a child's vocabulary grows at an incredible rate (multiple words per day) all on its own
  - increased vocabulary size after training could therefore reflect the training or maturation

Confounding from Time-Related Variables: Instrumentation

- **Instrumentation** refers to changes in a measurement instrument that occur over time
- *Validity threat because:* differences between treatments could reflect changes in the measuring instrument instead of the treatment
- For example, a researcher observes a group of children and records instances of aggressive behaviour:
  - the subjective interpretation of the observer may change over time—the same behaviour may be judged differently at different times
  - changes in the participants scores may be caused not by the treatment but by the measurement instrument

Confounding from Time-Related Variables: Regression to the Mean

- **Regression to the mean** is when extreme scores (high or low) on one measurement tend to be less extreme on a second measurement
- *Validity threat because:* changes in participants scores across treatment conditions can be caused by regression instead of the treatments
- For example, a researcher examines the effects of a working memory training intervention on participants with scores in the 25th percentile of a working memory task:
  - after the working memory training, participants are measured on the original working memory task again
  - if performance improves after training, it could reflect the training, regression to the mean, or both

Confounding from Time-Related Variables: Order Effects

- Whenever individuals are tested in a series of treatment conditions, participation in one treatment may affect participants' scores in subsequent treatments
- For example, becoming fatigued in one treatment may lead to poorer performance in a subsequent treatment
- The term **order effect** refers to when any possible change in performance is caused by participation in a previous treatment
- This is a threat to internal validity because it provides an alternative explanation for the results
- There are various different types of order effects

Confounding from Time-Related Variables: Order Effects

1. **Fatigue effects:** Progressive decline in performance as a participant works through a series of treatment conditions
2. **Practice effects:** Progressive improvement in performance as a participant gains experience through a series of treatment conditions
3. **Carry over effects:** Occur when one treatment condition produces a change in the participants that affects their scores in subsequent treatment conditions
4. **Contrast effect:** A type of carryover effect in which the subjective perception of a treatment condition is influenced by its contrast with a previous treatment

Separating Time-Related Factors and Order Effects

- Time-related threats to internal validity are typically grouped together
- However, they are sometimes grouped into:
    1. those related exclusively to *time*, and
    2. those related to previous *experience* in the experiment
- Threats from history, maturation, instrumentation, and regression are related exclusively to *time*
- Order effects are directly related to *experience* obtained participating in previous treatment conditions

Order effect as a Confounding Variable

Table 1: Hypothetical data showing how order effects can distort experimental results

Original Scores (No Order Effect)		Modified Scores (5-Point Order Effect)	
Treatment I	Treatment II	Treatment I	Treatment II
20	21	20	26 (21 + 5)
23	23	23	28 (23 + 5)
25	23	25	28 (23 + 5)
19	20	19	25 (20 + 5)
26	25	26	30 (25 + 5)
17	16	17	21 (16 + 5)
14	14	14	19 (14 + 5)
16	18	16	23 (18 + 5)
Mean = 20	Mean = 20	Mean = 20	Mean = 25

Order effect as a Confounding Variable

- This example demonstrates how order effects, like any confounding variable, can distort results
- In this example, the order effect creates what at first blush looks like a treatment effect but it is in fact an order effect
- In other situations, order effects can diminish or exaggerate a real effect
- Either way, order effects pose a significant threat to the internal validity of a within-participants experiment

Managing Order Effects

Dealing With Time-Related Threats and Order Effects

- Within-participants designs can control environmental threats to internal validity using the same techniques available for between-participants designs
- Environmental factors (e.g., room, experimenter, time of day) can be controlled by:
    1. Randomisation
    2. Holding them constant
    3. Matching across treatment conditions

- Time-related and order effects require new control strategies

Dealing With Time-Related Threats and Order Effects

- There are three strategies for dealing with time-related threats and order effects:
    1. Controlling Time
    2. Switch to a Between-Participants Design
    3. Counterbalancing: Matching Treatments with Respect to Time

