Missing Data

PSY 410: Data Science for Psychology

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Why missing data matters

The data you don't have

In a typical longitudinal psychology study, 30–50% of participants drop out before the final wave.

If you just delete their data, you might be throwing away the most important part of the story — because **who drops out** is rarely random.

Today we learn to detect, explore, and handle missing data honestly.

Types of missing data

Explicit missing: NA

Explicit missing means you can see the `NA`:

```
survey <- tibble(
  participant = 1:5,
  age = c(25, NA, 30, 22, NA),
  depression = c(12, 18, NA, 10, 15)
)

survey
```

```
# A tibble: 5 × 3
  participant   age depression
        <int> <dbl>      <dbl>
1           1    25         12
2           2    NA         18
3           3    30         NA
4           4    22         10
5           5    NA         15
```

The `NA` values are obvious.

Implicit missing: Rows don't exist

Implicit missing means entire rows are absent:

```
appointments <- tibble(
  name = c("Alice", "Bob", "Alice", "Carol"),
  day = c("Mon", "Mon", "Wed", "Wed"),
  attended = c(TRUE, TRUE, TRUE, TRUE)
)

appointments
```

```
# A tibble: 4 × 3
  name  day   attended
  <chr> <chr> <lgl>
1 Alice Mon   TRUE
2 Bob   Mon   TRUE
3 Alice Wed   TRUE
4 Carol Wed   TRUE
```

Who didn't show up? You can't tell because they're not in the data!

Why implicit missing matters

In longitudinal studies, missing rows often mean dropout:

```
# Three-wave study
longitudinal <- tibble(
  id = c(1, 1, 1, 2, 2, 3),  # Person 2 missing wave 3, person 3 missing wave
  wave = c(1, 2, 3, 1, 2, 1),
  depression = c(20, 15, 12, 25, 22, 18)
)

longitudinal
```

```
# A tibble: 6 × 3
     id  wave depression
  <dbl> <dbl>      <dbl>
1     1     1         20
2     1     2         15
3     1     3         12
4     2     1         25
5     2     2         22
6     3     1         18
```

Person 2 and 3's missing waves are **implicit** — they're not `NA`, they're just absent.

Exploring missing data

Checking for NAs

```r
survey <- tibble(
  id = 1:6,
  age = c(25, NA, 30, 22, NA, 28),
  depression = c(12, 18, NA, 10, 15, NA),
  anxiety = c(15, 20, 12, NA, 18, 16)
)

# Check if any NAs exist
any(is.na(survey))
```

```
[1] TRUE
```

```r
# Count total NAs
sum(is.na(survey))
```

```
[1] 5
```

NAs by column

```
# Count NAs in each column
survey |>
  summarize(
    age_missing = sum(is.na(age)),
    depression_missing = sum(is.na(depression)),
    anxiety_missing = sum(is.na(anxiety))
  )
```

```
# A tibble: 1 × 3
  age_missing depression_missing anxiety_missing
        <int>              <int>           <int>
1           2                  2               1
```

Better approach: across()

`across(columns, function)` applies the same function to multiple columns at once:

```
survey |>
  summarize(
    across(
      everything(),       # which columns: all of them
      ~ sum(is.na(.x))    # what to do: count NAs (.x = "this column")
    )
  )
```

```
# A tibble: 1 × 4
     id   age depression anxiety
  <int> <int>      <int>   <int>
1     0     2          2       1
```

Or as proportions

```
survey |>
  summarize(
    across(
      everything(),
      ~ mean(is.na(.x))
    )
  )
```

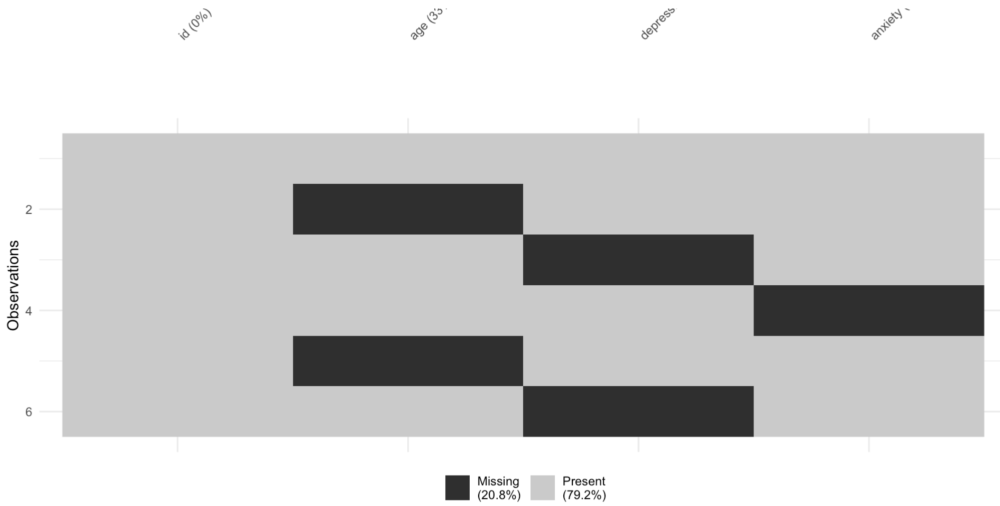
```
# A tibble: 1 × 4
     id   age depression anxiety
  <dbl> <dbl>      <dbl>   <dbl>
1     0 0.333      0.333   0.167
```

