Harnessing R for Medical Education Research

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HANDS-ON WORKSHOP ON MULTILEVEL MODELING

Harnessing R for Medical Education Research

From data preparation to multilevel models.

Norman B. Mendoza, PhD · **May 2026**
Assistant Professor, C&I

Social Psychology of Education (2020) 23:795–814
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Check for updates

Achievement goal contagion: mastery and performance goals spread among classmates

Ronnel B. King[1] · Norman B. Mendoza[2]

Received: 4 November 2019 / Accepted: 17 April 2020 / Published online: 29 June 2020

Abstract
Past studies that explored the antecedents of achievement goals have mostly focused on the role of personal characteristics and parental/teacher influences. However, the role of one's classmates has not been given much attention. Drawing on the concept of goal contagion, the present study aimed to examine whether classmates' achievement goals influence one's achievement goals. We recruited 848 secondary school students nested within 30 classes and asked them to answer relevant questionnaires at Time 1 and Time 2. Multilevel analysis was used to examine whether classmates' achievement goals at Time 1 predicted one's achievement goals at Time 2 thereby demonstrating achievement goal contagion. To rule out alternative explanations, we controlled for baseline achievement goals at Time 1, social desirability bias, and other relevant demographic factors. Results indicated that mastery-approach, performance-approach, and performance-avoidance goals were contagious, but mastery-avoidance goals were not. Our study highlights the importance of understanding achievement goal contagion among classmates.

Keywords Social contagion · Achievement goals · Goals contagion · Mastery goals · Performance goals

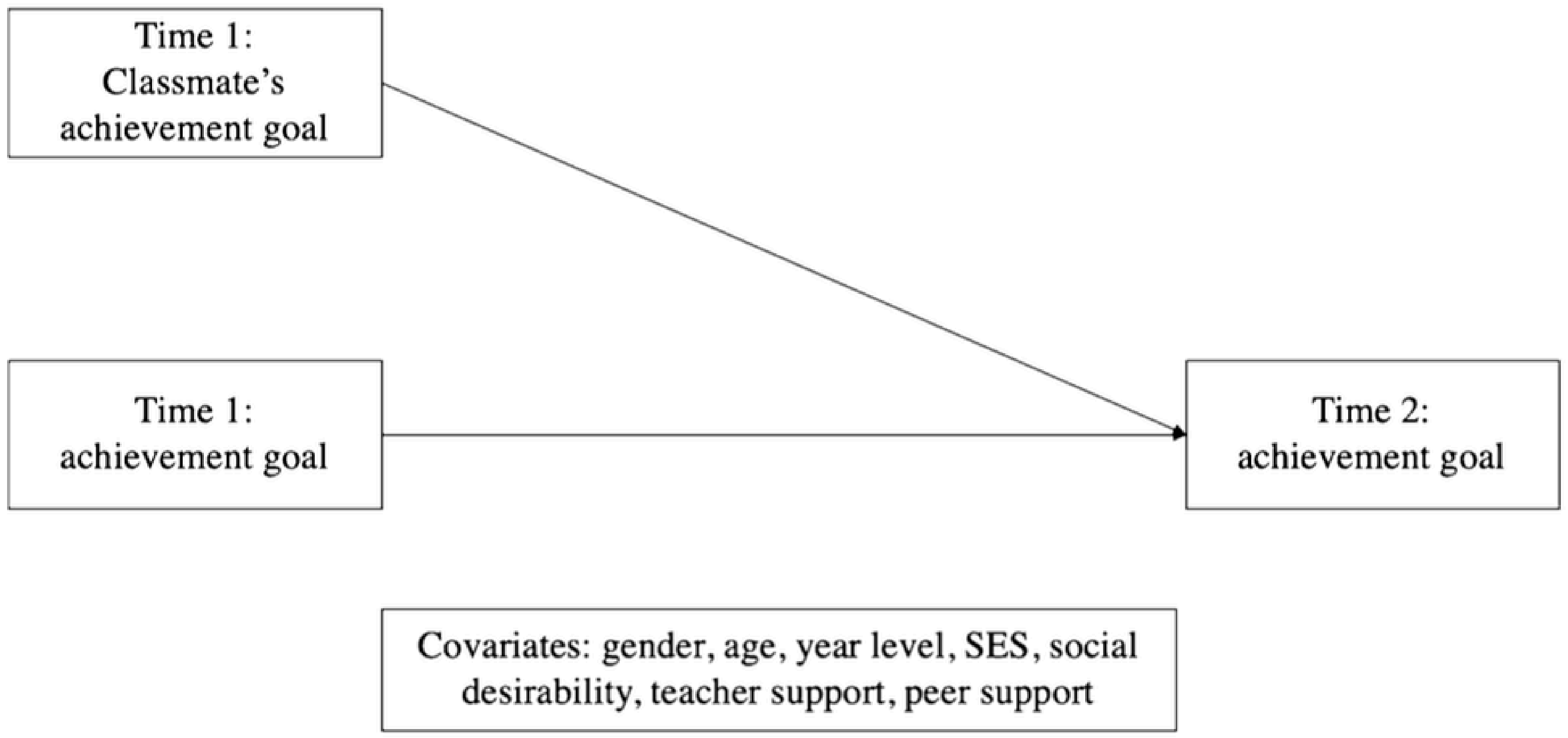

Fig. 1 Conceptual framework

European Journal of Psychology of Education
https://doi.org/10.1007/s10212-020-00521-1

The social contagion of work avoidance goals in school and its influence on student (dis)engagement

Norman B. Mendoza[1] · Ronnel B. King[2]

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Published online: 06 January 2021

Abstract
Work avoidance goals, which refer to wanting to do as little as possible in school, are detrimental to school success. Given its maladaptive nature, studies have investigated the antecedents of work avoidance, such as the role of personal characteristics and social-contextual factors. The influence of one's classmates, however, remains under-explored. Drawing from social contagion research, we examined whether work avoidance goals spread among classmates. Questionnaires were administered to 1524 adolescent students nested within 50 classes. Two waves of data were collected one semester apart. Multilevel modeling was used to analyze the data. Results showed that a student's work avoidance in Time 2 was predicted by his/her classmates' work avoidance in Time 1. These results held even after controlling for one's own Time 1 work avoidance. Moreover, work avoidance goals led to higher levels of disengagement and lower levels of engagement. The findings demonstrate that work avoidance goals are socially contagious and that they have negative consequences for students' engagement. This study extends our theoretical understanding of work avoidance by highlighting the vital role played by one's classmates in shaping students' avoidance of schoolwork and the deleterious consequences that come with it.

Keywords Social contagion · Work avoidance goals · Avoidance goal contagion · Engagement · Disengagement

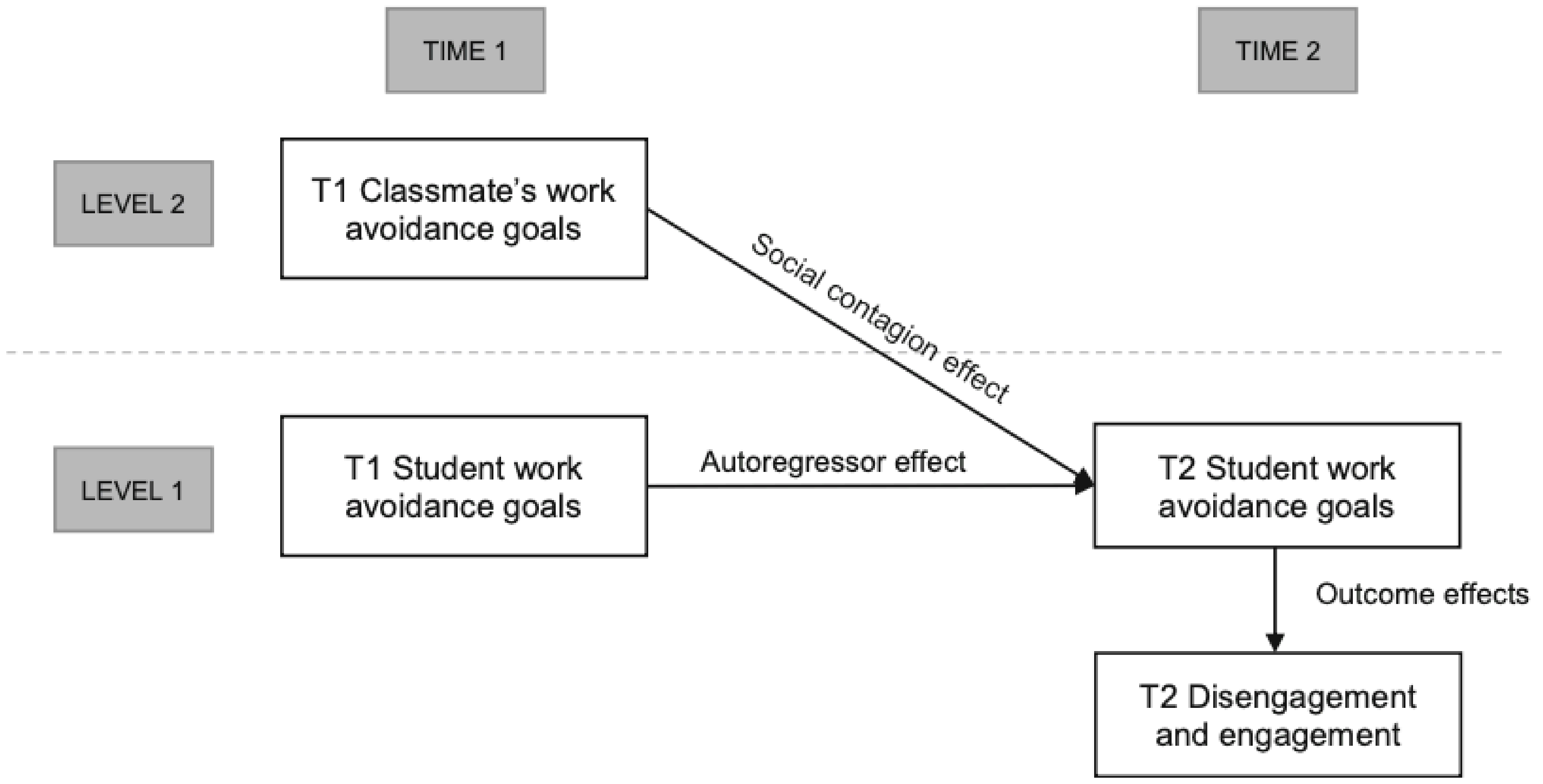

Fig. 1 Conceptual framework of the social contagion of work avoidance goals predicting student engagement and disengagement


