Causality and Validity

EDP 619 Week 12

Dr. Abhik Roy

Experiments and Causation

Cause

Cause

- Variable that produces an effect or result

Cause

- Variable that produces an effect or result
- Most causes are **inus**

> A cause is an insufficient (**i**)
>
> but non-redundant (**n**)
>
> part of an unnecessary (**u**) but
>
> sufficient condition (**s**)

Cause

- Variable that produces an effect or result
- Most causes are **inus**

> A cause is an insufficient (**i**)
>
> but non-redundant (**n**)
>
> part of an unnecessary (**u**) but
>
> sufficient condition (**s**)

Example

Cause

- Variable that produces an effect or result
- Most causes are **inus**

> A cause is an insufficient (**i**)
>
> but non-redundant (**n**)
>
> part of an unnecessary (**u**) but
>
> sufficient condition (**s**)

Example

- A given event may have many different causes

Cause

- Variable that produces an effect or result
- Most causes are **inus**

> A cause is an insufficient (**i**)
>
> but non-redundant (**n**)
>
> part of an unnecessary (**u**) but
>
> sufficient condition (**s**)

Example

- A given event may have many different causes
- Many factors are required for an effect to occur, but they can rarely be fully known and how they relate to one another

Effect

Effect

- **Probabilistic Outcomes**. difference between what did happen and what would have happened

Effect

- **Probabilistic Outcomes**. difference between what did happen and what would have happened
- **Counterfactual**. generally requires some necessary factor without which the outcome would not have occurred

Counterfactual

Counterfactual

Knowledge of what would have happened in the absence of a suspected causal agent

Counterfactual

Knowledge of what would have happened in the absence of a suspected causal agent

Physically impossible since we cannot simultaneously receive and not receive a treatment

Counterfactual

Knowledge of what would have happened in the absence of a suspected causal agent

Physically impossible since we cannot simultaneously receive and not receive a treatment

So the central task of all cause-probing research is to approximate the physically impossible counterfactual

Criteria to Establish Causality

Criteria to Establish Causality

Survey Research Methods

1. **Temporal precedence**. cause preceded effect

Criteria to Establish Causality

1. **Temporal precedence**. cause preceded effect

2. **Covariation**. cause and effect move together

Criteria to Establish Causality

1. **Temporal precedence**. cause preceded effect

2. **Covariation**. cause and effect move together

3. **No plausible alternative explanations**. no other variable or factor is causing the outcome

Cause, Effect, and Causal Relationships in Experiments

Cause, Effect, and Causal Relationships in Experiments

- **Temporal precedence**. presumed causes are manipulated to observe their effect

Cause, Effect, and Causal Relationships in Experiments

- **Temporal precedence**. presumed causes are manipulated to observe their effect
- **Covariation**. variability in cause related to variation in an effect

Cause, Effect, and Causal Relationships in Experiments

- **Temporal precedence**. presumed causes are manipulated to observe their effect
- **Covariation**. variability in cause related to variation in an effect
- **No plausible alternative explanations**. elements of design and extra-study knowledge are used to account for and reduce the plausibility of alternative explanations

Causation, Correlation, and Confounds

Causation, Correlation, and Confounds

Survey Research Methods

Correlation does not prove Causation!

Causation, Correlation, and Confounds

Correlation does not prove Causation!

Fails **Temporal precedence**

Correlations do not meet the first premise of causal logic since we cannot determine direction

Causation, Correlation, and Confounds

Survey Research Methods

Correlation does not prove Causation!