Controlling Time

- The longer it takes to complete a study, the more likely it will be affected by time-related threats such as history or maturation:
  - a 45 minute study is highly unlikely to be vulnerable to such effects
  - a study conducted over a period of weeks is very vulnerable to such effects
- Controlling the time from one treatment to the next is one way to exercise control over time-related threats ✓
- However, shortening the time between treatments can also increase the likelihood of order effects ✗

Switch to a Between-Participants Design

- In some situations, order effects are so strong that a within-participants design is not suitable
- This is especially true if carryover effects are expected between treatments
- For example, a within-participants design is a poor choice for a study comparing two methods of teaching reading to children:
  - after children have been taught with method I they are permanently changed
  - you cannot erase what they have learned and teach them again with method II
- Switching to a between-participants design is a good strategy when significant order effects are expected ✓

Counterbalancing: Matching Treatments with Respect to Time

- **Counterbalancing** involves changing the order in which treatment conditions are administered across participants so treatment conditions are **matched** with respect to time
- Every possible order of treatments is used, with an equal number of individuals participating in each sequence
- For example, in the simplest case with two treatments:
  - 50% of participants would complete treatment I followed by treatment II
  - 50% of participants would complete treatment II followed by treatment I
- Disrupts any systematic relationship between time and order of treatment conditions

Counterbalancing and Order Effects

Table 2: Hypothetical Data Showing How Counterbalancing Distributes Order Effects Evenly Between Treatments

Original Scores (No Order Effect)		Modified Scores (5-Point Order Effect)		
Treatment I	Treatment II	Treatment I	Order	Treatment II
20	27	20	⟶	32 (27 + 5)
23	29	23	⟶	34 (29 + 5)
25	29	25	⟶	34 (29 + 5)
19	26	19	⟶	31 (26 + 5)
26	31	(26 + 5) 31	⟵	31
17	22	(17 + 5) 22	⟵	22
14	20	(14 + 5) 19	⟵	20
16	24	(16 + 5) 21	⟵	24
Mean = 20	Mean = 26	Mean = 22.5		Mean = 28.5

Counterbalancing and Order Effects

- Counterbalancing prevents any order effects from accumulating in one particular treatment condition ✓
- Instead, the order effects are spread *evenly* across the different conditions
- Counterbalancing does not eliminate order effects ✗:
  - they are still present in the data!
- Moreover, order effects are hidden in the data:
  - we cannot observe them and see how large they are (contrary to our omniscient example)

Limitations of Counterbalancing

- There are three limitations of counterbalancing:
    1. Counterbalancing and Variance
    2. Asymmetrical Order Effects
    3. Number of Treatments

Limitations of Counterbalancing: Counterbalancing and Variance

- Counterbalancing adds order effects to some, but not all, individuals within each treatment
- For example, in Table 2 some of the individuals in treatment I receive an extra 5 points and some do not
- Consequently, the differences between scores are increased within each treatment, which adds to the *variance within treatments*
- Recall from Lecture 2 that large variance within treatments can obscure treatment effects
- When order effects are relatively large, counterbalancing can reduce the likelihood of finding reliable differences between treatments

Limitations of Counterbalancing: Asymmetrical Order Effects

- We typically assume order effects are *symmetrical*
- However, it is not unreasonable to expect they may sometimes be *asymmetrical*
  - one treatment might provide more of an opportunity for practice
  - one treatment might be more demanding and create more fatigue
- If order effects are asymmetrical, counterbalancing will not balance the order effects

Limitations of Counterbalancing: Number of Treatments

- **Complete counterbalancing** requires every possible ordering of treatment conditions to be used
- With two treatment conditions, complete counterbalancing is easy
- As the number of treatments increases, the number of different sequences rises sharply
- For a given number of treatment conditions n, the number of different sequences $n!$ (n factorial) is given by:

$$n! = n(n-1)(n-2)(n-3)... \quad (1)$$

Limitations of Counterbalancing: Number of Treatments

- 3 treatments: $3 \times 2 \times 1 = 6$ sequences
- 4 treatments: $4 \times 3 \times 2 \times 1 = 24$ sequences
- 5 treatments: $5 \times 4 \times 3 \times 2 \times 1 = 120$ sequences
- 6 treatments: $6 \times 5 \times 4 \times 3 \times 2 \times 1 = 720$ sequences