Learning and Individual Differences 88 (2021) 102004

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The social contagion of students' social goals and its influence on engagement in school

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ARTICLE INFO

Keywords:
Social goals
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Prosocial goal
Social responsibility goal
Engagement

ABSTRACT

Social goals, such as prosocial and social responsibility goals, are crucial predictors of learning and optimal functioning. Past studies on social goals have usually focused on how teachers and peers influence social goal pursuit. However, the role of social contagion among classmates has seldom been explored. This study aimed to test the social contagion of social goals (prosocial and social responsibility goals) among classmates and the implications this might have on students' engagement in school. We recruited 1524 students nested within 50 classes and asked them to respond to surveys across two time points. Multilevel path analysis was used to analyze the data. Students embedded in classes with higher social goals at Time 1 had higher social goals themselves at Time 2, demonstrating social contagion effects. Social contagion effects remained robust despite controlling for auto-regressor effects and other alternative explanations. Higher social goals (prosocial and social responsibility), in turn, were positively associated with greater engagement. This study has important implications for theorizing on social goals and highlights the need to examine the important role played by social contagion in understanding motivational processes.

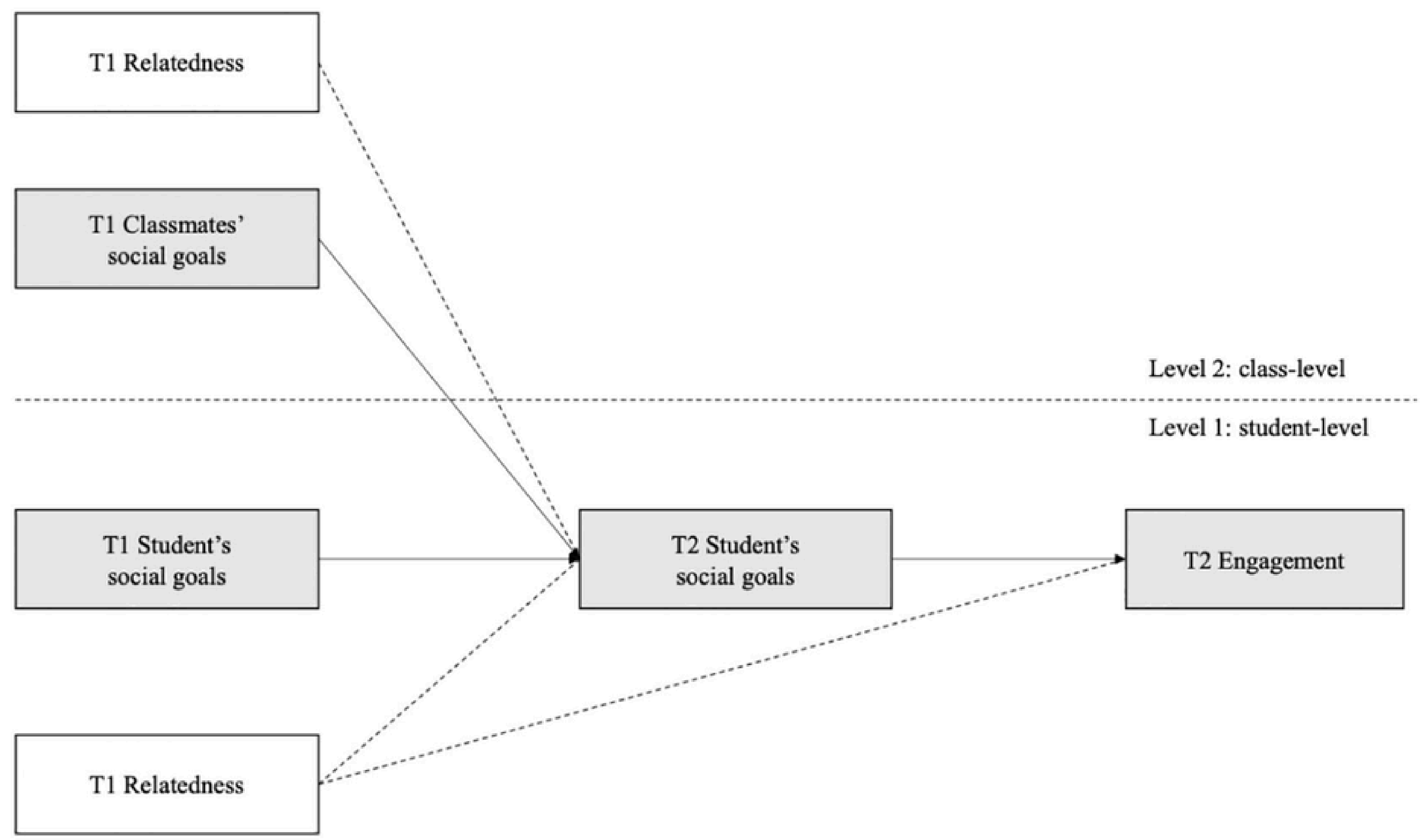

Fig. 1. Social contagion of student social goals and its influence on engagement.

European Journal of Psychology of Education
https://doi.org/10.1007/s10212-022-00620-1

Domain-specific motivation and self-assessment practice as mechanisms linking perceived need-supportive teaching to student achievement

Norman B. Mendoza[1] · Zi Yan[1] · Ronnel B. King[2]

Received: 16 September 2021 / Revised: 2 May 2022 / Accepted: 4 May 2022

Abstract
The self-system model of motivational development was used in this study to examine whether and how student motivation and self-assessment practices—as psychological and behavioural mechanisms, respectively—link need-supportive teaching to students' objective achievement scores in English language learning. We applied a multilevel mediation analysis on Rasch-calibrated data from 796 students (53% females; mean age = 14.12, $SD = 1.51$) nested within 30 classes (mean class size = 26.53) in a secondary school in the Philippines. We collected all predictor variables (i.e. need-supportive teaching, motivation, self-assessment practice) in time 1, while achievement scores were collected eight weeks later (time 2). Lower-level mediation results show that students' perceptions of involved teaching and structured teaching are associated with higher controlled motivation and autonomous motivation. Furthermore, only autonomous motivation was associated with higher achievement in time 2. Self-assessment practice significantly mediated the link between both controlled and autonomous motivation to achievement. These results held while controlling for age, gender, and socioeconomic status. Hence, involved teaching and structured teaching correlated with higher motivation and increased self-assessment practice, which, in turn, leads to higher achievement in English language learning. The findings highlight that motivation and self-assessment practices are psychological and behavioural pathways that can theoretically and empirically explain how need-supportive teaching practices impact student achievement in a specific subject. Implications and directions for future research are discussed.

Keywords Need-supportive teaching · Motivation · Self-assessment practices · English achievement · Domain-specific · Lower-level mediation analysis