Fails **Temporal precedence**

Correlations do not meet the first premise of causal logic since we cannot determine direction

Fails **No plausible alternative explanations**

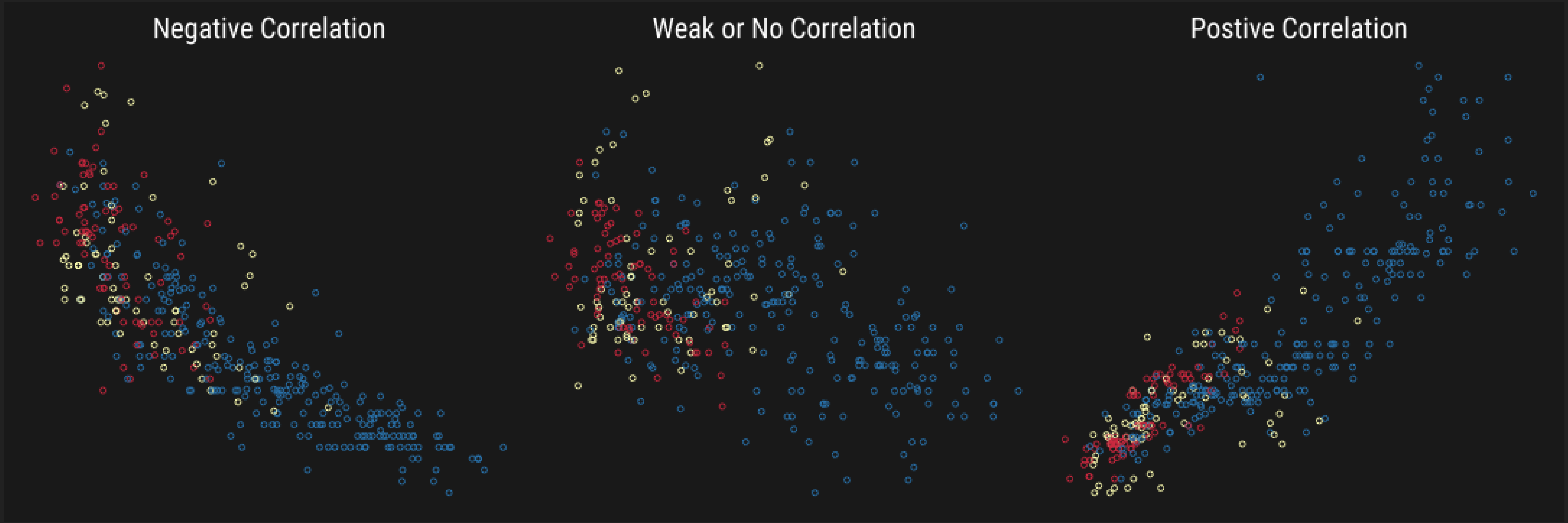
These relationships are often due to a third variable (i.e., a confound)

Correlations: Making Some Sense Out Of a Mess

Survey Research Methods

Correlations: Making Some Sense Out Of a Mess

Survey Research Methods



Manipulable and Nonmanipulable Causes

Manipulable and Nonmanipulable Causes

Experiments involve causal agents that can be *manipulated*

Manipulable and Nonmanipulable Causes

Experiments involve causal agents that can be *manipulated*

Rigid criteria (e.g., ethnicity, gender) are *non manipulable* causes in experiments because they cannot be deliberately varied

Causal Description and Causal Explanation

Causal Description and Causal Explanation

- **Causal description**. identifying that a causal relationship exists between X and Y

Causal Description and Causal Explanation

Survey Research Methods

- **Causal description**. identifying that a causal relationship exists between X and Y
- **Molar causation**. the overall relationship between a treatment package and its effects

Causal Description and Causal Explanation

- **Causal description**. identifying that a causal relationship exists between X and Y
- **Molar causation**. the overall relationship between a treatment package and its effects
- **Causal explanation**. explaining how X causes Y