Limitations of Counterbalancing: Number of Treatments

Note that the sequence ABCD indicates that treatment A is first, B second, C is third, and D is fourth

ABCD	BACD	CABD	DABC
ABDC	BADC	CADB	DACB
ACBD	BCAD	CBAD	DBAC
ACDB	BCDA	CBDA	DBCA
ADBC	BDAC	CDAB	DCAB
ADCB	BDCA	CDBA	DCBA

Limitations of Counterbalancing: Number of Treatments

- The solution to this problem is **partial counterbalancing**
- We use enough orderings to ensure each treatment condition features in each position with the same frequency
- Since we are not using every possible sequence of treatment conditions, how do we decide which sequences to use?
- There are two solutions:
    1. **Latin square**
    2. **Digram-balanced Latin square**

How to construct a Latin Square

A B C D

How to construct a Latin Square

A	B	C	D
D	A	B	C

How to construct a Latin Square

A	B	C	D
D	A	B	C
C	D	A	B

How to construct a Latin Square

A	B	C	D
D	A	B	C
C	D	A	B
B	C	D	A

How to construct a Latin Square

A	B	C	D
D	A	B	C
C	D	A	B
B	C	D	A

- Each row in the square provides a sequence of treatment conditions for one group of participants
- We use randomisation to allocate participants to the different sequences

A common but poor example of partial counterbalancing:

- Fails to balance every possible sequence of treatment conditions
- The solution is to use a digram-balanced Latin square ...

How to construct a Digram-Balanced Latin Square

A	B	C	D
D	C	B	A

How to construct a Digram-Balanced Latin Square

A B C D

D C B A

A D B C C B D A

How to construct a Digram-Balanced Latin Square

A B C D

D C B A

A D B C C B D A

B

C

D

How to construct a Digram-Balanced Latin Square

A		B		C		D	
	D		C		B		A

A	D	B	C	C	B	D	A
B	A						
C	B						
D	C						

How to construct a Digram-Balanced Latin Square

A B C D

D C B A

A D B C C B D A

B A C

C B D

D C A

How to construct a Digram-Balanced Latin Square

A B C D

D C B A

A D B C C B D A
B A C D
C B D A
D C A B

How to construct a Digram-Balanced Latin Square

A		B		C		D	
	D		C		B		A

A	D	B	C	C	B	D	A
B	A	C	D	D			
C	B	D	A	A			
D	C	A	B	B			

How to construct a Digram-Balanced Latin Square

A		B		C		D	
	D		C		B		A

A	D	B	C	C	B	D	A
B	A	C	D	D	C		
C	B	D	A	A	D		
D	C	A	B	B	A		

How to construct a Digram-Balanced Latin Square

A		B		C		D	
	D		C		B		A

A	D	B	C	C	B	D	A
B	A	C	D	D	C	A	
C	B	D	A	A	D	B	
D	C	A	B	B	A	C	

How to construct a Digram-Balanced Latin Square

A		B		C		D	
	D		C		B		A

A	D	B	C	C	B	D	A
B	A	C	D	D	C	A	B
C	B	D	A	A	D	B	C
D	C	A	B	B	A	C	D

How to construct a Digram-Balanced Latin Square

A	D	B	C	C	B	D	A
B	A	C	D	D	C	A	B
C	B	D	A	A	D	B	C
D	C	A	B	B	A	C	D

How to construct a Digram-Balanced Latin Square

Square I				Square II			
A	D	B	C	C	B	D	A
B	A	C	D	D	C	A	B
C	B	D	A	A	D	B	C
D	C	A	B	B	A	C	D