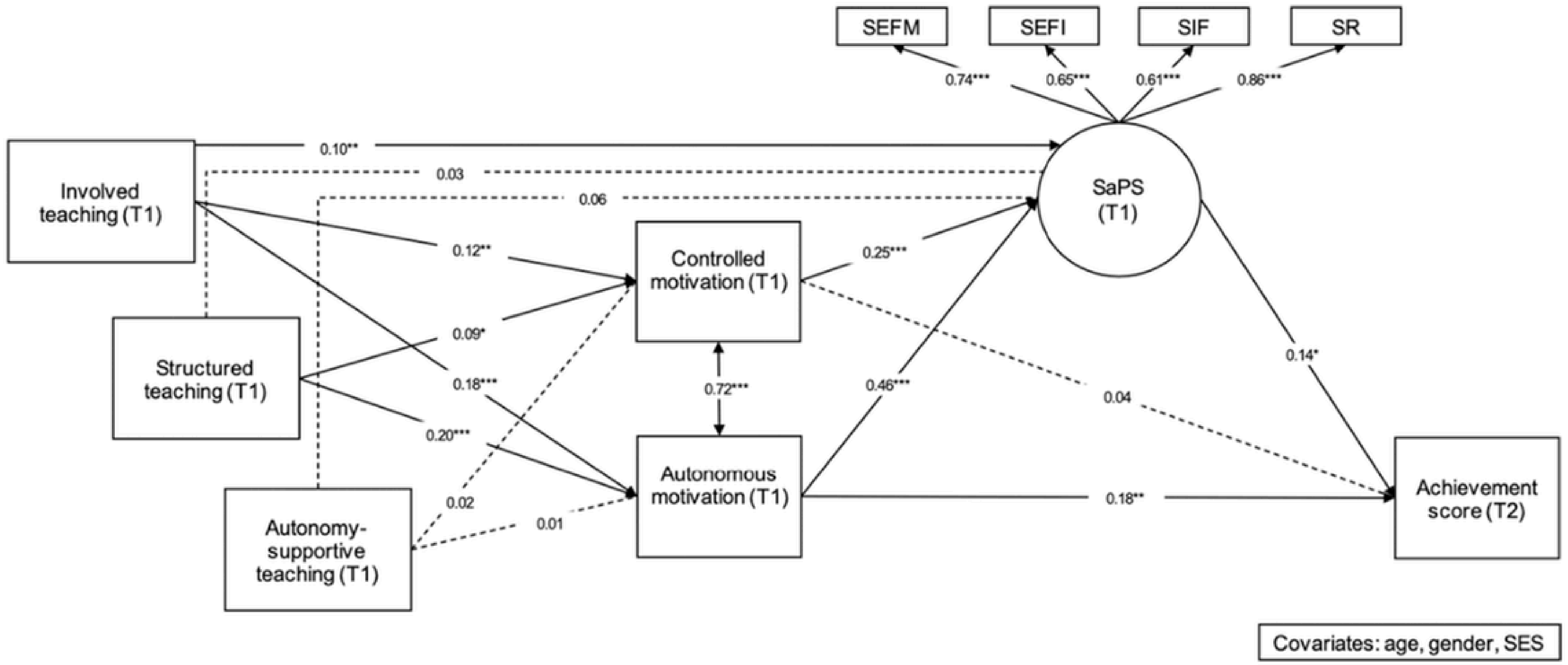

Fig. 2 Lower-level mediation model where need-supportive teaching (i.e. involved, structured, and autonomy-supportive teaching) was entered as predictors of motivation and self-assessment practices. Notes. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; SaPS, self-assessment practices; broken lines are non-significant paths; paths for age, gender, and socioeconomic status as covariates are not illustrated for figure parsimony

ASSESSMENT IN EDUCATION: PRINCIPLES, POLICY & PRACTICE
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Learning and practicing simultaneously: the synergistic effect of online self-assessment diaries and teacher self-assessment instruction on learning and growth mindset

Zi Yan and Norman B. Mendoza

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ABSTRACT

Self-assessment (SA) interventions show promise for enhancing learning and motivational outcomes, yet their effectiveness varies considerably depending on implementation approaches. This randomised controlled experiment examined whether combining teacher instruction with student SA diaries creates synergistic effects beyond either approach alone. Over 10 weeks, 118 Grade 10 students were assigned to four conditions: SA Diary only, SA Instruction only, SA Diary + Instruction, or Control, with English language learning achievement and growth mindset as outcomes. Results revealed that only the combined SA Diary + Instruction condition yielded significant improvements in objective learning outcomes and growth mindset compared to other conditions. Neither SA instruction nor SA diaries alone produced benefits relative to control. Multilevel analysis of 1,068 diary entries showed the combined intervention consistently promoted higher growth mindset throughout the intervention period. These findings suggest that learning SA principles and practicing SA skills simultaneously is crucial for intervention efficacy. Implications and limitations are discussed.

ARTICLE HISTORY
Received 28 October 2024
Accepted 9 July 2025

KEYWORDS
Self-assessment; self-assessment diary; self-assessment instruction; English language learning outcome; growth mindset

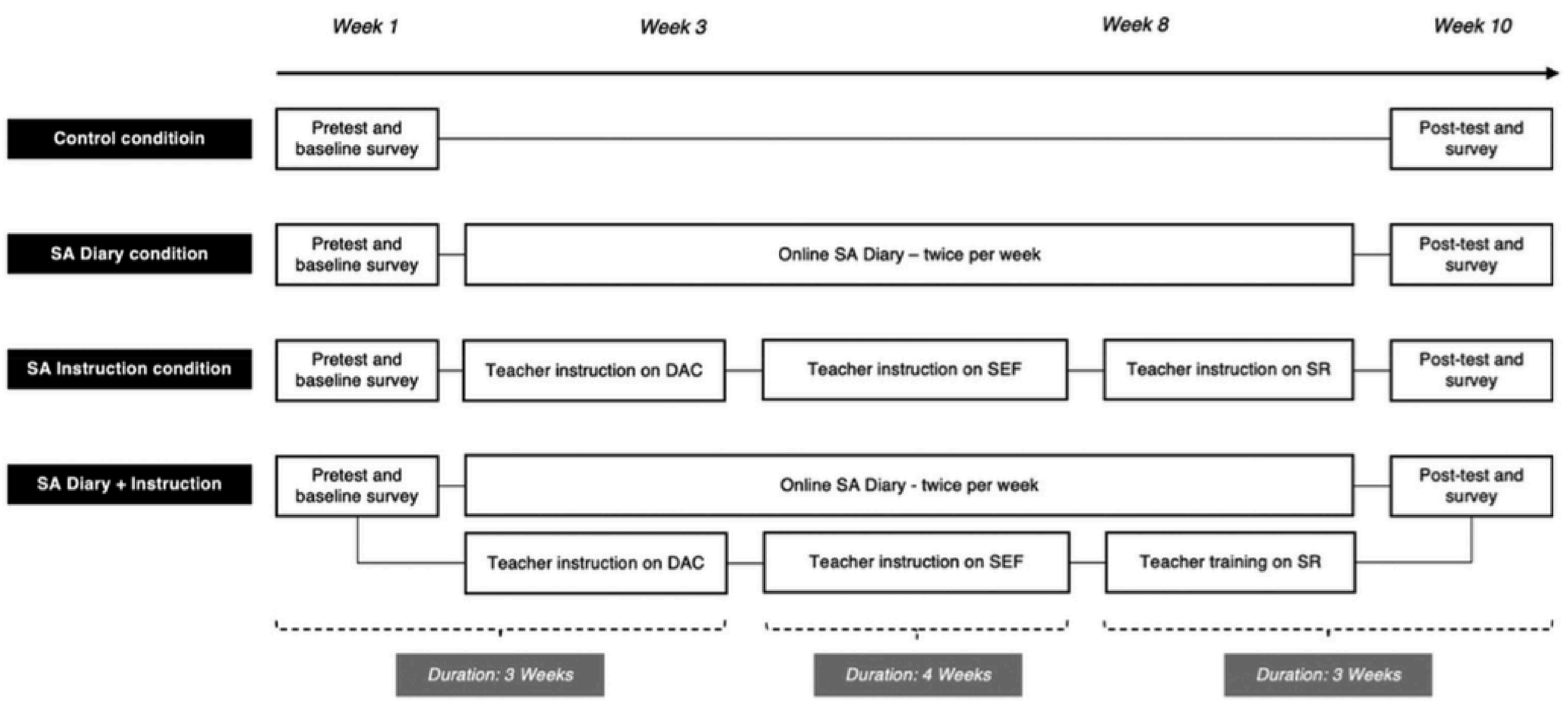

Figure 1. Details of the procedures.

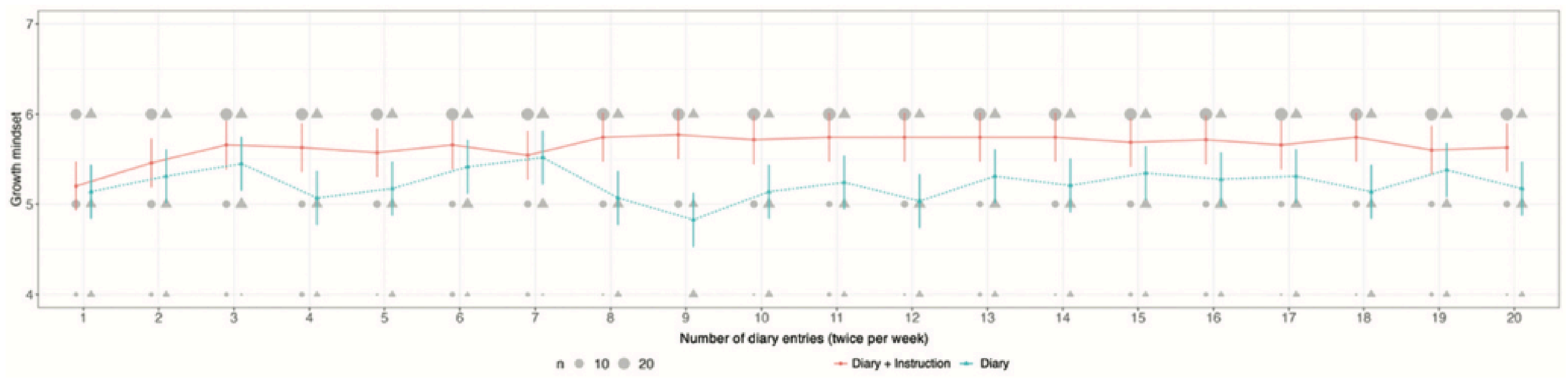

Figure 4. Trajectories of growth mindset over 20 data entries.

Let’s stary: bit.ly/MLMatBAU

A folder should download automatically to your downloads folder.

HANDS-ON WORKSHOP ON MULTILEVEL MODELING

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Norman B. Mendoza, PhD · May 2026
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Today's goal is to move from raw educational data to interpretable models.

01	02	03	04	05	06	07	08
Import	Inspect	Clean	Summarise	Visualise	Model	Interpret	Report

01 Import and inspect a dataset in R.

02 Clean variables for analysis.

03 Summarise student, course, and assessment data.

04 Create clear, publication-ready graphs.

05 Fit a basic random-intercept multilevel model.

06 Interpret fixed effects, random intercepts, ICC, and R^2.

07 Reuse scripts and templates for your own projects.

WHY R

R makes analysis transparent, reusable, and easier to audit.