Causal Description and Causal Explanation

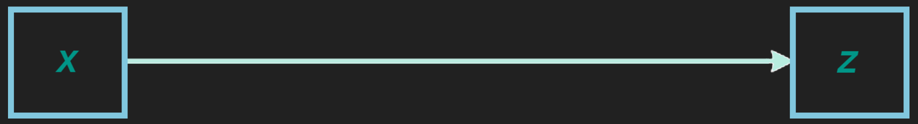
- **Causal description**. identifying that a causal relationship exists between X and Y
- **Molar causation**. the overall relationship between a treatment package and its effects
- **Causal explanation**. explaining how X causes Y
- **Molecular causation**. knowing which parts of a treatment are responsible for which parts of an effect

Causal Models (1)

Causal description (direct)

Causal Models (1)

Causal description (direct)



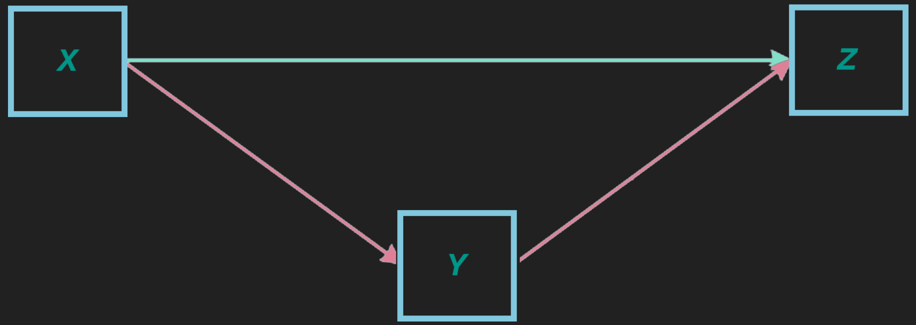
Causal explanation (indirect)

Causal Models (1)

Causal description (direct)

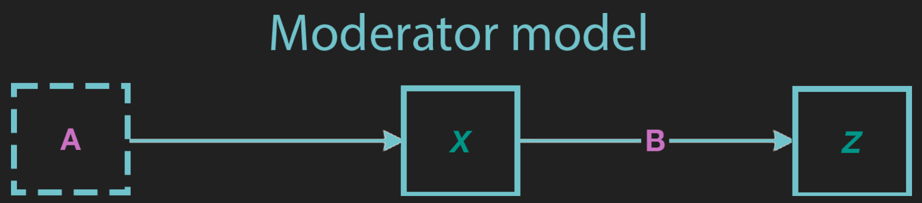
Causal explanation (indirect)

Causal explanation (direct & indirect)



Causal Models (2)

Causal Models (2)



Causal Models (2)

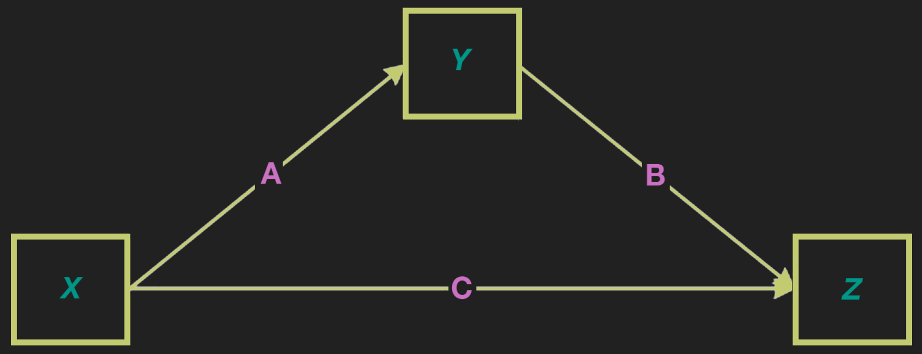
Moderator model

Example

Causal Models (2)