Visualizing missingness

The `naniar` package provides great visualization tools:

```
library(naniar)

# Visual summary
vis_miss(survey)
```



Handling missing data

Strategy 1: Complete case analysis

Complete case analysis (listwise deletion) removes any row with *any* `NA`:

```
survey |>
  drop_na()
```

```
# A tibble: 1 × 4
     id   age depression anxiety
  <int> <dbl>      <dbl>   <dbl>
1     1    25         12      15
```

Dangers of complete case analysis

```r
# Started with 6 participants
nrow(survey)
```

```
[1] 6
```

```r
# Only 2 complete cases
survey |>
  drop_na() |>
  nrow()
```

```
[1] 1
```

Warning

You just lost 67% of your data!

Selective dropping

Only drop rows missing *specific* variables:

```
# Drop only if depression is missing
survey |>
  drop_na(depression)
```

```
# A tibble: 4 × 4
     id   age depression anxiety
  <int> <dbl>      <dbl>   <dbl>
1     1    25         12      15
2     2    NA         18      20
3     4    22         10      NA
4     5    NA         15      18
```

Drop on multiple variables

```r
# Drop only if depression OR anxiety is missing
survey |>
  drop_na(depression, anxiety)
```

```
# A tibble: 3 × 4
     id   age depression anxiety
  <int> <dbl>      <dbl>   <dbl>
1     1    25         12      15
2     2    NA         18      20
3     5    NA         15      18
```

When is dropping okay?

Dropping is fine when:

- Missing data is rare (< 5-10%)
- Missingness is truly random
- You have adequate sample size

Be cautious when:

- Missing data is common (> 20%)
- Certain groups have more missingness (systematic bias)
- Sample size is small

Strategy 2: Filling values

Sometimes you can **reasonably fill** missing values:

```r
# Carry forward the last observation
time_series <- tibble(
  day = 1:5,
  mood = c(5, NA, NA, 4, 6)
)

time_series |>
  fill(mood)  # Fills downward by default
```

```
# A tibble: 5 × 2
    day  mood
  <int> <dbl>
1     1     5
2     2     5
3     3     5
4     4     4
5     5     6
```

Fill directions

```r
# Fill upward
time_series |>
  fill(mood, .direction = "up")
```

```
# A tibble: 5 × 2
    day  mood
  <int> <dbl>
1     1     5
2     2     4
3     3     4
4     4     4
5     5     6
```

When is filling okay?

Filling makes sense for:

- Time series with repeated measures (carry forward last observation)
- Grouping variables that apply to multiple rows
- Values that don't change often

> ⚠ **Warning**
>
> **NEVER fill** when it means making up data you don't have!

Strategy 3: Replace with a specific value

```
# Replace NAs with a value
survey |>
  mutate(
    age = replace_na(age, 99),  # Code 99 = "no response"
    depression = replace_na(depression, -999)  # Obvious invalid code
  )
```

```
# A tibble: 6 × 4
     id   age depression anxiety
  <int> <dbl>      <dbl>   <dbl>
1     1    25         12      15
2     2    99         18      20
3     3    30       -999      12
4     4    22         10      NA
5     5    99         15      18
6     6    28       -999      16
```

Strategy 3: Replace with a specific value

> **Important**
>
> If you use placeholder codes, **document them clearly** and make sure they can’t be mistaken for real data.