How to construct a Digram-Balanced Latin Square

Square I				Square II			
A	D	B	C	C	B	D	A
B	A	C	D	D	C	A	B
C	B	D	A	A	D	B	C
D	C	A	B	B	A	C	D

How to construct a Digram-Balanced Latin Square

Square I

A	D	B	C
B	A	C	D
C	B	D	A
D	C	A	B

How to construct a Digram-Balanced Latin Square

Square I

A	D	B	C
B	A	C	D
C	B	D	A
D	C	A	B

How to construct a Digram-Balanced Latin Square

Square I

A	D	B	C
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D	C	A	B

How to construct a Digram-Balanced Latin Square

Square I

A	D	B	C
B	A	C	D
C	B	D	A
D	C	A	B

How to construct a Digram-Balanced Latin Square

Square I

A	D	B	C
B	A	C	D
C	B	D	A
D	C	A	B

How to construct a Digram-Balanced Latin Square

Square I

A	D	B	C
B	A	C	D
C	B	D	A
D	C	A	B

How to construct a Digram-Balanced Latin Square

Square I

A	D	B	C
B	A	C	D
C	B	D	A
D	C	A	B

How to construct a Digram-Balanced Latin Square

Square I

A	D	B	C
B	A	C	D
C	B	D	A
D	C	A	B

- The digram-balanced latin square is the gold standard for partial counterbalancing
- Controls for:
  - first-order dependencies: treatment–position frequency
  - second-order dependencies: treatment–treatment frequency

When the Number of Treatment Conditions is Odd

- In the preceding example, we had an even number of treatment conditions
- We obtained two different squares and either one in isolation could be used to control for order effects
- If you have an odd number of treatment conditions, you must use both squares
- Specifically, each participant must complete the experiment twice—once with an ordering from Square 1, and again with an ordering from Square 2

Comparing Designs

Advantages of Within-Participants Designs

- Requires relatively few participants
- As it requires only one group it is helpful in situations where participants are hard to find
- It eliminates the problem of *individual differences* associated with between-participant designs:
    1. Confounding from individual differences
    2. High variance caused by individual differences within treatments
- First, there are no individual differences between groups, as there is only one group
- Second, variance caused by individual differences can be measured and removed

Comparing Between- and Within-Participants Experiments

Table 3: Hypothetical data showing results from a between- and within-participants experiment

(A) Between-Participants Experiment

Treatment I		Treatment II		Treatment III	
John	20	Sue	25	Beth	30
Mary	31	Tom	36	Bob	38
Bill	51	Dave	55	Don	59
Kate	62	Ann	64	Zoe	69
Mean =	41	Mean =	45	Mean =	49

(B) Within-Participants Experiment

Treatment I		Treatment II		Treatment III	
John	20	John	25	John	30
Mary	31	Mary	36	Mary	38
Bill	51	Bill	55	Bill	59
Kate	62	Kate	64	Kate	69
Mean =	41	Mean =	45	Mean =	49

Advantages of Within-Participants Designs

- Table 3 shows the following measurements are possible in within-participants designs
- We can measure differences between treatments without involving any individual differences:
  - since the same participants are in every treatment condition, the treatment effects and the individual differences are not linked
- We can measure differences between individuals:
  - individual differences can be measured and removed from the rest of the variance in the data
  - this can greatly reduce the negative effects of large variance

Removing Individual Differences

- How do we remove the individual differences in Table 3B?
- First, calculate the mean scores for each participant, collapsed across treatment conditions
- Next, subtract these individual scores from the mean of the scores
- Finally, add these difference scores to the individual participant scores in each of the treatments
- The individual differences have now been removed, but notice the treatment means in Table 4 are still the same as in Table 3B

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Removing Individual Differences

Table 4: Removing Individual Differences from Within-Participants Data

Treatment I		Treatment II		Treatment III		Mean
John	20	John	25	John	30	25
Mary	31	Mary	36	Mary	38	35
Bill	51	Bill	55	Bill	59	55
Kate	62	Kate	64	Kate	69	65
Mean =	41	Mean =	45	Mean =	49	Mean = 45