Moderator model

Mediator model



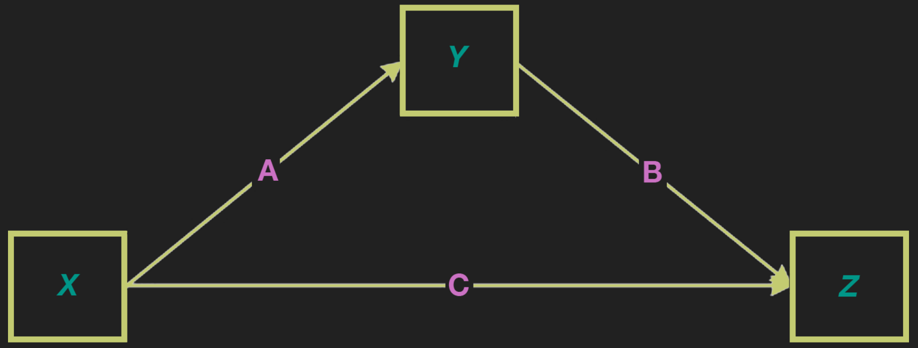
Example

Causal Models (2)

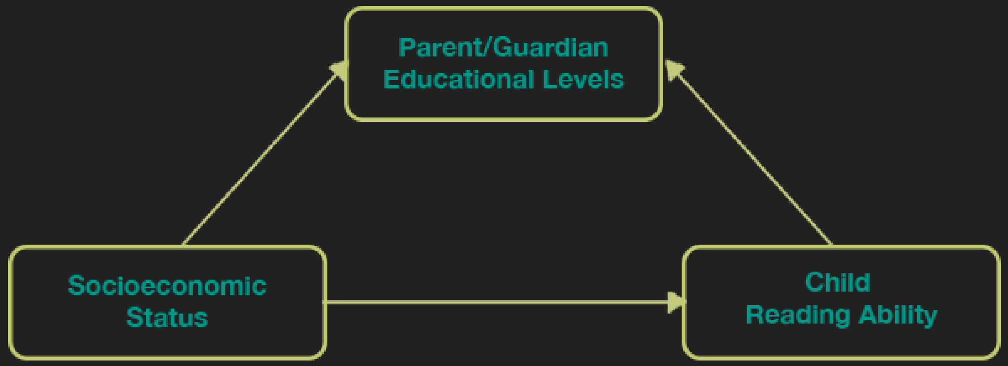
Moderator model

Example

Mediator model



Example



Modern Descriptions of Experiments

Randomized Experiment

Randomized Experiment

- Units are assigned to conditions randomly

Randomized Experiment

- Units are assigned to conditions randomly
- Randomly assigned units are probabilistically equivalent based on expectancy (if certain conditions are met)

Randomized Experiment

- Units are assigned to conditions randomly
- Randomly assigned units are probabilistically equivalent based on expectancy (if certain conditions are met)
- Under the appropriate conditions, randomized experiments provide unbiased estimates of an effect

Quasi-Experiment

Quasi-Experiment

> Shares all features of randomized experiments except assignment

Quasi-Experiment

> Shares all features of randomized experiments except assignment
>
> Assignment to conditions occurs by self-selection

Quasi-Experiment

Shares all features of randomized experiments except assignment

Assignment to conditions occurs by self-selection

Greater emphasis on enumerating and ruling out alternative explanations through

- logic
- reasoning
- design
- measurement

Natural Experiment

> Naturally-occurring contrast between a treatment and comparison condition

Natural Experiment

> Naturally-occurring contrast between a treatment and comparison condition
>
> Typically concern nonmanipulable causes

Natural Experiment

> Naturally-occurring contrast between a treatment and comparison condition
>
> Typically concern nonmanipulable causes
>
> Requires constructing a counterfactual rather than manipulating one

Nonexperimental Designs

Survey Research Methods

- Often called correlational or passive designs (i.e., cross-sectional)

Nonexperimental Designs

- Often called correlational or passive designs (i.e., cross-sectional)
- Statistical controls often used in place of structural design elements

Nonexperimental Designs

Survey Research Methods

- Often called correlational or passive designs (i.e., cross-sectional)
- Statistical controls often used in place of structural design elements
- Generally do not support strong causal inferences