Strategy 4: Leave them as NA

Often the best approach is to **keep NAs** and handle them in analysis:

```
# Most functions have na.rm argument
survey |>
  summarize(
    mean_age = mean(age, na.rm = TRUE),
    mean_depression = mean(depression, na.rm = TRUE)
  )
```

```
# A tibble: 1 × 2
  mean_age mean_depression
     <dbl>           <dbl>
1     26.2            13.8
```

This is transparent about what data you have.

Implicit missing → Explicit missing

The problem with implicit missing

▶ Code

```
# A tibble: 7 × 3
  participant timepoint depression
        <dbl>     <dbl>      <dbl>
1           1         1         20
2           1         2         15
3           1         3         12
4           2         1         25
5           2         2         22
6           3         1         18
7           3         3         14
```

Who's missing which timepoints? Hard to tell.

complete(): Make implicit missing explicit

```r
study_completion |>
  complete(participant, timepoint)
```

```
# A tibble: 9 × 3
  participant timepoint depression
        <dbl>     <dbl>      <dbl>
1           1         1         20
2           1         2         15
3           1         3         12
4           2         1         25
5           2         2         22
6           2         3         NA
7           3         1         18
8           3         2         NA
9           3         3         14
```

Now we can see: Participant 2 missing timepoint 3, Participant 3 missing timepoint 2.

Why this matters

Makes dropout visible for analysis:

```
study_completion |>
  complete(participant, timepoint) |>
  group_by(timepoint) |>
  summarize(
    n_completed = sum(!is.na(depression)),
    n_missing = sum(is.na(depression))
  )
```

```
# A tibble: 3 × 3
  timepoint n_completed n_missing
      <dbl>       <int>     <int>
1         1           3         0
2         2           2         1
3         3           2         1
```

Flagging completion

Common pattern: make implicit explicit, then flag who completed each timepoint:

```
study_completion |>
  complete(participant, timepoint) |>
  mutate(
    completed = if_else(is.na(depression), FALSE, TRUE)
  )
```

```
# A tibble: 9 × 4
  participant timepoint depression completed
        <dbl>     <dbl>      <dbl> <lgl>
1           1         1         20 TRUE
2           1         2         15 TRUE
3           1         3         12 TRUE
4           2         1         25 TRUE
5           2         2         22 TRUE
6           2         3         NA FALSE
7           3         1         18 TRUE
8           3         2         NA FALSE
9           3         3         14 TRUE
```

This `completed` flag is the building block for attrition analysis — coming up later in the deck.

Pair coding break

Your turn: Analyze missing data patterns

You have survey data from a therapy study:

```
therapy_survey <- tibble(
  id = 1:8,
  age = c(25, 30, NA, 22, 28, NA, 35, 26),
  baseline_depression = c(22, 25, 18, 20, 24, 19, NA, 21),
  followup_depression = c(12, 23, NA, 15, NA, NA, NA, 16),
  satisfaction = c(4, 3, NA, 5, 4, NA, NA, 5)
)
```

1. How many participants are missing baseline data? Followup data?
2. How many participants have **complete data** (no NAs anywhere)?
3. Create a version that drops rows missing followup data
4. What percentage of participants completed the followup?

Time: 10 minutes

Before we move on

📤 Submit your code on Canvas for participation credit. Paste what you have — it doesn't need to work perfectly.

Psychology-specific considerations

Missing data mechanisms

Statisticians distinguish three types:

1. **MCAR (Missing Completely At Random)** — Missingness unrelated to anything
2. **MAR (Missing At Random)** — Missingness related to observed variables
3. **MNAR (Missing Not At Random)** — Missingness related to the missing value itself

Example: Depression study

MCAR: Computer randomly failed to save 5% of responses

- No bias introduced

MAR: Older participants more likely to skip online surveys

- Can account for this by including age as a predictor

MNAR: People with severe depression skip the depression questionnaire

- **This is a problem** — missing values are related to what you're measuring

Why it matters

- **MCAR:** Complete case analysis is fine (but you lose power)
- **MAR:** More sophisticated methods can help (beyond this course)
- **MNAR:** No easy fix — missing data is fundamentally informative

> **Tip**
>
> **Your job:** Always **document and report** how much data is missing and why you think it's missing.