MANUAL SPREADSHEET WORKFLOW

- Edits made directly in the data file
- Choices live in memory, not on paper
- Plots regenerated by hand
- Hard to rerun, hard to audit

SCRIPTED R WORKFLOW

- A script records every analytic decision
- Cleaning, analysis, and plots can be rerun
- Easier to reproduce for papers, theses, and grants
- Strong for surveys, assessments, and longitudinal data

A script is not extra work — it is the work, written down once.

DATA STRUCTURE

The first modeling decision is understanding what one row represents.

Dataset	One row means	Grouping structure
Course evaluation	One student response	Students within classes
Assessment scores	One student score record	Students within tutorial groups
Weekly wellbeing	One student at one week	Weeks within students
Course–site data	One student in one course/site	Students within sites

COMMON MISTAKE

One row is not automatically one independent observation.

CHOOSING A MODEL

Use the structure of the data to choose the model.

01 · Independent rows

One response per independent participant

Start with descriptives, plots, and ordinary regression.

```
lm(y ~ x)
```

02 · Nested in classes / sites

Students grouped inside classes, courses, or sites

Course evaluations, assessment scores in tutorial groups.

```
lmer(y ~ x + (1 | class_id))
```

03 · Repeated measures

Same students measured across time

Weekly wellbeing, confidence, or workload reports.

```
lmer(y ~ time + (1 | student_id))
```

04 · Effect depends on context

The student-level effect varies by class context

Teaching clarity may work differently by class climate.

```
lmer(y ~ x * class_context + (1 | class_id))
```

OPENING ACTIVITY

Before using R, classify the structure of the dataset.

DATASET A

Course evaluation survey

Students rate teaching clarity and engagement in different classes.

STRUCTURE

Students nested in classes → basic MLM.

DATASET B

Pre/post assessment

Students taught in tutorial groups complete pre- and post-tests.

STRUCTURE

Students nested in tutorial groups → basic MLM with pre-test adjustment.

DATASET C

Weekly wellbeing survey

The same students report wellbeing each week during a rotation.

STRUCTURE

Repeated measures within students → repeated-measures MLM.

YOUR TURN

For your own dataset — what is one row?

We will use three sample datasets and one annotated R script.

Files you receive

CSV	course_evaluation.csv	survey data
CSV	assessment_scores.csv	pre/post scores
CSV	wellbeing_long.csv	weekly long format
.R	workshop_annotated_syntax.R	runnable script

Packages we will load

- **tidyverse** Import, clean, summarise, plot.
- **lme4** Multilevel models.
- **lmerTest** P-values for `lmer()`.
- **performance** ICC and R^2.
- **interactions** Plotting cross-level interactions.

STEP 01 · SETUP

Packages add the tools we need for cleaning, plots, and models.

```r
library(tidyverse)
library(lme4)
library(lmerTest)
library(performance)
library(interactions)
```

WHAT THIS CODE DOES

- `tidyverse` — data import, cleaning, summaries, graphs
- `lme4` — multilevel models
- `lmerTest` — p-values for `lmer()`
- `performance` — ICC and R^2
- `interactions` — interaction plots

STEP 01 · IMPORT

Importing data creates an object that R can analyse.

```r
survey <- read_csv("course_evaluation.csv")
```

`course_evaluation.csv` → `survey (R object)`

WHAT THIS CODE DOES

Reads the CSV file from disk

Stores it as `survey`

Keeps the original file unchanged

COMMON MISTAKE

The file must be in your working folder, or you must provide the full file path.

STEP 02 · INSPECT

Always inspect the dataset before changing it.

```r
glimpse(survey)
summary(survey)
dim(survey)
names(survey)
```

```
> glimpse(survey) Rows: 412 Columns: 6 $ student_id <chr> "S001"
"S002" ... $ class_id <chr> "C03" "C03" ... $ teaching_clarity <dbl>
4.2 3.8 4.5 ... $ engagement <dbl> 4.0 3.6 4.4 ... $ learning_climate
<dbl> 3.9 3.9 4.1 ...
```

WHAT THIS CODE DOES

- `glimpse()` — variable names and types
- `summary()` — quick descriptive summaries
- `dim()` — rows and columns
- `names()` — lists variables

YOUR TURN

Which variable is the outcome? Which one identifies the class?

Cleaning makes variables usable for summaries, graphs, and models.

```
survey_clean <- survey %>%
  mutate(
    class_id         = factor(class_id),
    engagement       = as.numeric(engagement),
    teaching_clarity = as.numeric(teaching_clarity),
    learning_climate = as.numeric(learning_climate)
  ) %>%
  drop_na(engagement, teaching_clarity, class_id)
```

WHAT THIS CODE DOES

Converts `class_id` into a grouping variable

Ensures engagement & clarity are numeric

Removes rows missing any required variable

COMMON MISTAKE

Do not model IDs as numeric scores. IDs should usually be factors.

Group summaries show whether classes differ before we model them.

```
survey_by_class <- survey_clean %>%
  group_by(class_id) %>%
  summarise(
    n               = n(),
    mean_engagement = mean(engagement),
    sd_engagement   = sd(engagement),
    .groups = "drop"
  )
```

class_id	n	mean	sd
C01	22	3.84	0.62
C02	19	4.12	0.55
C03	24	3.51	0.71
C04	21	4.05	0.49
C05	23	3.78	0.66

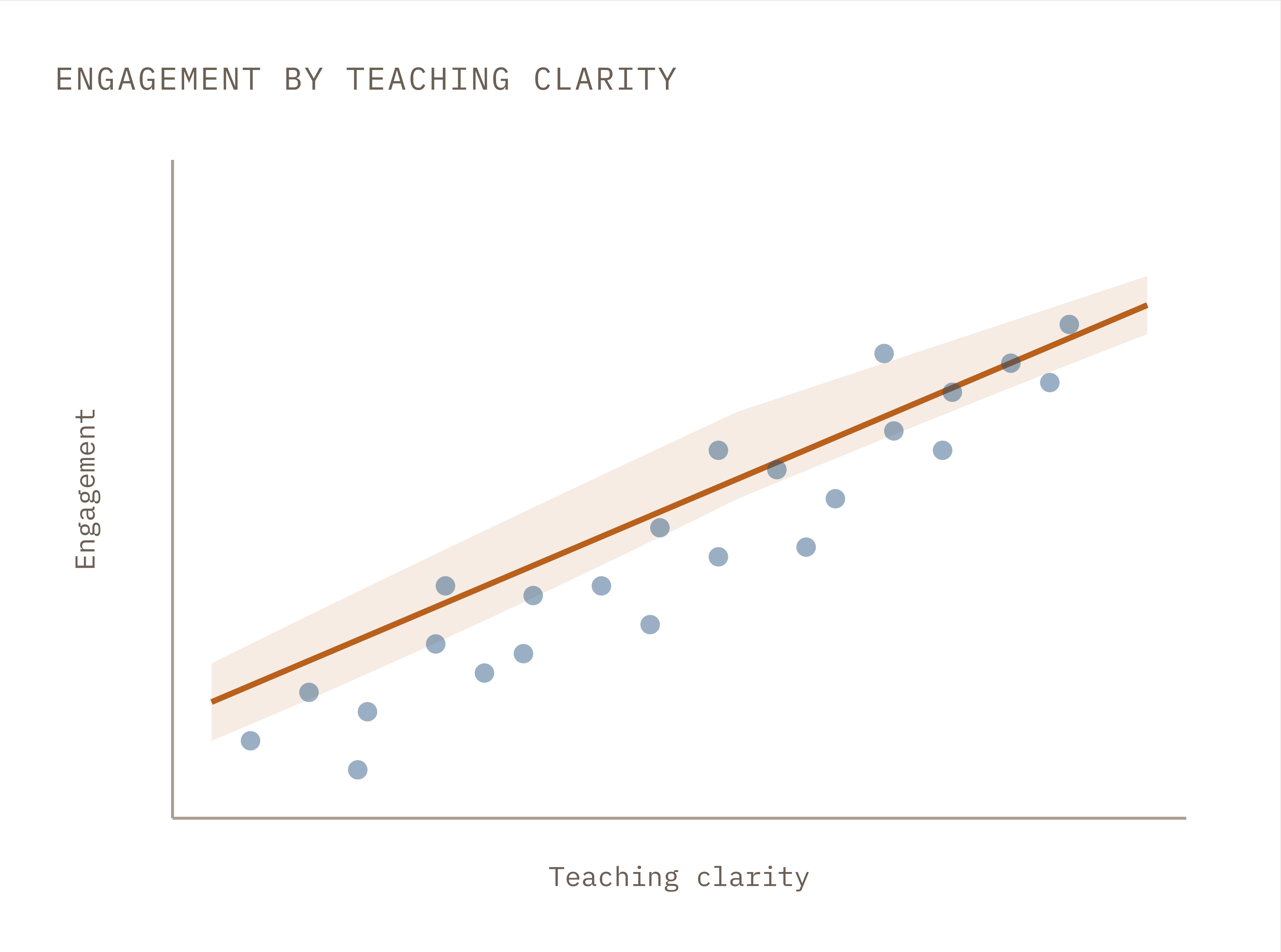
INTERPRETATION PROMPT

Do some classes appear to have higher engagement than others?