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Treatment I		Treatment II		Treatment III		Mean	Diff. Scores
John	20	John	25	John	30	25	
Mary	31	Mary	36	Mary	38	35	
Bill	51	Bill	55	Bill	59	55	
Kate	62	Kate	64	Kate	69	65	
Mean =	41	Mean =	45	Mean =	49	Mean = 45	

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Mean =	41	Mean =	45	Mean =	49	Mean = 45	

Removing Individual Differences

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Kate	42	Kate	64	Kate	69	65	−20
Mean =	41	Mean =	45	Mean =	49	Mean = 45	

Removing Individual Differences

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John	40	John	45	John	30	25	20
Mary	41	Mary	46	Mary	38	35	10
Bill	41	Bill	45	Bill	59	55	−10
Kate	42	Kate	44	Kate	69	65	−20
Mean =	41	Mean =	45	Mean =	49	Mean = 45	

Removing Individual Differences

Table 4: Removing Individual Differences from Within-Participants Data

Treatment I		Treatment II		Treatment III		Mean	Diff. Scores
John	40	John	45	John	50	25	20
Mary	41	Mary	46	Mary	48	35	10
Bill	41	Bill	45	Bill	49	55	−10
Kate	42	Kate	44	Kate	49	65	−20
Mean =	41	Mean =	45	Mean =	49	Mean = 45	

Removing Individual Differences

- How do we remove the individual differences in Table 3B?
- First, calculate the mean scores for each participant, collapsed across treatment conditions
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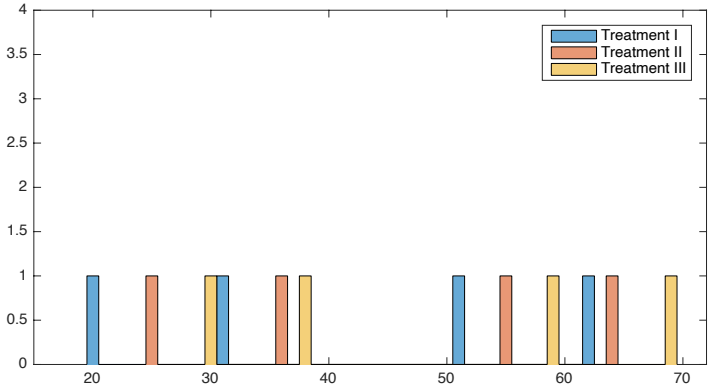
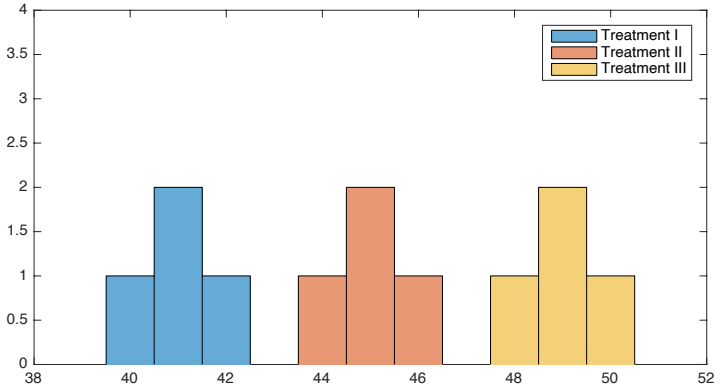
Data Including Individual Differences (Table 3B)



Data Excluding Individual Differences (Table 4)



Advantages of Within-Participants Designs

- By measuring and removing individual differences, the within-participants design reduces variance ✓
  - reveals treatment effects that may not be apparent in a between-participants design
- In statistical terms, a within-participants design is generally more powerful than a between-participants design ✓:
  - it is more likely to detect a treatment effect
- In our example, we removed the individual differences by equalising all the participants
- Typically, this process is accomplished by statistical analysis
  - however, the result is the same—variance caused by individual differences is removed