Experiments and the Generalization of Causal Connections

Experiments and the Generalization of Causal Connections

- Most experiments are localized but have general aspirations

Experiments and the Generalization of Causal Connections

- Most experiments are localized but have general aspirations
- Limited samples of **utos**

> units (**u**)
>
> treatments (**t**)
>
> observations (**o**)
>
> settings (**s**)

Experiments and the Generalization of Causal Connections

- Most experiments are localized but have general aspirations
- Limited samples of **utos**

> units (**u**)
>
> treatments (**t**)
>
> observations (**o**)
>
> settings (**s**)

- Known as **local molar causal validity**

Construct Validity: Causal Generalization as Representation

Survey Research Methods

Construct Validity: Causal Generalization as Representation

- Premised on generalizing from particular sampled instances of units, treatments, observations, and settings to the abstract, higher order constructs that sampled instances represent

External Validity: Causal Generalization as Extrapolation

External Validity: Causal Generalization as Extrapolation

- Inferring a causal relationship to unsampled units, treatments, observations, and settings from sampled instances

External Validity: Causal Generalization as Extrapolation

- Inferring a causal relationship to unsampled units, treatments, observations, and settings from sampled instances
- Enhanced when probability sampling methods are used

External Validity: Causal Generalization as Extrapolation

- Inferring a causal relationship to unsampled units, treatments, observations, and settings from sampled instances
- Enhanced when probability sampling methods are used

Broad → Narrow

Narrow → Broad

Approaches to Making Causal Generalizations

Approaches to Making Causal Generalizations

- Applying probability sampling techniques

Approaches to Making Causal Generalizations

- Applying probability sampling techniques
- Arguing causal reasoning

Approaches to Making Causal Generalizations

- Applying probability sampling techniques
- Arguing causal reasoning
- Employing interpolation and extrapolation

Approaches to Making Causal Generalizations

- Applying probability sampling techniques
- Arguing causal reasoning
- Employing interpolation and extrapolation
- Establishing discrimination

Approaches to Making Causal Generalizations

Survey Research Methods

- Applying probability sampling techniques
- Arguing causal reasoning
- Employing interpolation and extrapolation
- Establishing discrimination
- Implementing a Grounded Theory approach

Approaches to Making Causal Generalizations

- Applying probability sampling techniques
- Arguing causal reasoning
- Employing interpolation and extrapolation
- Establishing discrimination
- Implementing a Grounded Theory approach
- Ruling out irrelevancies

Approaches to Making Causal Generalizations

- Applying probability sampling techniques
- Arguing causal reasoning
- Employing interpolation and extrapolation
- Establishing discrimination
- Implementing a Grounded Theory approach
- Ruling out irrelevancies
- Uncovering heterogeneous instances

Approaches to Making Causal Generalizations

- Applying probability sampling techniques
- Arguing causal reasoning
- Employing interpolation and extrapolation
- Establishing discrimination
- Implementing a Grounded Theory approach
- Ruling out irrelevancies
- Uncovering heterogeneous instances
- Using targeted purposive sampling

Approaches to Making Causal Generalizations

- Applying probability sampling techniques
- Arguing causal reasoning
- Employing interpolation and extrapolation
- Establishing discrimination
- Implementing a Grounded Theory approach
- Ruling out irrelevancies
- Uncovering heterogeneous instances
- Using targeted purposive sampling
- Utilizing surface and structural similarity in analogical reasoning

Validity

Validity

> Approximate truthfulness of correctness of an inference

Validity

> Approximate truthfulness of correctness of an inference
>
> Not an all or none, either or, condition, rather a matter of degree

Validity

Approximate truthfulness of correctness of an inference

Not an all or none, either or, condition, rather a matter of degree

Efforts to increase one type of validity often reduce others

Statistical Conclusion Validity

Validity of inferences about the covariation between a treatment (cause) and corresponding outcome (effect)