STEP 05 · VISUALISE

A plot helps us see the relationship before fitting the model.

```r
ggplot(survey_clean,
       aes(x = teaching_clarity, y = engagement)) +
  geom_point(alpha = .4) +
  geom_smooth(method = "lm", se = TRUE) +
  labs(x = "Teaching clarity",
       y = "Student engagement")
```



WHAT THIS CODE DOES

Each point is one student

The line shows the average trend

The shaded band shows uncertainty

YOUR TURN

Is the relationship positive, negative, or unclear?

Saving cleaned data makes the workflow reusable.

```
write_csv(survey_clean,
          "course_evaluation_clean.csv")
```

course_evaluation.csv
raw — never overwrite

→ script.R → course_evaluation_clean.csv

WHAT THIS CODE DOES

Saves the cleaned dataset to disk

Preserves the raw dataset as it was

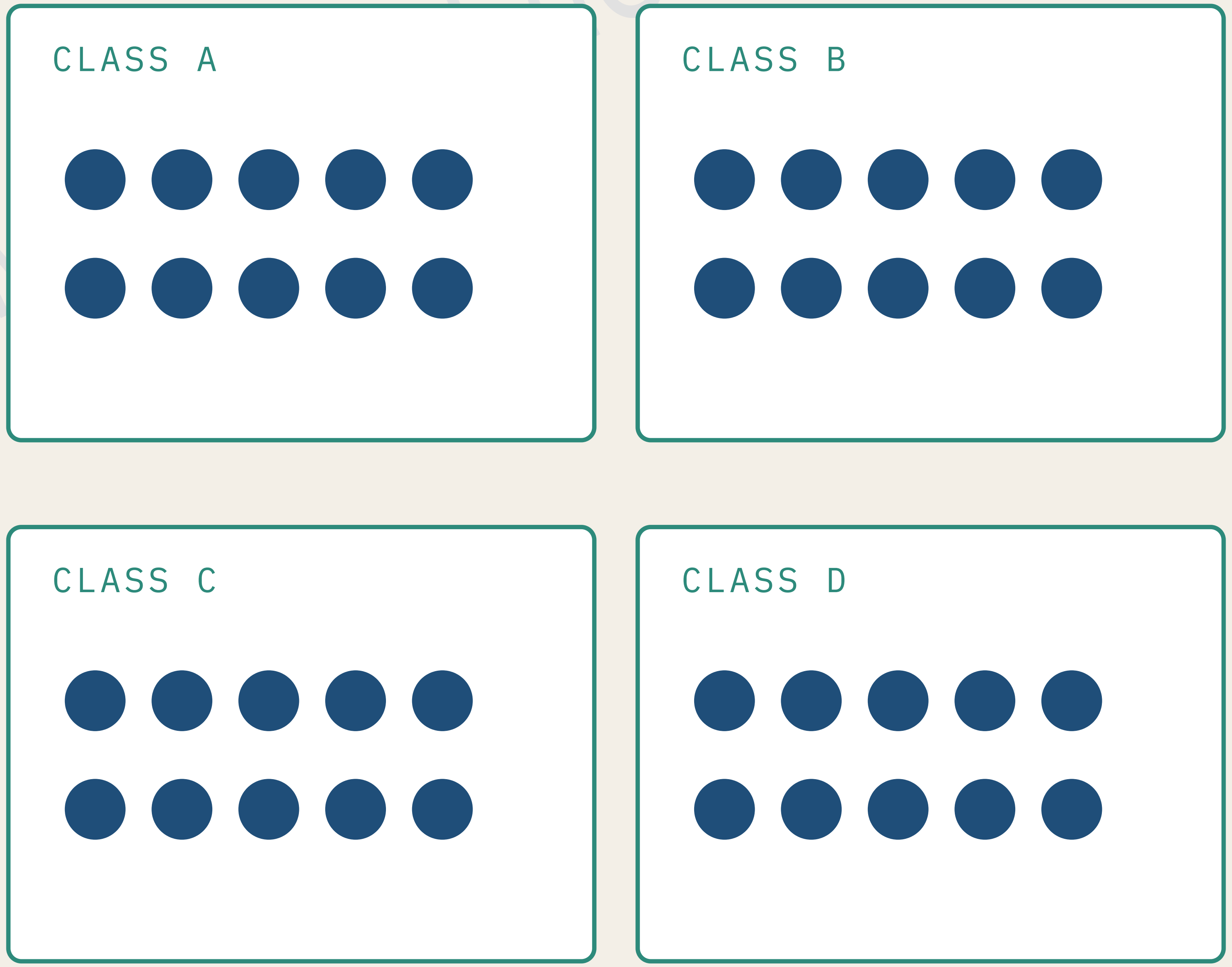
Makes later analyses easier to rerun

Students in the same class often share the same teaching context.

Students in the same class may share:

- the same teacher
- the same course design
- the same workload
- the same learning climate
- the same assessment schedule

Their responses may be more similar than responses from students in other classes.



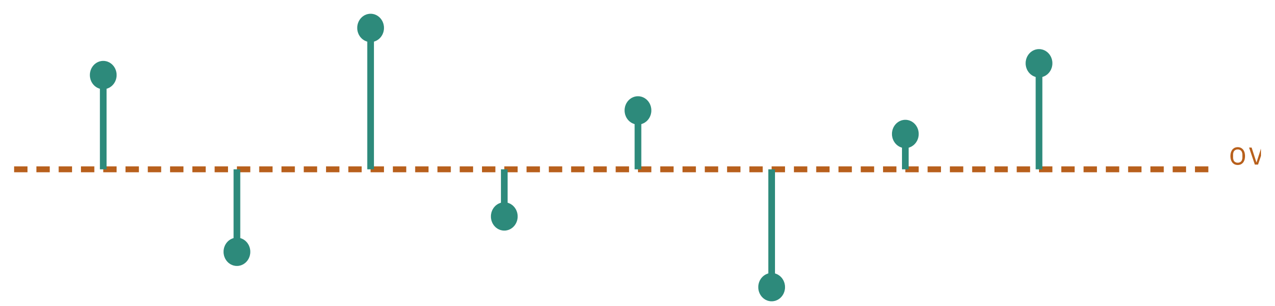
STEP 06 · MODEL

The null model asks whether engagement differs across classes.

```r
m0 <- lmer(
  engagement ~ 1 + (1 | class_id),
  data = survey_clean
)

summary(m0)
icc(m0)
```

CLASS DEVIATIONS FROM THE OVERALL MEAN



WHAT THIS MODEL MEANS

One overall engagement mean

Each class deviates from that mean

ICC = share of variance between classes

INTERPRETATION TEMPLATE

The ICC tells us what percentage of engagement differences are attributable to between-class differences.

STEP 06 · MODEL

The next model asks whether teaching clarity predicts engagement.

```r
m1 <- lmer(
  engagement ~ teaching_clarity + (1 | class_id),
  data = survey_clean
)

summary(m1)
r2_nakagawa(m1)
```

WHAT THIS MODEL DOES

Estimates the clarity → engagement relationship

Accounts for students nested in classes

Allows each class its own baseline engagement

engagement = teaching clarity effect + class difference + residual

The fixed effect is the average relationship across all classes.

Term	Estimate	Plain-language meaning
`teaching_clarity`	**+0.42**	Higher clarity is associated with higher engagement
`(Intercept)`	2.18	Average engagement when clarity is 0 (rescale for meaning)

EXAMPLE INTERPRETATION

Students who report higher teaching clarity tend to report higher engagement, after accounting for class clustering.