Disadvantages of Within-Participants Designs

- Confounding from time-related threats and order effects are the main disadvantage of within-participants designs ✗:
  - time-related threats can be controlled to some extent by reducing time between treatments
  - order effects can be controlled through counterbalancing but this does not guard against asymmetrical order effects
- Another problem is **participant attrition** ✗:
  - there is a chance participants may drop out of the study between treatments especially with long time delays
  - if attrition is expected, begin the research with more participants than are needed

Choosing Within- or Between-Participants Design

- There are at least three factors relevant to choosing between a within- or between-participant design:
    1. Individual differences
    2. Time-related factors and order effects
    3. Fewer participants

Choosing Within- or Between-Participants Design: Individual Differences

- The threat of confounding from individual differences is a serious disadvantage of a between-participants design
- These problems are eliminated in a within-participants design
- A within-participants design also reduces variance, increasing the likelihood of detecting a treatment effect
- If you anticipate large individual differences, it is better to use a within-participants design

Choosing Within- or Between-Participants Design: Time-Related Factors

- There is often potential for time-related factors to distort results of a within-participants design
- However, this problem is eliminated in a between-participants design
- If you expect one or more treatment conditions to have a large and long-lasting effect on future conditions, use a between-participants design

Choosing Within- or Between-Participants Design: Fewer Participants

- A strength of a within-participants design is that it requires fewer participants
- If you have many treatments and the risk of order effects is relatively low, it is more economical to use a within-participants design
- Whenever it is difficult to find or recruit participants (e.g., from specialist populations), a within-participants design is a better choice

Key Terms and Definitions

- **Within-participants design:** a within-participants design, or **repeated-measures design**, compares two or more different treatment conditions (or compares a treatment and a control) by measuring the same group of individuals in all of the treatments being compared.
- **History:** when a group of individuals is being tested in a series of treatment conditions, any outside event(s) that influence the participants' scores in one treatment differently than in another treatment is called a history effect. History is a threat to internal validity because any differences that are observed between treatment conditions may be caused by history instead of treatments.
- **Maturation:** when a group of individuals is being tested in a series of treatment conditions and physiological or psychological changes that occur in participants influences their scores. Maturation is a threat to internal validity because observed differences between treatment conditions may be caused by maturation instead of the treatments.

Key Terms and Definitions

- **Instrumentation:** refers to changes in the measuring instrument that occur during a research study in which participants are measured in a series of treatment conditions. Instrumentation is a threat to internal validity because any observed differences between treatment conditions may be caused by changes in the measuring instrument instead of the treatments.
- **Regression toward the mean:** a mathematical phenomenon in which extreme scores (high or low) on one measurement tend to be less extreme on a second measurement. Regression is a threat to internal validity because changes that occur in participants' scores from one treatment to the next can be caused by regression instead of the treatments.
- **Order effects:** occur when the experience of being tested in one treatment condition (participating and being measured) has an influence on the participants' scores in a later treatment condition(s). Order effects threaten internal validity because any observed differences between treatment conditions may be caused by order effects rather than the treatments.

Key Terms and Definitions

- **Carry-over effects:** occurs when one treatment condition produces a change in the participant that affects their scores in subsequent treatment conditions.
- **Counterbalancing:** changing the order in which treatment conditions are administered from one participant to another so that the treatment conditions are matched with respect to time. In **complete counterbalancing**, we use every possible order of treatments with an equal number of individuals participating in each sequence. The purpose of counterbalancing is to eliminate the potential for confounding by disrupting any systematic relationship between the order of treatments and time-related factors.
- **Partial counterbalancing:** instead of using every possible order of treatments, as would be the case in complete counterbalancing, we instead use enough orderings to ensure that each treatment features in each position with the same frequency (first-order dependencies), and each treatment precedes and follows every other treatment with the same frequency (second-order dependencies). We do this by creating a **digram-balanced Latin square** which controls for first- and second-order dependencies.

In Next Weeks Lecture

- Factorial designs

That’s All Folks!