Internal Validity

Survey Research Methods

Validity of inferences about whether observed covariation between X (treatment/cause) and Y (outcome/effect) reflects a causal relationship from X to Y as those variables were manipulated or measured

Construct Validity

Survey Research Methods

Validity of inferences about the higher order constructs that represent sampling particulars

External Validity

Survey Research Methods

Validity of inferences about whether a cause-effect relationship holds over variations in units, treatments, observations, and settings

Internal Validity

Internal Validity

Inferences about whether the observed covariation between X and Y reflects a causal relationship from X to Y in the form in which the variables were manipulated or measured

Note

In most cause-probing studies, internal validity is the primary focus

Threats to Validity

Threats to Validity

Reasons why an inference may be partly or wholly incorrect

Threats to Validity

Reasons why an inference may be partly or wholly incorrect

Design controls can be used to reduce many validity threats, but not in all instances

---

Threats to Validity

Reasons why an inference may be partly or wholly incorrect

Design controls can be used to reduce many validity threats, but not in all instances

---

Generally context-dependent

Threats to Internal Validity

Single Group Studies (1)

Single Group Studies (1)

History

an unrelated event influences the outcomes

Example

A week before the closing of a survey on worker well-being, a new CEO takes over and announces to all employees in an email that there will be layoffs resulting in a 20% reduction in the total number of workers. As a result survey responses moving forward are skewed.

Single Group Studies (1)

Survey Research Methods

History

an unrelated event influences the outcomes

Example

A week before the closing of a survey on worker well-being, a new CEO takes over and announces to all employees in an email that there will be layoffs resulting in a 20% reduction in the total number of workers. As a result survey responses moving forward are skewed.

Maturation

the outcomes of a study vary as a natural result of time.

Example

Most participants are new to their job at the time of an employee ability survey assessment. A month later, their productivity has improved as a result of time spent working in the position

Single Group Studies (2)

Single Group Studies (2)

Instrumentation

different measures are used in pre-test and post-test phases

Example

survey participants are given 5 minutes to complete a pre-test survey prior to a training session causing some to leave some items blank. However the same participants are asked to fill out a post-test survey with identical questions, but are afforded 15 minutes for completion allowing everyone adequate time to address all items

Single Group Studies (2)

Instrumentation

different measures are used in pre-test and post-test phases

Example

survey participants are given 5 minutes to complete a pre-test survey prior to a training session causing some to leave some items blank. However the same participants are asked to fill out a post-test survey with identical questions, but are afforded 15 minutes for completion allowing everyone adequate time to address all items

Testing

a pre-test influences the outcomes of the post-test

Example

low-performing students are given an self-reported survey of skills prior to a six week math and science camp. After the camp comes to a close, the same participants are asked to fill out an identical survey. Outcomes indicate higher self-reported scores due to the familiarity and/or awareness of the survey's purpose.

Countering Threats to Single Group Studies

Countering Threats to Single Group Studies

> Adding a comparable control group counters all threats to single-group studies. If comparable control and treatment groups each face the same threats, the outcomes of the study won’t be affected by them

Countering Threats to Single Group Studies

> Adding a comparable control group counters all threats to single-group studies. If comparable control and treatment groups each face the same threats, the outcomes of the study won't be affected by them
>
> A large sample size counters testing, because results would be more sensitive to any variability in the outcomes

Survey Research Methods

Countering Threats to Single Group Studies

> Adding a comparable control group counters all threats to single-group studies. If comparable control and treatment groups each face the same threats, the outcomes of the study won't be affected by them
>
> A large sample size counters testing, because results would be more sensitive to any variability in the outcomes
>
> Using filler-tasks or questionnaires to hide the purpose of study also counters testing threats

Multi-group Studies (1)

Multi-group Studies (1)

Survey Research Methods

Attrition

unexplained or uncontrollable dropout from participants

Example

due to an error in your survey's functionality that was caught a day after the initial launch, 20% of participants provided unusable data. Almost all of the responses were from a control group making it impossible hard to compare the responses with those from a treatment groups that did not experience said error.