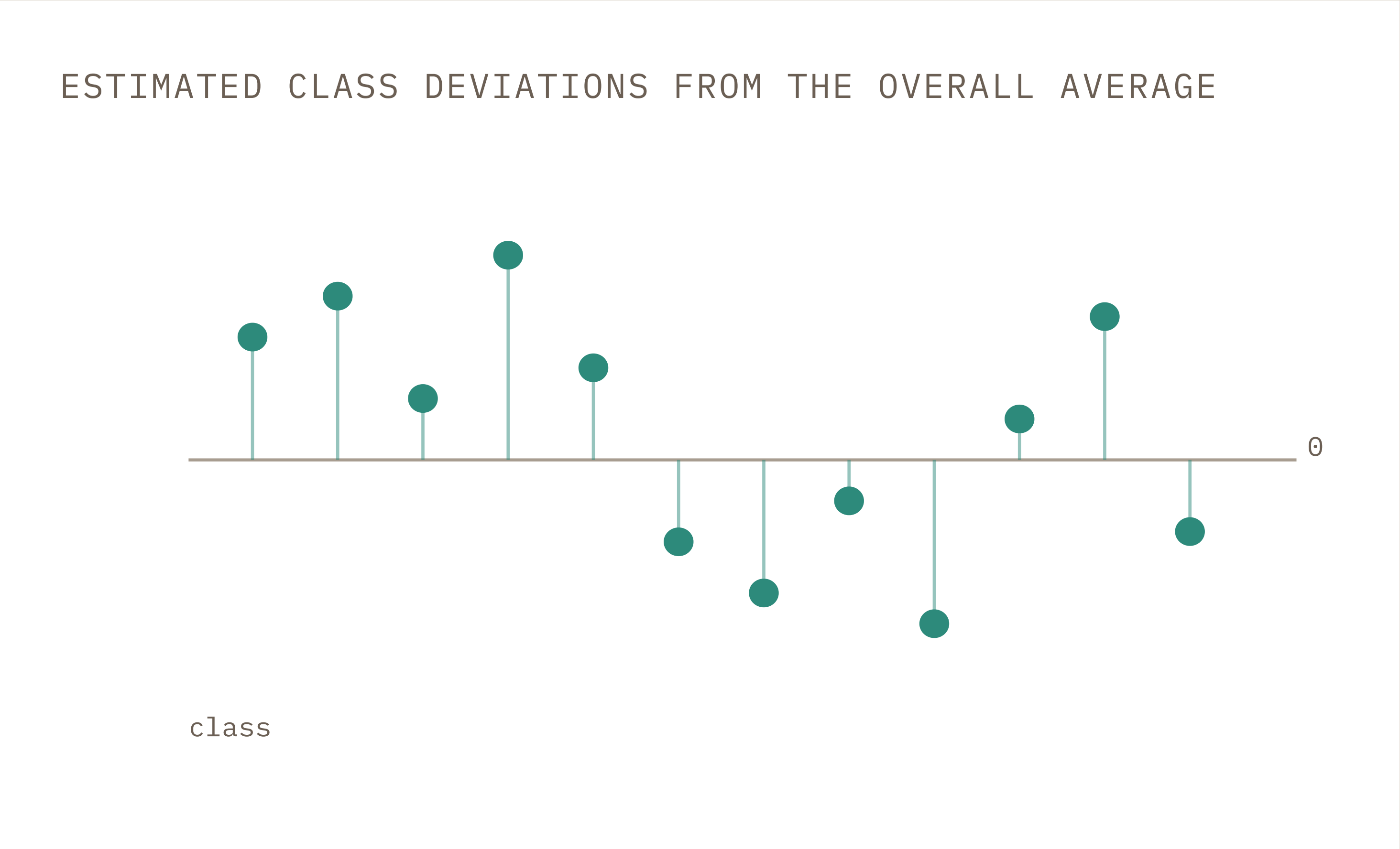
COMMON MISTAKE

Do not say teaching clarity *causes* engagement unless the study design supports causality.

STEP 07 · INTERPRET

The random intercept shows that classes differ in average engagement.

- Some classes are above the overall average.
- Some classes are below the overall average.
- The model accounts for these class-level differences.



STEP 08 · REPORT

Report the model by linking the structure to the interpretation.

> *"Because students were nested within classes, we fitted a random-intercept multilevel model with class as the grouping variable. The ICC indicated that* __ *% of the variance in engagement was attributable to between-class differences. Teaching clarity was* positively / negatively / not *associated with engagement after accounting for class-level clustering."*

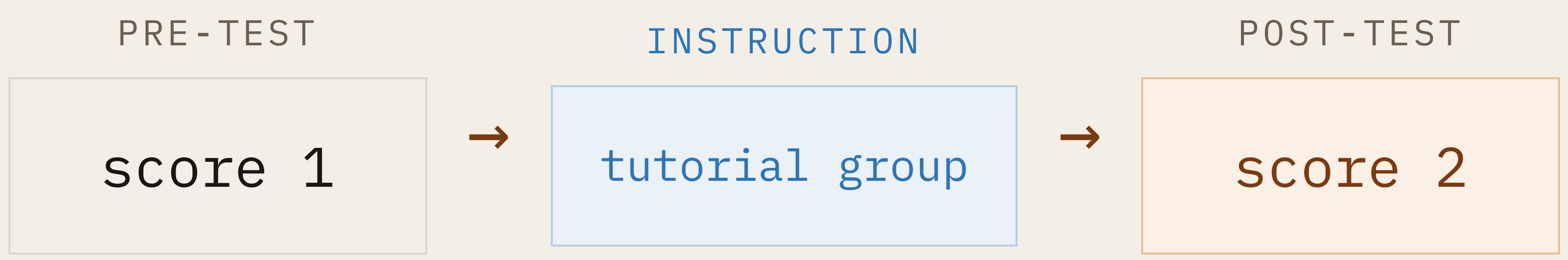
YOUR TURN

Write one sentence interpreting the teaching clarity coefficient.

Assessment data often contain students nested in tutorial groups or sites.

> Do post-test clinical reasoning scores differ across tutorial groups *after controlling for pre-test scores*?

- One row = one student assessment record
- Outcome = `post_score`
- Predictor = `pre_score`
- Grouping variable = `group_id`
- Optional predictor = `intervention`



STEPS 01–03

Import the assessment file, then clean variables before any modelling.

```
assessment <- read_csv("assessment_scores.csv")

assessment_clean <- assessment %>%
  mutate(
    group_id     = factor(group_id),
    intervention = factor(intervention),
    pre_score    = as.numeric(pre_score),
    post_score   = as.numeric(post_score)
  ) %>%
  drop_na(group_id, pre_score, post_score)
```

WHAT THIS CODE DOES

Imports the dataset

Converts group and intervention to factors

Ensures pre/post scores are numeric

Drops missing values for key variables

Summarise scores by group to see whether groups differ before and after.

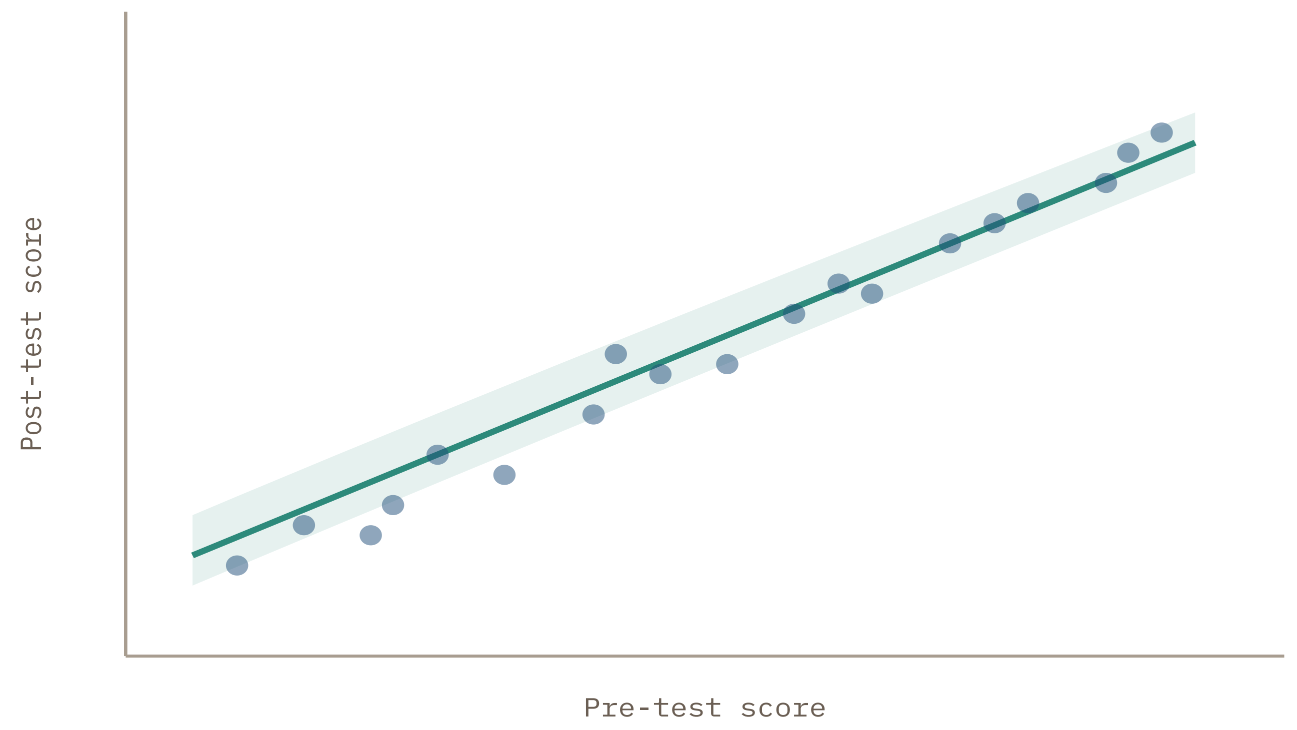
```
assessment_clean %>%
  group_by(group_id, intervention) %>%
  summarise(
    n         = n(),
    mean_pre = mean(pre_score),
    mean_post= mean(post_score),
    .groups   = "drop"
  )
```

group_id	intervention	n	mean_pre	mean_post
G01	control	14	62.4	68.1
G02	control	15	60.9	66.5
G03	treatment	13	61.7	74.8
G04	treatment	16	63.0	76.2
G05	treatment	14	59.8	72.4

A scatterplot reveals the pre–post relationship at a glance.

```
ggplot(assessment_clean,
       aes(x = pre_score, y = post_score)) +
  geom_point(alpha = .4) +
  geom_smooth(method = "lm", se = TRUE) +
  labs(x = "Pre-test score",
       y = "Post-test score")
```

POST-TEST BY PRE-TEST



YOUR TURN

Do students with higher pre-test scores tend to have higher post-test scores?

STEP 06 · MODEL

The adjusted model accounts for baseline performance and group clustering.

```r
m0 <- lmer(post_score ~ 1 + (1 | group_id),
           data = assessment_clean)
icc(m0)

m1 <- lmer(post_score ~ pre_score + (1 | group_id),
           data = assessment_clean)
summary(m1)
r2_nakagawa(m1)
```

WHAT THIS MODEL DOES

Controls for the pre-test score

Accounts for students nested in tutorial groups

Estimates group-level differences in post-test scores

```
post_score = pre_score effect + group difference + residual
```

Add an intervention predictor to compare conditions.

```
m2 <- lmer(
  post_score ~ pre_score + intervention
             + (1 | group_id),
  data = assessment_clean
)

summary(m2)
```

INTERPRETATION

`pre_score` — expected post-test difference associated with baseline performance

`intervention` — expected post-test difference between intervention and control, adjusted for pre-score and group clustering

COMMON MISTAKE

Do not interpret intervention causally unless the intervention was assigned in a design that supports causal inference.