Attrition analysis

In longitudinal studies, always check *who* drops out:

```
study <- tibble(
  id = 1:10,
  condition = rep(c("Treatment", "Control"), each = 5),
  baseline_depression = c(22, 18, 25, 20, 24, 19, 21, 23, 17, 22),
  followup_depression = c(15, 12, NA, NA, NA, 14, 13, 11, 16, 18)
)

study
```

```
# A tibble: 10 × 4
      id condition baseline_depression followup_depression
   <int> <chr>                   <dbl>               <dbl>
 1     1 Treatment                  22                  15
 2     2 Treatment                  18                  12
 3     3 Treatment                  25                  NA
 4     4 Treatment                  20                  NA
 5     5 Treatment                  24                  NA
 6     6 Control                    19                  14
 7     7 Control                    21                  13
 8     8 Control                    23                  11
 9     9 Control                    17                  16
10    10 Control                    22                  18
```

A missing followup score = a dropout.

Who dropped out?

```
study |>
  filter(is.na(followup_depression))
```

```
# A tibble: 3 × 4
     id condition baseline_depression followup_depression
  <int> <chr>                   <dbl>               <dbl>
1     3 Treatment                  25                  NA
2     4 Treatment                  20                  NA
3     5 Treatment                  24                  NA
```

Dropout by condition

```
study |>
  filter(is.na(followup_depression)) |>
  count(condition)
```

```
# A tibble: 1 × 2
  condition     n
  <chr>     <int>
1 Treatment     3
```

All dropouts are from the Treatment condition — this could seriously bias results!

Reporting missing data

In your write-up, report:

1. **How much data is missing** (by variable)
2. **Patterns of missingness** (related to other variables?)
3. **How you handled it** (dropped? kept as NA?)
4. **Potential biases** (who's missing? does it matter?)

Example:

> "Eight participants (12%) did not complete the follow-up assessment. Dropout was unrelated to baseline depression scores ($t = 1.2$, $p = .24$). Analyses used complete case analysis ($N = 60$)."

Advanced topic: Multiple imputation

Beyond this course

More sophisticated approaches exist for handling missing data:

- **Multiple imputation** — create multiple plausible versions of missing data
- **Maximum likelihood** — estimate parameters using all available data
- **Bayesian methods** — incorporate uncertainty about missing values

Packages in R: `mice`, `Amelia`, `missForest`

> **Note**
>
> We won't cover these methods, but know they exist for when you need them in future research!

Wrapping up

Decision tree for missing data

1. **How much is missing?**
   - < 5%: Usually safe to drop
   - 5-20%: Investigate patterns
   - > 20%: Be very careful
2. **Why is it missing?**
   - Random: Less concerning
   - Systematic: Potentially biasing
3. **What's your plan?**
   - Drop complete cases?
   - Drop specific variables?
   - Keep as NA and use `na.rm`?
   - Fill (carefully)?
4. **Document everything!**

Key takeaways

1. **Missing data is normal** in psychology research
2. **Explicit vs implicit** missing — make implicit explicit with `complete()`
3. **Explore patterns** before deciding how to handle
4. **Complete case analysis** (dropping rows) is simple but can lose power
5. **Never make up data** — be transparent about missingness
6. **Document your decisions** — report what's missing and why
7. **Check for bias** — does missingness relate to key variables?

Functions cheat sheet

Function	Purpose
`is.na()`	Check if values are missing
`drop_na()`	Remove rows with NAs
`replace_na()`	Replace NAs with a value
`fill()`	Fill NAs with nearby values
`complete()`	Make implicit missing explicit
`na.omit()`	Remove rows with NAs (base R)
`naniar::vis_miss()`	Visualize missing data

Before next class

📖 **Read:**

- R4DS Ch 19: Joins

✅ **Do:**

- ⚠️ **Finish Assignment 6 — due Sunday May 17 at 11:59 PM**
- Start Assignment 7 — the missing-data half is fair game now
- Submit your final project draft (due next Wednesday before class)
- Check your own final project data for missingness

The one thing to remember

Missing data isn't a problem to solve — it's information about your study. Treat it that way.

See you Wednesday for joins!

On your own

Practice: Longitudinal missing data

You have a three-wave study:

```r
longitudinal_study <- tibble(
  participant = c(1, 1, 1, 2, 2, 3, 3, 3, 4, 4),
  wave = c(1, 2, 3, 1, 2, 1, 2, 3, 1, 3),
  depression = c(25, 20, 15, 30, 28, 22, 18, 16, 20, NA),
  anxiety = c(28, 25, 22, 32, NA, 24, 20, 18, 22, 19)
)
```

Your tasks

1. Make implicit missing waves **explicit** using `complete()`
2. Count how many assessments each participant completed
3. What percentage of participants completed all three waves?
4. Reshape the depression data so each participant has one row with columns for wave 1, 2, and 3. Then compute the wave-1-to-wave-3 change for participants with both timepoints. What's the mean change?