Multi-group Studies (1)

Survey Research Methods

Attrition

unexplained or uncontrollable dropout from participants

Example

due to an error in your survey's functionality that was caught a day after the initial launch, 20% of participants provided unusable data. Almost all of the responses were from a control group making it impossible hard to compare the responses with those from a treatment groups that did not experience said error.

Regression to the mean

there is a statistical tendency for people who score extremely low or high on a test to score closer to the middle the next time

Example

Participants are placed into groups based on their initial scores on a survey following a training. As a result, it is difficult to determine whether the outcomes would be due to the treatment or statistical norms

Multi-group Studies (2)

Multi-group Studies (2)

Selection bias

groups are not comparable at the beginning of the study

Example

Scores on a survey administered to assess loneliness groups participants into two groups: high and low. Without the researchers' awareness, the groups also happen to consist of extroverts and introverts, respectively. Since there are already systematic differences between the groups at the baseline, any improvements or declines in group assessments may be due to reasons other than a treatment intended to address loneliness.

Multi-group Studies (2)

Selection bias

groups are not comparable at the beginning of the study

Example

Scores on a survey administered to assess loneliness groups participants into two groups: high and low. Without the researchers' awareness, the groups also happen to consist of extroverts and introverts, respectively. Since there are already systematic differences between the groups at the baseline, any improvements or declines in group assessments may be due to reasons other than a treatment intended to address loneliness.

Social interaction

participants from different groups may compare notes and either figure out the aim of the study or feel resentful of others.

Example

Two groups of participants in a single-blind study are asked to take a pre-screening survey at different times. After submitting their responses, some of the individuals in the first group discover that participants who answered the items on the survey in a certain way guaranteed that they were placed into the experimental group. The information is passed along to most participants in the second group ensuring their admittance as well.

Countering Threats to Multi-Group Studies

Countering Threats to Multi-Group Studies

> Blinding participants to the aim of the study counters the effects of social interaction.

Countering Threats to Multi-Group Studies

> Blinding participants to the aim of the study counters the effects of social interaction.
>
> Random assignment of participants to groups counters selection bias and regression to the mean by making groups comparable at the start of the study.

Estimating Internal Validity in Experiments

Estimating Internal Validity in Experiments

> By definition randomized experiments eliminate selection through random assignment to conditions

Estimating Internal Validity in Experiments

> By definition randomized experiments eliminate selection through random assignment to conditions
>
> Most other threats are likely probabilistically distributed as well

Estimating Internal Validity in Experiments

> By definition randomized experiments eliminate selection through random assignment to conditions
>
> Most other threats are likely probabilistically distributed as well
>
> Typically only two likely validity threats arise from experiments

Estimating Internal Validity in Experiments

Survey Research Methods

> By definition randomized experiments eliminate selection through random assignment to conditions
>
> Most other threats are likely probabilistically distributed as well
>
> Typically only two likely validity threats arise from experiments

Attrition

Estimating Internal Validity in Experiments

> By definition randomized experiments eliminate selection through random assignment to conditions
>
> Most other threats are likely probabilistically distributed as well
>
> Typically only two likely validity threats arise from experiments

Attrition

Testing

Estimating Internal Validity in Quasi-Experimen

Estimating Internal Validity in Quasi-Experimen

> Differences between groups tend to be more systematic than random

Estimating Internal Validity in Quasi-Experime

> Differences between groups tend to be more systematic than random
>
> All threats should be made explicit and then ruled out one by one

Estimating Internal Validity in Quasi-Experime

> Differences between groups tend to be more systematic than random
>
> All threats should be made explicit and then ruled out one by one
>
> Once identified, threats can be systematically examined

Thats it!

If you have any questions, please reach out

Thats it!

If you have any questions, please reach out