STEP 08 · REPORT

Reporting template for the adjusted assessment model.

> *"Post-test scores were modelled as a function of pre-test scores, with students nested within tutorial groups. The pre-test coefficient indicates the expected difference in post-test score associated with a one-unit difference in baseline performance. The random intercept accounted for between-group differences in average post-test scores."*

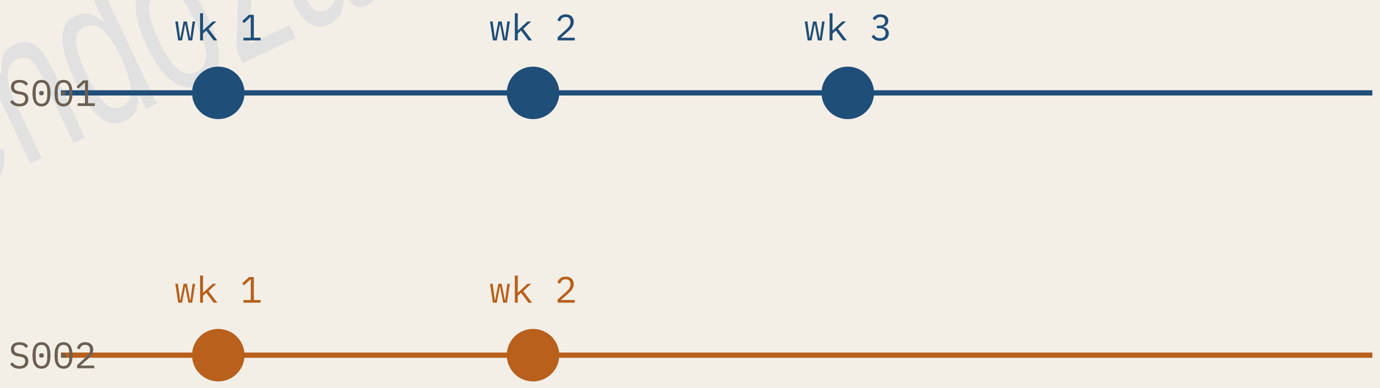
YOUR TURN

Write one sentence interpreting the pre-test coefficient.

Repeated-measures data usually need one row per person per time point.

student_id	week	wellbeing
S001	1	3.8
S001	2	3.7
S001	3	3.5
S002	1	4.1
S002	2	4.0

The same student appears in multiple rows.



STEPS 01–04

Import, clean, and summarise the wellbeing data.

```
wellbeing <- read_csv("wellbeing_long.csv")

wellbeing_clean <- wellbeing %>%
  mutate(
    student_id = factor(student_id),
    week       = as.numeric(week),
    wellbeing  = as.numeric(wellbeing)
  ) %>%
  drop_na(student_id, week, wellbeing)

wellbeing_clean %>%
  group_by(week) %>%
  summarise(
    n              = n(),
    mean_wellbeing = mean(wellbeing),
    sd_wellbeing   = sd(wellbeing)
  )
```

WHAT THIS CODE DOES

Imports the long-format wellbeing data

Converts `student_id` to a factor

Ensures `week` and `wellbeing` are numeric

Removes rows missing any required variable

Summarises wellbeing by week

Plot individual trajectories to see repeated measures directly.

```
ggplot(wellbeing_clean,
       aes(x = week, y = wellbeing,
           group = student_id)) +
  geom_line(alpha = .2) +
  geom_smooth(aes(group = 1),
              method = "lm", se = TRUE) +
  labs(x = "Week", y = "Wellbeing")
```

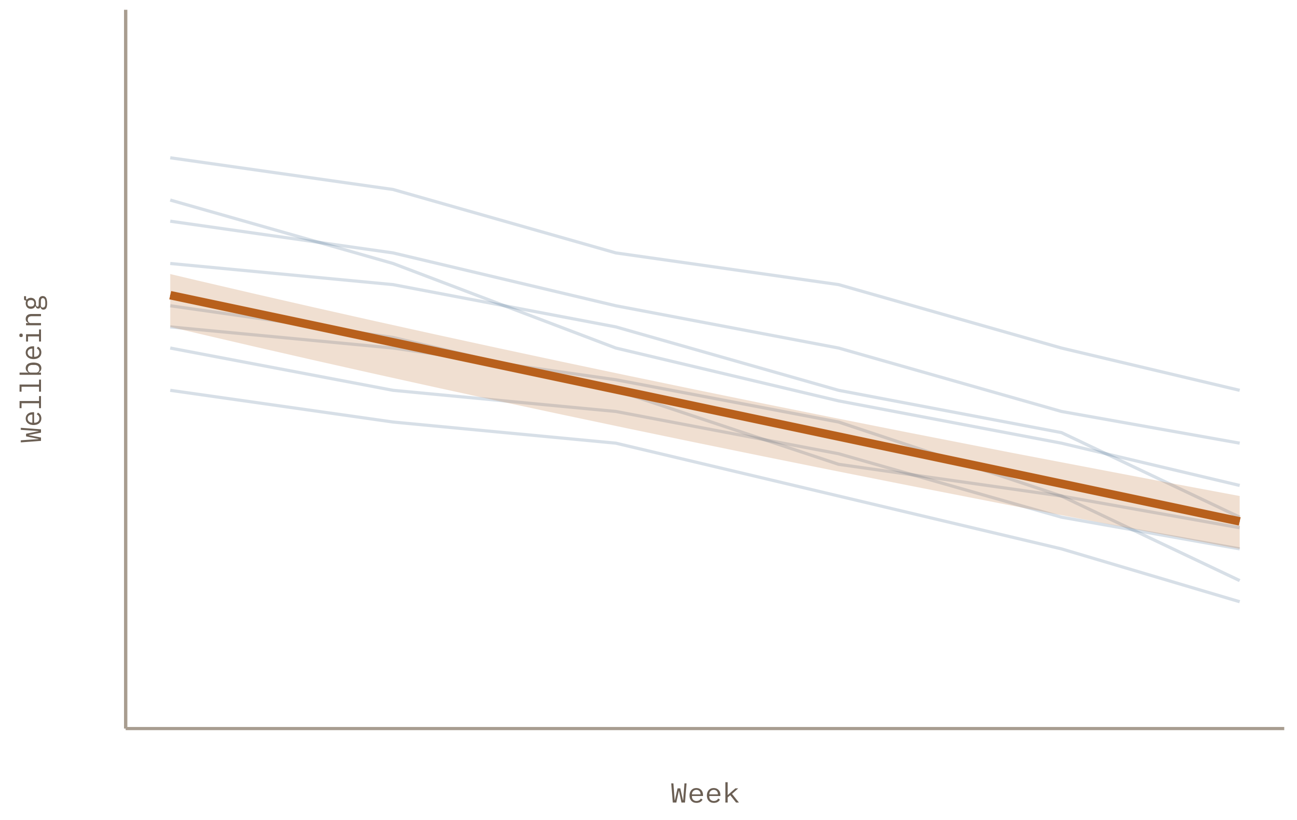
WHAT THE PLOT SHOWS

Thin lines — individual students

Thick line — average trend

Repeated measures — each student has multiple rows

WELLBEING OVER WEEKS — INDIVIDUAL TRAJECTORIES



STEP 06 · MODEL

Random intercepts let students start at different baseline levels.

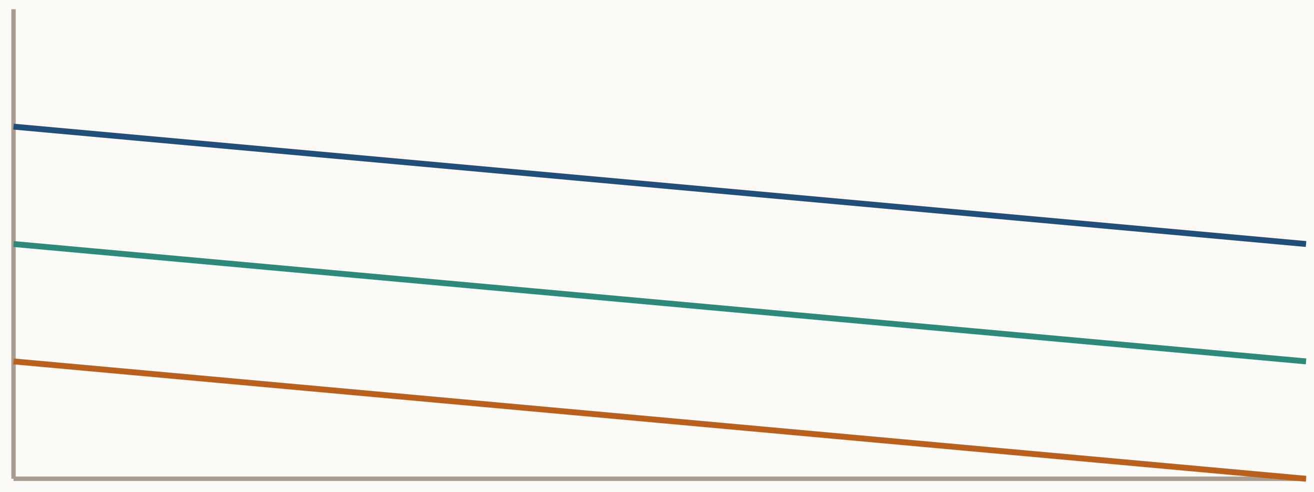
```
m0 <- lmer(wellbeing ~ 1 + (1 | student_id),
           data = wellbeing_clean)
icc(m0)

m1 <- lmer(wellbeing ~ week + (1 | student_id),
           data = wellbeing_clean)
summary(m1)
r2_nakagawa(m1)
```

INTERPRETATION

Random intercept — students differ in baseline wellbeing

Week coefficient — average change in wellbeing per week



OPTIONAL PREVIEW

Random slopes let students change at different rates.

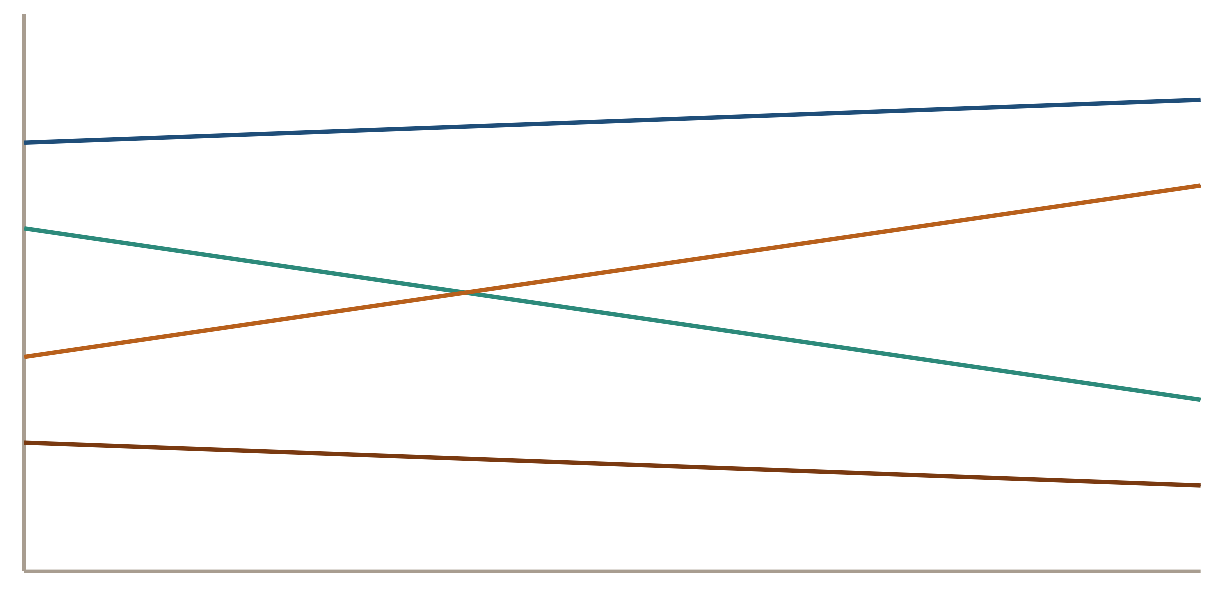
```
m2 <- lmer(
  wellbeing ~ week + (week | student_id),
  data = wellbeing_clean
)
```

IN PLAIN LANGUAGE

Random intercept model — students start at different levels

Random slope model — students may also change at different rates

DIFFERENT STARTING POINTS AND SLOPES

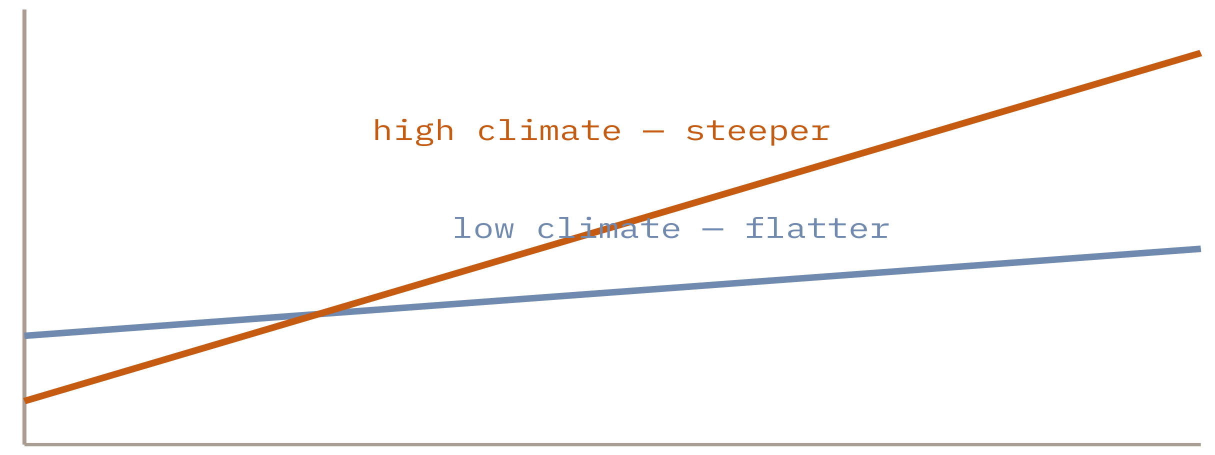


A cross-level interaction asks whether a student-level relationship changes by class context.

> Does the relationship between teaching clarity and engagement depend on class learning climate?

- **Student-level predictor** — teaching clarity → engagement
- **Class-level moderator** — class learning climate
- **Interaction** — learning climate changes the slope

SLOPE BY CLASS CLIMATE



Build a class-level moderator and centre the student-level predictor.

```
survey_cross <- survey_clean %>%
  group_by(class_id) %>%
  mutate(
    class_climate       = mean(learning_climate, na.rm = TRUE),
    teaching_clarity_c = teaching_clarity
                         - mean(teaching_clarity, na.rm = TRUE)
  ) %>%
  ungroup()
```

WHAT THIS CODE DOES

Creates `class_climate` as the class average of learning climate

Creates `teaching_clarity_c` centred within class

Allows testing whether class climate changes the student-level slope

CAUTION

Avoid using the same item set to define the class-level moderator *and* the outcome unless theoretically justified.

Build the model in three steps: basic, context, interaction.

```r
m_basic <- lmer(
  engagement ~ teaching_clarity_c
             + (1 | class_id),
  data = survey_cross)

m_context <- lmer(
  engagement ~ teaching_clarity_c + class_climate
             + (1 | class_id),
  data = survey_cross)

m_interaction <- lmer(
  engagement ~ teaching_clarity_c * class_climate
             + (1 | class_id),
  data = survey_cross)

summary(m_interaction)
```

STEP 1 · BASIC
Student-level predictor only.

STEP 2 · CONTEXT
Add class-level main effect.

STEP 3 · INTERACTION
Test whether the slope varies by climate.

WHAT THIS ASKS

Does the teaching-clarity → engagement relationship differ depending on class learning climate?

STEP 07 · INTERPRET

Plot the interaction, then interpret the slope by class climate.

```
interact_plot(
  m_interaction,
  pred = teaching_clarity_c,
  modx = class_climate,
  plot.points = TRUE,
  x.label = "Teaching clarity",
  y.label = "Student engagement",
  legend.main = "Class learning climate"
)
```

IF POSITIVE

Teaching clarity is more strongly associated with engagement in classes with stronger learning climate.

IF NEGATIVE

Teaching clarity is less strongly associated with engagement in classes with stronger learning climate.

IF NON-SIGNIFICANT

The association between teaching clarity and engagement does not appear to differ meaningfully by class climate.

Three reporting templates: structure, predictor, grouping, interpretation.

BASIC MLM

Because students were nested within classes, we fitted a random-intercept multilevel model with class as the grouping variable. The ICC indicated that __ *% of the variance in* outcome *was attributable to between-class differences.* Predictor *was* positively / negatively / not *associated with* outcome*, after accounting for class-level clustering.*

REPEATED MEASURES

Because each student provided repeated observations over time, we fitted a random-intercept model with student as the grouping variable. The coefficient for week indicates the average change in outcome *per week.*

CROSS-LEVEL INTERACTION

The interaction tested whether the association between student-level predictor *and* outcome *differed depending on* class-level moderator*. A positive interaction indicates that the student-level association was stronger in classes with higher* moderator*.*

TAKE IT HOME

Use the same logic for your own dataset.

01 What is one row in my dataset?

02 What is the outcome?

03 What is the student-level predictor?

04 What is the grouping variable?

05 Is the structure nested or repeated?

06 What is the simplest null model?

07 What does the ICC mean here?

08 What predictor should I add first?

09 How would I interpret the fixed effect in one sentence?

10 What do I need to report?

MATERIALS

The take-home materials are designed to be adapted.

.R	Annotated R script	runnable, well commented
CSV	Three sample datasets	survey · assessment · wellbeing
CSV	Cleaned-data export example	reproducibility check
DOC	Basic MLM reporting templates	for papers and theses
DOC	Cross-level interaction template	for moderation write-ups
PDF	Participant worksheet	10 questions for your data

HANDS-ON WORKSHOP ON MULTILEVEL MODELING

Harnessing R for Medical Education Research

From data preparation to multilevel models.

Norman B. Mendoza, PhD · **May 2026**
Assistant Professor, C&I

CLOSING

Start simple: clean the data, plot the pattern, then fit the model that matches the structure.

01 R scripts make analyses transparent and reusable.

02 Always inspect and clean data before modelling.

03 Start with plots and group summaries.

04 Use MLM when students are nested in classes, sites, or repeated over time.

05 Interpret models in plain language: predictor, outcome, grouping structure, and claim.

“The goal is not to make models more complicated. The goal is to make the analysis match the data structure.”

Prepared by Dr Noman B. Mendoza. EdUHK 2026